Evaluating heterogeneous effects of housing-sector-specific macroprudential policy tools on Belgian house price growth

Lara Coulier[1], Selien De Schryder[2]

Department of Economics, Ghent University, Sint-Pietersplein 5, 9000 Ghent, Belgium

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Abstract

This paper sheds more light on the heterogeneity of the effects of national macroprudential policy changes on local house price growth. More specifically, we employ an extensive dataset of Belgian municipalities containing a multitude of drivers of local house price dynamics and examine the potential heterogeneity of housing-related macroprudential policy changes driven by local characteristics related to financially constrained and high-risk residents, the degree of local housing market activity, and changes in local household mortgage indebtedness. Our results point to more dampening effects of the common macroprudential policy tightenings on local house price growth for municipalities characterized by low-income and young (i.e., more risky) residents, which increase in hot housing markets. Housing-related macroprudential tools are thus found to lower house price growth in hot local housing markets characterized by more financially-constrained and high-risk households while having less drastic effects in other local markets. Our findings therefore indicate the possibility to stabilize local housing market booms.

Keywords: macroprudential policy, local housing markets, heterogeneity, dynamic panel data, quantile regressions

JEL-Classifications: C22, C23, E58, O18, R3

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[1]Lara.Coulier@UGent.be
[2]Selien.Deschryder@UGent.be

1. Introduction

Housing markets are often at the center of policymakers' attention, not in the least since the start of the Global Financial Crisis (GFC), and this for good reason. First, housing market dynamics can importantly impact overall economic activity. From the perspective of households, housing typically represents the largest liability which makes that volatility in housing markets is associated with sizable income and wealth effects. Housing-related consumption further accounts for a substantial part of total private consumption, mounting to 25.7 per cent of households' total final consumption expenditures in the European Union in 2020 which in turn represents 13 per cent of GDP (Eurostat, 2022). Second, housing itself of course also represents the basic human need for a safe and decent place to live. Ensuring housing affordability is thus a key priority for politicians and constitutes a prime component of national housing policies. Especially in the light of increasing house prices, the ability to take on a mortgage, i.e., to leverage, crucially enables households to purchase a house and contributes to housing affordability. High or rapidly increasing levels of leverage in the aggregate, however, represent financial vulnerabilities for the economy. Through the high importance of housing loans for bank lending (Jordà et al., 2016), there is a systemic risk dimension associated with dynamics in housing markets. House price dynamics are hence important for both macroeconomic and financial stability given the effects on household wealth and consumption, and the importance of housing-related loans in total bank lending.

Given the inherent dangers of housing market bubbles for financial and macroeconomic stability, macroprudential policymakers have several instruments at their disposal that are specifically targeted at the mortgage and housing market. These instruments have the explicit goal to dampen the vicious feedback loops between the housing market, financial intermediaries, and the real economy. The different tools furthermore complement each other. An increase in bank capital requirements for residential mortgages offers a direct way to strengthen the resilience of banks to house price busts. Limits to loan-to-value (LTV) and loan-to-income (LTI) ratios on the other hand can be considered to serve as entry barriers in the mortgage market for borrowers, lowering the proportion of risky borrowers in the overall market. Debt-to-income (DTI) and debt-service-to-income (DSTI) caps are likewise directed to creating a buffer that allows borrowers to better withstand income and interest rate shocks throughout the mortgage. The borrower-based tools (LTV, LTI, and D(S)TI caps) hence target the level of indebtedness of mortgagors in different ways but with the aim to lower the vulnerability of lenders to adverse housing market dynamics, as is the case for increased capital requirements.

While the attention is mainly focused on these measures' effects on the vulnerability of financial institutions to housing market risks, the macroprudential tools targeting the housing market can also noticeably affect residential house price dynamics to the extent that the measures significantly affect households' financing conditions, which are considered to be one of the main indicators of residential house price changes (Duca et al., 2016). If one looks at the macro literature on the effects of these tools on house prices, however, the evidence tends to be rather mixed. Some papers find no effects, while others point to significant but relatively small effects. For example, using a large panel of advanced and emerging countries, Cerutti et al. (2017) find that borrower-based macroprudential policy tools (i.e., LTV and DTI limits) are associated with lower house prices and household credit growth, although not in a significant way for house prices. Kuttner and Shim (2016) similarly focus on credit and tax policies targeting the housing sector and conclude that tightenings jointly have a strong effect on household credit growth while growth in real house prices is only significantly lowered by tax increases. Alam et al. (2019) find in addition significant impacts of loan-targeted demand instruments (such as LTV and DSTI limits) on house prices for a group of advanced economies.

A caveat in these studies based on country-level data is that they can only make conclusions about the average effects of macroprudential policy instruments on house prices. It is, however, well-known that housing markets are segmented in nature as they respond to a wide array of demand and supply-side factors that vary by location (Case and Shiller, 2003, Glaeser et al., 2008, Beraja et al., 2018) next to reflecting different sensitivities to common shocks (Del Negro and Otrok, 2007). In addition, the macroprudential tools targeting mortgage borrowers do not target the overall mortgage market, but specifically the high-risk borrowers which might be active in specific segments of the housing market.

In this work, we therefore explicitly zoom in on the potential heterogeneities of country-wide macroprudential policies on local house price dynamics driven by local housing market characteristics and residents' financing constraints. More specifically, we estimate the effects of the National Bank of Belgium's (NBB) policy actions concerning housing market-related risks (see infra, section 2.3) on municipality-level house price growth rates and examine whether and to which extent these rates are affected in a heterogeneous way depending on indicators of housing financing constraints, the hotness of the municipal housing market, and household indebtedness. We allow for heterogeneous effects by considering interactions terms of these local characteristics and the common macroprudential measures and carrying out quantile regressions whilst accounting for house price growth determinants at the local level. This analysis contributes to the economic literature in different ways. First, knowledge on the impact of the macroprudential tools on local house price dynamics gives a better insight in the heterogeneity of the effects of common macroprudential measures. Such heterogeneity can be unnoticed based on average effects but can eventually also blur these averages. Second, knowledge on the driving factors of these geographic heterogeneous effects offers valuable information for policymakers having to deal with local housing market bubbles and/or having an interest into the distribution of the effects.

Our work relates to the small number of recent papers that have focused on heterogeneous effects of country-wide macroprudential policy (see infra, section 2.2). Moreover, it is close to the earlier studies that document a sizeable impact of regional housing market heterogeneity on the effects of nation-wide monetary policy. Fratantoni and Schuh (2003) for example have documented that the effectiveness of common monetary policy shocks depends on regional heterogeneous housing market conditions, despite the fact that monetary policy does not target those regional conditions. More recently, Beraja et al. (2018) outlined that the regional distribution of housing equity crucially determines the aggregate impact of monetary policy and can exacerbate pre-existing cross-regional variation in economic activity.

The remainder of the paper is structured as follows. First, we discuss in section 2 the literature on the local heterogeneity of house price growth and on the effects of housing-related macroprudential regulation on local housing markets. This is followed by an overview of the housing market-related measures that the NBB has taken since 2013. In section 3, we describe the baseline model, the employed data series, and the baseline model estimates. Next, we introduce quantile regressions to consider potential heterogeneous reactions depending on the magnitude of house price changes and discuss their outcome in section 4. We report the results of a large set of robustness checks in section 5. Finally, the conclusions are presented in section 6.

2. Local housing market dynamics and macroprudential policy

2.1. Heterogeneity of local house price growth

Given the importance of housing market dynamics for financial stability, the focus of this paper is on house price growth rates following, among others, Peydró et al. (2020) and Acharya et al. (2022). In our analysis, we want to account for the driving factors of house price dynamics. The literature on these drivers is vast and offers multiple candidates linked to either the demand for or the supply of houses. On the demand side, the conventional macroeconomic factors concern income, (un)employment, interest rates, and demography (Case and Shiller, 2003). Typical supply-side factors are the existing housing stock, construction costs, and housing market regulation (Favara and Imbs, 2015).

Traditionally, macroeconomic research has mainly put the focus on country-wide house prices, in part due to data availability. Standard dynamic urban real estate models instead highlight that most variation in house prices is local in nature rather than national. Regional data allow to take account of the (more) sizeable variation of local house price changes (Glaeser et al., 2014, Favara and Imbs, 2015, Galati and Teppa, 2017).

The geographical location of houses and the associated amenities are typically taken to be the driving factors of heterogeneity in local housing markets (Gao et al., 2009) and are considered to be relatively constant over time. Heterogeneity in local house price dynamics can, however, further be driven by local variation in the standard house price determinants such as income per capita, local economic activity, credit availability and conditions, construction costs, housing market regulation, demographic factors, and the tax treatment of homeowners (see infra, section 3.4). To examine the potentially different effects of macroprudential policies on local house price dynamics, we hence need to take into account the time and geographic variation in these drivers.

2.2. Related findings on macroprudential policy and local housing markets

A small number of recent papers have focused on the heterogeneous effects of macroprudential policies on housing markets. Catapano et al. (2021) for example document small aggregate effects of LTV and DSTI caps on house prices in an agent based model for Italy, but signal sizeable different effects depending on the quality of houses and the degree to which the borrowers are constrained. In particular, the authors document a shift in housing demand towards lower quality houses for which prices decline relatively less following the measures as well as differential effects for different income quantiles. These theoretically derived heterogeneous effects are also found in the work of Acharya et al. (2022) on Irish data where county-level house price growth rates differed after the implementation of LTV and LTI limits driven by a re-allocation of credit to counties with borrowers further away from the limit (typically high-income borrowers in rural counties) and away from counties with borrowers closer to the lending limits (typically low-income borrowers in urban counties). In particular, house price growth is found to be lowered in counties with borrowers closer the limit, whereas the growth rate remained stable for high-distance counties. Peydró et al. (2020) similarly find dampening effects of a limit on new high-LTI mortgages on house price growth in the UK in local areas with more constrained lenders and more low-income borrowers. Both Peydró et al. (2020) and Acharya et al. (2022) provide evidence for a heterogeneous impact depending on the type of property as the downward effects on house price growth are respectively found to be larger for the lower-end of the distribution of housing transaction prices and for small properties.

These findings are in line with the study of Tzur-Ilan (2020) which shows that the imposed Israeli LTV-based limits in 2010 and 2012 have impacted the location choice of houses, i.e. away from the center and towards lower socioeconomic neighborhoods, for those borrowers that were affected by the limit. Laufer and Tzur-Ilan (2021), using the Israeli data as well, moreover document a larger impact of the 2010 LTV-based risk weights limits on house prices in the more expensive parts of the country and especially for the lower-quality houses within these areas. Considering the Belgian experience, Damen and Schildermans (2022) document that prices for houses located closer to a local bank that is constrained by the Belgian risk weight add-on on housing loans (see infra, section 2.3) declined significantly. Whereas these works are based on loan-level data combined with housing characteristics, our paper relies on municipality-level data. On the one hand, we are forced to do so since a merge of Belgian datasets on individual residential mortgage loans, housing characteristics, ánd borrower information is not (yet) possible up to this date. On the other hand, the use of municipality-level data allows to focus more explicitly on the regional heterogeneity of the effects of common macroprudential housing regulation, similar to the above-mentioned papers related to monetary policy (see supra, section 1).

2.3. The Belgian experience

The NBB has introduced multiple instruments to explicitly stimulate financial institutions to be more prudent in their residential mortgage lending policies. First, the NBB has focused on regulatory risk weights of Belgian mortgage loans. The NBB imposes since 8 December 2013 an add-on to the risk weights used to calculate capital buffers on Belgian residential real estate exposures based on internal models (i.e., for banks following the internal ratings-based (IRB) approach, which are responsible for more than 90% of all mortgages (Damen and Schildermans, 2022)). The NBB took this decision based on its sectoral analysis of risk weights on mortgage loans of Belgian banks, conducted in 2012, which signalled that risk weights employed by IRB banks were not only lower than the ones based on the standardized approach but also low relative to other European countries. The NBB considered this worrisome in an environment of an increasing debt ratio of Belgian households and an overvaluation of house prices in Belgium. Hence, since December 2013, a flat add-on of 5 percentage points for IRB models has been in place. On 30 April 2018, this regulatory risk weight got replaced by a more strict regulation based on a general and targeted component. The general component contains the flat add-on of 5 percentage points for IRB banks while the targeted component concerns a risk-sensitive add-on based on a multiplication of the microprudential risk weights by a factor of 1.33. The aim of the targeted component is to especially reduce the share of loans with a high risk profile, which was considered to be too high.

Next, from 1 January 2020 onward, the NBB has implemented its so-called prudential expectations for banks and insurance companies which relate new mortgages to certain caps on the LTV ratio, and combinations of the LTV with DTI and DSTI ratios (NBB, 2022). The prudential expectations contain thresholds for LTV ratios, being 80% for buy-to-let loans and 90% for owner-occupied loans, representing the idea that loans with higher LTV ratios are more risky. For both types of loans, the NBB has foreseen in tolerance margins which are wider for owner-occupied loans than for buy-to-let loans and with a distinction between first-time buyers and other buyers for the owner-occupied loans. In addition, the prudential expectations provide thresholds for combinations of a high LTV ratio (i.e., more than 90%) with either a DSTI above 50% or a DTI ratio above 9, associated with a fixed tolerance margin of 5%. These prudential expectations originated from the continued easing of credit conditions for Belgian mortgage loans and came on top of the risk weights on Belgian mortgage loans.

3. Data and baseline model

This section starts with an introduction of the data and the baseline econometric model used in our analysis. First, we elaborate on the measurement of the two main variables of interest, being local house price dynamics (section 3.1) and the Belgian housing-related macroprudential tools (section 3.2). Next, we present the baseline econometric model (section 3.3), followed by a description of the data on the main driving factors of local house price growth (section 3.4). In sections 3.5.1 to 3.5.3, we respectively present the variables we use to proxy the share of constrained or high-risk borrowers, the indicators of the hotness of a local housing market, and the extent of household indebtedness in local housing markets. A detailed overview of all the variables and its sources can be found in 7. Finally, we outline the results in section 3.6.

3.1. Hedonic price index

A key aspect of analyzing house price dynamics is to find a reliable measure of house prices. As houses are highly differentiated goods which are infrequently traded, housing prices at a local level can be notoriously volatile. A house price index based on average transaction price data can, for example, be very volatile as the quality (and thus the price) of the pool of houses sold within municipalities can vary quite a lot from period to period, especially in small municipalities. In this paper, we make use of a hedonic price index which allows to compare changes in prices of identical dwellings as the index is constructed in a way that it controls for changes in the composition of the sold properties. More specifically, we use the municipality-level hedonic house price index for Belgium constructed in the work of Reusens et al. (2022) in which the authors have estimated municipality-level house price premia for a wide range of housing characteristics.[3] Our variable of interest, the growth rate of the municipality-level hedonic index ranges from 2012 to 2020.[4]

Despite the advantage of having a more reliable metric of the evolution of prices across time, using the municipal hedonic house price index also comes with two limitations. A first one is the lower (annual) frequency of the series compared to the quarterly transaction price data at the municipal level which lowers the amount of observations. This disadvantage of the lower data frequency is, however, compensated by the fact that it leads to substantially less municipalities with a very small number of housing transactions.[5] A second limitation is the loss of some transactions due to missing data on the associated dwelling characteristics (e.g., energy performance certificate (EPC) scores), which makes that those housing transactions gets excluded (i.e., 11% of the observations for the Flemish and Brussels Region and 27% for the Walloon Region). This results in a slightly lower coverage of municipalities, namely 562 out of all 581 Belgian municipalities.

A general concern related to both the hedonic house price index and the house price index based on average transaction prices, however, is that the variation in growth rates of the index is elevated for smaller municipalities (Reusens et al., 2022). To reduce noise related to low numbers of housing transactions, i.e., volatility caused by a (very) low number of housing transactions and not just any variation in the data, we take the following approach to further clean the house price index: when the average amount of housing transactions in a municipality over the period 2012-2021 is lower

[3]The characteristics considered are dwelling type, dwelling surface, garden size, average building year, the number of years since the latest officially recorded renovation, energy performance (EPC scores), and municipality. It must be noted that the hedonic index is based on cleaned data on houses in Belgium, newly-built and multi-family houses are for example not included and extreme outliers have been removed. For more details on the construction of the hedonic house price index, we refer to Reusens et al. (2022).

[4]We take into account that house price transactions are recorded with a lag of about four months between the time of the actual sale and the legal deed of sale with the notaries and consider the period of housing transactions running from the third quarter of year t to the second quarter of year t+1 as belonging to year t. For example, transaction data during 2020Q3-2021Q2 are considered to make up the 2020 house price index (instead of 2021).

[5]Peydró et al. (2020) for example motivate their switch from quarterly to half-year data by pointing to the reduction of noise by having more transactions in one time observation.

than the 10th percentile of the entire distribution, this municipality gets dropped from our sample. In this way, 65 municipalities get dropped and we maintain a balanced house price series for 497 Belgian municipalities.[6] The pool of dropped municipalities turns out to be spatially centered in the South-East of Belgium. This should not affect our estimation results to the extent that any atypical characteristics of those municipalities are constant or regional in nature as our econometric model picks up constant municipal and time-varying regional factors (see infra, section 3.3). Table 1 shows the summary statistics of the hedonic house price index growth rate before and after this cleaning.

Table 1: Descriptives of house price growth rates before and after cleaning

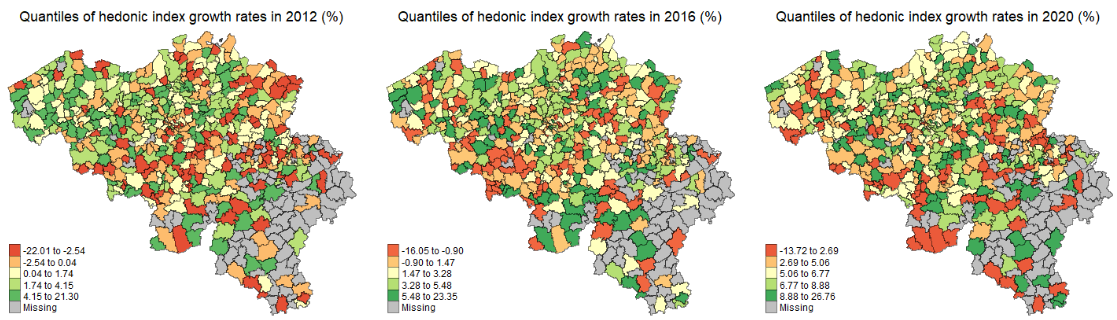
	Mean	Std. Dev.	Min	Max	N
House price growth (no cleaning)	2.26	5.96	-31.69	49.74	5,058
House price growth (after cleaning)	2.22	4.89	-22.01	26.76	4,473

Figure 1 further shows the extent of the cross-sectional variation in this house price growth rate for the Belgian municipalities across time using the map of Belgium.[7] The color scale represents the quantiles of the distribution of annual growth rates for three years within the time period under consideration, namely for 2012, 2016, and 2020. This division in quantiles visualizes the considerable shift over time in terms of ranking of the growth rates for the municipalities within the entire group over and above the variation across time within the municipalities. For example, Knokke-Heist (the most eastern coastal municipality) lies with a house price growth rate of -3.34% in the first quantile of the distribution in 2012 while in 2016 the growth rate becomes slightly positive (0.51%) and the municipality ends up in the second quantile. In 2020, the growth rate was more elevated (17.09%), positioning the municipality in the fifth quantile.

[6] In section 5, we show that different choices of this cut-off value do not importantly affect our results.

[7] In 2019, some Belgian municipalities merged together resulting in a decrease in the number of Belgian municipalities from 589 to 581. The Belgian map figures always show the geographical borders of the 581 post-merge municipalities. To calculate the values for the merged municipalities before 2019, we sum or average the data, depending on the specific variables.

Figure 1: House price growth across 562 Belgian municipalities for 2012, 2016, and 2020 (%)



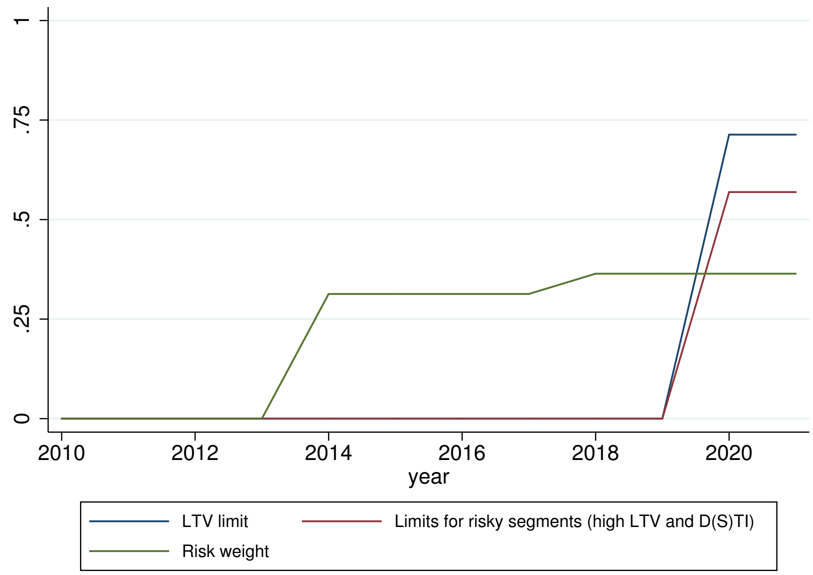
3.2. Intensity-adjusted macroprudential index

Our work focuses on measuring the potentially heterogeneous effects of common macroprudential policy changes on local housing markets. A good yardstick of the policy changes is hence essential. Related works on the local effects of an LTV policy (Peydró et al., 2020, Laufer and Tzur-Ilan, 2021, Acharya et al., 2022) base their analysis on a treatment effect and use a dummy variable equal to 1 once the tool has been implemented while being zero before and interact it with a treatment indicator respectively signaling the extent to which borrowers, lenders, and individual housing units are constrained by the imposed limit. Our measure of macroprudential policy changes is instead closely related to the existing studies on macroprudential policy which employ a '-1/0/+1' dummy to measure the effects of macroprudential actions on the macro economy (Cerutti et al., 2017, Fendoğlu, 2017, Akinci and Olmstead-Rumsey, 2018). This dummy approach offers a clean and simple signal of the timing and the direction of changes in countries' macroprudential policy. To better capture the restrictiveness of policy changes next to their timing and sign, we follow Coulier and De Schryder (2022) and construct intensity-adjusted indices for the Belgian housing-related macroprudential instruments (see supra, section 2.3) that take account of the scope, restrictiveness, and legal enforceability of macroprudential policy implementations.[8]

As mentioned in section 2.3, the housing-related macroprudential implementations in Belgium consist of the tightening of risk weights related to residential mortgages in 2013 and 2018 and prudential expectations with LTV limits and combinations of LTV and D(S)TI limits in 2020. Figure 2 shows the cumulative path of the different macroprudential implementations implemented in these years. The figure is confined to the positive value segment as Belgium has up to now only experienced tightenings of the housing-related measures. In the econometric analysis, we focus on the change in housing-sector-specific macroprudential policy, meaning that we take the changes for all three instruments (risk weights, LTV and the combinations of the LTV and D(S)TI limits) together in one index (see infra, section 3.3).

[8]With a '-1/0/+1' dummy, the particular extent to which a policy is tightened or loosened is completely neglected. Tightening actions of different magnitudes all get the value -1, and all loosening actions a value of 1 irrespective of the strength of the action. We describe the results with the use of this standard unadjusted dummy in section 5 as a robustness check. Given the use of yearly data, we do not discriminate between announcement and enforcement dates as these took place during the same year.

Figure 2: Intensity-based indices for housing-sector-specific macroprudential policy in Belgium based on the enforcement date.



3.3. Baseline model specification

As a first step, we estimate a basic dynamic panel data model on the Belgian municipal data from 2012 to 2020, represented by equation (1):

$$y_{i,r,t} = \gamma y_{i,r,t-1} \; + \; \boldsymbol{\delta}\mathbf{x}_{i,r,t-1} \; + \; \boldsymbol{\beta}(map_t * \mathbf{INT}) \; + \; \alpha_i \; + \; \theta_t \; + \; \varphi_{r,t} \; + \; \epsilon_{i,r,t} \tag{1}$$

with $\mathbf{INT} = (\mathbf{X}_{i,r,t=2010/2011}, hotness_{i,r,t-1}, debt_{i,r,t-1})$ and where capital letters indicate variables in levels and small letters variables in growth rates.

The dependent variable ($y_{i,r,t}$) represents the growth of the hedonic house price index (see supra, section 3.1) for municipality i in region r at year t. It is regressed on its lagged value ($y_{i,r,t-1}$), a vector of drivers of local house price growth ($\mathbf{x}_{i,r,t-1}$, see infra section 3.4) lagged by one year to limit reverse causality, and a set of interaction terms ($map_t * \mathbf{INT}$) including the Belgian housing-market-related macroprudential tools to evaluate the potentially heterogeneous effects of macroprudential policy changes.

More specifically, we interact the macroprudential intensity-adjusted index (map_t, see section 3.2) with a set of variables that (i) pick up different aspects of financial constraints of local residents as well as characteristics of high-risk borrowers, ($\mathbf{X}_{i,r,t=2010/2011}$), (ii) indicate the degree of hotness of the local housing market ($hotness_{i,r,t-1}$), and (iii) the extent of household mortgage indebtedness ($debt_{i,r,t-1}$). Section 3.5.1 presents these variables in more detail. We include pre-determined and lagged variables next to the macroprudential index since we do not want local house price growth to reversely affect our regressors. The pre-determined variables relate to the degree of constrained/high-risk borrowers in municipalities for which we consider the data *before* the policy implementations, namely at the level of the year 2010 when many of the data series start[9] with the exception of one variable (the share of highly educated young people) for which the data only start in 2011 (see infra, section 3.5.1). As also mentioned in Füss and Zietz (2016), the interaction terms allow for a weighted impact of the common macroprudential policy changes on individual municipalities as the estimates on the interaction terms explicitly incorporate characteristics of the municipalities.

Municipality-fixed effects (α_i) and time-fixed effects (θ_t) are included to respectively pick up any municipality-specific time-invariant factors (e.g., local amenities) and common time-varying factors (e.g., the monetary policy stance). The time*region effects ($\varphi_{r,t}$) in addition pick up the effects on local house price growth of any time-varying factor at the level of the Belgian regions (e.g., changes in mortgage-related tax deductions which vary at the level of the Belgian regions (see infra, section 5.4)). The inclusion of municipality-fixed effects makes that the direct effect of the pre-determined level variables gets absorbed by the effects. Moreover, the time-fixed effects absorb the direct effects of any common shock, including changes in macroprudential policy as this policy is common to all Belgian municipalities.

The standard errors are clustered at the municipality level to account for the fact that error terms are likely correlated within a municipality while assuming error term independence across municipalities. Since we are estimating a dynamic panel with fixed effects on a sample with limited

[9] We have checked whether our results change if different preceding years were chosen. This is not the case.

T (T=9), the coefficient estimate of the lagged dependent variable might be biased (Nickell, 1981). We use a sample-split jackknife correction to limit this bias following Dhaene and Jochmans (2015), who prove that a sample-split jackknife correction alleviates the Nickell bias to a large extent, even in short panels (T$= 4, 6$).

Next to the use of municipality-level predetermined variables, the outlined model identifies the heterogeneous effects of the common housing-related macroprudential tools on the municipal housing growth rates under the assumption that macroprudential policymakers do not change their policy stance based on price evolutions in a local housing market (i.e., a municipality). Moreover, given that the policies have the goal to preserve the resilience of the financial system and rather target risks arising in the mortgage market rather than the housing market, it is highly unlikely that the policymaker will react to house price movements. However, to the extent that other common fluctuations affect local house price dynamics in a heterogeneous way, omitted variable bias concerns can arise even with the inclusion of time effects. This would be the case when such common variables change at roughly the same time and the heterogeneous effects run via the same drivers (i.e., the same interaction variables) such that we cannot infer the causal effects arising from the macroprudential changes. Two prime candidates for such effects are the COVID-19 pandemic and interest rates changes. In section 5.3, we specifically control the robustness of our results to these factors.

3.4. Driving factors of local house price growth

In the baseline model, we focus on four regressors to proxy the most important municipal-level drivers of local house price growth.[10] First, we include traditional demand factors, being growth of median income per fiscal declaration (hereafter: median income growth), employment growth to capture local economic condition, next to the growth in the number of households relative to

[10]Given the absence of data on incoming/outgoing residents who buy/sell a house in a municipality, we cannot control for short-run spillovers between the municipality-level housing markets. Dreesen (2019), however, documents that the tendency to move beyond a certain municipality in the short run is limited within Flanders for the period 2011-2015, with the average distance being 11.4 kilometres and even less than 4 kilometres for half of the movers. To the extent that this tendency is similar to the other regions in Belgium, Brussels and Wallonia, short-run movements between municipalities are expected to be relatively limited.

the number of inhabitants (hereafter: household growth) to proxy for demographic conditions. Next, we include growth in the housing stock (i.e., the number of houses relative to the number of inhabitants) as a housing supply factor.

Table 13 shows the descriptives of these variables for the 497 Belgian municipalities in our sample. Figures 15 to 18 in turn show that there is both substantial cross-sectional variation across the Belgian municipalities as well as variation across time, since the same municipality can be in different quantiles of the distribution for different time periods. This signals that there is sizeable heterogeneity in the driving factors that will not be picked up by the municipality or time fixed effects.

3.5. Driving factors of potential heterogeneous reaction to macroprudential policies

The macroprudential policy index gets interacted with a set of regressors at the level of Belgian municipalities related to the presence of financially constrained and high-risk borrowers, the activity of the local housing market, and the degree of household indebtedness. The underlying hypotheses, based on the findings discussed in section 2.2, are that more constrained and risky borrowers, a very active local housing market, and more household debt lead to a more pronounced negative effect of tightening macroprudential regulation on house price growth.

3.5.1. Indicators of constrained/high-risk borrowers

We first assess the heterogeneous effects of macroprudential policy with respect to the presence of constrained or high-risk borrowers. These borrowers are expected to be most sensitive to the macroprudential policy changes which would in turn result in a larger response of house price growth. Since our data is at municipality level, and not at the borrower level, we do not capture in detail how constrained actual home-buyers are but, based on the extensive dataset, we do investigate multiple proxies that capture financial constraints at the local level.

First, following Peydró et al. (2020) and Acharya et al. (2022), we include an indicator of low-income borrowers. We do this by measuring the share of fiscal declarations indicating a yearly net taxable income between 10000 and 20000 euro (hereafter: share of low-income declarations). The reason why we use this definition is that this income group has an income below the median income in the majority of municipalities in 2010, while it excludes the group with a net taxable yearly income below 10000 euro, which might not even be able to enter the housing market.

Other household aspects that have been linked to high-risk borrowers are people of young age, adults living on their own, and single-parent households (Wunsch, 2022). Therefore we also include the share of 25-34 year olds in a municipality (hereafter: the share of young people), the share of single-person households in a municipality, and the share of single-parent households in a municipality. Young people predominantly belong to the group of first-time home-buyers which are most likely affected by the regulatory constraints. A similar reasoning holds for the single-person households who rely on a single adult income next to single-parent households who are likely to be even further constrained by the costs associated with the care for their (dependent) children. Next, we also look at the amount of overdue mortgage credit relative to total mortgage credits (hereafter: the share of overdue credits), since this might indicate a large share of high-risk borrowers. From the opposite perspective, we include the share of highly-educated young people (25-34 year old), as this group on the one hand has the age where one typically buys a first house but on the other hand gets associated with higher income and wealth compared to their peers (Reusens et al., 2022) and thus can be considered to be less constrained than their peers.

We focus on the (large) cross-sectional variation in these indicators of the share of financially constrained or high-risk borrowers since we include these variables at a fixed time period before the start of our sample (i.e., pre-determined) in our baseline model (see supra, section 3.3). Figures 19 and 20 show this variation for the variables of interest in 2010 except for the share of highly-educated young people, for which we only have the values in 2011. While for some variables, such as share of overdue credits and share of single-parent households, a north-south division is visible, this is not the case for multiple other variables. In some cases, e.g., in the case of the share of single-person households, the coastal region is different from its neighbouring municipalities.

3.5.2. The hotness of local housing markets

From Acharya et al. (2022), we know that a tightening of housing-related macroprudential policies can induce a larger downward effect on house price growth in a hot housing market relative to a cold housing market. To capture the hotness of the local housing market, we use the growth of the number of housing transactions relative to the number of inhabitants (hereafter: transaction growth) since this factor indicates elevated activity in the housing market. Figure 21 shows the substantial time and cross-sectional variation which is important for the identification of heterogeneous effects of macroprudential policy with respect to this variable.

3.5.3. Household indebtedness

Finally, we use the growth of the number of outstanding mortgages relative to the number of inhabitants (hereafter: growth in outstanding mortgages) to measure the indebtedness of households in the local housing market. An increasing amount of indebtedness could signal more risky positions in the local housing market which can strengthen the effects of macroprudential policy tools due to an increased sensitivity to the regulation. Similar to section 3.5.2, figure 22 shows the substantial time and cross-sectional variation for this indicator.

3.6. Results baseline model

In this section, we show the results for our baseline model in tables 2 and 3, where we focus on the coefficients of the interaction terms. As shown in the tables, the driving factors of house price growth have the expected sign, albeit not significant. We expect the coefficients of the interaction terms to have negative signs since a macroprudential policy tightening is expected to have a more dampening effect on house price growth in hot housing markets, in housing markets with a high share of constrained or high-risk borrowers, and in housing markets where there is an increasing amount of outstanding debt.

Table 2 shows the coefficients of the interaction terms when including one interaction at a time in the model. For all the indicators of a high share of constrained or high-risk borrowers, we do find a negative and significant coefficient, supporting our hypothesis. Moreover, these results are in line with Peydró et al. (2020) and Acharya et al. (2022), who find that house price growth decreases more in areas where borrowers are closer to the limit and with a high share of low-income borrowers. The indicator we use to proxy the hotness of the housing market, the growth of housing transactions, shows a negative sign similar to the findings of Acharya et al. (2022), although it is not significant. The coefficient for the growth of outstanding mortgages is also not significant and has a positive sign in contrast to expectations. A possible explanation for this could be the fact that this proxy captures changes in the extensive margin of mortgage debt but not in the intensive margin. Therefore, this variable might not be a sufficiently good proxy for increasing *risky* debt positions.

In table 3, we combine multiple interactions in the same estimation. In column (1), we combine the interaction terms measured in growth rates, i.e., the indicator for hotness of the housing market and the indicator for increasing debt positions. In column (2), we combine the interactions of the share of young people and the share of highly-educated young people, since the latter is a subgroup of the former. We argue in section 3.5.1 that highly-educated young people are a proxy for less-constrained borrowers who are at the typical age of buying a (first) house. The coefficient of this variable is positive and significant, in line with the hypothesis described above, while the coefficient for the share of young people is still negative and significant. In column (3), all proxies for constrained or high-risk borrowers are combined, except for the share of overdue credits and the share of highly-educated young people since these are highly correlated with the share of low-income (i.e., having an absolute correlation above 70%). Column (4) combines the interactions from column (1) and (3). For the majority of the coefficient estimates, the conclusions stay the same as when the interactions have been included separately. However, the coefficients of the share of single-parent households and the share of single-person households become insignificant and the coefficient of the latter even switches of sign. From this we infer that, when controlling for heterogeneous effects of macroprudential policy related to income and age, the composition of the household is of less importance.

Overall, the estimates make us conclude that macroprudential policy changes affect local housing markets in a heterogeneous way. More specifically, house price growth rates in municipalities with more constrained or high-risk residents will be more affected by housing-sector-specific macroprudential policy. Restrictive policy changes cause house price growth to decrease more in housing markets with a high share of this type of residents. This result is especially strong for a high share of low-income declarations and a high share of young people in the local housing market. In contrast, macroprudential policy seems to have a more upward effect on house price growth in local housing markets with a high share of highly-educated young people, which are considered to be less constrained.

Table 2: Results for the baseline model with interactions separately

Specification	(1)	(2)	(3)	(4)	(5)	(7)	(8)
Dependent variable	ΔHP	ΔHP	ΔHP	ΔHP	ΔHP	ΔHP	ΔHP
Lagged growth of median income	0.0500	0.0319	0.0679	0.0528	0.0519	0.0530	0.0409
	(0.0882)	(0.0874)	(0.0803)	(0.101)	(0.0922)	(0.0733)	(0.0841)
Lagged growth of households	0.233	0.194	0.239	0.238	0.219	0.226	0.221
	(0.207)	(0.177)	(0.235)	(0.213)	(0.222)	(0.227)	(0.200)
Lagged employment growth	0.0665	0.0402	0.0881	0.0740	0.0641	0.0663	0.0745
	(0.0818)	(0.0717)	(0.0872)	(0.0816)	(0.0871)	(0.0838)	(0.0957)
Lagged growth of housing stock	-0.0184	-0.178	-0.0143	-0.0240	-0.0147	-0.0141	-0.0117
	(0.157)	(0.150)	(0.159)	(0.147)	(0.154)	(0.166)	(0.199)
Share of low-income declarations (2010) * ΔMAP			-0.155***				
			(0.0318)				
Share of overdue credits (2010) * ΔMAP				-0.721***			
				(0.250)			
Share of young people (2010) * ΔMAP					-0.289***		
					(0.0868)		
Share of single-person households (2010) * ΔMAP						-0.0754**	
						(0.0316)	
Share of single-parent households (2010) * ΔMAP							-0.177*
							(0.118)
Lagged growth of housing transactions	-0.00192						
	(0.00311)						
Lagged growth of housing transactions * ΔMAP	-0.00298						
	(0.00832)						
Lagged growth of outstanding mortgages		0.215***					
		(0.0734)					
Lagged growth of outstanding mortgages * ΔMAP		0.0860					
		(0.150)					
Number of municipalities	497	497	497	497	497	497	497
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region * time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged ΔHP	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Results for baseline model with combined interactions

Specification	(1)	(2)	(3)	(4)
Dependent variable	ΔHP	ΔHP	ΔHP	ΔHP
Lagged growth of median income	0.0423	0.0722	0.0732	0.0770
	(0.0835)	(0.0827)	(0.0937)	(0.0759)
Lagged growth of households	0.204	0.232	0.238	0.222
	(0.174)	(0.220)	(0.217)	(0.186)
Lagged employment growth	0.0431	0.0620	0.0879	0.0712
	(0.0692)	(0.0935)	(0.0896)	(0.0815)
Lagged growth of housing stock	-0.180	-0.0247	-0.0128	-0.170
	(0.178)	(0.156)	(0.135)	(0.155)
Share of low-income declarations (2010) * ΔMAP			-0.137***	-0.134***
			(0.0373)	(0.0323)
Share of young people (2010) * ΔMAP		-0.230***	-0.232**	-0.236**
		(0.0820)	(0.110)	(0.108)
Share of highly-educated young people (2011) * ΔMAP		0.0558***		
		(0.0175)		
Share of single-person households (2010) * ΔMAP			0.00913	0.00615
			(0.0396)	(0.0364)
Share of single-parent households (2010) * ΔMAP			-0.0569	-0.0646
			(0.115)	(0.125)
Lagged growth of housing transactions	-0.00164			-0.00171
	(0.00324)			(0.00349)
Lagged growth of housing transactions * ΔMAP	-0.00245			-0.00160
	(0.00882)			(0.00855)
Lagged growth of outstanding mortgages	0.217***			0.217***
	(0.0740)			(0.0655)
Lagged growth of outstanding mortgages * ΔMAP	0.0837			0.0296
	(0.122)			(0.131)
Number of municipalities	497	497	497	497
Municipality fixed effects	Yes	Yes	Yes	Yes
Region * time FE	Yes	Yes	Yes	Yes
Lagged ΔHP	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4. Quantile regressions

4.1. Model outline

In the baseline model, we use the number of housing transactions as an indicator of the hotness of the housing market to test for heterogeneous effects of housing-sector-specific macroprudential tools related to differential degrees of hotness of the local housing market. A quantile regression model offers an alternative approach as the estimated coefficients get associated to a certain percentile of the distribution of the dependent variable, in our case the house price growth rates varying across the Belgian municipalities and over time.

In this set-up, the magnitude of the price change acts as a direct signal of the degree of hotness of the local market similar to Acharya et al. (2022). More specifically, municipalities on the right tail of the distribution are considered to be hot housing markets in a certain time period, while the reverse can be said for municipalities on the left tail of the distribution. The quantile regression estimation technique hence allows áll variables to have a heterogeneous impact depending on the hotness of the housing market. Relative to the baseline model, this offers more flexibility to pick up heterogeneous effects related to the hotness of the housing market as all the included variables, including the interaction terms, are allowed to vary according to the hotness of the housing market. To examine the heterogeneity of the effects, we estimate equation (2) for each decile of the house price growth distribution across the 497 municipalities.

$$y_{i,r,t,\tau} = \gamma_\tau y_{i,r,t-1} \ + \ \boldsymbol{\delta}_\tau \mathbf{x}_{i,r,t-1} \ + \ \boldsymbol{\beta}_\tau (map_t * \mathbf{INT}) + \ \alpha_{i,\tau} \ + \ \theta_{t,\tau} \ + \ \varphi_{r,t,\tau} \ + \ \epsilon_{i,r,t,\tau} \qquad (2)$$

Different from equation (1), the potential heterogeneous effects of macroprudential policy changes are captured by the $\boldsymbol{\beta}_\tau$ coefficients where the betas for each decile τ reflect the heterogeneous impact of the macroprudential policy changes on local house price dynamics for various levels of housing market activity. We hence do no longer include the *hotness* variable as an interaction with the macroprudential policy variable and $map_t * \mathbf{INT}$ includes now only interactions of map_t with $\mathbf{X}_{i,r,t=2010/2011}$ and $debt_{i,r,t-1}$.

We follow the 'Quantiles via Moments' methodology of Machado and Santos-Silva (2019) which uses estimates of the location and scale functions to estimate conditional quantiles. The advantages of this approach are that it offers a straightforward implementation even in samples with large N and fixed effects[11] and it allows the fixed effects to affect the entire distribution, in contrast to previous work that only allows the fixed effects to be location shifters.[12] A disadvantage of this approach is that in samples where N/T>10 (which is the case in our sample with N=497 and T=9), the coverage of the confidence intervals is rather poor. However, Machado and Santos-Silva (2019) prove that this coverage is much improved when using a sample-split jackknife correction. Therefore, as in section 3.3, we correct our estimates using the same sample-split jackknife correction by Dhaene and Jochmans (2015).

4.2. Results quantile regressions

The results of the quantile regressions are shown in the figures below. In each figure, the solid blue line shows the coefficient of interest across the deciles of the house price growth rate (shown on the x-axis). More specifically, the left part of each graph shows the effect in cold housing markets, while the right part of the graph shows the effect in hot housing markets. Similar to section 3.6, our hypothesis is that macroprudential policy will have a more dampening effect on house price growth in housing markets with a high share of constrained or high-risk borrowers and in housing markets where there is an increasing amount of outstanding debt. We thus expect the interaction terms to have a negative sign, meaning that we expect the blue line to always be below the zero line. Moreover, based on Acharya et al. (2022), we expect that a macroprudential policy tightening has a more dampening effect on house price growth in hot housing markets which on top increases in the extent of household financing and debt constraints. This means that we expect the blue line to also have a negative slope.

[11]Because the approach of Machado and Santos-Silva (2019) allows to partial out the fixed effects in the estimation of the location and scale parameters, the estimator is computationally much easier to implement than any other estimator for quantile regression models with fixed effects.

[12]This is a more realistic assumption since factors typical to one municipality and constant over time (i.e., municipality fixed effects) cannot only affect the location of the distribution of the dependent variable, but also lead to an different shape of the distribution.

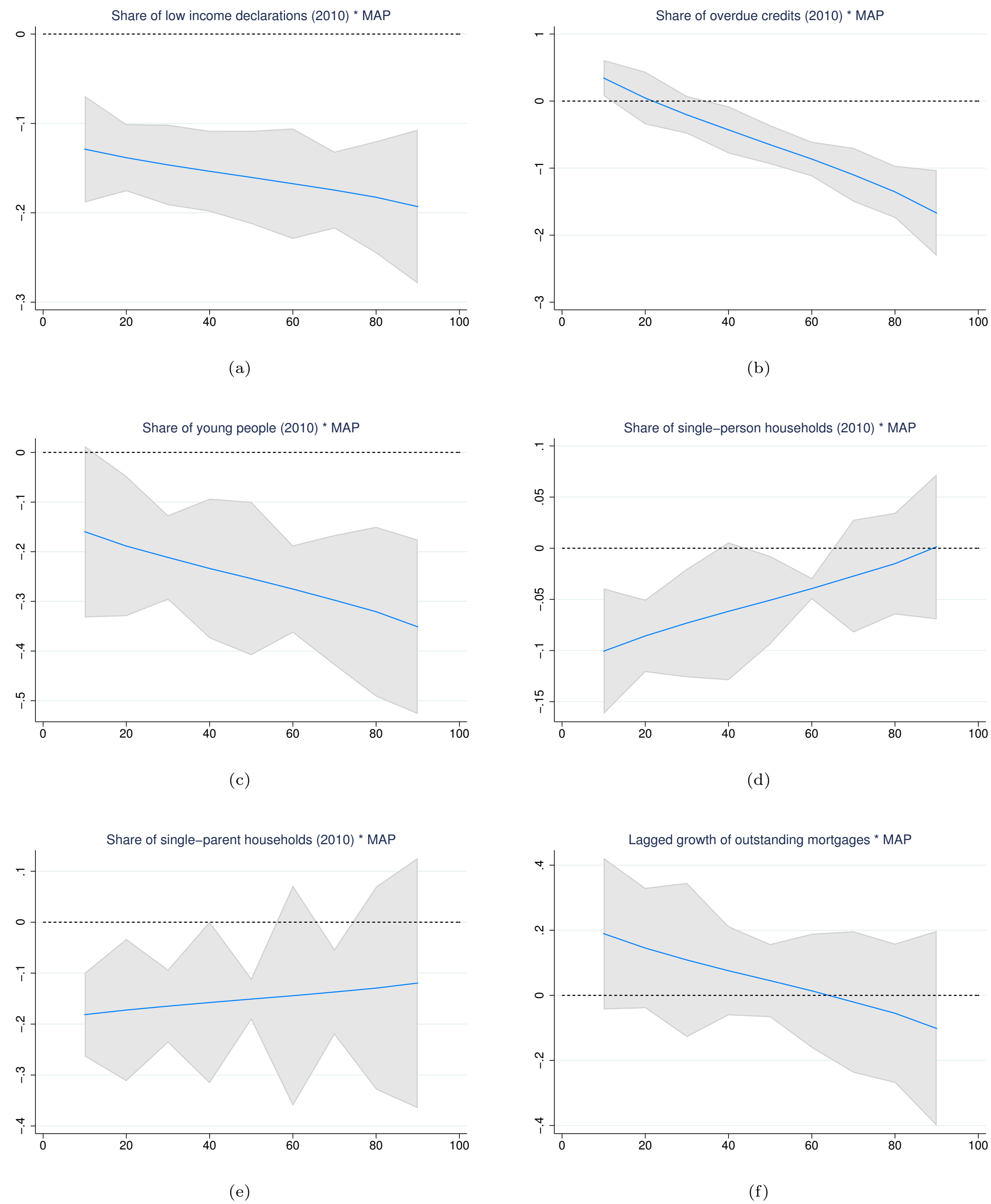
Figure 3 shows the results for the interaction term when including one interaction at a time in the model. Similar to the baseline model, every specification includes the lagged house price growth, lagged driving factors of house price growth, municipality and time fixed effects, and time*region fixed effects. We limit the visual representation to the coefficients of the interaction terms in this section but our results do indicate that the driving factors of local house price have a differential effect on house price growth across the house price growth distribution.[13]

First, one can see that for the share of low-income declarations we do find a negative effect that becomes more pronounced in hot housing markets (figure 3a). This means that, in hot housing markets, macroprudential policy has a more dampening effect on house price growth when the share of low-income declarations is high compared to cold housing markets although the effect is also negatively significant in these cold housing markets. Similarly, we find that macroprudential policy has a more dampening effect on house price growth when the share of overdue credits is high in hot housing markets than in cold housing markets where the effect is actually not significant (figure 3b). The dampening effect of the share of young people on house price growth is also larger in hot versus cold housing markets while being overall significant (figure 3c). In figures 3d and 3e, the message is less clear. Although we do find a more dampening effect of macroprudential policy when there is a high share of single-person households or single-parent households across the whole distribution of house price growth, the effect does not become more pronounced in hot housing markets.[14] Next, figure 3f depicts the estimates for the lagged growth of outstanding mortgages. Although the coefficient line does have a negative slope, the effects are not always negative and never significant. As mentioned before in section 3.6, this could be due to the fact that our variable is not a good proxy for increasing risky debt positions.

[13]The figures for the full models with and without interactions are available upon request.

[14]Because of the bootstrapping procedure related to the bias correction (as explained in section 3.3) combined with the inclusion of time*region fixed effects, some of the figures show some volatility in the confidence bands across the distribution. These patterns largely disappear when combining the interactions together in the estimation (see below).

Figure 3: Quantile regression results for the interaction terms when included separately. The blue line shows the coefficient estimates across the deciles of the distribution of house price growth. The grey areas reflect the 90% error bands.



Figures 4 to 6 show the results of the combination of interactions in the same way as in section 3.6. Figure 4, combining the share of young people and the share of highly-educated young people, is in line with the expectations. As mentioned before, we use the share of highly-educated young people as a proxy for people that are at the typical age of buying their (first) house while being typically less financially constrained. Therefore, we would expect the blue line to be above the zero line and have a positive slope while the estimates for the share of young people remain negative and increasing for hot housing markets. The results for the other combined interactions in figures 5 and 6 are the most clear for the effects of the share of low income and the share of young people, which are consistently negative and increasing in magnitude for hot housing markets. Similar to the separate interaction regressions, the coefficient line for the growth of outstanding mortgages is negatively sloping but does not lie below zero throughout the whole distribution. The share of single-person households now crosses the zero line with an upward slope and shows a significant upward effect of macroprudential policy when the share of single-person households is high in hot housing markets, in contrast to our expectations. The coefficient line for the share of single-parent households is now either slightly positively or negatively sloping, although not significant.

Based on these results, we conclude that macroprudential policy changes have differential effects on local house price growth rates for different levels of hotness of the market. More specifically, we find that heterogeneity of the housing market conditions leads to differential effects of macroprudential policy changes related to borrower heterogeneity. Similar to our baseline model, these results are especially clear for the share of low-income declarations, the share of young people, and the share of highly-educated young people.

Figure 4: Quantile regression results for the interaction terms of the share of young people (2010) and the share of highly-educated young people (2011). The blue line shows the coefficient estimates across the deciles of the distribution of house price growth. The grey areas reflect the 90% error bands.

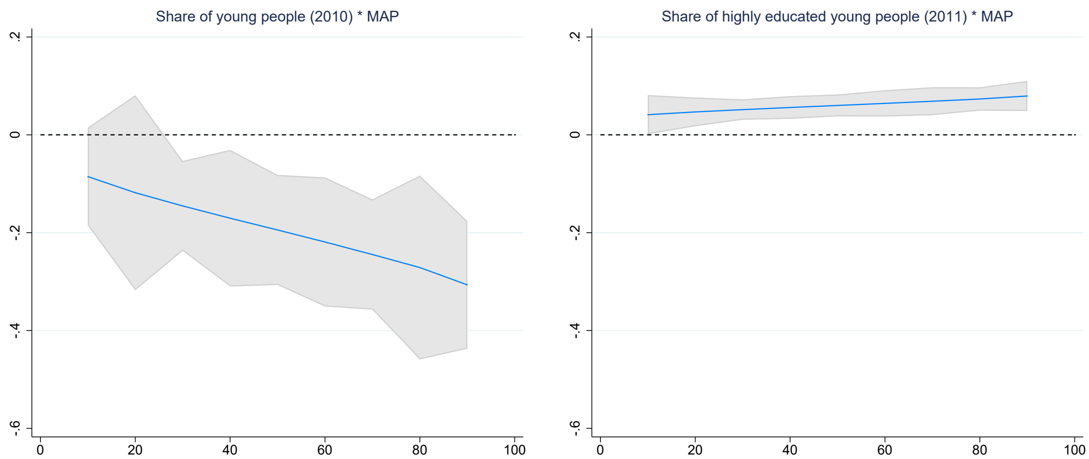


Figure 5: Quantile regression results for the interaction terms that indicate a large share of constrained or high-risk borrowers. The blue line shows the coefficient estimates across the deciles of the distribution of house price growth. The grey areas reflect the 90% error bands.

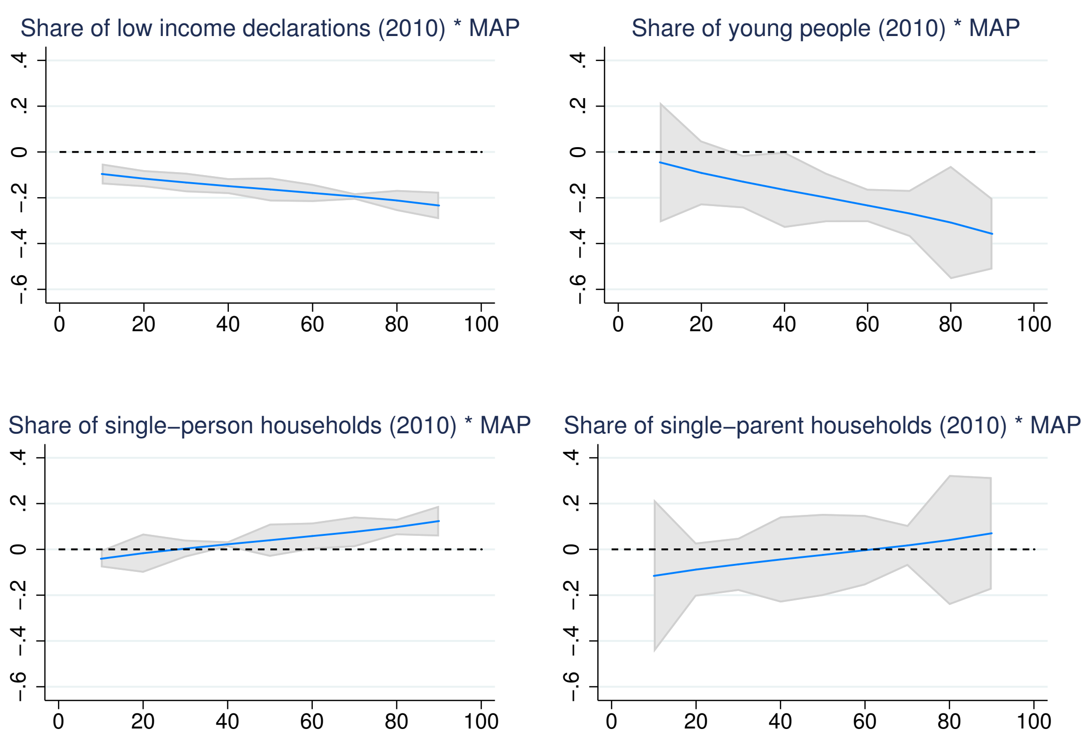
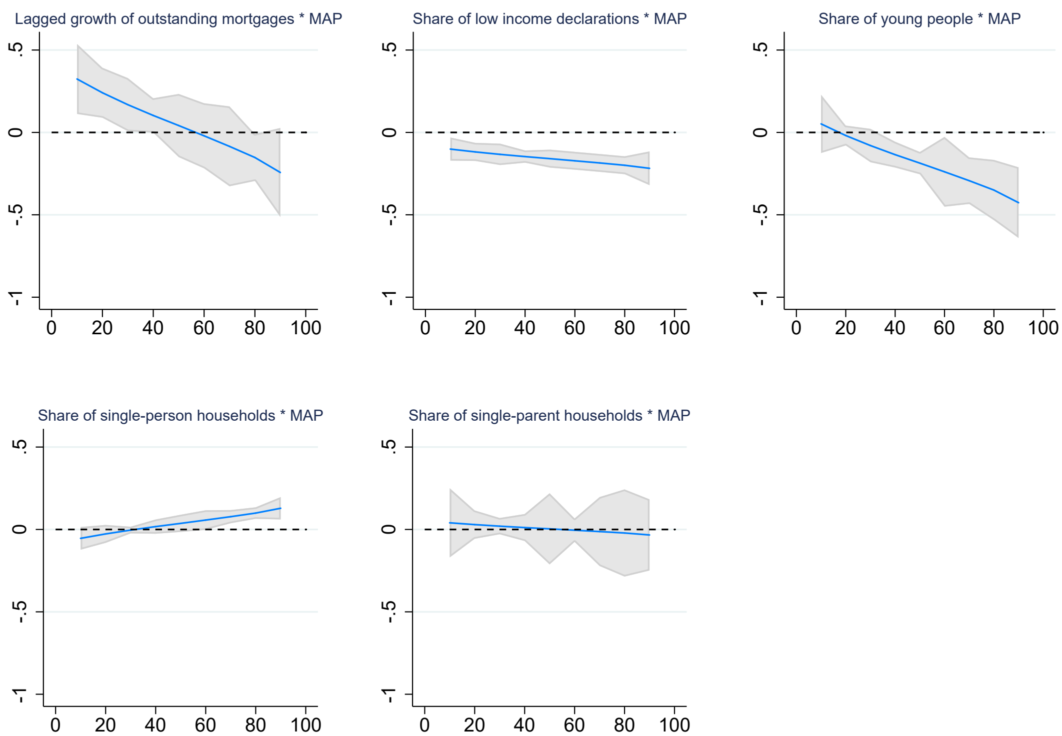


Figure 6: Quantile regression results for all interaction terms together. The blue line shows the coefficient estimates across the deciles of the distribution of house price growth. The grey areas reflect the 90% error bands.



5. Robustness checks

We conduct a series of robustness checks to explore the sensitivity of our baseline results, both for the dynamic fixed effects model and the quantile regressions. We test if our results are sensitive to using a different threshold to drop municipalities from our sample and to using different proxies of some baseline variables. As an extension to our analysis, we control for (i) potentially heterogeneous effects of other common shocks to the Belgian economy, in particular the COVID-19 crisis and changes in interest rates and (ii) the effects of Belgian taxation rules related to the purchase of a house, better known as the 'woonbonus' or 'bonus logement' on the Belgian housing market. In each robustness check, we show the results for the models that combine multiple interactions at the same time. For the sake of brevity, we only show the quantile regression results for the combinations of (a) the interactions with share of young people and share of highly-educated young people and (b) all interactions together.[15] Moreover, we have checked whether using different strategies for the bias correction (e.g., splitting the sample differently for the sample-split jackknife correction or using a different initial value for the bootstrap procedure) as well as using other years than 2010 for the pre-determined control variables in levels affect our results. These results are available upon request. In general, our main conclusions hold across the robustness checks and extensions.

5.1. Different thresholds for data cleaning

In this robustness check, we check whether our results change if we use a different threshold to remove municipalities with a small number of housing transactions from our sample. In the baseline model, we remove municipalities that are below the 10^{th} percentile of the distribution of average housing transactions over time. To test the sensitivity of our results to this cut-off point, we will look at two different thresholds, namely the 5^{th} and 25^{th} percentile of this distribution. Table 4 visualizes the detailed summary statistics of the dependent variable, house price growth, when the different thresholds are used. Overall, the distributions are very similar to each other. The more municipalities are removed, the closer the distribution gets to a normal distribution (i.e.,

[15]Results for the dynamic fixed effect and quantile regression models with separate interactions and coefficients of the full model are available upon request.

skewness close to zero, kurtosis close to three). Table 5 shows the average amount of transactions linked to the various percentiles (structured per 5 percentiles) of house price growth for the three cut-off values. The most extreme growth rates (smaller than the 5^{th} percentile and larger than the 95^{th} percentile) are linked to between 35 and 75 transactions, depending on the threshold. These sizeable amount of housing transactions allow us to argue that the large growth rates are not driven by too few transactions.

Table 6 shows the estimation results for these different thresholds. We find that the results for the interaction terms are very similar across the different specifications, with significant effects for the share of low income, the share of young people, and the share of highly-educated young people. When using the 25^{th} percentile as a cut-off point, we even find a negative significant effect for the interaction of macroprudential policy with the indicator of the hotness of the housing market.

Figures 7 and 8 depict the results for the quantile regressions. Again, the figures are very close to the baseline results for the quantile regressions. Some small differences are visible for the slopes of the share of low-income declarations and the share of single-parent households. Based on this analysis, we conclude that the results are robust to using a different threshold to remove municipalities with a small number of housing transactions from our sample and this for both the baseline fixed effects model and the quantile regression model.

Table 4: Descriptive statistics of house price growth when using different thresholds to drop municipalities from the sample. The top line represents the baseline scenario.

	Mean	Std. Dev.	Min	P5	P10	P25	P50	P75	P90	P95	Max	Skew.	Kurt.	N
House price growth (10^{th} p.)	2.22	4.89	-22.01	-5.54	-3.66	-0.67	2.07	5.04	8.09	10.32	26.76	0.15	4.58	4,473
House price growth (5^{th} p.)	2.23	5.31	-25.43	-6.03	-3.96	-0.83	2.06	5.14	8.41	10.84	28.06	0.21	5.07	4,779
House price growth (25^{th} p.)	2.22	4.24	-14.70	-4.76	-2.99	-0.42	2.09	4.88	7.56	9.36	19.23	0.11	3.56	3,762

Table 5: Average amount of housing transactions for the different percentiles of the distribution of house price growth when using different thresholds to drop municipalities from the sample

Percentiles of house price growth	Average number of transactions		
	Cut-off 10^{th} p.	Cut-off 5^{th} p.	Cut-off 25^{th} p.
Percentile 0-5	44	35	61
Percentile 6-10	64	57	83
Percentile 11-15	86	75	100
Percentile 16-20	90	85	108
Percentile 21-25	96	97	107
Percentile 26-30	132	104	144
Percentile 31-35	102	120	122
Percentile 36-40	126	121	135
Percentile 41-45	121	115	129
Percentile 46-50	140	137	161
Percentile 51-55	138	135	147
Percentile 56-60	145	141	163
Percentile 61-65	125	129	136
Percentile 66-70	149	150	163
Percentile 71-75	135	124	145
Percentile 76-80	162	142	172
Percentile 81-85	118	119	146
Percentile 86-90	113	99	131
Percentile 91-95	72	64	103
Percentile 96-100	54	41	75
Total	111	104	127

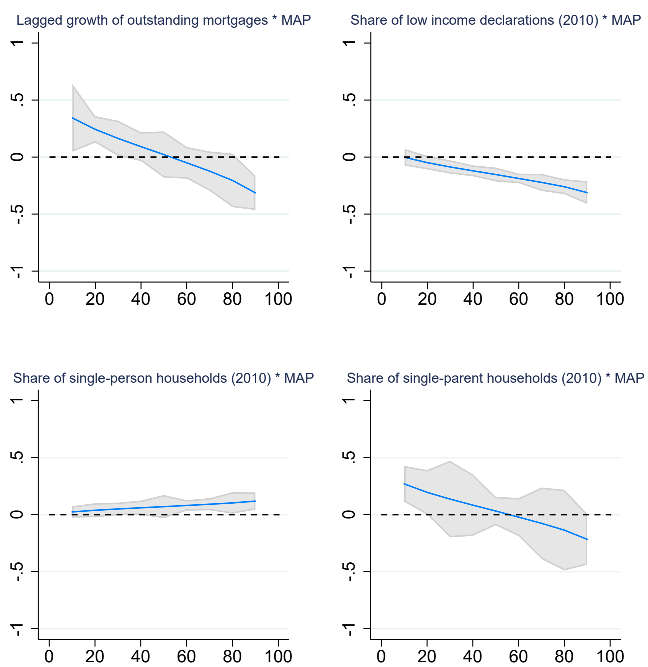
Table 6: Results when using a different cut-off point in cleaning the data (interactions combined)

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable	ΔHP	ΔHP	ΔHP	ΔHP	ΔHP	ΔHP	ΔHP	ΔHP	ΔHP	ΔHP	ΔHP	ΔHP
Share of low-income declarations (2010) * ΔMAP							-0.137***	-0.180***	-0.111***	-0.134***	-0.180***	-0.0975***
							(0.0341)	(0.0472)	(0.0335)	(0.0276)	(0.0495)	(0.0322)
Share of young people (2010) * ΔMAP				-0.230***	-0.257**	-0.240***	-0.232***	-0.266**	-0.211**	-0.236**	-0.271**	-0.236**
				(0.0825)	(0.110)	(0.0729)	(0.0891)	(0.122)	(0.0847)	(0.0970)	(0.118)	(0.0980)
Share of highly-educated young people (2011) * ΔMAP				0.0558***	0.0598***	0.0462***						
				(0.0164)	(0.0226)	(0.0164)						
Share of single-person households (2010) * ΔMAP							0.00913	0.0596	0.00174	0.00615	0.0651	-0.00717
							(0.0313)	(0.0402)	(0.0290)	(0.0339)	(0.0428)	(0.0277)
Share of single-parent households (2010) * ΔMAP							-0.0569	0.125	0.00741	-0.0646	0.161	-0.0149
							(0.120)	(0.122)	(0.123)	(0.101)	(0.133)	(0.114)
Lagged growth of housing transactions * ΔMAP	-0.00245	0.0368	-0.219							-0.00160	0.0750	-0.267*
	(0.0114)	(0.162)	(0.140)							(0.00980)	(0.136)	(0.137)
Lagged growth of outstanding mortgages * ΔMAP	0.0837	0.00930	0.00748							0.0296	0.00962	0.00691
	(0.127)	(0.0102)	(0.00919)							(0.127)	(0.0110)	(0.00977)
Threshold cut-off	10th percentile	5th percentile	25th percentile	10th percentile	5th percentile	25th percentile	10th percentile	5th percentile	25th percentile	10th percentile	5th percentile	25th percentile
Number of municipalities	497	530	417	497	530	417	497	530	417	497	530	417
Driving factors of ΔHP (lagged)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region * time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged ΔHP	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

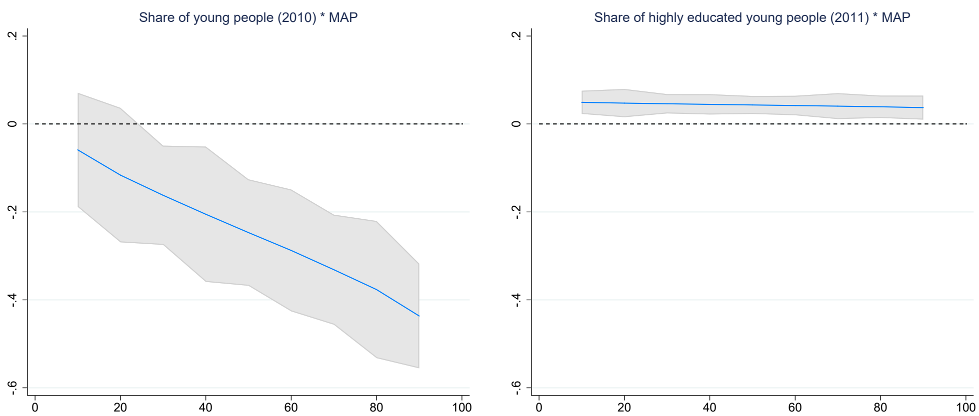
Figure 7: Quantile regression results when using the 5^{th} percentile as a threshold to remove municipalities from the sample. The blue line shows the coefficient estimates across the deciles of the distribution of house price growth. The grey areas reflect the 90% error bands.

(a)

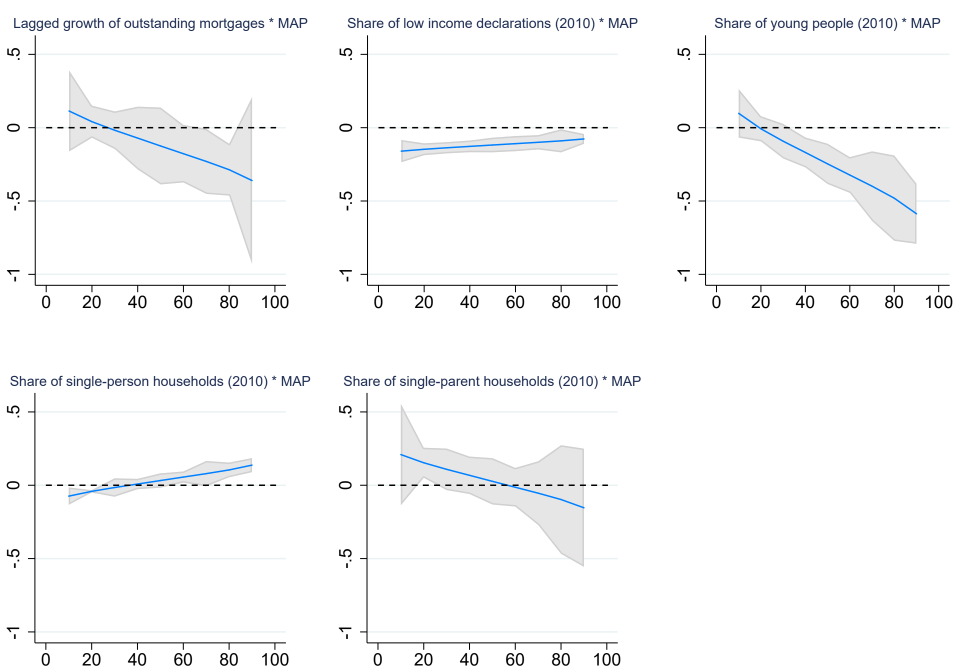


(b)

Figure 8: Quantile regression results when using the 25^{th} percentile as a threshold to remove municipalities from the sample. The blue line shows the coefficient estimates across the deciles of the distribution of house price growth. The grey areas reflect the 90% error bands.



(a)



(b)

5.2. Different proxies

In this section, we test the sensitivity of our baseline results to using different proxies for the housing supply indicator, the share of low-income declarations, and the indicator for macroprudential policy.

5.2.1. Housing supply indicator

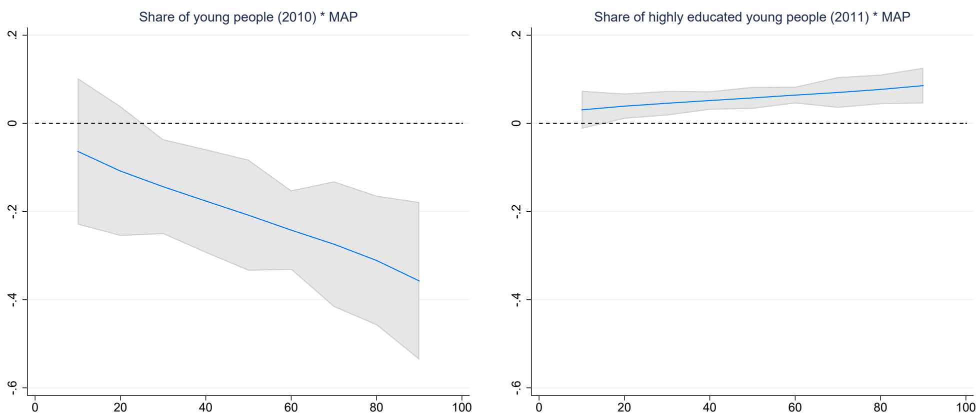
Another option than using the growth in the housing stock (i.e., number of existing buildings relative to number of inhabitants) to capture housing supply in our benchmark models is to use the growth in the number of building permits (relative to the number of existing buildings). More specifically, building permits measure the construction flow, which eventually indicates an increase in new supply of housing rather than being a measure of the housing stock (Duca et al., 2021, Bolhuis et al., 2022). The results are shown in table 7 and figure 9 which indicate qualitatively the same results as in the benchmark models. Similar to the coefficient of the growth in the housing stock, the coefficient of growth in building permits is negative but insignificant as well.

Table 7: Results for baseline model with building permits as a housing supply indicator

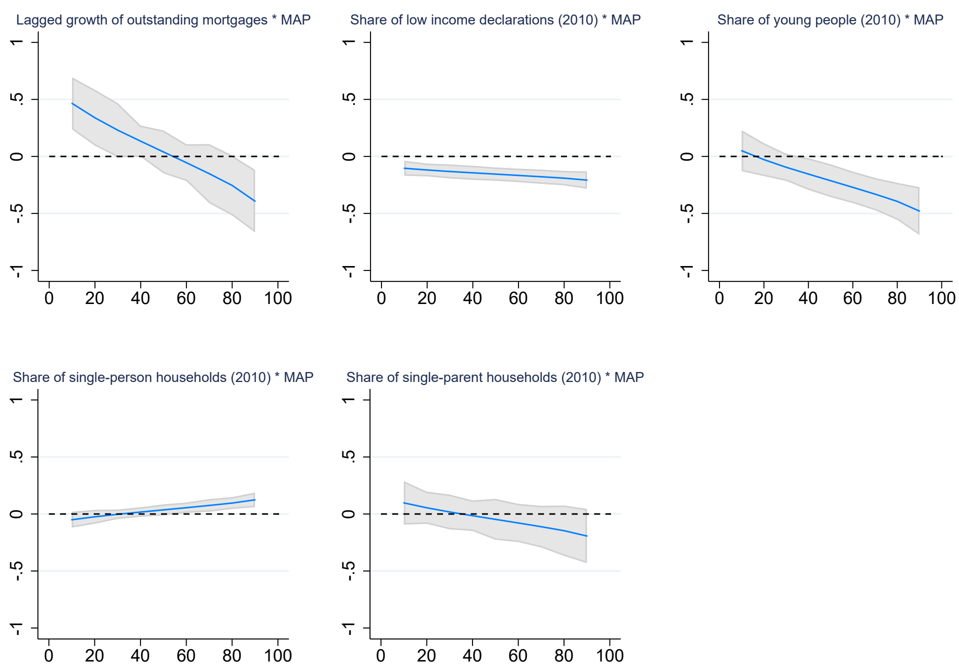
Specification Dependent variable	(1) ΔHP	(2) ΔHP	(3) ΔHP	(4) ΔHP
Share of low-income declarations (2010) * ΔMAP			-0.136*** (0.0365)	-0.132*** (0.0405)
Share of young people (2010) * ΔMAP		-0.193* (0.101)	-0.204** (0.0895)	-0.220** (0.0912)
Share of highly-educated young people (2011) * ΔMAP		0.0593*** (0.0183)		
Share of single-person households (2010) * ΔMAP			0.00820 (0.0306)	0.00506 (0.0360)
Share of single-parent households (2010) * ΔMAP			-0.117 (0.100)	-0.125 (0.124)
Lagged growth of housing transactions * ΔMAP	-0.00153 (0.00934)			-0.000582 (0.00896)
Lagged growth of outstanding mortgages * ΔMAP	0.0760 (0.113)			0.0120 (0.112)
Number of municipalities	497	497	497	497
Driving factors of ΔHP (lagged)	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes
Region * time FE	Yes	Yes	Yes	Yes
Lagged ΔHP	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 9: Quantile regression results when using building permits as a housing supply indicator. The blue line shows the coefficient estimates across the deciles of the distribution of house price growth. The grey areas reflect the 90% error bands.



(a)



(b)

5.2.2. Share of low-income in 2010

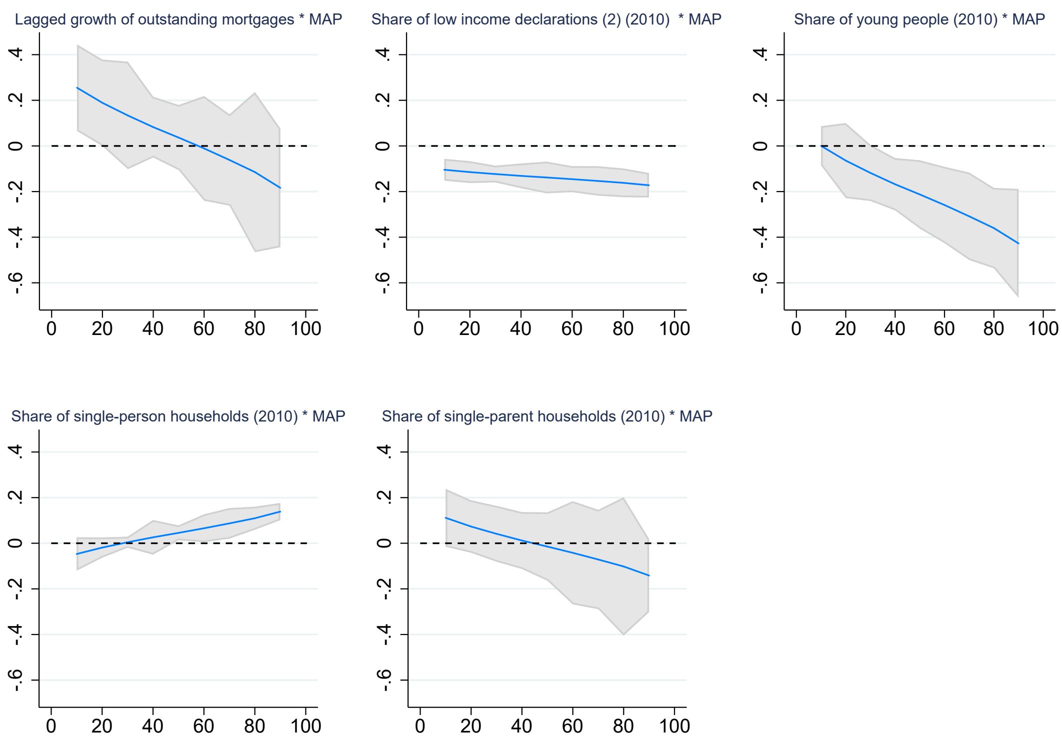
Next, we check whether our results are sensitive to the definition of the share of low-income declarations in 2010. In our baseline model, we use the share of declarations that indicated to have a yearly net taxable income between 10000 and 20000 euro. As a robustness check, we now use a more broad definition of low-income declarations and look at the share of declarations that indicated to have a yearly net taxable income lower than 20000 euro, including the declarations with a net taxable income below 10000 euro as well. Again, our results for the dynamic fixed effect model are very similar to the results of the baseline model with comparable coefficients for the share of low-income term (see table 8). In terms of the quantile regressions (figure 10), we find very comparable results for the majority of the interactions as well.

Table 8: Results for baseline model when using a different measure of share of low-income declarations in 2010

Specification Dependent variable	(1) ΔHP	(2) ΔHP	(3) ΔHP
Share of low-income declarations (2) (2010) * ΔMAP	-0.146***	-0.139***	-0.133***
	(0.0309)	(0.0347)	(0.0344)
Share of young people (2010) * ΔMAP		-0.254**	-0.259***
		(0.0997)	(0.0851)
Share of single-person households (2010) * ΔMAP		0.0271	0.0223
		(0.0339)	(0.0327)
Share of single-parent households (2010) * ΔMAP		-0.0589	-0.0705
		(0.113)	(0.110)
Lagged growth of housing transactions * ΔMAP			-0.00211
			(0.00995)
Lagged growth of outstanding mortgages * ΔMAP			0.0285
			(0.150)
Number of municipalities	497	497	497
Driving factors of ΔHP (lagged)	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes
Region * time FE	Yes	Yes	Yes
Lagged ΔHP	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 10: Quantile regression results when using a measure of share of low-income declarations in 2010. The blue line shows the coefficient estimates across the deciles of the distribution of house price growth. The grey areas reflect the 90% error bands.



5.2.3. Indicator for macroprudential policy

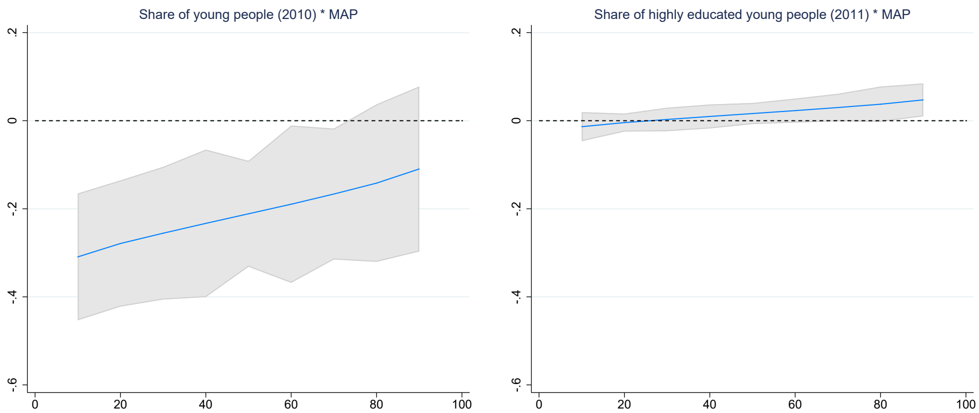
The chosen indicator for macroprudential policy is an intensity-adjusted indicator (see supra, section 3.2). With such control for the bindingness of the actions, the Belgian tightenings in the risk-weight regulation do not get the same weight as the tightening in the LTV-related regulation which would be the case for the more simple and commonly used way of capturing macroprudential policy changes based on the '-1/0/+1' indicator. When using this more common dummy variable to capture macroprudential policy changes, we find that the coefficients of some variables remain insignificant but change sign (e.g., for the growth in outstanding mortgages and the share of single-person households, see table 9). However, using this dummy takes significance away from the coefficients of the share of low-income and the share of highly-educated young people. Moreover, the coefficient of the share of single-parent households becomes positively significant, which is not in line with the expectations. Similar to these results, the quantile regressions in figure 11 show some changes as well, in terms of slope and significance and are generally considered to be less intuitive. From this, we conclude that taking into account the intensity of the regulatory changes matters for some of our benchmark results, making them more in line with theoretical expectations.

Table 9: Results when using a dummy variable to capture changes in macroprudential policy

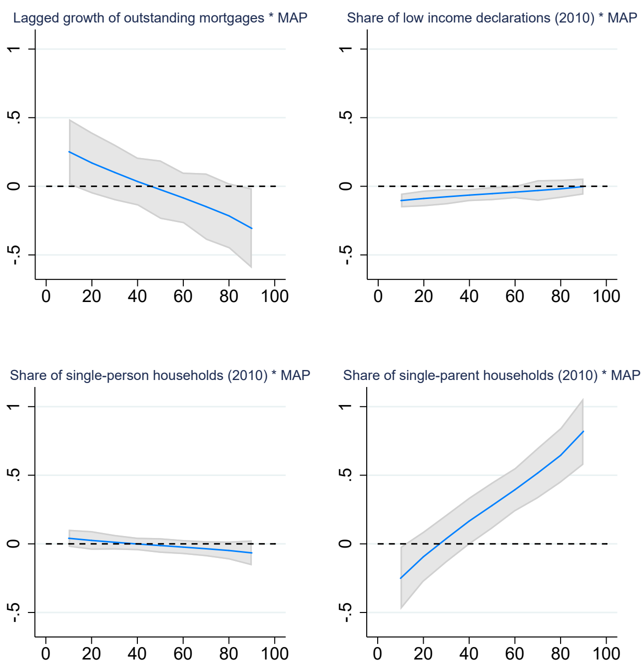
Specification Dependent variable	(1) ΔHP	(2) ΔHP	(3) ΔHP	(4) ΔHP
Share of low-income declarations (2010) * ΔMAP (dummy)			-0.0374	-0.0330
			(0.0338)	(0.0371)
Share of young people (2010) * ΔMAP (dummy)		-0.272***	-0.233***	-0.218**
		(0.0855)	(0.0886)	(0.106)
Share of highly-educated young people (2011) * ΔMAP (dummy)		0.00868		
		(0.0165)		
Share of single-person households (2010) * ΔMAP (dummy)			-0.00659	-0.0114
			(0.0316)	(0.0309)
Share of single-parent households (2010) * ΔMAP (dummy)			0.239**	0.232**
			(0.117)	(0.114)
Lagged growth of housing transactions * ΔMAP (dummy)	-0.00336			-0.00240
	(0.00619)			(0.00614)
Lagged growth of outstanding mortgages * ΔMAP (dummy)	-0.0741			-0.0347
	(0.116)			(0.124)
Number of municipalities	497	497	497	497
Driving factors of ΔHP (lagged)	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes
Region * time FE	Yes	Yes	Yes	Yes
Lagged ΔHP	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 11: Quantile regression results when using a dummy variable to capture changes in macroprudential policy. The blue line shows the coefficient estimates across the deciles of the distribution of house price growth. The grey areas reflect the 90% error bands.



(a)



(b)

5.3. Heterogeneous effects of common shocks to the Belgian economy

As mentioned in section 3.3, if there are common shocks to the Belgian economy other than macroprudential policy that can affect local house price dynamics in a heterogeneous way, omitted variable bias concerns can arise. In this section, we dig deeper into the potential heterogeneous effects of interest rate changes and the COVID-19 crisis and analyze whether these results impact our conclusions on the effects of macroprudential policy.

First, we focus on interest rate changes. Although the timing of changes in the interest rates during our sample does not coincide with the macroprudential policy changes, it could be argued that both shocks could heterogeneously affect the local house price growth rates through some of the same interaction variables since both policies' instruments affect household financing conditions. To test whether the effects of the macroprudential policy changes still hold when allowing for potentially heterogeneous effects of interest rate changes, we add the interactions of our variables of interest with the changes in the interest rate. To capture interest rate changes, we use the change in the yearly lending rate for house purchase by households in Belgium since this is the interest rate that affects the demand for housing credit and thus could affect house prices. More details on this variable can be found in 7.

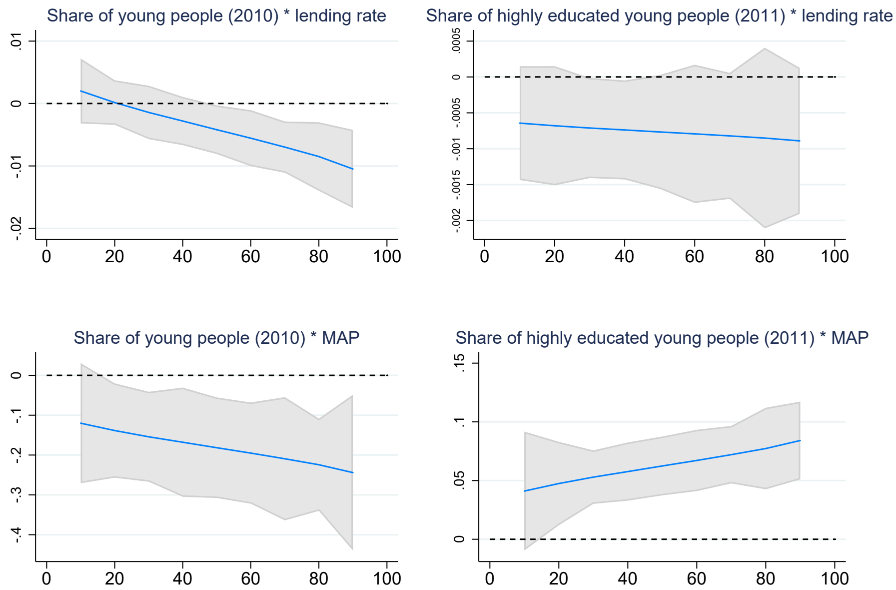
The results for the dynamic fixed effect model, depicted in table 10 show that the interactions with the macroprudential policy index are almost exactly the same as our baseline results, both in terms of sign and significance. The quantile regression results shown in figure 12 confirm this conclusion. The interactions with the interest rate changes shows some significance as well, although not always with the expected sign or slope. Overall, these results show that, when controlling for potential heterogeneous effects of common interest rate changes, our baseline results are not affected.

Table 10: Results when adding interactions with interest rate changes

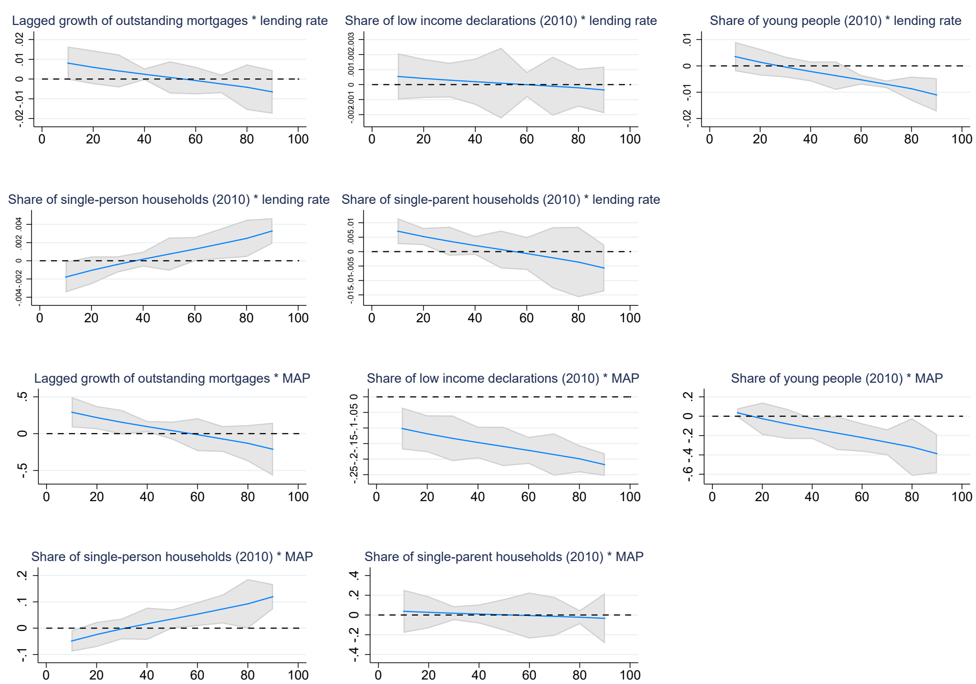
Specification	(1)	(2)	(3)	(4)
Dependent variable	ΔHP	ΔHP	ΔHP	ΔHP
Share of low-income declarations (2010) * lending rate			-0.000958	-0.000934
			(0.001000)	(0.000915)
Share of low-income declarations (2010) * ΔMAP			-0.132***	-0.129***
			(0.0356)	(0.0393)
Share of young people (2010) * lending rate		-0.00454*	-0.00531	-0.00440*
		(0.00250)	(0.00323)	(0.00253)
Share of young people (2010) * ΔMAP		-0.207***	-0.210**	-0.220**
		(0.0756)	(0.0900)	(0.0879)
Share of highly-educated young people (2011) * lending rate		-0.000499		
		(0.000378)		
Share of highly-educated young people (2011) * ΔMAP		0.0577***		
		(0.0128)		
Share of single-person households (2010) * lending rate			0.00182**	0.00181*
			(0.000862)	(0.00102)
Share of single-person households (2010) * ΔMAP			0.00259	0.00179
			(0.0366)	(0.0286)
Share of single-parent households (2010) * lending rate			0.000154	0.000869
			(0.00270)	(0.00289)
Share of single-parent households (2010) * ΔMAP			-0.0527	-0.0651
			(0.124)	(0.123)
Lagged growth of housing transactions	0.226*			0.273**
	(0.135)			(0.109)
Lagged growth of housing transactions * lending rate	0.000370***			0.000384***
	(0.000130)			(0.000136)
Lagged growth of housing transactions * ΔMAP	-0.00248			-0.00216
	(0.0105)			(0.0104)
Lagged growth of outstanding mortgages	0.00677			0.00717
	(0.00501)			(0.00448)
Lagged growth of outstanding mortgages * lending rate	0.000443			0.00290
	(0.00396)			(0.00354)
Lagged growth of outstanding mortgages * ΔMAP	0.0851			0.0258
	(0.108)			(0.115)
Number of municipalities	497	497	497	497
Driving factors of ΔHP	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes
Region * time FE	Yes	Yes	Yes	Yes
Lagged ΔHP	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 12: Quantile regression results when when adding interactions with interest rate changes. The blue line shows the coefficient estimates across the deciles of the distribution of house price growth. The grey areas reflect the 90% error bands.



(a)



(b)

Next, we investigate the role that the onset of the COVID-19 crisis could have on our estimation results. More specifically, since our sample includes data for house price growth in 2020 (corresponding to housing transaction data from 2020Q3-2021Q2, see footnote 4), the start of the pandemic is included in our data. The COVID-19 pandemic has impacted the housing market in various ways. First, in the early stages of the pandemic, housing transactions dropped since in-person housing visits were not possible during 8 weeks due to the health-related lockdown measures. Later, as a result of the lockdowns and change to working from home, housing preferences also changed (Reusens et al., 2022). People started to look for larger houses with more rooms and more outdoor space, preferably outside of the city (Liu and Su, 2021, D'Lima et al., 2022). Our analysis takes account of these evolutions in multiple ways. First, any impact on house price growth of the COVID-19 crisis that is common to all municipalities, is picked up by the time fixed effects. Second, by using the hedonic index, we are able to measure house price growth of an identical dwelling, controlling already for quality-related preference shifts. Third, based on the analysis of Reusens et al. (2022), we argue that the shift in location preferences and subsequent relocations is a medium- to long-term shift that will not be visible in our dataset yet since household relocation decisions take time to materialize. More specifically, the authors do not find evidence for a reversal of urban house price patterns. In the first year of COVID-19, house price growth remained slightly higher in most cities compared to the surrounding rural-urban fringe and commuter belt which supports the fact that any relocation effects still remain to be seen in the data from 2021 onwards. Nevertheless, the COVID-19 crisis could still heterogeneously impact the local housing markets, although this is not expected to work through the same channels as the heterogeneous effects of macroprudential policy.

To examine what happens to coefficient of the interaction terms with macroprudential policy, we control at the same time for any heterogeneous effects of the COVID-19 crisis. To do this, we use the number of new confirmed cases per 1000 inhabitants at the municipal level as measure of the strength of the pandemic in at the local level. Although the registered confirmed cases are highly likely to underestimate the real amount of confirmed cases in the early months of the pandemic due to the underdeveloped testing strategy at the time, this indicator does allow us to control for the COVID-19 effects at the level of the local housing market while distinguishing them from the impact of the 2020 macroprudential policy changes.[16]

Table 11 shows the results of this exercise for the dynamic fixed effects model. The coefficient for the interaction with macroprudential policy of the share of young people is still negative and significant, as in the baseline results. The signs of the interaction with the share of low-income and share of single-parent households switch relative to the baseline results, although the sign for the share of low income is negative for the alternative definition of low-income declarations (see section 5.2.2). Remarkably, we now find significant effects for lagged growth in outstanding credits interacted with the macroprudential policy index, with the expected sign (i.e., pointing to a dampening effect of tightening macroprudential regulation on house price growth with increases in household debt). For the interaction of the share of highly-educated young people, the positive significant effect from our baseline results seems to be picked up by the COVID-19 interaction. From the quantile regressions results in panel (a) of figure 13, we note that the solid blue lines for the interactions with the macroprudential policy index still have the expected sign, but not the expected slope and show less significance compared to the benchmark quantile regressions results. Looking at panel (b) of figure 13, we find that, similar to the benchmark quantile regression results, the interaction of macroprudential policy with the share of young people still has a negative sign and slope. The interaction with the share of low income is negative as well, although the slope is slightly positive. Similar to the baseline quantile regression results, the effects for the lagged growth of outstanding mortgages and the share of single-person and single-parent households are less clear.

While taking into account the short time span of the COVID-19 crisis in our sample in contrast to the more medium-term behavioural change, we can conclude that the macroprudential policy changes still show more dampening effects on house price growth for some of the indicators of a large share of constrained or high risk borrowers. The heterogeneous effects in municipalities with a high share of young people is highly robust, whereas the share of low income continues to show a dampening impact on local house price growth as well, albeit more obvious when differentiating over the distribution of house price growth.

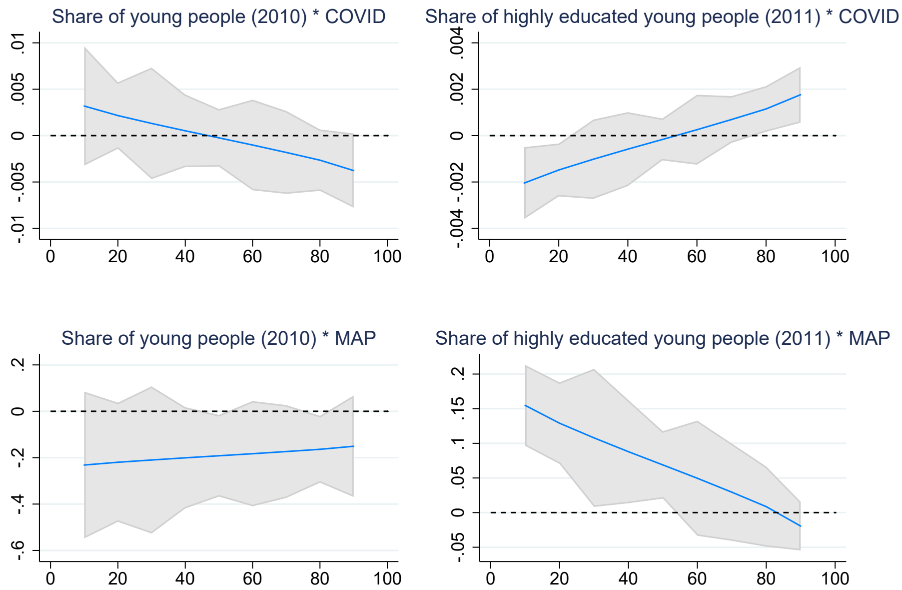
[16] Another option would be to look at hospitalisation numbers which give a more clear message of the severity of the pandemic in its early stages. However, this indicator is only available at the province level, which reduces its cross-section dimension a lot. Moreover, there is no reason to believe that the underestimation of confirmed cases was worse in some municipalities relative to others.

Table 11: Results when adding interactions with a COVID-19 indicator

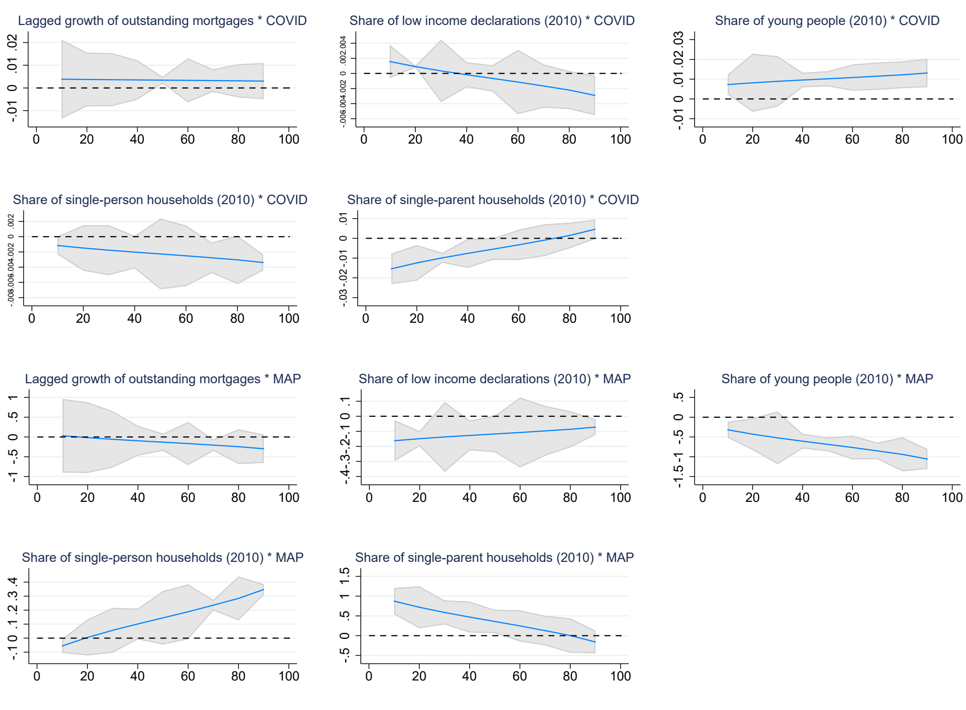
Specification Dependent variable	(1) ΔHP	(2) ΔHP	(3) ΔHP	(4) ΔHP	(5) ΔHP	(6) ΔHP
COVID-19 cases	-0.0367**	-0.199**	0.0257	0.0150	0.0183	0.0106
	(0.0144)	(0.0794)	(0.0895)	(0.0795)	(0.0831)	(0.0838)
Share of low-income declarations (2010) * COVID cases			-0.00240	-0.00308		
			(0.00168)	(0.00179)		
Share of low-income declarations (2010) * ΔMAP			0.00619	0.0451		
			(0.0998)	(0.102)		
Share of low-income declarations (2010) (2) * COVID cases					-0.000816	-0.00126
					(0.00204)	(0.00182)
Share of low-income declarations (2010) (2) * ΔMAP					-0.0920	-0.0619
					(0.109)	(0.107)
Share of young people (2010) * COVID cases		0.0110*	0.00987*	0.0102**	0.00964**	0.00983
		(0.00636)	(0.00557)	(0.00412)	(0.00473)	(0.00629)
Share of young people (2010) * ΔMAP		-0.797**	-0.776***	-0.789***	-0.785***	-0.791**
		(0.316)	(0.278)	(0.236)	(0.249)	(0.316)
Share of educated young people (2011) * COVID cases		0.00149**				
		(0.000662)				
Share of highly-educated young people (2011) * ΔMAP		-0.0225				
		(0.0364)				
Share of single-person households (2010) * COVID cases			-0.00145	-0.00168	-0.00178	-0.00207
			(0.00162)	(0.00155)	(0.00181)	(0.00178)
Share of single-person households (2010) * ΔMAP			0.0916	0.0916	0.129	0.130
			(0.0916)	(0.0845)	(0.0843)	(0.0916)
Share of single-parent households (2010) * COVID cases			-0.00427	-0.00310	-0.00568	-0.00452
			(0.00470)	(0.00425)	(0.00480)	(0.00439)
Share of single-parent households (2010) * ΔMAP			0.235	0.192	0.317	0.272
			(0.315)	(0.280)	(0.276)	(0.262)
Lagged growth of housing transactions	-0.00210			-0.00236		-0.00238
	(0.00311)			(0.00328)		(0.00360)
Lagged growth of housing transactions * COVID cases	-0.000224			-0.000257		-0.000272
	(0.000383)			(0.000433)		(0.000492)
Lagged growth of housing transactions * ΔMAP	0.0130			0.0163		0.0166
	(0.0242)			(0.0282)		(0.0275)
Lagged growth of outstanding mortgages	0.247***			0.230***		0.232***
	(0.0738)			(0.0758)		(0.0787)
Lagged growth of outstanding mortgages * COVID cases	0.0130***			0.01000**		0.0105*
	(0.00417)			(0.00448)		(0.00563)
Lagged growth of outstanding mortgages * ΔMAP	-0.717***			-0.558*		-0.586*
	(0.267)			(0.287)		(0.339)
Number of municipalities	497	497	497	497	497	497
Driving factors of ΔHP	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Region * time FE	Yes	Yes	Yes	Yes	Yes	Yes
Lagged ΔHP	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 13: Quantile regression results when adding interactions with a COVID-19 indicator. The blue line shows the coefficient estimates across the deciles of the distribution of house price growth. The grey areas reflect the 90% error bands.



(a)



(b)

5.4. Woonbonus

As explained in section 3.3, we include time*region fixed effects in our baseline model to capture all the factors that are region-specific and vary over time. These time*region fixed effects thus also capture changes in regional taxation rules related to the purchase of a house. One of the most important changes in the tax regulation happened in 2005, when the Belgian government introduced the so-called 'woonbonus' which allowed tax payers to deduct mortgage costs from their taxes. After the creation of the 'woonbonus' at the federal (Belgian) level in 2005, the regulation was moved to the regions (Flanders, Brussels, and Wallonia) in 2015. Since then, the regions have handled the mortgage tax deduction regulation differently. In Flanders, after diminishing the benefits a first time in January 2016, the 'woonbonus' has ended from 2020 onwards while Brussels removed the woonbonus and instead has offered lower registration rights from 2017 onwards. The Walloon region also replaced the 'woonbonus' in 2016, but with a different fiscal reduction based on income rather than on mortgage costs called the 'chèque habitat' (FOD financiën, 2019). This 'chèque habitat' is currently still in place.

As this tax subsidy was considered to be important for the Belgian housing market, we investigate the effects of the 'woonbonus'. To set up an indicator for the 'woonbonus', we can follow the regulatory evolution of the 'woonbonus' and exploit this different timing of abolishing the 'woonbonus' across the Belgian regions in our empirical setting. More specifically, we construct a categorical variable that indicates the changes in the mortgage rate deduction scheme, with a decrease or abolishment of the 'woonbonus' indicated by the value '-1'. For Flemish municipalities, the indicator gets the value of '-1' in 2016 and 2020. For all Brussels municipalities, the indicator is '-1' in 2017. The indicator stays at '0' for municipalities in Wallonia. To examine the impact of the regional changes in the 'woonbonus' on our estimates, we introduce an additional variable to models (3.3) and (4.1). We do not interact this control with the considered interaction variables as housing-related taxes and subsidies are expected to affect house prices regardless of whether households are financially constrained or highly indebted. We do have to estimate the econometric models without time*region fixed effects as these effects hinder us to explicitly capture the effects of the 'woonbonus'.

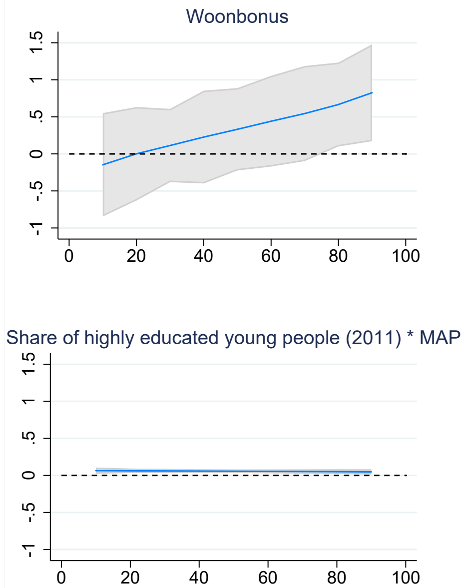
The results in table 12 and figure 14 show that our conclusions about the interactions terms are very close to the benchmark models. Although our measure of the 'woonbonus' is blunt, the positive coefficient and the solid blue lines above the zero line for this indicator signal that a decrease or abolishment of the 'woonbonus' has decreased house price growth. This is in line with the expectations, since revoking the tax benefits decreases demand for housing (Winters et al., 2021). The term even becomes significant in some specifications. This contradicts some of the claims that the abolishment of the 'woonbonus' was not able to lower house prices. The slope of the solid blue line for the 'woonbonus', however, shifts depending on which interactions are combined and is not always significant, meaning that we cannot make a clear conclusion on the heterogeneous impact of the 'woonbonus' in hot versus cold housing markets.

Table 12: Results when explicitly including a 'woonbonus' indicator

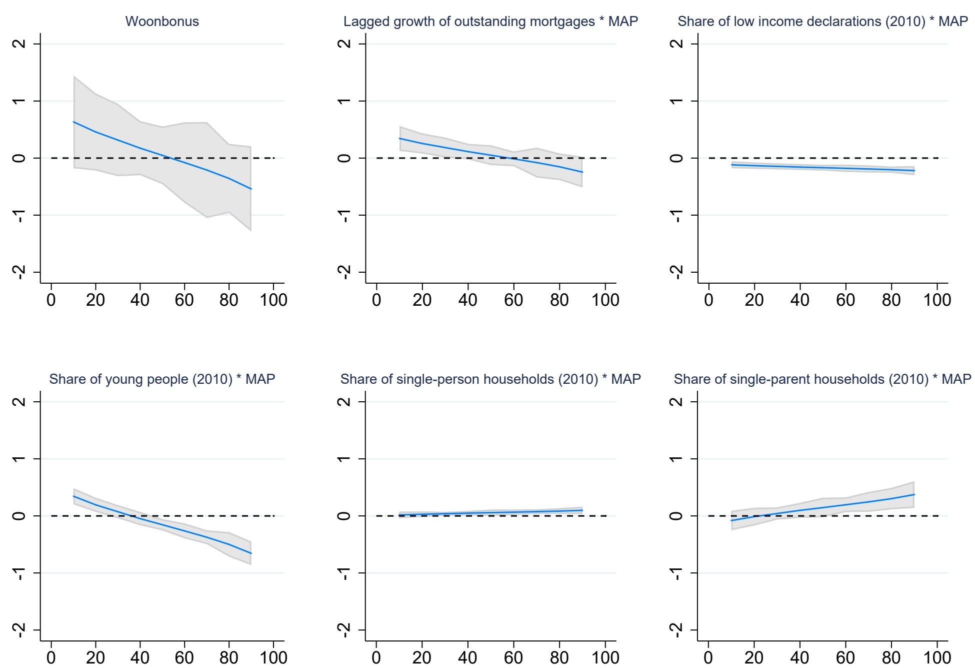
Specification Dependent variable	(1) ΔHP	(2) ΔHP	(3) ΔHP	(4) ΔHP
Woonbonus indicator	0.353	0.492	0.763**	0.687**
	(0.314)	(0.332)	(0.324)	(0.350)
Share of low-income declarations (2010) * ΔMAP			-0.148***	-0.145***
			(0.0350)	(0.0367)
Share of young people (2010) * ΔMAP		-0.150**	-0.176*	-0.182**
		(0.0763)	(0.0898)	(0.0895)
Share of highly-educated young people (2011) * ΔMAP		0.0629***		
		(0.0168)		
Share of single-person households (2010) * ΔMAP			0.0259	0.0249
			(0.0300)	(0.0278)
Share of single-parent households (2010) * ΔMAP			-0.0617	-0.0441
			(0.0727)	(0.0874)
Lagged growth of housing transactions * ΔMAP	-0.000841			-0.000282
	(0.0108)			(0.00810)
Lagged growth of outstanding mortgages * ΔMAP	0.113			0.00912
	(0.117)			(0.0903)
Number of municipalities	497	497	497	497
Driving factors of ΔHP (lagged)	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes
Region * time FE	No	No	No	No
Lagged ΔHP	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 14: Quantile regression results when explicitly including a 'woonbonus' indicator. The blue line shows the coefficient estimates across the deciles of the distribution of house price growth. The grey areas reflect the 90% error bands.



(a)



(b)

6. Conclusion

In this paper, we assess whether Belgian housing-sector-specific macroprudential policy has a heterogeneous effect on house price growth in Belgian municipalities depending on indicators of housing financing constraints, the hotness of the municipal housing market, and household indebtedness, while at the same time controlling for the driving factors of local house price growth. We use a hedonic house price index which controls for quality-related changes in the composition of the sold properties to measure house price evolutions of identical dwellings and an intensity-adjusted index to capture macroprudential policy that accounts for differences in the restrictiveness of macroprudential implementations.

First, we estimate a dynamic fixed effects model with interaction terms to analyze heterogeneous effects of macroprudential policy. In line with Peydró et al. (2020) and Acharya et al. (2022), we find that geographic heterogeneity of the residents matters. More specifically, our results indicate that a macroprudential tightening causes house price growth to decrease more in housing markets with a high share of constrained or high-risk residents as indicated by high shares of low fiscal income declarations and young people at the municipal level and, from the opposite perspective, house price growth increases in municipalities with a high share of highly-educated young people who are considered to be less constrained. Next, we estimate quantile regressions which allow all variables to have a heterogeneous impact depending on the hotness of the housing market. We find that the heterogeneous effects of macroprudential policy related to residents' characteristics additionally depend on the hotness of the local housing market. In particular, our results show that a macroprudential policy tightening has a more dampening effect in hot housing markets with a high share of constrained or high-risk residents, compared to cold housing markets. Again, we find the opposite effects for a high share of highly educated young people.

House price developments play a pivotal role in financial cycles and macroprudential policies are considered to be most appropriate to mitigate housing-related risks to financial stability. Our results suggest that housing-market-specific macroprudential policy is more effective in curtailing these risks in housing markets with a high share of financial constrained or high-risk residents, and especially in hot housing markets. Since housing markets are segmented and local markets vary in terms of housing market activity and characteristics related to financing constraints of citizens, housing-related macroprudential changes will have geographically heterogeneous effects, depending on the specific conditions of the local housing markets at that point in time. Housing-sector-specific macroprudential polices can therefore be an adequate tool to stabilize hot local housing markets characterized by more financially constrained and high-risk residents while having less drastic price effects in other local markets.

However, from a societal perspective, the results could be worrisome. More specifically, a downward effect on house prices combined with a high share of constrained or high-risk borrowers could signal that these constrained or high-risk borrowers are being pushed out of the market. According to our results, this effect is strongest for low-income residents and young people. Policymakers should thus take account of possible distributional effects of macroprudential policies.

To further pinpoint the pass-through of these housing-sector-specific policies to the Belgian housing market, future work should try to obtain micro-level data in order to explore the link of housing transactions and the specific underlying house, mortgage, and borrower characteristics in more detail.

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7. Data visualisation and sources

7.1. Driving factors of local house price growth

Table 13: Descriptives of main driving forces of house price growth

	Mean	Std. Dev.	Min	Max	N
Median income growth	2.44	1.78	-7.78	19.38	4,644
Employment growth	0.64	1.30	-21.51	23.57	4,644
Growth housing stock	0.01	0.70	-4.24	6.02	5,676
Household growth	0.29	0.55	-8.21	4.11	5,664

Figure 15: Median income growth across 497 Belgian municipalities for 2012, 2016, and 2019 (%)

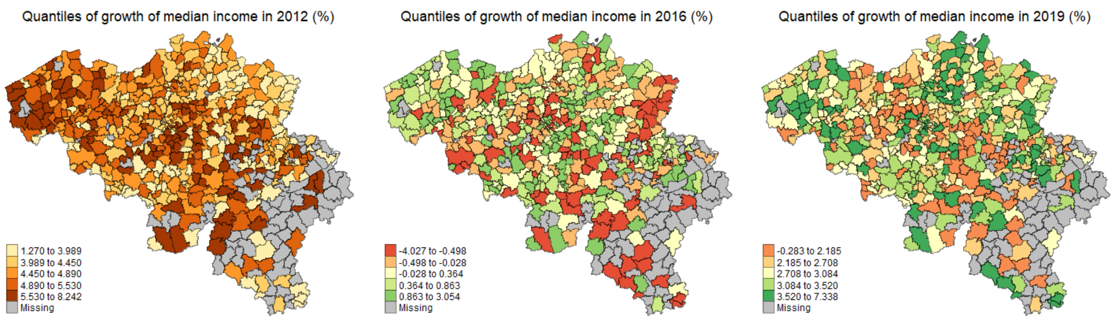


Figure 16: Employment growth across 497 Belgian municipalities for 2012, 2016, and 2019 (%)

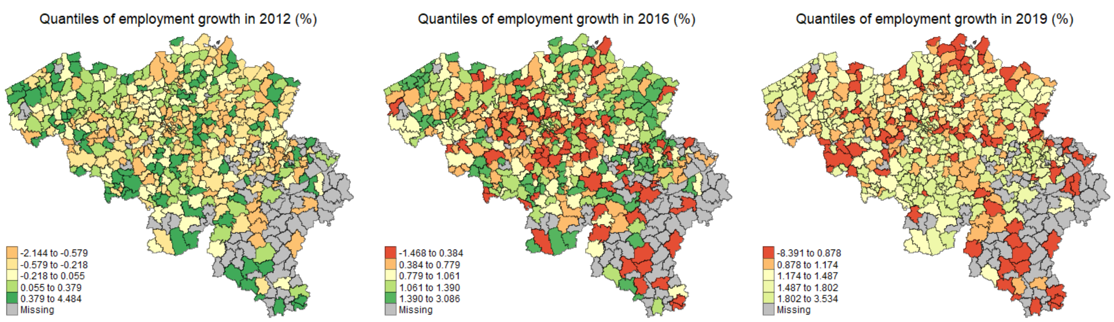


Figure 17: Growth of households across 497 Belgian municipalities for 2012, 2016, and 2020 (%)

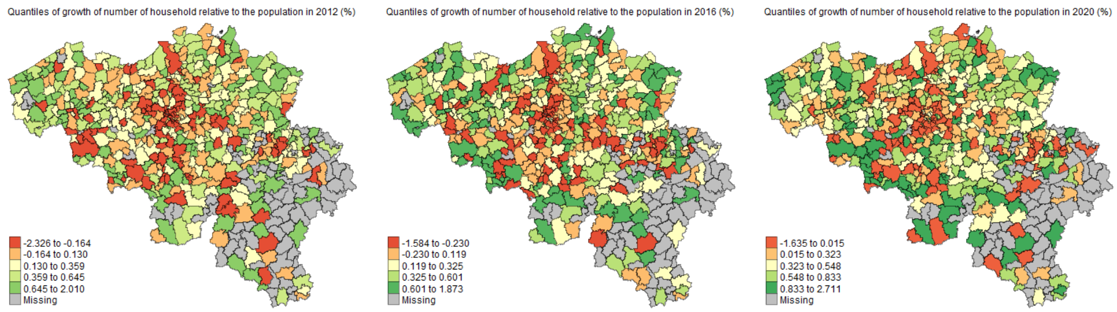
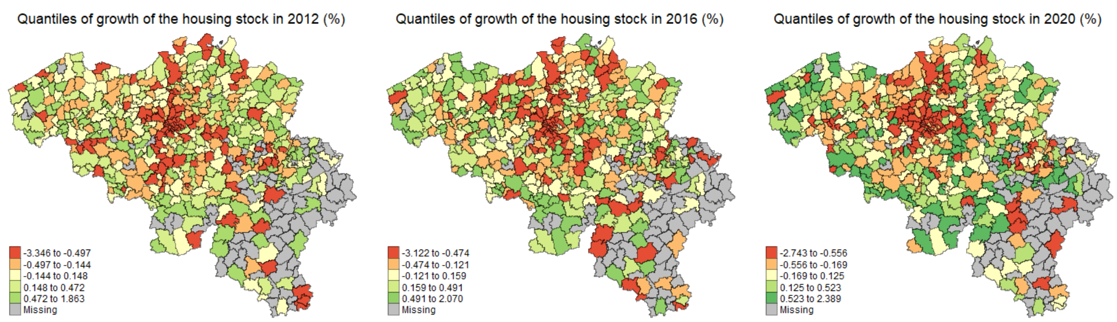


Figure 18: Growth of the housing stock across 497 Belgian municipalities for 2012, 2016, and 2020 (%)



7.2. Driving factors of potential heterogeneous reaction to macroprudential policies

Figure 19: Cross-sectional variation in the share of low-income declarations (2010), share of overdue mortgage credits (2010), and the share of young people (2010) across 497 Belgian municipalities

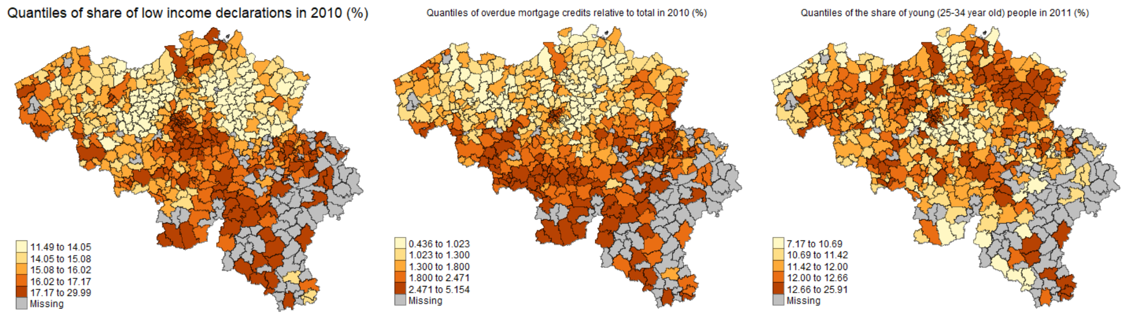


Figure 20: Cross-sectional variation in the share of single-person households (2010), the share of single-parent households (2010), and the share of highly-educated young people (2011) across 497 Belgian municipalities

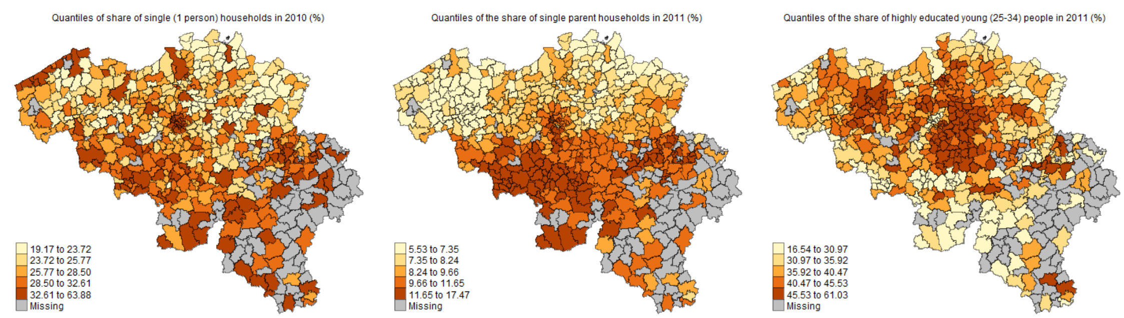


Figure 21: Growth of housing transactions across 497 Belgian municipalities for 2012, 2016, and 2020 (%)

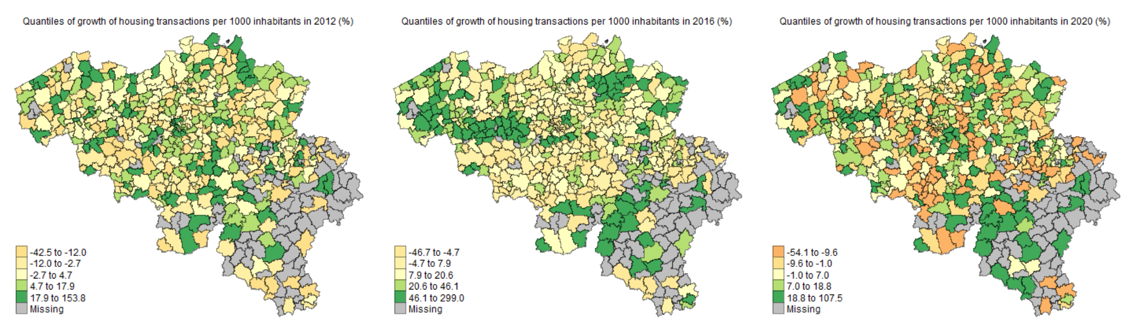
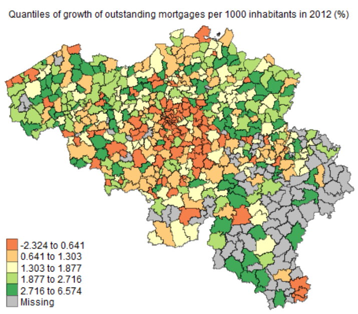
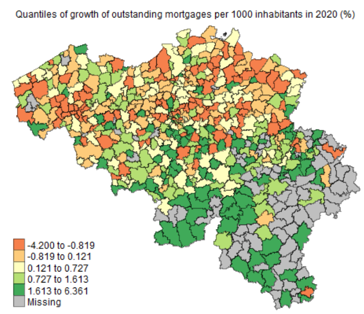


Figure 22: Growth of outstanding mortgages across 497 Belgian municipalities for 2012, 2016, and 2020 (%)





Appendix .1. Data sources

Table .14: Data variables and their sources

Variable	Description	Source
House price growth	Growth rate of the hedonic price index based on the analysis of Reusens et al. (2022). We set the hedonic index for 2020Q3-2021Q2 equal to 2020.	Analysis of Reusens et al. (2022)
Macroprudential policy index	Change in the restrictiveness of macroprudential policy, including the changes in risk-weigts for mortgages backed by residential property, LTV regulation and the combined LTV and D(S)TI regulation.	Based on previous work in Coulier and De Schryder (2022)
Growth in median income	Growth rate of the median net taxable income per fiscal declaration (based on both individual and common declarations) by place of residence. Data available at municipality level on annual frequency from 2005-2020.	STATBEL (fiscal income statistics)
Employment growth	Growth of the employment rate (employed persons relative to the population). Data available at municipality level on annual frequency from 2005-2019.	Steunpunt Werk (local labour market)
Growth in housing stock	Growth of the housing stock (number of residential buildings (sum of closed, semi-detached, and detached residential buildings) per 1000 inhabitants). Data available at municipality level on annual frequency from 1995-2021	STATBEL (building stock and population data)
Growth in building permits	Growth of building permits for new residential buildings (excluding renovations) per 100 residential buildings. Data available at municipality level at monthly frequency (aggregated to annual frequency) from 2012-2021.	STATBEL (building permits and building stock)
Growth in households	Growth of the number of households per 100 inhabitants. Data available at municipality level from 1992-2021.	STATBEL (population and household type)
Growth of housing transactions	Growth of housing transactions (exact number of transactions used to calculate the hedonic price index) per 1000 inhabitants. We set the transactions for 2020Q3-2021Q2 equal to 2020.	Analysis of Reusens et al. (2022)
Share of low income declarations (1)	The share of fiscal income declarations that indicated to have an annual net taxable income between 10000 and 20000 euro in 2010 (based on both individual and common declarations). Data available at municipality level on annual frequency from 2005-2020.	STATBEL (fiscal income declarations)
Share of low income declarations (2)	The share of fiscal income declarations that indicated to have an annual net taxable income below 20000 euro in 2010 (based on both individual and common declarations). Data available at municipality level on annual frequency from 2005-2020.	STATBEL (fiscal income declarations)
Share of overdue credits	The share of outstanding overdue mortgage credits[a] relative to total outstanding mortgage credits in 2010. Data available at municipality level from 2007-2020.	NBB Central Individual Credit Register
Share of young people	Share of 25-34 year olds in the total population. Data available at municipality level on annual frequency from 2010-2022.	STATBEL (age open data)
Share of highly educated young people	Share of highly educated (bachelor, master, or PhD diploma) 25-34 year olds relative to the total amount of 25-34 year olds in 2011	Census 2011
Share of single households	Share of single (one person) households relative to total amount of households. Data available at municipality level from 1992-2021.	STATBEL (population household type)
Share of single parent households	Share of single parent households relative to total amount of households. Data available at municipality level from 1992-2021.	STATBEL (population household type)
Change in the lending rate for house purchases	Yearly growth rate of the lending rate for house purchases to households and non-profit institutions serving households by MFIs except MMFs and central banks (excluding revolving loans and overdrafts, convenience and extended credit card debt, total calculated by weighting the volumes with a moving average). Data available at the country level on monthly frequency (averaged to yearly level) from 2003M1 to 2022M7.	ECB Statistical Data Warehouse
COVID cases	New confirmed cases of COVID-19. Smaller than 5 is counted as 5 cases. Data available at municipality level on daily frequency (aggregated at annual frequency) since the 4^{th} of March 2020.	Epistat-Sciensano
‘Woonbonus’ indicator	Indicator that captures relaxations and abolishments of the ´woonbonus’ regulation across the Belgian regions by assigning the value of ‘-1’. See section 5.4 for more details.	Own calculations

[a]The criteria for overdue debt are mainly related to a failure of full or in part payment of the instalments for three months. More information can be found on https://www.nbb.be/en/central-credit-register/credits-individuals/information-reported/recording-criteria.