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Housing and credit misalignments in a two-market disequilibrium framework

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Abstract

During the COVID-19 pandemic, house prices and mortgage credit rose at a long-unseen pace. It is unclear, however, whether such increases are warranted by the underlying market and macroeconomic fundamentals. This paper offers a new structural two-market disequilibrium model that can be estimated using full-information methods and applied to analyse housing and credit dynamics. Dealing with econometric specification uncertainty, we estimate a large ensemble of the two-market disequilibrium model specifications for Lithuanian monthly data. Using the model estimates, we identify the historical drivers of Lithuania's housing and credit demand and supply, as well as price and market quantity variables. The paper provides a novel approach in the financial stability literature to jointly measure house price overvaluation and mortgage credit flow gaps. We find that, by mid-2021, Lithuania was experiencing a heating-up in housing and mortgage credit markets, with home prices overvalued by around 16% and the volume of mortgage credit flow being 20% above its fundamentals.

Keywords: disequilibrium, fundamentals, misalignments, house prices, mortgage credit, early warning indicators.
JEL: C34, D50, E44, E51, G21.

1 Introduction

The housing market in the EU has been remarkably resilient to the COVID-19 pandemic, with residential real estate prices soaring in most member states – contrary to most analysts' initial expectations. This trend has been particularly strong in Lithuania: after a sudden halt in the first half of 2020, activity in the housing market picked up in the second half, and by the end of 2021 the volume of transactions reached record highs. The increased demand for housing in 2021 led to a 24% increase in house prices and a 34% increase in new mortgage flows, compared to the previous year (see Figure 1).[1]

The dramatic increase in both house prices and mortgage credit flows deserves attention from the financial stability perspective. The relationship between housing and credit markets has been discussed in the literature, with authors showing that the two-way interaction could lead to a build-up of vulnerabilities and thus raise the likelihood of a subsequent financial crisis (e.g. Jordà et al., 2014; Rünstler and Vlekke, 2018; Filipe, 2018). Macroprudential policy measures, such as the counter-cyclical capital buffer (CCyB) or the sectoral systemic risk buffer (SyRB), can be used to address the accumulation of risks by strengthening the resilience of the banking sector to a possible housing market correction. However, an increase in house prices and credit might not necessarily be a signal of imbalance, if it can be explained by underlying economic fundamentals. Therefore, statistical and econometric techniques are needed to understand the economic drivers behind these increases, identify misalignments in the housing and credit markets, and also account for their mutually reinforcing relationships.

In order to evaluate whether the recent sudden increase in activity in the housing and credit markets is a signal of imbalance, first, we need to understand the underlying drivers of demand and supply. For example, the increases in housing demand and, consequently, house prices might be caused by demographic changes, rising incomes or household savings, which can, for the most part, be considered as fundamental drivers. On the other hand, market dynamics may be driven by an overheating economy, optimistic expectations or myopic lending policies, which may inflate a housing and credit bubble.

Although market demand and supply variables, as well as misalignments, could be useful for policy-making institutions, they are unobservable variables. This paper offers a structural econometric framework that can be used to understand the drivers behind housing and mortgage growth, as well as identify periods when market prices were overvalued. We generalise and extend the single-market disequilibrium framework of Fair and Jaffee (1972) and Maddala and Nelson (1974) to the two-market case, in order to study the endogenous interaction between housing and credit markets. Our two-market disequilibrium setting is a regime-dependent structural VAR model with exogenous variables,

[1] Throughout this paper, we will use the terms credit, mortgages, and mortgage credit interchangeably when referring to flows of new credit secured with residential real estate.

which can be estimated using full-information maximum likelihood.

Using Lithuanian historical monthly data, and dealing with model specification uncertainty, we estimate the proposed model by running millions of predictor combinations and aggregating the results – similarly to the Bayesian model averaging approach (Sala-i-Martin, 1997; Sala-i-Martin et al., 2004). Our estimated ensemble of model specifications is used to identify the historical series of housing and credit demand and supply, as well as their drivers. By solving the estimated structural model, we are able to decompose the evolution of house prices and credit dynamics in Lithuania over the period of 2006-2021. On the basis of the model, we propose a novel framework that can be used to jointly identify housing and credit market misalignments, or gaps. Our recent results show that, in mid-2021, Lithuania was experiencing a heating-up of the housing and mortgage credit markets, with home prices overvalued by around 16% and the volume of mortgage credit flow 20% above its fundamentals.

The contribution of this paper is threefold. First, by proposing and estimating a new two-market model, we contribute to the econometric disequilibrium literature of Maddala and Nelson (1974), Gouriéroux et al. (1980), Ito (1980) and others. Importantly, our framework is able to capture the endogenous two-way interaction of housing and credit, and model the disequilibrium spillovers from one market to another. Second, by using the two-market model to jointly identify the fundamental levels of housing and credit, and to estimate the associated house price and credit gaps, we provide a new method for the financial stability literature on misalignment detection. Our approach may be of practical significance and can be used by analysts at policy-making institutions. Third, we expand Lithuania's local literature on misalignment detection and early warning models (Valinskytė and Rupeika, 2015; Kulikauskas, 2016; Naruševičius et al., 2019) by jointly assessing the imbalances in both housing and mortgage credit markets. As the paper offers an analysis of the estimates for the period between 2006 and 2021, we also complement the work of Kuodis and Ramanauskas (2009), Ramanauskas (2011), Ramanauskas et al. (2015, 2018) and others, who discuss the macrofinancial history of Lithuania.

The paper is structured as follows. Section 2 reviews the econometric disequilibrium literature and proposes a structural two-market disequilibrium model for estimation and analysis. Section 3 reviews the historical dynamics of housing and credit in Lithuania, estimates the proposed two-market disequilibrium model, and carries out impulse-response and driver analyses. Section 4 jointly disentangles the historical fundamental levels of house prices and mortgage credit flows. We conclude by describing three episodes of the Lithuanian housing and credit markets and their misalignments.

2 The disequilibrium framework

In a normally functioning market, demand and supply are always equilibrated by the price mechanism. However, in some cases a market can be characterised by a disequilibrium, where the price level cannot fully adjust to ensure that demand is exactly matched by supply. This situation can lead to a shortage of goods, i.e. demand is greater than supply, or to an excess supply.

For example, credit rationing might occur in lending markets, when borrowers cannot acquire all credit demanded, even at the market interest rates – the demand for lending exceeds supply. Credit rationing can arise even when lenders are rational and profit maximising (Jaffee and Modigliani, 1969), but are subject to capacity constraints, such as capital and other requirements. Jaffee and Russell (1976) and Stiglitz and Weiss (1981) show that, due to asymmetric information between creditors and debtors, credit rationing might be the norm – *equilibrium credit rationing*. On the other hand, there may be a surplus of credit, which the market demand cannot absorb, and creditors do not find it optimal to decrease interest rates – a failure of the price mechanism. This could happen in markets, e.g., where macroprudential borrower-based measures, such as the loan-to-value (LTV) and debt-service-to-income (DSTI) caps, are in place.

The disequilibrium may be the *modus operandi* of the housing market as well. This is especially true because housing is a durable good which takes time to build; thus, supply and demand cannot adjust instantly to ever-changing market prices. As is well known, the housing market has a matching friction in that all housing units are different, and it takes time and effort to buy a suitable apartment or house.

Indeed, one may question the above argumentation of the disequilibrium phenomenon and claim that prices always equilibrate markets, in spite of any capacity or time constraints.[2] However, the usual and implicit assumption of a market equilibrium is actually more binding than the disequilibrium assumption. In fact, as will be shown below, the disequilibrium framework is a generalisation of a simple "demand always equals supply" equilibrium approach to econometric modelling.

In this section, we will present the basic single-market disequilibrium econometric model and generalise it to the two-market case. We will later show how the two-market disequilibrium model can be used to estimate the fundamental level of prices and quantities in both markets, as well as associated gaps.[3]

[2] For instance, Malinvaud (2006) argues that "it seems hardly satisfactory to rely on a theoretical model organized around the minimum condition stating that the minimum of supply and demand is traded in the aggregate". Instead, one can assume that disequilibria or rationing occur at the micro, or transactional, level (e.g. Bouissou et al., 1986).

[3] Although the *equilibrium* and *fundamental* terms are often conflated in the financial stability literature, we explicitly make a distinction in this paper. By 'equilibrium level of prices and quantities', we refer to the case where demand is exactly matched by supply. By 'fundamental level', we mean that the market prices and quantities can be explained or warranted by some long-term fundamental factors, derived from demand and supply equations.

2.1 Single-market model

The single-market disequilibrium model was formulated by Fair and Jaffee (1972) and Maddala and Nelson (1974). The econometric specification of a disequilibrium market can be formulated as:

$$D_t = \alpha_0 X_t + \alpha_1 P_t + u_t, \tag{1}$$

$$S_t = \beta_0 Z_t + \beta_1 P_t + v_t, \tag{2}$$

$$Q_t = \min\left(D_t, S_t\right), \tag{3}$$

where the first two equations represent market demand and supply, respectively. The last equation is the disequilibrium condition, which generalises the equilibrium case when $D_t = S_t$. The equation (3) states that if demand is greater than supply, the prevailing market quantity will be equal to supply, and vice versa.

In markets like housing or credit, the researcher observes market quantities, prices and some demand and supply shifters; however, the demand and supply are unobservable. It is difficult to estimate the above system of equations without making some identifying assumptions about sample separation, i.e. periods when demand is observed ($Q_t = D_t$), or when supply is observed ($Q_t = S_t$). On the basis of the work by Fair and Jaffee (1972), Maddala and Nelson (1974) offer four model variations and their estimation methods that are also applied to housing market data.

Model 1 does not include any other assumptions and does not use any *a priori* information on demand and supply regimes. Consequently, this model is difficult to implement and is subject to stability issues, as witnessed by us and other authors. Interestingly, in this setting the price mechanism collapses and there is no way for the price to endogenously react to changes in demand or supply – the price level becomes exogenous, as noted by Maddala and Nelson (1974) and Everaert et al. (2015).

Models 2 (directional) and 3 (quantitative) make an identifying assumption about the direction of the price change and the corresponding demand-supply regime; thus, the sample separation is known. In essence, if the price is increasing, the demand must be greater than supply ($\Delta P_t > 0 \equiv D_t > S_t \equiv Q_t = S_t$). Conversely, if the price is decreasing, the supply is great than demand ($\Delta P_t < 0 \equiv D_t < S_t \equiv Q_t = D_t$). In addition to this, Model 3 assumes that the magnitude of the price change is proportional to excess demand:

$$\Delta P_t = \gamma \left(D_t - S_t\right), \tag{4}$$

with a positive price adjustment parameter $\gamma > 0$. Note that the latter equation ensures not only the identification of the model, but also implies a self-correcting mechanism. If demand is greater than supply, the price will increase over time, given $\gamma > 0$. A gradually increasing price will bring down demand and increase supply, so that they are matched in a state of equilibrium, assuming that shocks are mute and demand-supply shifters are constant.

Models 2 and 3 could be estimated either using least squares techniques by separating periods of supply and demand – a limited-information method, or by full-information maximum likelihood methods. Model 4 complicates the system by augmenting equation (4) with a stochastic error term, and creating an extra layer of uncertainty about the demand and supply regimes, and the associated price increases.

The single-market disequilibrium methods of Maddala and Nelson (1974) have been applied to model credit or housing markets by Laffont and Garcia (1977), Pazarbasioglu (1996), Ghosh and Ghosh (1999), Carbó-Valverde et al. (2009), and others. The more recent applications include Čeh et al. (2011), Everaert et al. (2015), Farinha and Félix (2015). The methodology of Maddala and Nelson (1974) was extended by Hurlin and Kierzenkowski (2002, 2003) to deal with non-stationarity by using first differences of quantity variables, and by Bauwens and Lubrano (2007) and Vouldis (2018) for Bayesian estimation. Note that some authors use the disequilibrium concept in an error-correction framework (e.g. Dupuis and Zheng, 2010; Holmberg, 2012). The single-market framework has also been used exclusively for Lithuania by Karmelavičius (2013) and Ramanauskas et al. (2015), and a recent application was presented in the Financial Stability Review of Lietuvos bankas (2021).

2.2 Two-market model

While single-market models seem like rich analytical structures, they either entirely omit the potential cross-market relationships or exogenise them. For instance, housing market demand and supply should, at least in theory, be dependent on credit market conditions, such as credit quantity (availability) or interest rates. However, a single-market model cannot fully capture this dependence in an endogenous fashion; thus, it implicitly assumes that there is no feedback loop from housing to credit.

To allow for spillover effects and to maintain the disequilibrium structure, the model has been extended to a multi-market case by several authors, including Gouriéroux et al. (1980), Ito (1980), Laroque and Salanie (1989), and summarised in Maddala (1983). To the best of our knowledge, no one has attempted to estimate these models in practice because they are highly rigid structures that often involve even more unobserved variables, including the "effective" and "notional" demand and supply. As later argued by Malinvaud (2006), estimation of aforementioned multi-market models is challenging, since functions, which linked observable variables with parameters, often did not have analytical solutions.

As the cited multi-market cases are cumbersome both theoretically and practically, we propose a relatively simple two-market disequilibrium model that generalises and extends the quantitative method of Fair and Jaffee (1972) or Model 3 of Maddala and Nelson

(1974). We carry forward in a similar fashion to the single-market model derivations contained in Laffont and Garcia (1977).

2.2.1 The structural model

Our proposed theoretical two-market modelling framework is based on three main economic assumptions. First, both markets may experience disequilibria. This is the most fundamental assumption of disequilibrium models. Note that this assumption does not rule out an equilibrium at any given moment, in any given market.

Second, the price mechanism adjusts proportionately to excess demand. As in the quantitative model of Fair and Jaffee (1972), this assumption is used for identification of periods when demand is greater than supply, and vice versa – sample separation. Also, the assumption endogenises the prices and ensures a self-correcting mechanism; thus, the market returns to equilibrium over time, if shocks are absent and demand-supply shifters are constant.

Third, each market's demand and supply may depend on the other market's price and quantity. This assumption is crucial for the endogenous two-way interaction of both markets. For example, if there is a shock in a market that changes its price and quantity, this will also shift the other market's demand or/and supply curves. If that shock induces a disequilibrium in one market, it will likely create disequilibrium in another market – a spillover effect.

The structural equations for the credit ($\cdot^C$) market are as follows:

$$D_t^C = \alpha_0^C X_t^C + \alpha_1^C P_t^C + \alpha_2^C P_t^H + \alpha_3^C Q_t^H + u_t^C \tag{5}$$

$$S_t^C = \beta_0^C Z_t^C + \beta_1^C P_t^C + \beta_2^C P_t^H + \beta_3^C Q_t^H + v_t^C \tag{6}$$

$$Q_t^C = \min\left(D_t^C, S_t^C\right) \tag{7}$$

$$\Delta^k P_t^C = \Delta^k R_t^C + \gamma^C \left(D_t^C - S_t^C\right) \tag{8}$$

Likewise, the housing ($\cdot^H$) market can be characterised by the following equations:

$$D_t^H = \alpha_0^H X_t^H + \alpha_1^H P_t^H + \alpha_2^H P_t^C + \alpha_3^H Q_t^C + u_t^H \tag{9}$$

$$S_t^H = \beta_0^H Z_t^H + \beta_1^H P_t^H + \beta_2^H P_t^C + \beta_3^H Q_t^C + v_t^H \tag{10}$$

$$Q_t^H = \min\left(D_t^H, S_t^H\right) \tag{11}$$

$$\Delta^k P_t^H = \Delta^k R_t^H + \gamma^H \left(D_t^H - S_t^H\right) \tag{12}$$

Equations (5)-(12) comprise a system that fully describes the two markets, and thus should be analysed simultaneously. Both markets have demand (D_t^j) and supply (S_t^j) curves which depend on their respective exogenous shifters (X_t^j) and (Z_t^j), as well as independent homoskedastic structural shocks $u_t^i \sim iiN(0, \sigma_u^i)$ and $v_t^i \sim iiN(0, \sigma_v^i)$, with

$i \in \{C, H\}$. Each demand and supply curve contains its own-price, cross-price and cross-quantity terms with attached coefficients α_1^i and β_1^i, α_2^i and β_2^i, α_3^i and β_3^i, respectively.

Equations (7) and (11) are disequilibrium conditions, while the price adjustment mechanism is entailed by equations (8) and (12). Note that the operator $\Delta^k P_t^i$ refers to $P_t^i - P_{t-k}^i$, and R_t^i stands for reference rates or indices. The market price adjusts one-to-one in response to the relevant reference rate, and proportionately to the associated demand-supply wedge.[4]

Equations (5) and (6), (9) and (10) can be stacked in matrix form:

$$\begin{pmatrix} D_t^C \\ S_t^C \\ D_t^H \\ S_t^H \end{pmatrix} = \begin{pmatrix} 0 & \alpha_1^C & \alpha_3^C & \alpha_2^C \\ 0 & \beta_1^C & \beta_3^C & \beta_2^C \\ \alpha_3^H & \alpha_2^H & 0 & \alpha_1^H \\ \beta_3^H & \beta_2^H & 0 & \beta_1^H \end{pmatrix} \begin{pmatrix} Q_t^C \\ P_t^C \\ Q_t^H \\ P_t^H \end{pmatrix} + \begin{pmatrix} \alpha_0^C & 0 & 0 & 0 \\ 0 & \beta_0^C & 0 & 0 \\ 0 & 0 & \alpha_0^H & 0 \\ 0 & 0 & 0 & \beta_0^H \end{pmatrix} \begin{pmatrix} X_t^C \\ Z_t^C \\ X_t^H \\ Z_t^H \end{pmatrix} + \begin{pmatrix} u_t^C \\ v_t^C \\ u_t^H \\ v_t^H \end{pmatrix},$$

which can be rewritten more compactly as:

$$\mathbf{D}_t = B_1 \mathbf{Q}_t + B_2 \mathbf{X}_t + \mathbf{u}_t. \tag{13}$$

Note that coefficients α_0^i and β_0^i are row-vectors that are attached to exogenous demand and supply shifters X_t^i and Z_t^i, which are column-vectors, whereas coefficients α_j^i, β_j^i and γ^i are scalars, with $i \in \{C, H\}$ and $j \in \{1, 2, 3\}$. Also, note that 0's in matrix B_2 are row-vectors that are conformable to corresponding α_0^i and β_0^i row-vectors. The above matrix form can be useful for practical computations such as demand-supply decomposition (see application in Section 3.3.2), however, it is not sufficient for model estimation as it still contains unobserved demand-supply series in $\mathbf{D}_t$.[5]

2.2.2 Model solution for each regime

The non-linear eight-equation system (5)-(12) can be re-written into a regime-dependent VAR model, which will be used as a basis for estimation, as well as analytical purposes.

At any given point in time, each market may be in one of the two disequilibrium regimes: 1) demand is lower than supply; 2) or demand is greater than supply. As we combine the two markets into one system, there are four regimes in total. To be able to solve the model, we need to describe each regime and the accordingly rearranged system.

[4]Note that our framework implicitly assumes that the price adjustment coefficient γ^i is constant across all demand-supply regimes, unlike Laffont and Garcia (1977) or Gouriéroux et al. (1980). We chose this simplification to reduce the number of parameters in an already highly parametrised system that requires a large amount of data for accurate estimation.

[5]Unlike Gouriéroux et al. (1980, Theorem on p. 81) or Ito (1980, p. 103-104), we do not find it necessary to specify the model coherence conditions (see also Maddala, 1983, p. 338).

Regime I: $D_t^C < S_t^C, \quad D_t^H < S_t^H$ This regime characterises a situation when demand is lower than supply in both markets, and can be identified by a joint decrease in credit margins and real house prices. As demand is binding and both markets are on the demand curve (buyer's markets), demand shifters affect each market directly through impacts on quantities and indirectly via price adjustment mechanisms. As supply is large and non-binding, supply shifters will only affect the market conditions through the price adjustment equations, since supply does not enter the quantity equations directly. Algebraically, the eight-equation system boils down to four equations:

$$I \begin{cases} Q_t^C = \alpha_0^C X_t^C + \alpha_1^C P_t^C + \alpha_2^C P_t^H + \alpha_3^C Q_t^H + u_t^C \\ P_t^C = P_{t-k}^C + \Delta^k R_t^C + \gamma^C \Big[\alpha_0^C X_t^C - \beta_0^C Z_t^C + \left(\alpha_1^C - \beta_1^C \right) P_t^C + \\ \qquad + \left(\alpha_2^C - \beta_2^C \right) P_t^H + \left(\alpha_3^C - \beta_3^C \right) Q_t^H + u_t^C - v_t^C \Big] \\ Q_t^H = \alpha_0^H X_t^H + \alpha_1^H P_t^H + \alpha_2^H P_t^C + \alpha_3^H Q_t^C + u_t^H \\ P_t^H = P_{t-k}^H + \Delta^k R_t^H + \gamma^H \Big[\alpha_0^H X_t^H - \beta_0^H Z_t^H + \left(\alpha_1^H - \beta_1^H \right) P_t^H + \\ \qquad + \left(\alpha_2^H - \beta_2^H \right) P_t^C + \left(\alpha_3^H - \beta_3^H \right) Q_t^C + u_t^H - v_t^H \Big] \end{cases} \tag{14}$$

The periods that belong to Regime I will be denoted as:

$$R^I := \left\{ \forall t : \Delta^k \left(P_t^C - R_t^C \right) < 0 \right\} \cap \left\{ \forall t : \Delta^k \left(P_t^H - R_t^H \right) < 0 \right\}, \tag{15}$$

using the identifying assumption and equations (8) and (12).

Regime II: $D_t^C > S_t^C, \quad D_t^H > S_t^H$ The second regime labels the situation when there is a shortage of both credit and housing, being seller's markets. The situation puts upward pressure on credit margins as well as real house prices, which is the regime-identifying assumption. Importantly, and contrary to Regime I, the markets are on their supply curves, thus only the supply shifters can directly affect market outcomes. The demand factors impact the market only indirectly through the price correction equations (8) and (12). The regime-specific system of equations is:

$$II \begin{cases} Q_t^C = \beta_0^C Z_t^C + \beta_1^C P_t^C + \beta_2^C P_t^H + \beta_3^C Q_t^H + v_t^C \\ P_t^C = P_{t-k}^C + \Delta^k R_t^C + \gamma^C \Big[\alpha_0^C X_t^C - \beta_0^C Z_t^C + \left(\alpha_1^C - \beta_1^C \right) P_t^C + \\ \qquad + \left(\alpha_2^C - \beta_2^C \right) P_t^H + \left(\alpha_3^C - \beta_3^C \right) Q_t^H + u_t^C - v_t^C \Big] \\ Q_t^H = \beta_0^H Z_t^H + \beta_1^H P_t^H + \beta_2^H P_t^C + \beta_3^H Q_t^C + v_t^H \\ P_t^H = P_{t-k}^H + \Delta^k R_t^H + \gamma^H \Big[\alpha_0^H X_t^H - \beta_0^H Z_t^H + \left(\alpha_1^H - \beta_1^H \right) P_t^H + \\ \qquad + \left(\alpha_2^H - \beta_2^H \right) P_t^C + \left(\alpha_3^H - \beta_3^H \right) Q_t^C + u_t^H - v_t^H \Big] \end{cases} \tag{16}$$

Regime II periods will be denoted as:

$$R^{II} := \left\{\forall t : \Delta^k \left(P_t^C - R_t^C\right) > 0\right\} \cap \left\{\forall t : \Delta^k \left(P_t^H - R_t^H\right) > 0\right\}, \tag{17}$$

using equations (8) and (12).

Regime III: $D_t^C < S_t^C, \quad D_t^H > S_t^H$ This regime is a variation in which there is a credit supply surplus and a housing supply shortage. It is the sub-sample where credit interest rates are falling and house prices are rising. The associated reduced system of equations is:

$$III \begin{cases} Q_t^C = \alpha_0^C X_t^C + \alpha_1^C P_t^C + \alpha_2^C P_t^H + \alpha_3^C Q_t^H + u_t^C \\ P_t^C = P_{t-k}^C + \Delta^k R_t^C + \gamma^C \Big[\alpha_0^C X_t^C - \beta_0^C Z_t^C + \left(\alpha_1^C - \beta_1^C\right) P_t^C + \\ \qquad\qquad + \left(\alpha_2^C - \beta_2^C\right) P_t^H + \left(\alpha_3^C - \beta_3^C\right) Q_t^H + u_t^C - v_t^C\Big] \\ Q_t^H = \beta_0^H Z_t^H + \beta_1^H P_t^H + \beta_2^H P_t^C + \beta_3^H Q_t^C + v_t^H \\ P_t^H = P_{t-k}^H + \Delta^k R_t^H + \gamma^H \Big[\alpha_0^H X_t^H - \beta_0^H Z_t^H + \left(\alpha_1^H - \beta_1^H\right) P_t^H + \\ \qquad\qquad + \left(\alpha_2^H - \beta_2^H\right) P_t^C + \left(\alpha_3^H - \beta_3^H\right) Q_t^C + u_t^H - v_t^H\Big] \end{cases} \tag{18}$$

Periods for Regime III are:

$$R^{III} := \left\{\forall t : \Delta^k \left(P_t^C - R_t^C\right) < 0\right\} \cap \left\{\forall t : \Delta^k \left(P_t^H - R_t^H\right) > 0\right\}. \tag{19}$$

Regime IV: $D_t^C > S_t^C, \quad D_t^H < S_t^H$ The last regime can be described by excess credit demand and rising interest rates, along with excess housing supply with falling house prices. The system of equations in this regime is the following:

$$IV \begin{cases} Q_t^C = \beta_0^C Z_t^C + \beta_1^C P_t^C + \beta_2^C P_t^H + \beta_3^C Q_t^H + v_t^C \\ P_t^C = P_{t-k}^C + \Delta^k R_t^C + \gamma^C \Big[\alpha_0^C X_t^C - \beta_0^C Z_t^C + \left(\alpha_1^C - \beta_1^C\right) P_t^C + \\ \qquad\qquad + \left(\alpha_2^C - \beta_2^C\right) P_t^H + \left(\alpha_3^C - \beta_3^C\right) Q_t^H + u_t^C - v_t^C\Big] \\ Q_t^H = \alpha_0^H X_t^H + \alpha_1^H P_t^H + \alpha_2^H P_t^C + \alpha_3^H Q_t^C + u_t^H \\ P_t^H = P_{t-k}^H + \Delta^k R_t^H + \gamma^H \Big[\alpha_0^H X_t^H - \beta_0^H Z_t^H + \left(\alpha_1^H - \beta_1^H\right) P_t^H + \\ \qquad\qquad + \left(\alpha_2^H - \beta_2^H\right) P_t^C + \left(\alpha_3^H - \beta_3^H\right) Q_t^C + u_t^H - v_t^H\Big] \end{cases} \tag{20}$$

Regime IV periods are:

$$R^{IV} := \left\{\forall t : \Delta^k \left(P_t^C - R_t^C\right) > 0\right\} \cap \left\{\forall t : \Delta^k \left(P_t^H - R_t^H\right) < 0\right\}. \tag{21}$$

The sample separation space will be the collection of regimes:

$$\mathbb{R} := \left\{R^I, R^{II}, R^{III}, R^{IV}\right\}. \tag{22}$$

2.2.3 VAR representation

Each of the multi-equation systems (14, 16, 18, 20) can be cast into the following matrix form:

$$\mathbf{Q}_t = A_0 \mathbf{Q}_{t-k} + A_0 \Delta^k \mathbf{R}_t + A_1^r \mathbf{Q}_t + A_2^r \mathbf{X}_t + A_3^r \mathbf{u}_t, \tag{23}$$

where $\mathbf{R}_t := \left(0, R_t^C, 0, R_t^H\right)'$, $r \in \{I, II, III, IV\}$ denotes regimes, and matrices A_0, A_1^r, A_2^r, A_3^r are defined in Appendix A.1.

The matrix equation above is essentially a structural VAR model with exogenous variables (SVARX). Very importantly, the two quantities (Q_t^C, Q_t^H) and the two prices (P_t^C, P_t^H) are endogenous variables, contained in 4×1 column-vector $\mathbf{Q}_t$, that are simultaneously determined within the system in each regime.

We can express the structural system (23) into its reduced form for each regime:

$$\mathbf{Q}_t = \Gamma_1^r \mathbf{Q}_{t-k} + \Gamma_1^r \Delta^k \mathbf{R}_t + \Gamma_2^r \mathbf{X}_t + \Gamma_3^r \mathbf{u}_t, \tag{24}$$

where $\Gamma_1^r := (I - A_1^r)^{-1} A_0$, $\Gamma_2^r := (I - A_1^r)^{-1} A_2^r$ and $\Gamma_3^r := (I - A_1^r)^{-1} A_3^r$. The relevant regime-specific covariance matrices for reduced-form residuals $(\Gamma_3^r \mathbf{u}_t)$ are $\Gamma_3^r \Sigma_u \Gamma_3^{r\prime}$, where $\Sigma_u := \operatorname{diag}\left(\sigma_u^C, \sigma_v^C, \sigma_u^H, \sigma_v^H\right)$.

Now the endogenous vector $\mathbf{Q}_t$ is expressed as a linear combination of its own lag, the reference rates and demand-supply shifters, and structural shocks – a reduced-form VARX model.

2.2.4 Maximum likelihood estimation

The reduced-form system (24) does not contain the unobserved demand and supply variables (column-vector $\mathbf{D}_t$), therefore it can be used for parameter estimation. Note that the four regimes are non-stochastic and they do not switch endogenously, i.e. the sample separation $\mathbb{R}$ is *a priori* known, unlike in Model 4 of Maddala and Nelson (1974), which would warrant endogenous switching.

The model may be estimated using the two stage least squares (TSLS) or the indirect least squares techniques; however, these are limited-information methods, as estimation would be done separately for each regime sub-sample $(R^I, R^{II}, R^{III}, R^{IV})$. Although such an exercise is computationally quite easy, it would be highly inaccurate, especially for shorter time-series or if the regime distribution is highly unequal.

We outline a maximum likelihood (ML) estimation, which is based on the single-market version in Amemiya (1974), Maddala and Nelson (1974) and Laffont and Garcia (1977). Contrary to the TSLS, the ML approach we used is a full-information technique, i.e. the model parameters are estimated for four regimes simultaneously, thus using all available information.

Each period's conditional likelihood function is $f_t^r := f_t^r\left(\mathbf{Q}_t | \mathbf{Q}_{t-k}, \Delta^k \mathbf{R}_t, \mathbf{X}_t; \theta\right)$, where

$\theta := \mathrm{vec}\,(B_1, B_2, \Sigma_u)$ and $r \in \{I, II, III, IV\}$. Assuming normality of structural shocks $\mathbf{u}_t$, the likelihood function would be:

$$f_t^r = f_t^r\left(\mathbf{Q}_t|\mathbf{Q}_{t-k}, \Delta^k\mathbf{R}_t, \mathbf{X}_t; \theta\right) = \frac{\exp\left(-\frac{1}{2}(\mathbf{Q}_t - \boldsymbol{\mu}_t^r)'\left(\Gamma_3^r\Sigma_u\Gamma_3^{r\prime}\right)^{-1}(\mathbf{Q}_t - \boldsymbol{\mu}_t^r)\right)}{\sqrt{(2\pi)^4\det\left(\Gamma_3^r\Sigma_u\Gamma_3^{r\prime}\right)}},$$

where the conditional mean is $\boldsymbol{\mu}_t^r := \Gamma_1^r\mathbf{Q}_{t-k} + \Gamma_1^r\Delta^k\mathbf{R}_t + \Gamma_2^r\mathbf{X}_t$.

The full-sample log-likelihood function that utilises the sample separation information in $\mathbb{R}$ is the following:

$$\log L = \sum_{t\in R^I}\log f_t^I + \sum_{t\in R^{II}}\log f_t^{II} + \sum_{t\in R^{III}}\log f_t^{III} + \sum_{t\in R^{IV}}\log f_t^{IV}. \tag{25}$$

The ML estimation requires the maximisation of the log-likelihood function $\log L$, subject to constrained parameter space (Θ_0):

$$\log L \longrightarrow \max_{\theta\in\Theta_0}.$$

The optimisation may be done using any optimisation algorithm, e.g. BFGS or Nelder-Mead, while standard errors can be obtained using the computed Hessian matrix.

2.2.5 Recovery of structural demand and supply shocks

Suppose we have estimated the two-market model and have the parameter estimate $\hat{\theta}$ and the conditional mean $\hat{\boldsymbol{\mu}}_t^r$ estimate. The reduced-form shocks of the VARX model (24) can be acquired as a time series for each regime: $\hat{\mathbf{e}}_t^r := \mathbf{Q}_t - \hat{\boldsymbol{\mu}}_t^r$. Note that the reduced-form shocks are necessarily correlated across the four endogenous variables, or across equations, with a regime-specific covariance matrix $\Gamma_3^r\Sigma_u\Gamma_3^{r\prime}$. The uncorrelated demand-supply structural shocks are of interest and can be recovered in at least two ways.

a) from the reduced-form model (24), the regime-specific structural shock may be acquired as $\hat{\mathbf{u}}_t^r := \left(\hat{\Gamma}_3^r\right)^{-1}\hat{\mathbf{e}}_t^r$. This is not satisfactory, however, as these structural shock series are specific to each regime. Unconditional series could be acquired using sample separation information $\mathbb{R}$. For example, if $t \in R^r$, then $\hat{\mathbf{u}}_t = \hat{\mathbf{u}}_t^r$. Another approach is to use the probabilities, or relative frequencies, of each regime: $\pi^r = (\#R^r)/T$ and $\hat{\mathbf{u}}_t = \sum_r \pi^r\hat{\mathbf{u}}_t^r$, with # being the set size operator and T denoting the sample size. The latter recovery on the basis of relative frequencies is our preferred option, as it gives more stability, and thus is used in Sections 3 and 4.

b) from the structural model equations (5)-(7) and (9)-(11) we have the demand and supply estimates:

$$\hat{D}_t^i = \hat{\alpha}_0^i X_t^i + \hat{\alpha}_1^i P_t^i + \hat{\alpha}_2^i P_t^j + \hat{\alpha}_3^i Q_t^j,$$
$$\hat{S}_t^i = \hat{\beta}_0^i Z_t^i + \hat{\beta}_1^i P_t^i + \hat{\beta}_2^i P_t^j + \hat{\beta}_3^i Q_t^j,$$

with $i, j \in \{C, H\}, i \neq j$. Given the information about demand/supply regimes in each market, based on decrease/increase in real price, the structural shocks could be recovered as follows:

$$\begin{aligned}
&\text{if } \Delta^k \left(P_t^i - R_t^i\right) < 0: \qquad \hat{u}_t^i = Q_t^i - \hat{D}_t^i, \qquad && \hat{v}_t^i = \max\left\{0, Q_t^i - \hat{S}_t^i\right\},\\
&\text{if } \Delta^k \left(P_t^i - R_t^i\right) > 0: \qquad \hat{u}_t^i = \max\left\{0, Q_t^i - \hat{D}_t^i\right\}, \qquad && \hat{v}_t^i = Q_t^i - \hat{S}_t^i.
\end{aligned}$$

2.2.6 Dynamic decomposition of quantities and prices

Iteration of the regime-specific VARX model (24) backwards (s-times) would yield the following result:

$$\mathbf{Q}_t = \Gamma_1^{rs} \mathbf{Q}_{t-sk} + \sum_{j=0}^{s-1} \Gamma_1^{rj} \left[\Gamma_1^r \Delta^k \mathbf{R}_{t-jk} + \Gamma_2^r \mathbf{X}_{t-jk} + \Gamma_3^r \mathbf{u}_{t-jk}\right]. \tag{26}$$

The matrix equation implies that market quantities and prices at time t depend on some initial conditions ($\mathbf{Q}_{t-sk}$) and past sequences of changes in reference rates ($\Delta^k \mathbf{R}_{t-jk}$), and demand-supply shifters ($\mathbf{X}_{t-jk}$), as well as series of structural demand-supply shocks ($\mathbf{u}_{t-jk}$). It is also possible to rewrite the latter equation while iterating forward s-times, starting with n_0 period:

$$\mathbf{Q}_{n_0+sk} = \Gamma_1^{rs} \mathbf{Q}_{n_0} + \sum_{j=0}^{\max\{s-1,0\}} \Gamma_1^{rj} \left[\Gamma_1^r \Delta^k \mathbf{R}_{n_0+(s-j)k} + \Gamma_2^r \mathbf{X}_{n_0+(s-j)k} + \Gamma_3^r \mathbf{u}_{n_0+(s-j)k}\right].$$

This dynamic relationship between quantities, prices, and shifters is a direct result of the dynamic price adjustment mechanism in equations (8) and (12). The dynamic relationship is stable, if the moduli of the eigenvalues of the Γ_1^r matrix are below unity. As can be seen from the the last two iterated equations, a present shift in supply or a sudden shock to demand will have a lasting, yet diminishing, impact on both markets' variables. The impact of one unit of change in reference rates, demand-supply shifters and structural shocks on the j-th period quantity-price variables, is captured by the following triplet of impulse-response functions (IRF):

$$\text{IRF}(Q, R; j; r) = \Gamma_1^{rj+1}, \tag{27}$$

$$\text{IRF}(Q, X; j; r) = \Gamma_1^{rj} \Gamma_2^r, \tag{28}$$

$$\text{IRF}(Q, u; j; r) = \Gamma_1^{rj} \Gamma_3^r. \tag{29}$$

On the basis of these IRF's, Section 3.3.3 contains an empirical shock analysis. The dynamic equation (26) can be used to decompose the historical time series of quantities and prices to analyse the drivers, which will be implemented in Section 3.3.4.

2.2.7 Decomposition into fundamental and cyclical parts

The dynamic equation (26) can be used to jointly decompose credit flows and housing prices into impacts of exogenous drivers. Although the exogenous drivers enter the model through the demand, supply and price adjustment equations, this does not necessarily imply that these shifters are fundamental, or are at their fundamental levels.

Since shocks ($\Gamma_3^r \mathbf{u}_t$) are only the residual part of quantities and prices that cannot be explained by the structural model, we assume them to be non-fundamental factors. Suppose that reference rates $\mathbf{R}_t$ and demand-supply shifters $\mathbf{X}_t$ can be decomposed into their fundamental and non-fundamental, or cyclical, parts: $\mathbf{R}_t = \mathbf{R}_t^F + \mathbf{R}_t^{\not F}$ and $\mathbf{X}_t = \mathbf{X}_t^F + \mathbf{X}_t^{\not F}$, with F denoting the fundamental part, and $\not F$ – the non-fundamental. Then, using equation (26), it is possible to separate the impacts of only the fundamental levels of exogenous drivers ($\mathbf{R}_t^F, \mathbf{X}_t^F$). This allows us to construct the fundamental level $\mathbf{Q}_t^F$ of the endogenous series $\mathbf{Q}_t$, assuming that k starting values of $\mathbf{Q}_t$ are fundamental, i.e. ($\forall t \leq k : \mathbf{Q}_t^F = \mathbf{Q}_t$). The relevant equation for computations is the following:

$$\mathbf{Q}_t^F := \Gamma_1^{r\,s} \mathbf{Q}_{t-sk}^F + \sum_{j=0}^{s-1} \Gamma_1^{r\,j} \left[\Gamma_1^r \Delta^k \mathbf{R}_{t-jk}^F + \Gamma_2^r \mathbf{X}_{t-jk}^F \right]. \tag{30}$$

The non-fundamental part, to which we later refer as the *gap*, or *misalignment*, will be denoted as: $\mathbf{Q}_t^{\not F} := \mathbf{Q}_t - \mathbf{Q}_t^F$. This type of analysis will allow us to estimate the credit flow and house price misalignments and will be carried out in Section 4.

3 Drivers of housing and credit

This section aims to bring the model to the data and showcase the rich analytical features of the two-market disequilibrium setting. We estimate the two-market disequilibrium model on Lithuanian monthly data ranging from 2006:M1 to 2021:M6, and outline the historical drivers of housing and credit markets.

Although the main endogenous variables are available for a longer period, the time horizon of our analysis is limited by the availability of explanatory data. Nevertheless, the dataset contains around 190 observations and covers a periods of strong economic growth and two recessionary periods: the Global Financial Crisis and the COVID-19 pandemic. It is important to note that the use of long monthly series is necessitated by the relatively complex two-market model which includes many parameters to be estimated.

3.1 Brief history of housing and credit in Lithuania

The main variables of the two-market model are quantities (Q_t^i) and prices (P_t^i). The credit quantity is the monthly flow of new mortgages, whereas the credit price is a monthly interest rate on new mortgages, both obtained from the Bank of Lithuania's monetary financial institution (MFI) database. Regarding the housing market, the quantity is the monthly volume of apartment transactions from the Centre of Registers, and house prices are measured as the Bank of Lithuania's Shiller-type house price index.[6] All four endogenous variables are seasonally adjusted and smoothed to isolate the month-to-month noise.

Since these four quantity-price series are the endogenous variables of the system, we briefly describe their historical evolution, which is depicted in Figure 1. Between 2005 and 2007, Lithuania experienced a rapid growth in mortgage flows and property prices. Starting from a relatively low level, mortgage flows grew at an average annual rate of 50% between 2005 and 2007, fuelling the high volume of housing transactions and tripling of house prices.[7]

The boom period of 2005-2007 was completely reversed in 2008. Since the peak, house prices fell by a cumulative 40% by 2010, and housing transactions declined by 60% in 2009 (see Figure 1 panels (b) and (c)). The burst of the housing bubble had a significant impact on bank lending, which declined by around 70% between the beginning of 2008 and the end of 2009. This episode coincided with an increase in lending rates, which peaked at around 6.5% at the end of 2008 and started to decline in 2009.

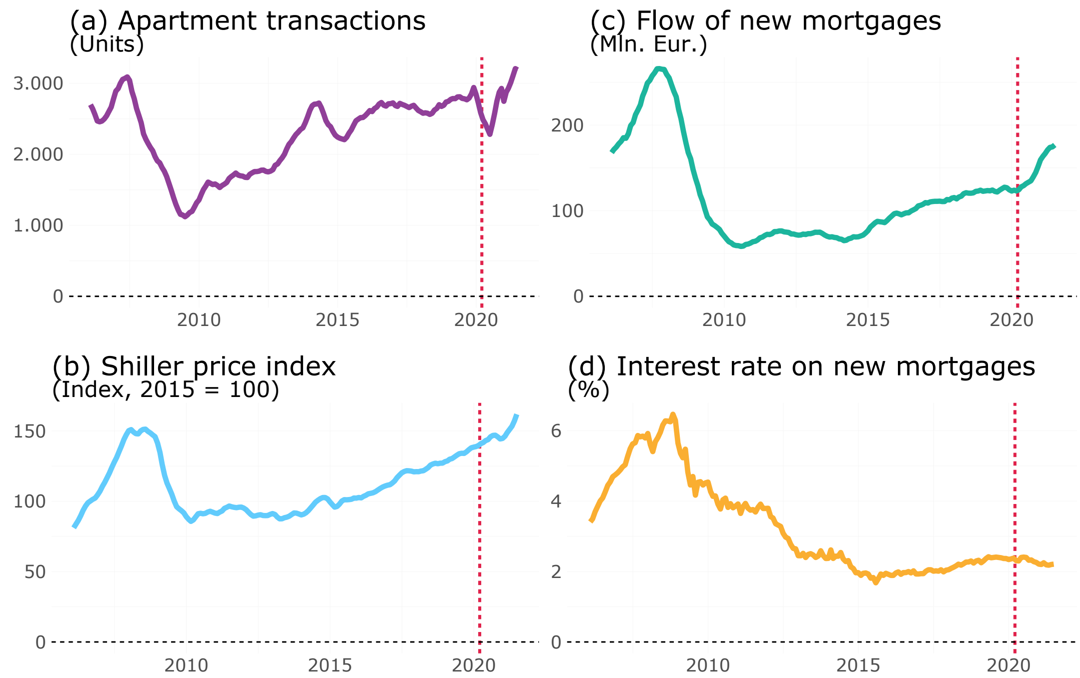
Following the crisis, house prices and mortgage flows in Lithuania remained relatively stable between 2009 and 2014. Market activity started to increase again in 2015-2019, with house prices rising on average by around 6.5% and mortgage flows by around 12% per year. Meanwhile, mortgage interest rates, although relatively low compared to the whole period analysed, became among the highest in the Euro area in 2019 (see Figure 1 panel (d) and Karmelavičius et al., 2022).

During the beginning phase of the COVID-19 pandemic, housing transactions stalled, due to the government-imposed lockdown. However, the number of transactions quickly recovered and only mildly reacted to the second lockdown in November 2020. Meanwhile, annual house price growth during the first quarantine slowed down only modestly and remained positive. However, in 2021, the Lithuanian housing market recorded the highest number of housing transactions and house prices levels in more than a decade. In the second quarter of 2021, house prices increased by around 10% and housing transactions

[6] The Bank of Lithuania's Shiller-type house price index is calculated by applying the repeat sales method, which uses data on each specific sale of the same dwelling sold at least twice (for details see Lietuvos bankas, 2019, in Lithuanian).

[7] As Kuodis and Ramanauskas (2009) argue, at least a fraction of this credit growth can be regarded as financial deepening, which was happening at the time in Central and Eastern European (CEE) countries, including Lithuania.

Figure 1: Housing and credit market endogenous variables



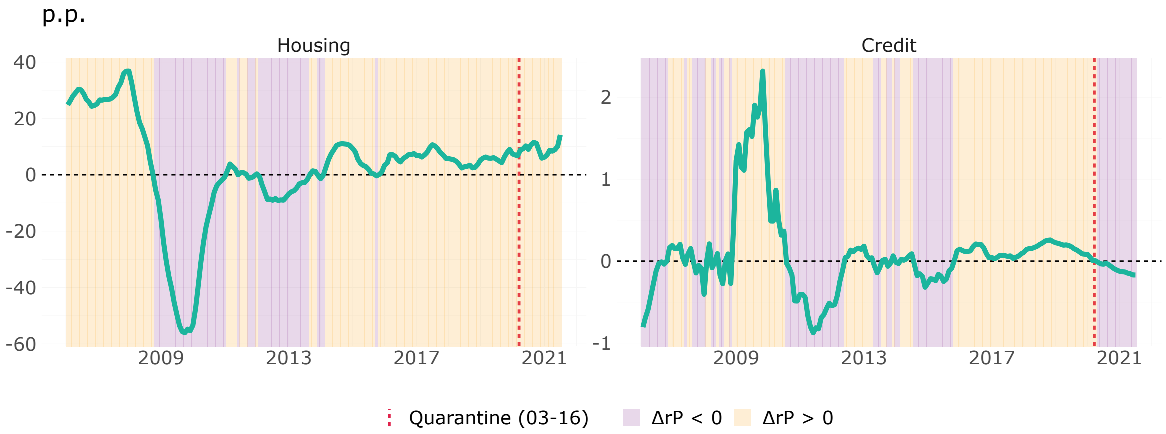
Notes: panel (a) shows the number of housing transactions in Lithuania, smoothed as a six-months average; panel (b) shows the Shiller price index (base year 2015 = 100); panel (c) shows the mortgage credit flows in mln. Eur., smoothed as an annual average; and panel (d) shows mortgage interest rates in percentages for euro and litas denominated loans. The red dashed line marks the beginning of the first COVID-19 quarantine in Lithuania (March 16, 2020).

by 25% compared to the previous year.

Figure 2 shows the evolution of annual changes in real house prices and mortgage interest margins. The change in real house price index (left panel) is calculated as the difference between the Shiller house price index and the consumer price index, the latter being the reference index (R_t^H). The change in the interest rate margin (right panel) is the difference between the mortgage interest rate and the reference rate Avibor (R_t^C). Throughout this paper, we use the term Avibor, which we coin after the average interbank offer rate, or benchmark rate for variable rate mortgages. The Avibor rate is computed as: a) the weighted average of Euribor and Vilibor (Vilnius interbank offer rate) before 2015; b) Euribor as of Lithuania's adoption of the euro in 2015.

The depicted variables in Figure 2 are used to identify periods of demand and supply, using equations (8) and (12). In the housing market, there are only two lengthy periods of falling real house prices: from 2009 to 2010, and from 2012 to mid-2013. With regards to the credit market, we observe several periods of rising and falling margins. The most marked increase in margins occurred during the crisis period from 2009 to mid-2010, when the annual change in margins reached more than 2 p.p. On the basis of a combination

Figure 2: Growth in real house prices and mortgage lending margins



Notes: the purple background indicates periods when there is a fall in real house prices or credit margins ($\Delta^k P_t^i - \Delta^k R_t^i < 0$), thus excess supply is identified. Yellow areas mark periods when demand is greater than supply in each market, identified by increasing real house prices or credit margins.

of these single-market demand-supply regimes and equations (15, 17, 19, 21), we identify the two-market Regimes I-IV. The relative frequencies, or empirical probabilities, of each each regime are as follows: I – 11%, II – 39%, III – 33%, IV – 17%. The rarest of the regimes is Regime I, which marks the situation when both markets experience a surplus in supply. The second rarest is the Regime IV, in which credit demand exceeds supply, and there is an excess supply of housing. Although regime frequencies are non-uniform, the ML method that was outlined in Section 2.2.4 is a full-information approach, which estimates all equations for all regimes simultaneously.

3.2 Empirical model specification

We estimate a restricted version of the general system of Section 2.2 equations (5)-(12), with parameter restrictions tabulated in Table 1. Essentially, we assume that mortgage demand is derived from housing market transactions, which can enter the credit demand equation with a positive coefficient. As credit flows are measured in nominal terms and transactions of housing units in real terms, we include house prices in both credit demand and supply equations. Although credit and housing are complements, we expect the sign of the coefficients attached to house prices in credit demand-supply equations to be positive, using the previously mentioned nominal-terms argument and the fact that housing value is used as collateral of credit. As mortgages are one of the means to finance housing transactions, credit market conditions, including both interest rate (negatively) and credit flows (positively), affect the demand for housing. Note that all market quantity and price variables are endogenously determined within the system, thus the model takes into account their two-way interactions. Lastly but very importantly, the price adjustment mechanism is our main identifying assumption, which requires γ^i coefficients to be positive.

Table 1: Endogenous variable parameter restrictions

	Equation	Coefficient	Variable
(5)	Credit demand (D_t^C)	$\alpha_1^C \leq 0$	P_t^C
		$\alpha_2^C > 0$	P_t^H
		$\alpha_3^C \geq 0$	Q_t^H
(6)	Credit supply (S_t^C)	$\beta_1^C > 0$	P_t^C
		$\beta_2^C \geq 0$	P_t^H
		$\beta_3^C = 0$	Q_t^H
(8)	Credit price ($\Delta^k P_t^C$)	$\gamma^C > 0$	$D_t^C - S_t^C$
(9)	Housing demand (D_t^H)	$\alpha_1^H < 0$	P_t^H
		$\alpha_2^H < 0$	P_t^C
		$\alpha_3^H \geq 0$	Q_t^C
(10)	Housing supply (S_t^H)	$\beta_1^H > 0$	P_t^H
		$\beta_2^H = 0$	P_t^C
		$\beta_3^H = 0$	Q_t^C
(12)	Housing price ($\Delta^k P_t^H$)	$\gamma^H > 0$	$D_t^H - S_t^H$

Notes: strict equality (=) restriction means that the variable is omitted from the equation altogether; non-strict inequality ($\geq, \leq$) restriction means that the variable could be included in a specification, however, those specifications with bad coefficient sign will be discarded; strict inequality ($>, <$) restriction refers to those variables which must be included in all specifications, however, only those specifications with the correct sign will be kept.

As per the demand-supply shifters (X_t^i, Z_t^i), there is large uncertainty about the relevant variables, which should enter housing and credit equations. Also, as mentioned in Section 2.2, the empirical disequilibrium models of Maddala and Nelson (1974) are quite hard to estimate accurately, as the models suffer from stability issues going from specification to specification, due to the high number of parameters and the existence of several local maxima of the likelihood function. Any researcher or policy-maker must account for model or specification uncertainty, especially when making policy decisions on the basis of an estimated model.

Instead of estimating one model specification and being subject to the model uncertainty issue, we tackle the problem by running millions of different model specifications in the spirit of Sala-i-Martin (1997) – a Bayesian model averaging approach (BMA, see Hoeting et al., 1999; Sala-i-Martin et al., 2004; Fragoso et al., 2018). The comprehensive list of all possible demand-supply shifters is tabulated in Table 2 of Appendix A.2. The choice of these variables is based on economic theory, relevant literature and evidence presented in other studies (Kulikauskas, 2016; Ramanauskas, 2011, among others).

Regarding the housing market, one of the main determinants of demand is personal income and savings. As income and savings increase, the financial capacity of households to afford housing increases and housing demand rises. In addition, remittances from emigrants can further increase savings. Moreover, demographic factors such as population growth, immigration and urbanization, indicating the need for housing, can stimulate housing demand. Furthermore, a favourable macroeconomic environment can stimulate demand for housing, contributing to positive expectations of future economic and house price growth. Other factors affecting the availability of credit, such as banks' lending standards, may also influence housing demand. Housing supply is strongly dependent on factors related to the costs incurred by real estate developers, as well as construction conditions and expectations. Moreover, housing supply may be constrained by high interest rates on corporate loans or other factors limiting the ability of companies to borrow, which makes it more difficult for construction companies to finance projects under development. Finally, some indicators directly reflect housing supply, such as housing completions.

Similarly, an increase in household income and savings can stimulate the demand for credit by increasing households' financial capacity to access credit. Favourable macroeconomic conditions reinforce expectations about future income. Moreover, inflation expectations may encourage household borrowing as the real cost of financing falls. Furthermore, credit demand might be related to the financial deepening. The supply of credit is mainly related to asset quality, e.g. non-performing loans, which may increase the risk aversion of banks and reduce banks' ability to extend credit. In addition, supply may depend on banks' funding costs, as well as other market conditions such as banking sector concentration. Moreover, banks' willingness to expand their loan portfolios may be reflected in lending standards. Finally, other factors such as macroeconomic conditions, income and expectations reflecting the financial situation of households may also influence banks' lending appetite.

If all these variables were included in each market's demand and supply equations, we would have billions of estimable simultaneous systems – an insurmountable task. To deal with this combinatorial explosion of model variations, we establish the following estimation order or algorithm.

First, we focus on each market separately using a single-market disequilibrium model in equations (1)-(4) (Model 3 of Maddala and Nelson, 1974). We manually explore different model specifications and produce a shortlist of demand-supply shifters that are consistent with our coefficient sign expectations as tabulated in Table 2 of Appendix A.2. Among the shifters are variables like GDP growth, unemployment, credit market concentration, household savings, urbanisation, and house price growth expectations.

Second, the shortlisted explanatory variables were grouped into broader categories (see Table 2) for each market model. To control the multidimensionality problem, each variable group may have a designated slot in a given market's demand or supply equation, however, there are no more than 3-6 slots for each equation. For the demand equation of the housing market, all specifications include at least one variable from the categories of household income, demographics, and expectations. The housing supply equation for all specifications includes one variable from each of these three categories: new housing supply (stock), construction costs and corporate financing costs. Regarding the credit market supply equation, non-performing loans are included in all models. Variables from other categories enter the model depending on the specification, however, no more than one variable from each category is included in each model.

This leads to 176 256 housing and 52 962 credit market models, which were estimated separately for housing market (equations 5-8), and for the credit market (equations 9-12). The coefficient densities of all model specifications are shown in Figures 14 and 15 of Appendix A.3.

Third, from the evaluated single-market models, 101 housing and 62 credit model specifications were selected based on the following criteria. We picked only the models where the optimisation algorithm converged, and where coefficients signs are consistent with our expectations and economic logic (Tables 1 and 2). To ensure model consistency with the main identifying assumption in equations (8) and (12), we choose models with a positive and relatively high γ^i coefficient. Also, we prioritise model specifications that are heterogeneous, i.e. they include different explanatory variables.

Fourth, by combining the 101 housing and 62 credit specifications chosen in the previous stage, we constructed and estimated 6 262 ($= 101 \times 62$) *joint two-market disequilibrium models*, using the ML approach of Section 2.2.4. Finally, we selected 56 best models that are heterogeneous-across, and that meet the coefficient sign restrictions of Tables 1 and 2. These 56 estimated two-market disequilibrium models will be used throughout the rest of this paper.

3.3 Discussion of estimation results

This section discusses the results of the two-market equilibrium model. The full model consists of 56 separately estimated specifications. Figures 3-7 show the average results of the estimated models. First, in subsection 3.3.1, we discuss the model fit, and periods in which the housing and credit markets were in disequilibria. In subsection 3.3.2 we decompose both markets' demand and supply to identify their main drivers. Subsection 3.3.3 describes how selected shocks affect the endogenous quantity-price variables, using IRF's. Finally, in subsection 3.3.4 we identify the factors associated with the recent rapid growth in house prices and credit flows.

3.3.1 Disequilibrium in housing and credit markets

Figure 3 shows the average results of the 56 estimated specifications of the two-market disequilibrium model. Panel (a) displays the average fitted demand and supply values, while panel (b) depicts the means of the associated supply surpluses. The estimated demand and supply fits for each of the separate 56 specifications are presented in Figure 16 of Appendix A.3.

Based on the pooled estimation results, we see that throughout the whole time horizon, housing supply was considerably less volatile than the estimated demand. This is hardly surprising, as it takes quite some time for supply to adjust, e.g., build new apartments. On the other hand, the variability of supply and demand in the credit market tends to be similar.

Figure 3: Model-estimated demand and supply for housing and credit markets

Panel (a): Demand and supply fits | Panel (b): Excess supply

Notes: average results across the 56 model specifications. Panel (a) shows demand and supply estimates, using equations (5, 6, 9, 10), and the market quantities. In panel (b), y-axis positive values indicate excess supply (or shortage of demand) and negative values indicate shortage of supply (or excess demand).

We see that both housing and credit markets were experiencing a significant discrepancy between demand and supply during the boom of the 2000's. Specifically, in 2006-2008 the housing market was severely under-supplied, which greatly contributed to the huge growth in house prices (see panel (b) and Figure 2). In contrast, the credit market was characterised by an excess supply, driven by foreign banks flooding the domestic market with cheap and abundant external financing, that also contributed to relatively low domestic lending rates (see Kuodis and Ramanauskas, 2009; Karmelavičius et al., 2022). This finding is in line with the results of Everaert et al. (2015), who use a single-market credit disequilibrium model to identify imbalances in the overall credit market. For the boom period, their model highlights that credit supply factors dominated the pace of credit expansion in Lithuania.

During and shortly after the Global Financial Crisis, there was a sharp drop in housing demand, which led to the largest surplus of housing supply over the period analysed, determining the free fall of house prices. This was accompanied by a sharp contraction in credit supply, which led to the largest credit shortage of the whole 2006-2021 time frame. Unsurprisingly, the credit crunch contributed to a significant increase in mortgage lending margins by over 2 p.p. In general, these findings are in line with Ramanauskas et al. (2018) who argue that a boom-bust cycle has been closely linked to high bank lending in the boom years and a sharp drop in lending in the downturn.

After the crisis, housing and credit markets were relatively balanced, with demand and supply moving more or less in parallel. For example, mortgage credit flow was comparatively low and constrained by both demand and supply factors. This result is consistent with IMF (2014), who study the post-crisis lending in the Baltic economies using bank-level data, and find that credit was constrained by both demand and supply factors. Later on, around 2017-2019, both markets experienced excess demand, which caused an acceleration in house price growth. The prolonged mismatch between credit demand and supply exerted upward pressure on mortgage rates, which became among the highest in the Euro area at that time (for in depth discussion see Karmelavičius et al., 2022).

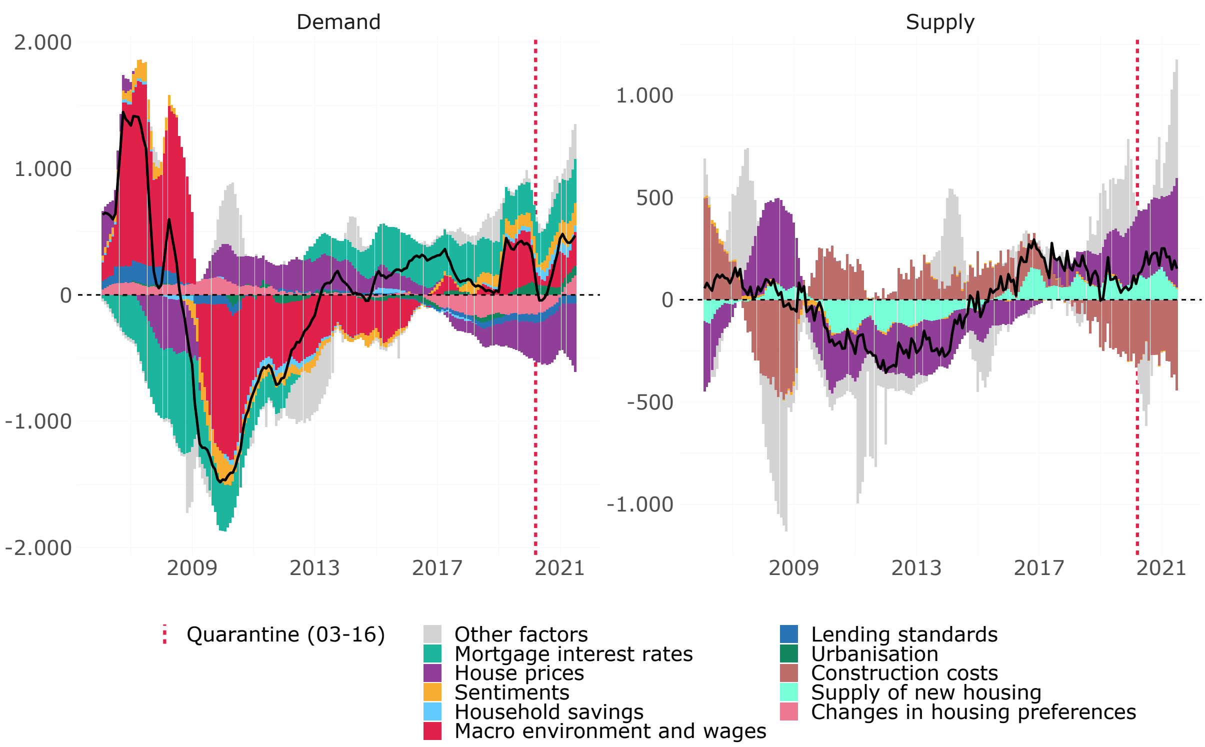
Interestingly, the housing disequilibrium temporarily disappeared during the first lockdown of the COVID-19 pandemic. In essence, due to the imposed curfew after March 16, 2020, there was a huge and sudden drop in demand for housing, contributing to the short-lived slow down in both house purchases and price growth. However, in the later stages of the pandemic there was a "shooting spring" effect – housing demand increased sharply and house price growth accelerated due to supply shortages. As per the mortgage market, there was a concurrent increase in both demand and supply, which nearly equilibrated the market and contributed to the decrease in lending rates.

3.3.2 Demand and supply decomposition

In the previous subsection we showed and discussed the historical dynamics of the estimated demand and supply values. Here we decompose each market's demand-supply curves, using equations (5, 6, 9, 10), and discuss their drivers.

Housing market. Figure 4 shows the decomposition of demand and supply in the housing market. The large fluctuations in housing demand can be explained mainly by changes in macroeconomic conditions and wage growth. In particular, the historically high levels of housing demand in the 2000's boom period can be attributed to the improving macro environment and rapid wage growth, as well as to the high availability of credit due to loose lending standards. In contrast, the decrease in these factors is linked to the sharp contraction of housing demand during and shortly after the crisis of 2009. In the aftermath of the crisis, the demand recovered slightly due to the fall in mortgage interest rates, however, it has not reached its previous peak.

Figure 4: Housing market: demand and supply decomposition



Notes: the figure shows the average decomposition of the demand and supply equations estimated by the 56 models, which reflects the impact of various factors on housing demand and supply compared to the average for the whole period. The black line indicates the estimated demand/supply fits. *Mortgage interest rates* also incorporate mortgage flows. *Household savings* include the time to save the down-payment, growth in the deposit-to-GDP ratio, remittances, and savings expectations. *Macroeconomic environment and wages* cover unemployment, inflation, disposable income growth and wages. *Urbanisation* includes variables related to urbanisation and demography. *Lending standards* includes bank lending standards (Bank Lending Survey, BLS) and mortgage minimal down-payment requirements. *Constructions costs* consists of construction costs, interest rates on business loans and banks' lending standards to companies (BLS). *Supply of new housing* includes the supply of new housing completions and building permits. *Changes in housing preferences* indicate the average size of the dwelling sold that month.

In 2016-2019, the effect of macro factors on demand was positive, albeit to a much lesser extent. Demand in the period was mainly driven by relatively low mortgage interest rates, as well as growing urbanisation, rising household savings, and improving expectations. On the other hand, tight lending standards and increasing house prices dampened demand growth.

The drop in housing demand at the beginning the COVID-19 pandemic was mainly linked to the deteriorating macro environment.[8] However, demand picked up in 2021 due to growth in household savings, improved expectations and changes in housing preferences, i.e. greater demand for more spacious housing units. We see that in spite of rising house prices, large increases in construction costs were limiting housing supply.

Credit market. The decomposition of credit demand and supply is shown in Figure 5. The rapid growth in credit demand during the 2006-2008 economic upturn can be mainly associated with a favourable macroeconomic environment and wage growth, and to a lesser extent by house prices, positive household sentiment and an increase in household savings.[9] The sharp reversal of those factors had a negative impact on credit between 2009 and 2017.[10] In 2018-2021, demand has been driven mainly by rising house prices and optimistic sentiment. A dramatic increase in the accumulation of household savings has been a particularly important source of housing and credit growth during the pandemic.

Credit supply during the economic upturn of the 2006-2008 can be linked to different factors, including a good macroeconomic environment, risk-taking behaviour of banks and optimistic expectations. When the recession of 2009 hit, the contraction in credit supply was associated with the worsening macroeconomic environment and wages, pessimistic expectations, and the changes in the credit risk perception related to the deteriorating bank asset quality (reflected by higher provisioning ratios). Overall, our results are in line with studies which suggest that the underestimation of credit risk played a crucial role in the boom-and-bust cycle of the global financial crisis. For example, Kuodis and Ramanauskas (2009) argue that although regulatory authorities encouraged banks to be more conservative, banks were slow to react. As Figure 5 highlights, banks changed their perception of credit risk only after the outbreak of the global financial crisis in 2009. Moreover, our results are in line with Ramanauskas et al. (2018), who find that mortgage supply fell during the crisis due to a change in banks' perception of credit risk and a sharp deterioration in economic conditions.

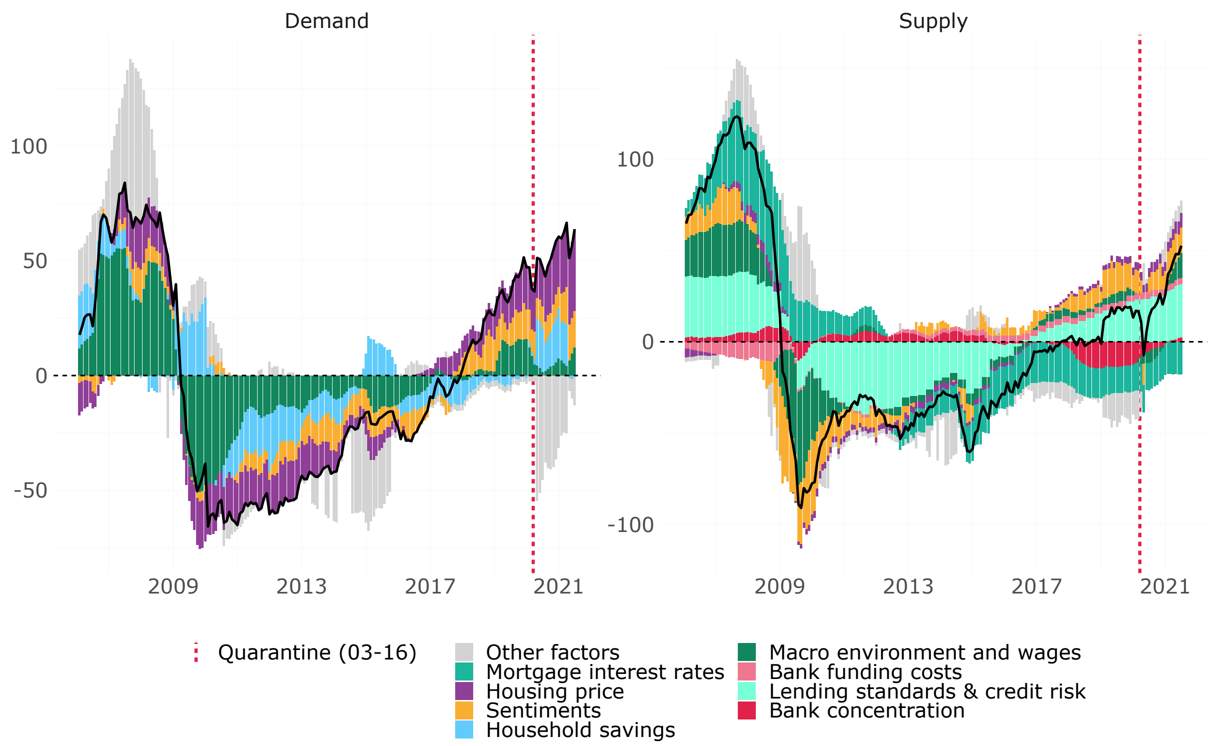
In the recent years, 2017–2021, credit supply has been expanding mainly due to banks' perception of credit risk, as mortgage NPL's (because of higher portfolio quality) have been very low compared to historical levels. On the other hand, a small number of significant lenders and a high banking market concentration has been constraining the mortgage supply, at least until 2021.

[8]Moreover, demand may also have decreased due to technical issues, which cannot be captured by our model, such as difficulties in inspecting properties in person and the inability of notaries to work remotely.

[9]Our results are in line with Kuodis and Ramanauskas (2009) who argue that credit demand in the boom period was driven by optimistic income prospects, rising wages, and declining unemployment.

[10]In 2015, households' savings increased due to a rise in bank deposits around the euro adoption period.

Figure 5: Credit market: demand and supply decomposition



Notes: the figure shows the average decomposition of the demand and supply equations estimated by the 56 models, which reflects the impact of various factors on housing demand and supply compared to the average for the whole period. The black line indicates the estimated demand and supply. The red vertical dashed lines indicate the beginning of the quarantine imposed in Lithuania due to the COVID-19 pandemic. *House prices* also include housing transactions. *Household savings* show the growth in the deposit-to-GDP ratio. *Macroeconomic environment and wages* include unemployment, inflation, annual growth of compensation per employee, wages and GDP. *Bank funding costs* refer to AVIBOR. *Bank concentration* is indicated by the HHI index. *Lending standards* includes mortgage minimal down-payment requirements.

3.3.3 Impulse-response analysis

Having estimated the two-market model, we can carry out an impulse-response analysis that was described in Section 2.2.6. Here we focus on the endogenous response of the quantity and price variables to one-time exogenous shocks.

Across all 56 model specifications and all demand-supply shifters (X_t^i, Z_t^i), as well as reference indices $(\mathbf{R}_t)$ and shocks $(\mathbf{u}_t)$, we calculate the average IRF's of quantity and price variables $(\mathbf{Q}_t)$, using equations (27)-(29). The IRF's are regime-specific, thus could be further averaged using the relative frequencies of each regime as weights $(\pi_t^r, r \in \{I, II, III, IV\})$. However, such averaging would eliminate useful information that is contained in each regime. In fact, as highlighted in this subsection, variable response to shocks can be quantitatively, or even qualitatively, very different across regimes. Our analysis illustrates that the two-market model can serve as a powerful tool in policy analysis to estimate credit and housing responses to changing market or macroeconomic conditions.

The responses of endogenous credit and housing variables to six selected shocks are depicted in Figure 6. The chart contains dynamic (semi-)elasticities of endogenous variables to a 1% (or 1 p.p.) temporary rise in selected demand-supply shifters and reference rates, over a 6-year horizon (x-axis, $j = \overline{0,5}$), averaged across 56 model specifications. Each panel-row of the chart represents an idiosyncratic shock to an exogenous variable. Each panel-column contains the responses or elasticities for each of the four endogenous variables.

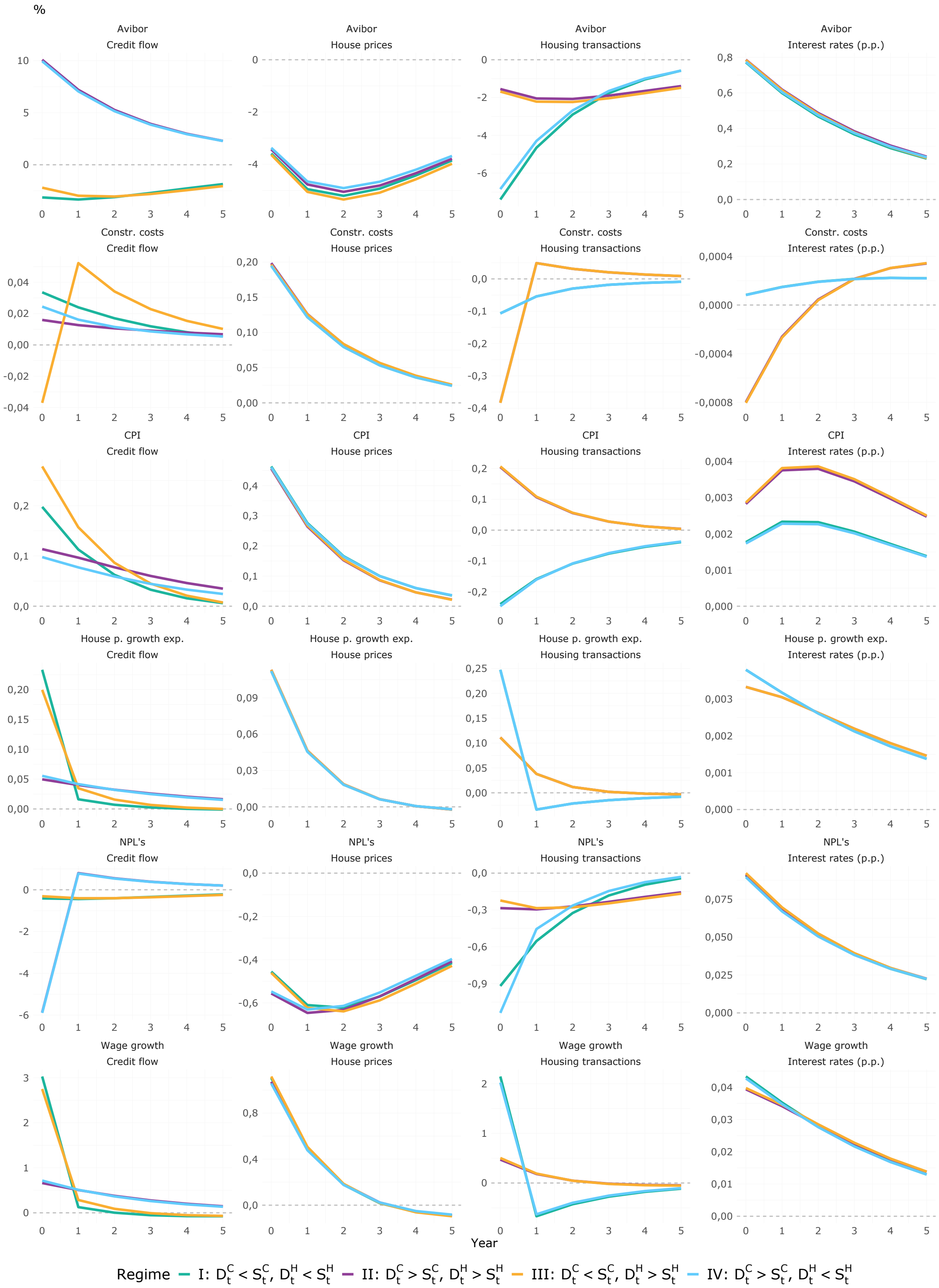
Interest rate shock is induced by 1 a p.p. increase in the Avibor rate, which serves as reference for variable rate mortgages. The shock primarily works through the pricing equation (8) and thus raises the lending rates which affect credit demand and supply curves, as well as housing demand. We see that higher mortgage interest rates decrease house prices by 3.5% on impact and cause a drop in housing transaction volume by -2 to -7%, depending on the regime. The impact on credit flows is more nuanced. In Regimes I and III, when credit demand is binding ($Q_t^C = D_t^C < S_t^C$), the shock further decreases demand and causes a fall in credit flows by around 3%. However, in an opposite case when there is excess credit demand (Regimes II and IV, $Q_t^C = S_t^C < D_t^C$), higher interest rates may lead to an increase in mortgage lending supply, thus contributing to an expansion in lending activities. Note that the latter effect does not take into account the very likely concurrent increase in bank funding costs, thus the expansion in credit supply must be overestimated. The impact of 1 p.p. Avibor on credit interest rates is equal to around 0.8 p.p. – less than 1-to-1, as the suppressed demand dampens the effect on lending rates.

Construction cost shock is entailed by a one-time increase in the construction cost index by 1%. Higher costs decrease housing supply and are instantaneously translated to 0.2% higher house prices and lower transaction volumes. Regarding the mortgage market, we see that there is mostly a slight positive effect on lending, which is caused by the nominal appreciation in house prices that serve as mortgage credit collateral or numeraire.

House price shock is induced using the price adjustment mechanism equation (12), by exogenously raising the CPI reference index.[11] The instantaneous impact on house prices is equal to -0.5%, yet the response of housing volume depends on the housing market regime. If the market is constrained by supply ($Q_t^H = S_t^H < D_t^H$), higher housing prices cause an expansion in the housing market, since the supply increases. In the contrary case, when demand is the binding factor ($Q_t^H = D_t^H < S_t^H$), an increase in house prices will further depress demand, thus decreasing the total amount of transactions. In

[11] Although the CPI index is shocked to induce a change in house prices, it should not be understood as a shock to general inflation, as the IRF in question does not take into account the inflation's impact on market demand or supply.

Figure 6: Quantity and price responses to one-time changes in exogenous variables



Notes: dynamic (semi)-elasticity means across 56 model specifications, using equations (27) and (28). The 0-year point (x-axis) represents instantaneous, or within-year, response of the endogenous variables.

all regimes, since inflation shock causes a significant increase in house prices, there is also a positive impact on credit flows and interest rates.

Housing market expectations shock represents a 1 p.p. increase in the expected house price growth rate. Essentially, both markets respond very positively to the expectation shock, which causes a 0.1% increase in house prices and 0.05-0.2% higher credit flows. Interestingly, in Regimes I and IV, when housing demand is low, the shock causes an overshooting effect in housing volumes. At first, the volume reaction is quite large, however, it later becomes slightly negative as buyers decrease their demand in response to higher house prices. This system's reaction to the shock illustrates how sudden changes in housing expectations can cause swings in both housing and credit markets.

Credit risk shock is represented by a one-time 1 p.p. increase in mortgage NPL's, which alters credit institutions' perception of risk. The shock causes a significant drop in credit supply and a concurrent rise in credit risk premium which is priced into higher interest rates by 0.1 p.p. The initial impact on mortgage flows is negative in all regimes, however, it is particularly strong and equal to -6% when credit supply is the limiting factor (Regimes II and IV). The 1 p.p. increase in perceived credit risk causes a negative reaction in the housing market, with housing prices falling by around 0.6% and transactions by -0.3- -0.9%, due to higher interest rates and limited credit supply.

Household income shock is induced by a temporary 1 p.p. rise of the average wage growth rate that enters housing demand and credit supply equations. Higher household income causes an increase in housing demand and credit supply, thus contributing to a 1% rise in house prices. The credit flow also responds quite strongly with 0.7% in Regimes II and IV, when lending supply is binding, and by around 3% when the credit demand is constrained. Lending rates also react positively by around 0.04 p.p. on impact, mainly due to increased credit demand. Similarly to the housing market expectation shock, a surge in household income may also cause a housing volume overshooting effect in regimes, when housing demand is binding.

3.3.4 Decomposition of quantities and prices

Previously we decomposed the historical variation in demand and supply values, however, the endogenous quantity and price variables are of the main interest. Using the impulse-response analysis and the dynamic equation (26) we deconstruct the historical variation of the quantity-price series.

The historical decomposition of the market quantity variables is depicted in Figure 7 panel (a), while the drivers of prices are shown in panel (b). The decomposition incorporates all exogenous variables from the credit and housing demand-supply equations, including the reference rates, demand-supply shifters and the recovered structural shocks. An exogenous variable may impact a market directly if the variable explicitly enters the market's structural equations. On the other hand, there may be an indirect or a spillover effect, when a variable impacts another market's quantity and price. A simple example of a direct effect is the impact of urbanisation on housing transactions, as urbanisation appears in the specification of the demand for housing equation. An indirect effect can be illustrated by the impact of urbanisation on credit flows – by affecting housing demand, urbanisation affects housing volume and price, and thus indirectly impacts the credit market.

Housing market. The results in the left column of Figure 7 show that during the boom period of 2006-2008, housing transactions and growth in house prices were strongly supported by favourable macroeconomic conditions, high wage growth, expectations (sentiments), loose lending standards and competition (low concentration) in the banking sector. We consider the latter two determinants to be indirect as they affect housing transactions and prices through the credit market conditions. For example, a relatively low concentration in the banking sector allows banks to lend at cheaper interest rates, which increases the demand for credit, and thus for housing. Similarly, when banks perceive the credit risk as low, they may increase supply and offer lower interest rates, which as a result increases demand for housing and hence has an upward pressure on house prices. In contrast, housing transactions were mostly constrained by high bank funding costs (i.e. Abivor interest rates) that pushed up interest rates on loans, which in turn dampened the demand for housing and alleviated the pressure on house prices. During and shortly after the Global Financial Crisis, the decline in housing transactions and prices can be attributed primarily to the deterioration of the macroeconomic environment, lower wages and depressed expectations.

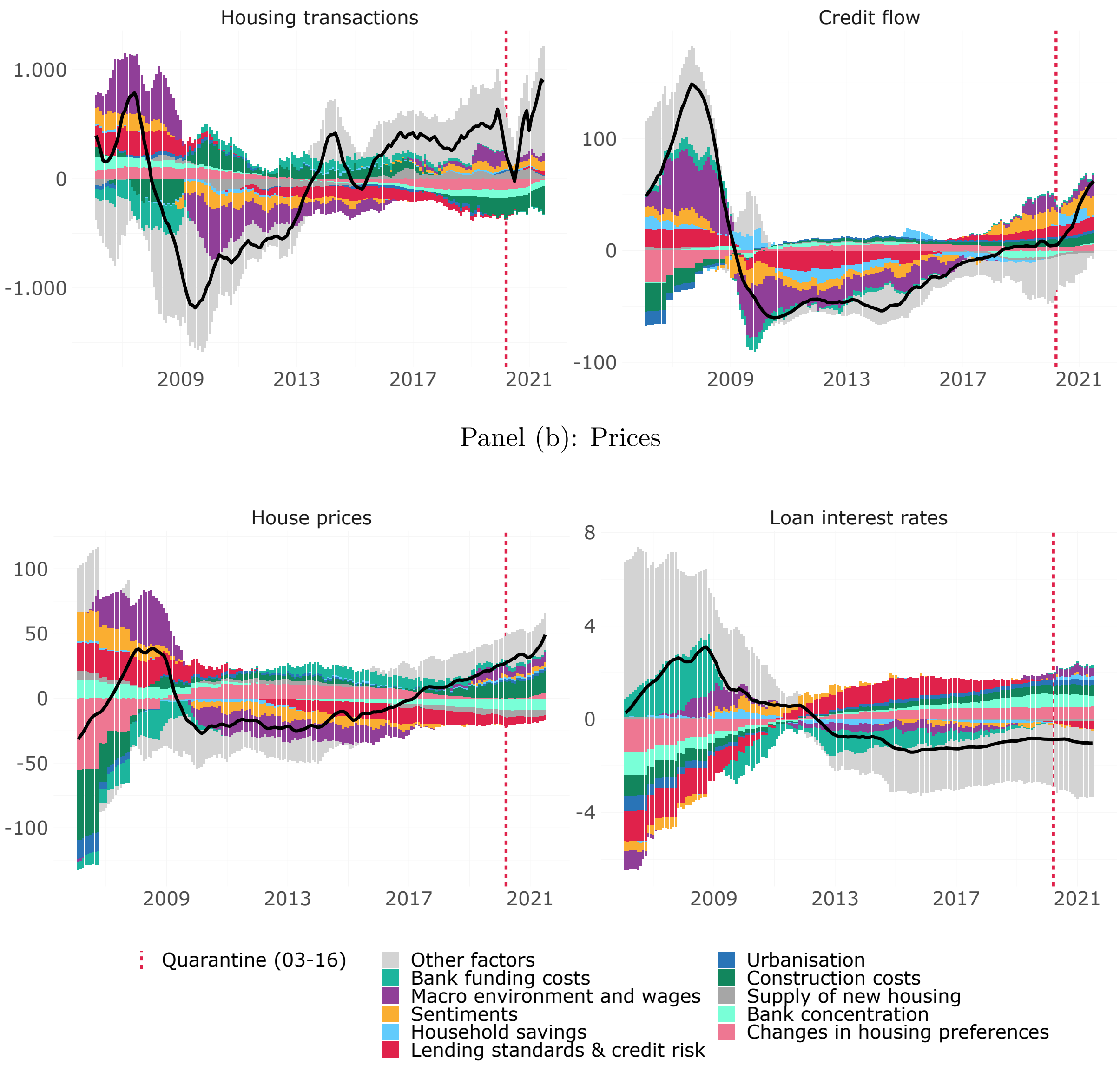
In recent years, 2016-2019, house price growth can be attributed to increasing construction costs, which, together with high bank concentration, have constrained the housing market. In addition, good economic conditions and income growth, coupled with positive household sentiments, also contributed to increasing house prices. Interestingly, a significant portion of the recent growth in the housing market cannot be explained by the model, or the traditional factors that worked over the last 15 years. This may pose a question about the sustainability of these market developments – a question we will tackle in Section 4 on misalignments.

Credit market. The decomposition of credit flows in the second column of panel (a) shows that the exuberant credit growth during the boom period of 2000's was stimulated by similar factors as in the housing market, i.e. macroeconomic environment, wages, sentiments, perceived credit risk, household savings and other factors. However, during the Global Financial crisis, credit flows declined sharply in tandem with a deterioration in the macroeconomic environment, falling wages, worsening sentiments and a change in banks' risk perception.[12]

[12] Our results are in line with Ramanauskas et al. (2018) who find that a change in bank risk perceptions and the sharply deteriorating economic outlook led to a collapse in new bank lending during the crisis.

Figure 7: Decomposition of quantities and prices

Panel (a): Quantities



Notes: the y-axis contains demeaned values. The mean results over the 56 models are presented. *Bank funding costs* refer to Avibor. *Macroeconomic environment and wages* cover unemployment, GDP growth, inflation, disposable income growth and wages. *Household savings* include the time necessary to accumulate funds for a mortgage downpayment, also growth in the deposit-to-GDP ratio, remittances, and savings expectations. *Urbanisation* includes variables related to urbanisation and demography. *Construction costs* also covers financing conditions in the business sector, i.e. interest rates on business loans and banks' lending standards to companies. *Supply of new housing* includes new housing completions and building permits. *Bank concentration* is measured by the HHI index. *Changes in housing preferences* indicate the monthly average size (sq. meters) of dwellings sold. The observed values, demeaned by averages over the entire period, are presented by black lines. The red vertical dashed lines indicate the beginning of the quarantine imposed in Lithuania due to the COVID-19 pandemic.

On the other hand, in line with the housing market, the role of the macroeconomic environment and wages on credit growth has been less pronounced in recent years. Instead, the growth in credit flows have been more related to positive sentiments and higher construction costs, which affected the credit market indirectly, through housing market demand and house prices. Finally, loan interest rates during the boom period were mostly linked to the bank funding costs (Avibor) and other factors.

Covid-19 pandemic. The effect of the quarantine of 2020 on credit and housing markets was limited. It mainly affected housing transaction volumes (see panel a), which dropped sharply due to a decline of other factors that had boosted housing transactions in the previous years.[13] However, this drop was short-lived, and the transaction volumes recovered in 2021.

In contrast, house prices and credit flows have risen sharply since the pandemic. In line with Duca et al. (2021), we argue that there are several reasons for that. First, a very quick and broad set of economic policy measures prevented a recession in Lithuania, thus the GDP contracted by only 0.8% in 2020. While unemployment increased (from 2.2% to 8.5% per year), the pandemic did not have a negative impact on wages, as average wage growth in 2020 was equal to 12.2%. Therefore, for the majority of households, their financial situation improved during the pandemic, which further reinforced households' positive sentiments about their future financial situation. Moreover, the COVID-19 pandemic has contributed to the rise in house prices by changing housing preferences towards larger apartments, as households spent more time working from home. Finally, pandemic-related supply chain disruptions and labour shortages further increased construction costs, which were already relatively high before the pandemic. The higher construction cost contributed to the higher house prices, and as a result to a higher credit volume.

4 Housing and credit misalignments

In the previous section we disaggregated the historical house price growth and credit flows into their drivers. Although housing and credit dynamics may be partially explained by demand-supply shifters, they may still be unsustainable – not aligned with the fundamentals. In this section we tackle this question by looking at the historical decomposition of quantity-price variables and disentangling the impacts of fundamental and non-fundamental drivers.

Using the method proposed in Section 2.2.7, we are able to reconstruct the fundamental series of house prices and mortgage flows, as well as estimate the associated gaps or misalignments. Note that we make the distinction here between the word *disequilibrium* which refers to the difference between the market demand and supply, and *gaps*

[13] Moreover, the transactions may also have decreased due to technical issues, such as difficulties in inspecting properties in person and the inability of notaries to work remotely.

or *misalignments* which are meant as quantity and price deviations from their respective fundamental levels. In the last part of this section we will show that our historical gap and disequilibrium series are related.

Short overview of measurement of misalignments

Before discussing the modelling results, we will provide a brief overview of the standard methods for detection of misalignments. In short, misalignments or gaps are thought of as deviations from some variable's fundamental level. The usual techniques that are used to differentiate between the fundamental and the non-fundamental part of a time series can be divided into three groups: i) statistical filters, ii) ratios, iii) econometric models.

Simple statistical filters (e.g. Hodrick-Prescott, Baxter-King, Christiano-Fitzgerald, Kalman filters) can be used to decompose credit or house price series into the trend and the cycle. The smooth trend is then considered as the sustainable level of credit or price, and deviations from the trend are interpreted as misalignments. Although such methods are easily applicable, they do not consider any additional information and identify fundamental levels on purely mechanistic statistical terms, thus lack economic intuition.

Time series ratios, such as the price-to-income and price-to-rent ratios for house prices and credit-to-GDP ratio for credit, can be used to address the one-dimensionality problem of simple statistical filters and their disconnect from economic theory. For instance, house price-to-income ratio reflects changing affordability of housing over time. Price-to-rent ratio is closely related to the notion of the user cost of housing: according to the asset pricing theory, in equilibrium, the annual cost of home ownership should equal annual rents (Himmelberg et al., 2005). Following this logic, price-to-rent ratio can be compared to the inverse of the user cost of home ownership (Girouard et al., 2006; Naruševičius et al., 2019). These ratio series are usually assumed to be mean-reverting and therefore are compared to their long-term averages. For example, Kulikauskas (2016) calculates price-to-income and price-to-rent ratios for the Baltic states and shows that the ratios exceeded their long-term averages in 2005-2008 and would have signalled house price overvaluation when the housing market was overheating.

However, empirical tests show that the mean-reversion assumption might not always hold true (see Philiponnet and Turrini, 2017). Structural breaks and long-run shifts in consumer preferences, as well as changes in other variables, might alter the means of ratios over time. To tackle this issue, techniques can be combined by applying statistical filters to time series ratios in order to extract house price and credit fundamentals (see e.g. Hejlova et al., 2017; Bank for International Settlements, 2020). For instance, the standard way of measuring credit misalignments is by calculating the "Basel gap," where the credit-to-GDP ratio is compared to its Hodrick-Prescott filtered trend. However, the denominator of a statistical ratio may also be imbalanced due to an overheated economy or inflated rents, putting downward pressure on the ratio. In this case, analysts would be likely to under-appreciate the possible existence of a housing or credit bubble.

Structural models or econometric techniques that combine more than two variables into a modelling framework could be used to address the one-dimensionality and lack-of-theory issues. These models usually estimate a long-run cointegrating relationship between house prices or credit and some fundamental determinants of demand and supply. Many authors also complement the long-run equation by estimating the short-run dynamics in an error-correction framework (see e.g. Girouard et al., 2006; Kulikauskas, 2016; Philiponnet and Turrini, 2017). Usually such models only focus on estimating the imbalances in one of the markets, without accounting for the possible misalignments of the demand and supply drivers included in the equilibrium equation. For example, some authors include credit in the cointegrating equation as one of the demand drivers for the housing market. However, one has to bear in mind that credit itself may be excessive, leading to underestimation of the house price gap. Likewise, models measuring equilibrium credit usually include house prices, which may be inflated and cause an under-appreciation of the credit gap. In response to this, Lang and Welz (2018) estimate a semi-structural model for measuring household credit gaps without including asset prices. Multivariate time series models, structural models or multi-dimensional Kalman filters can be used to capture the joint evolution of the credit and housing markets. For example, Oikarinen (2009) and Filipe (2018) estimate cointegrating relationships between house prices and mortgage credit and find that there indeed exists a strong two-way interaction between housing prices and lending. Filipe (2018) also finds that a shock in mortgage credit leads to a permanent increase in house prices.

Taking the drawbacks of one-dimensional models into account, we compute the housing and credit gaps *jointly* using our proposed and estimated disequilibrium model, which takes into account the interaction between the two markets.

4.1 Fundamentals of market drivers

To understand whether house prices and credit are in line with the fundamentals, it is first necessary to disaggregate their drivers, depicted in Figure 7, into fundamental and non-fundamental parts (see the method in Section 2.2.7). As fundamentals of drivers like GDP growth or NPLs are not observable, it poses a difficulty that needs to be addressed with assumptions.

First, we assume that the main determinants of housing demand, i.e. population, urbanisation, housing preferences in terms of house size (sq. meters), and savings, are always at their fundamental long-term levels. Moreover, we deem that some variables related to market supply – credit market concentration, reference rate Avibor, and construction permits – are also fundamental.[14] Second, bank lending standards, expectations

[14]Note that Avibor is the weighted average of Euribor and Vilibor interbank market rates, which are

and other behavioural variables, as well as macroeconomic time series, are treated as not necessarily fundamental, i.e. they may contain a cyclical part that may be inflated along the economic cycle. Figure 17 in Appendix A.3 shows the observed explanatory variables together with their fundamentals levels. We discuss in more detail below how the fundamental components are determined.

Macroeconomic variables. The level of general economic activity is not always sustainable; thus, it can produce imbalances in other sectors, such as housing or credit. For example, an overheating economy may have contributed to the housing and credit bubble of the 2000s in Lithuania. We therefore assume that GDP can be divided into fundamental and non-fundamental components, where the former is considered as the potential output and the latter is the output gap. The potential output and gap series are provided by the Economics Department of the Bank of Lithuania, and associated potential GDP growth is depicted in Figure 17. Similarly, we assume that the fundamental level of the unemployment rate is the Non-Accelerating Inflation Rate of Unemployment, NAIRU, provided by the Economics Department and plotted in Figure 17.

Wage growth. If the macroeconomy is overheating, it may create imbalances in the labour market and inflate wage growth, which is an important determinant of housing and credit demand, and is also taken into account for market supply decisions. We assume that wage growth is in line with fundamentals when the economy's output is at its potential and the unemployment rate is equal to NAIRU. To decompose wage growth into the fundamental and cyclical parts, we regress the observed wage growth on GDP growth and the rate of unemployment. The fundamental component is obtained by calculating the fitted values of this regression, using the potential GDP growth and NAIRU values as predictors. The cyclical part is computed as the difference between the observed values and the computed fundamental component. The observed and the fundamental series of wage growth, disposable income and growth of compensation per employee are depicted in Figure 17.

Expectations. Consumer sentiments or expectations are an important part of the decision-making process in the two markets. Similarly to Rakovská et al. (2020) and Gric et al. (2022), we assume that sentiments may be rational and consistent with macroeconomic fundamentals, or irrational deviations from fundamentals that are spurred by optimistic or pessimistic mood swings. As with wage growth, we decompose the behavioural variables by regressing each of them on GDP growth and the unemployment rate. The rational, or fundamental, part of the behavioural variables, such as consumer confidence, construction confidence, or intentions to buy real estate, is treated as the fitted regression values using potential output and NAIRU (see Figure 17). Regarding inflation expectations, we consider that the long-term average is the fundamental value.

mostly determined outside of Lithuania and can be treated as entirely exogenous to the local housing and credit markets.

Lending standards. Bank Lending Survey-based measures of lending standards were particularly loose during the boom of the 2000s (see Figure 17). At that time, banks granted loans with high loan-to-value ratios, which reached a peak of 95% in 2008. By contrast, preceding the crisis, the NPL indicator was very low, while the actual credit risk, as measured by the mortgage probability of default (PD), was at its all-time high. We therefore argue that lending standards were irrationally loose in the wake of the Global Financial Crisis due to aggressive bank lending policies (see also Ramanauskas, 2005, 2007; Kuodis and Ramanauskas, 2009). Taking this into account, we assume that the rational part of lending standards is consistent with values throughout 2015-2019, which can be considered as "normal" times.[15]

Perceived credit risk. Preceding the crisis of 2009, not only loose lending standards but also inadequate risk management practices led banks to lend to high-risk borrowers. As argued by Kuodis and Ramanauskas (2009), banks underestimated the credit risk during the whole boom period and, as a result, contributed to the housing and credit bubbles that led to the bust. Figure 17 compares the historical series of the mortgage NPL ratio, measuring the materialised credit risk – perceived risk, and the mortgage PD, measuring the probability that the loan will default during its lifetime – actual risk. Before the crisis, when the PD, as measured by a *logit* regression, was the highest, banks had the lowest levels of NPLs on their books. Given this, we assume that the mortgage credit risk is in line with fundamentals, if the perceived credit risk coincides with the actual credit risk. In other words, we consider the historical PD series to be the fundamental level of credit risk, and compute the cyclical part as the difference between the historical level of the NPL ratio and the mortgage PD series.

Construction costs. Although construction costs may be treated as a housing supply fundamental, housing and credit imbalances may spill over to the construction market, inflating construction costs and employee wages. We eliminate this spillover effect by treating the European Union Construction cost index as the exogenous and fundamental driver, which cannot be affected by imbalances in Lithuania. The fundamental part of the Lithuanian Construction cost index is derived by regressing the index on the EU counterpart and taking the fitted values (see Figure 17).

Limitations. We acknowledge the large uncertainty surrounding the level of fundamentals of the explanatory variables, which may spill over to the uncertainty on fundamentals of housing and credit. In particular, major uncertainty in the estimates arises from the definition of the fundamental variables, such as lending standards and perceived credit risk, as well as NAIRU and potential GDP that also determine the fundamental estimates of income and expectations. Although our treatment of the fundamentals of

[15]More specifically, we exclude the post-crisis period, 2011-2015, because it was characterised by a credit-less recovery (see Figure 1), limited credit supply (see Panel (b) of Figure 3) and banks' risk-aversion. Moreover, according to ECB Bank Lending Survey statistics, European bank lending standards stabilised around 2015, after several years of tightening (from 2008 to mid-2014).

model predictors is rather arbitrary, by combining this information and the estimated two-market disequilibrium model, we narrow down the uncertainty of housing and credit fundamentals, and the associated gaps. Furthermore, we alleviate this issue by using a suite of 56 estimated two-market models that contain differing sets of predictors. Finally, as discussed further in Section 4.4, our estimated gaps are broadly in line with other measures.

Lastly, we highlight the possibility that some of the misalignments in predictor values, such as the GDP growth, consumer sentiments or lending standards, may be endogenously linked to the imbalances in housing and credit markets. However, this joint two-market disequilibrium model can be regarded as a partial (dis-)equilibrium model, which does not take into account the macro feedback loops that could otherwise be captured by large-scale modelling techniques, endogenising all variables.

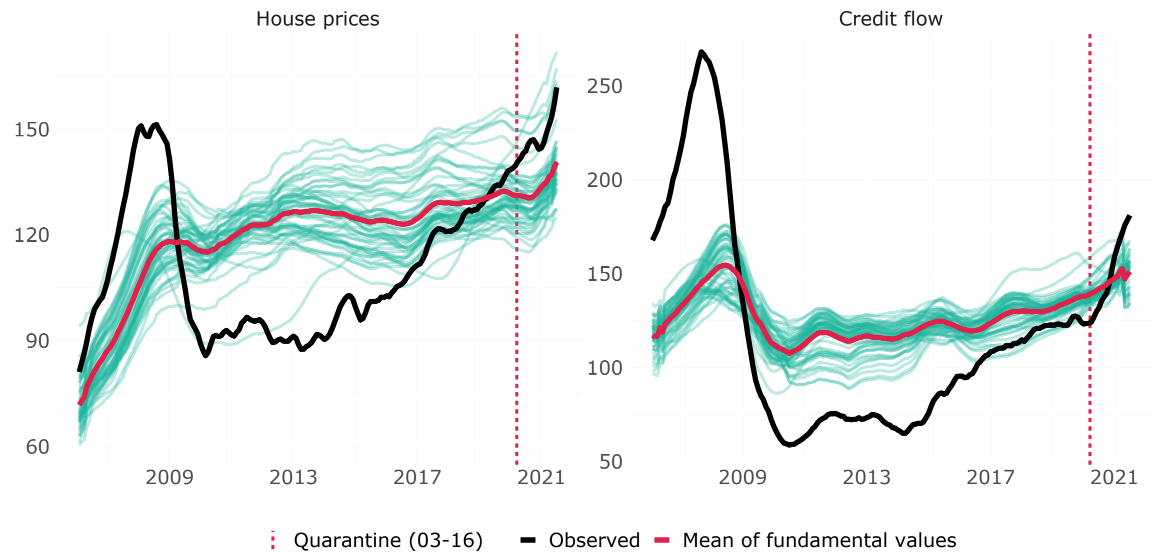
4.2 Discussion of results

Based on equation (30) and the above-discussed fundamental levels of explanatory variables ($\mathbf{R}_t^F, \mathbf{X}_t^F$, see also Figure 17), we estimated the fundamental quantity-price vector $\mathbf{Q}_t^F$ series, using the 56 model specifications. Note that the fundamental levels of the $\mathbf{Q}_t^F$ vector are regime-specific, so we averaged them using regime probabilities π^r.

The two-market disequilibrium model-implied fundamental levels of the house price index and mortgage credit flow are depicted in Figure 8. The estimates obtained from the different model specifications yield similar information. We see that in 2006-2008 both housing and credit markets were misaligned, or overvalued. In contrast, during and after the Global Financial Crisis, until around 2017, the market variables were below their respective fundamental levels. While the results show similar patterns across all specifications for house prices, there are some inconsistencies in 2017-2019, which only confirm our choice to rely on more than one model specification.

The computed fundamental levels were used to determine the house price and credit flow gaps, or misalignments, which are displayed in Figure 9 and expressed as percentage deviations. The results signal that the overvaluation of house prices peaked at the end of 2007 at around 40%. After the crisis, prices were below fundamentals, with an average gap of around -20% between 2010 and 2015. The positive house price gap started to re-emerge at the end of 2019 and reached its decade-high of 16% in June 2021. Similarly, credit flows were around 80% in excess of the fundamentals by mid-2007. During and long after the Global Financial Crisis, up until 2015, mortgage credit flows were around 40% below their fundamental levels. As with house prices, the credit gap turned positive during the COVID-19 pandemic and recently reached 20% in excess of the fundamentals. Interestingly, one can observe from Figure 9 that both gaps were large and positive well before the crisis of 2009. Although this suggests that the indicator series may have the

Figure 8: Fundamental values for 56 model specifications



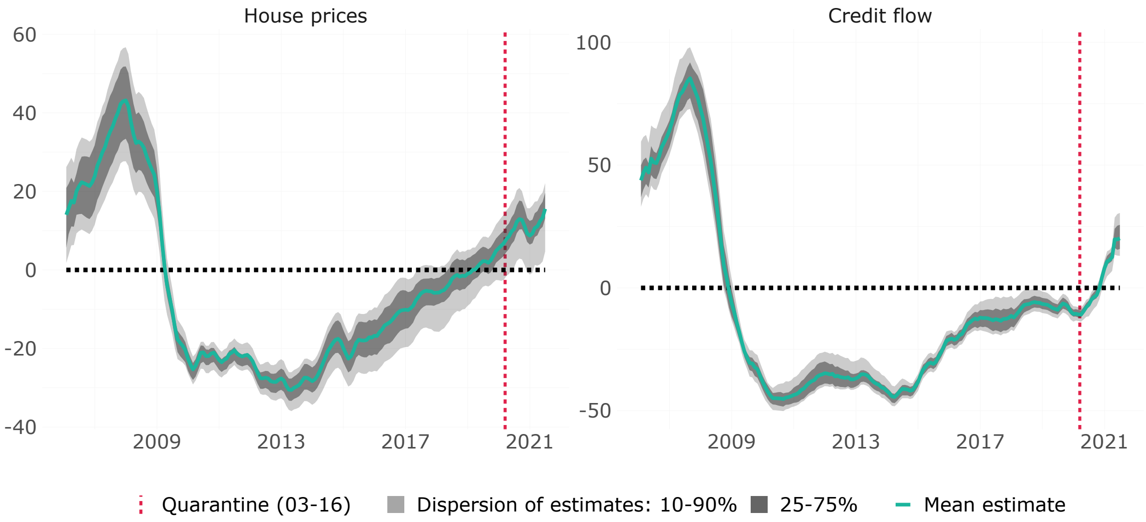
Notes: green lines represent the estimated fundamental values for 56 specifications and equation (30).

desirable early warning property (e.g. see Valinskytė and Rupeika, 2015), it does not necessarily imply that Lithuania is likely to experience a housing and credit bust in the near future.

Using the fundamental levels of explanatory variables, as well as their cyclical parts, equations (26) and (30), we are able to decompose the house price and credit gaps into their drivers, which are presented in Figure 10. Between 2006 and 2008, the widening of both gaps can be explained by loose lending standards and low perception of credit risk, an overheated economy and labour market, and other unexplained factors – structural demand and supply shocks. Note that housing and credit imbalances may have also contributed to the macroeconomic overheating; therefore, the estimate on the contribution of loose lending practices to the bubble may be under-appreciated. During and after the bust of 2009, the market values were below the fundamentals because of a deteriorated economic environment, consistently bad expectations or consumer confidence, and relatively tight credit standards.

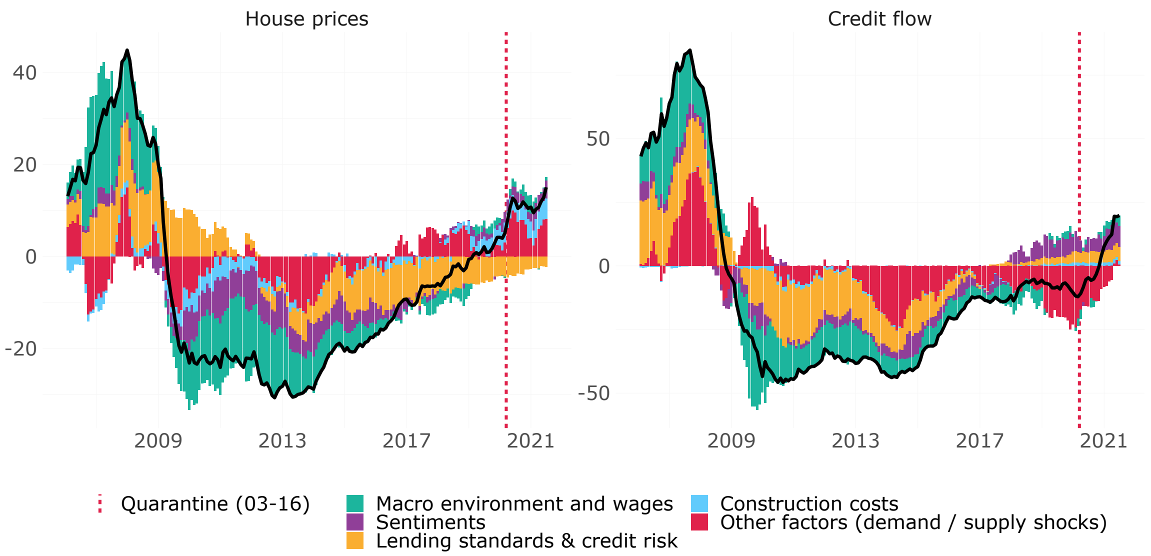
More recently, around the time of the COVID-19 pandemic, the house price gap has been driven by a large increase in construction costs, strong consumer confidence and optimistic expectations, and relatively good economic conditions, as well as positive housing demand shocks. While the pre-pandemic credit gap was negative, due to unknown factors or shocks, it later become positive, which can be associated with good overall consumer and business confidence levels and relatively lax perception of credit risk. The latter can be explained by the historically low NPLs, or perceived credit risk, which are well below

Figure 9: Gaps for 56 model specifications



Notes: gap is expressed as a percentage deviation from the fundamental values, in particular: $(actual - fundamental)/fundamental$.

Figure 10: Gap decomposition



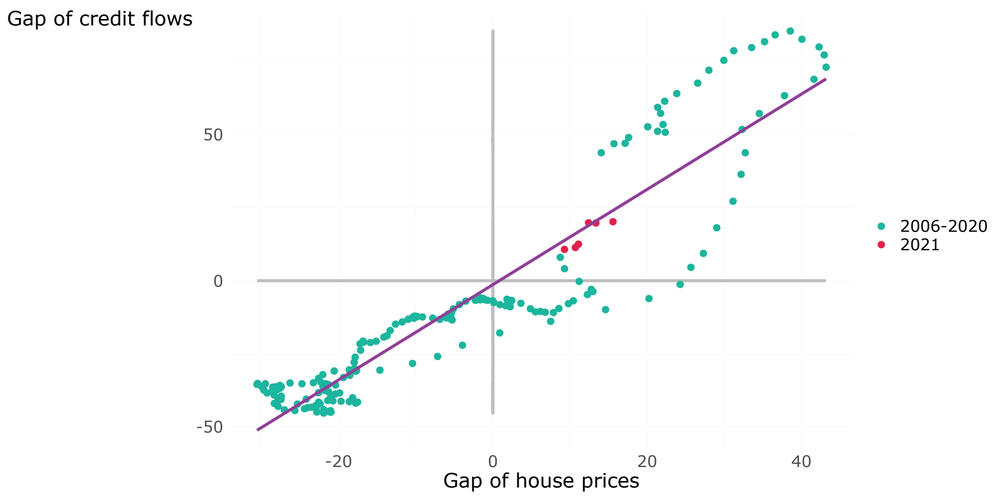
Notes: the black line indicates the estimated average gap series, using 56 model specifications, whereas the coloured stacked bars are the corresponding drivers of gap dynamics.

the actual risk in mortgage PD (*Non-performing loans* facet in Figure 17). In essence, similarly to the boom of 2000s, albeit not on the same scale, banks may have a low perception of credit risk. Note that the recent hike in construction costs not only affects house prices, but also slightly increases imbalances in the credit market through house price appreciation.

4.3 Spillovers of misalignments

The way we specified the two-market disequilibrium model in equations (5)-(12) and Table 1 allows demand-supply shifters of one market to indirectly affect the other market. For instance, if bank lending standards are lax, they may create imbalances not only in the credit market, but also in the housing market, contributing to the overvaluation of house prices. Essentially, misalignments that originate in one market may spill over and generate imbalances in the other market. A quick glance at Figure 9 suggests that the house price and credit flow gaps are not only well-correlated, but are also concordant, i.e. a positive gap in one market is often coupled with a positive gap in the other market, and vice versa.

Figure 11: Relationship between house prices and credit flow gaps



Notes: the purple line represents the linear regression.

Figure 11 shows a positive relationship between the house price and credit flow gaps, indicating that both markets tend to be overvalued simultaneously, or undervalued. To assess the extent of synchronisation across the housing price and credit flow misalignments, we use the concordance index, developed by Harding and Pagan (2002). The concordance index of the two gaps is equal to 0.87 and signals a very high degree of synchronisation between the misalignments in the two markets. More specifically, around 87% of the time the two markets are in the same phase, i.e. both are either over- or undervalued. Finally, cross-correlation analysis shows that the credit gap estimate leads the house price gap by approximately 1-2 quarters. That is, one might expect house prices to become overvalued after a positive credit gap emerges. The results are robust in sub-samples.

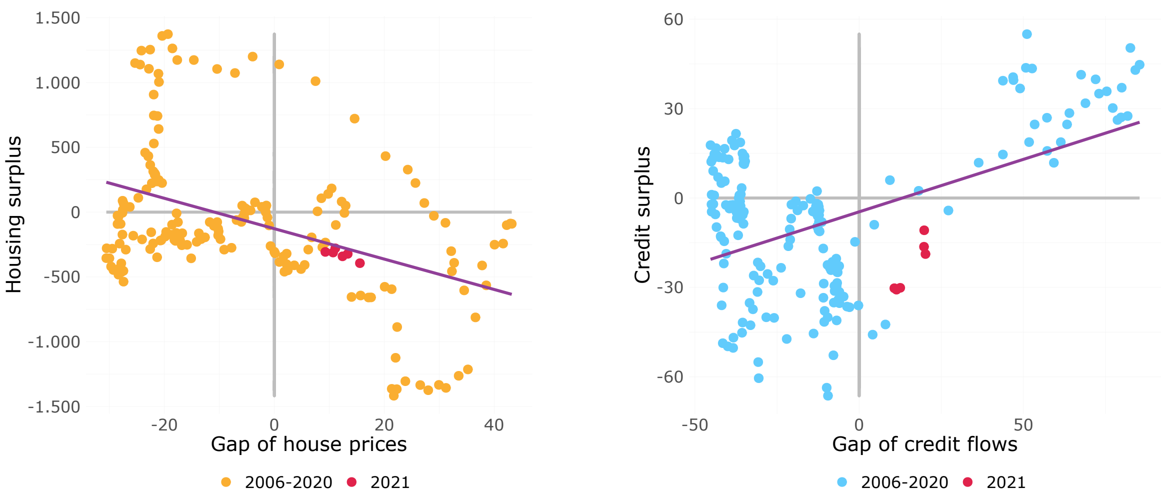
Disequilibrium and gaps

Market disequilibrium refers to excess demand or supply, whereas misalignment, or gap, refers to the situation, when an endogenous variable is above or below its fundamental level. Although the two terms are different, they are related. For instance, a sudden and unexplained increase in construction costs will decrease housing supply and induce an excess of housing demand, or a disequilibrium. At the same time, this supply shortage will put pressure on home prices, thus causing a positive house price gap.

Figure 12: Relationship between the gaps and market imbalances

Panel (a): Housing market

Panel (b): Credit market



Note: panel (a) shows a relationship between the estimated house price gap and surplus of supply of housing transactions. Panel (b) shows a relationship between the estimated credit flow gap and credit supply surplus. See Figures 3 and 9. Red dots indicate 2021; the regression line to a scatter plot is in purple.

Figure 12 plots the relationship between the gap and market quantity surplus for each respective market. The scattergram on the left-hand panel shows that the house price gap and the housing supply shortage often coincide, with the concordance index being equal to 0.73.[16] Although the general correlation is quite weak, we see a general tendency according to which the larger the housing shortage, the larger the gap in house

[16]The concordance index is computed when the housing supply surplus and house price gap are non-negligible, in order to ignore the cases when the market is nearly-balanced in one respect or another. For simplicity, we assume a rule of thumb and analyse periods only when housing market surplus is beyond +-250 transactional units.

prices. Interestingly, the recent gaps of 2021 fall exactly into this category, i.e. house price over-appreciation may be linked to excess housing demand. In addition, cross-correlation analysis shows that, generally, the excess housing demand leads the house price gap by approximately one year.

The chart on the right-hand panel shows that the credit flow gap and credit disequilibrium are highly correlated with two visible clusters. The concordance index suggests that the measures are synchronised 87% of the time.[17] In most cases, credit flows are too large when there is excess credit supply, and conversely, when credit is below its fundamental level, there is a shortage of credit supply. It is worth noting that the positive and large credit gap episodes are quite rare. Finally, cross-correlation analysis suggests that positive credit flow gaps were mostly preceded by an excess mortgage supply.

4.4 Comparison with other methods

As previously discussed, there is large uncertainty about the fundamental levels of housing and credit. Our gap estimates are based on the combination of the two-market disequilibrium model with rather arbitrary assumptions about the fundamentals of the demand-supply shifters. In this subsection we compare house price and credit gaps estimated using the two-market disequilibrium model with those obtained from other measurement methods.

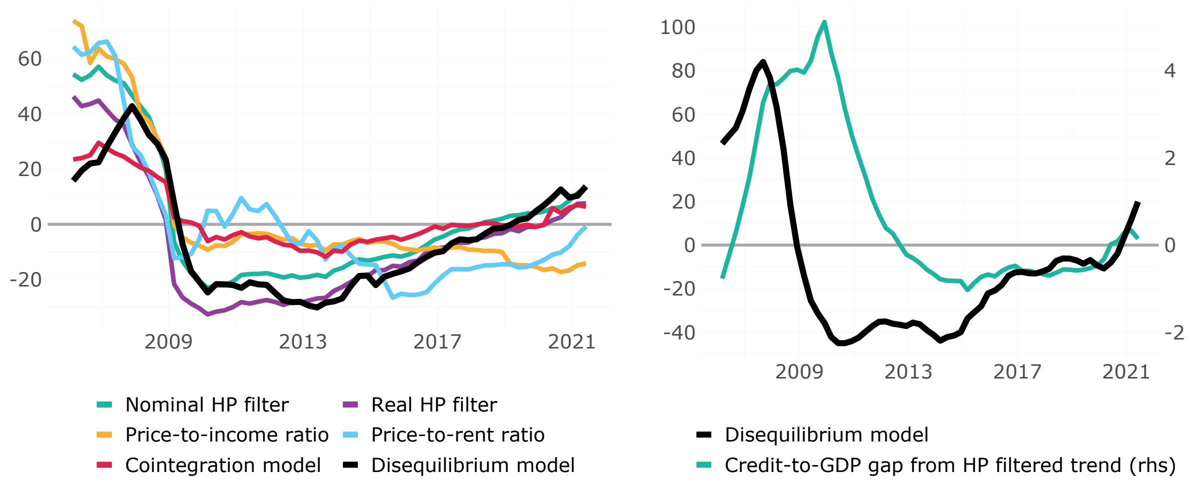
Panel (a) in Figure 13 shows house price misalignment estimates, using the methods proposed by Kulikauskas (2016). There is broad agreement among different methods on the qualitative trends of house price gaps, including the two-market disequilibrium model. Slight differences emerge in around 2006-2008, when the disequilibrium model signals a lesser overheating of house prices, and peaks later than other methods. As mentioned in Section 2.2.7, fundamental levels in the disequilibrium model are derived under the assumption that starting values of house prices are fundamental, which may lead to underestimation of the gap at the beginning of the analysis period.

Some disagreement among method results also occurs in the more recent period between 2019 and 2021. By mid-2021, the gap varies between negative and positive values, ranging from -14% to +15%. The approaches based on time series ratios, particularly the house price-to-income ratio, suggests high affordability of housing; thus, house prices may be undervalued. On the other hand, results from statistical filters and econometric models imply house price overvaluation. These differences might come from the assumptions related to fundamental values discussed in the previous Section 4.1. For example, the time series ratios assume that wages and rents are fundamental. However, wages may be inflated (not in line with fundamentals) when wage growth exceeds productivity growth, due to labour shortages. In addition, if house prices are overvalued, rents may

[17] Computed for periods when the credit market disequilibrium is no smaller than +- 15 mln. Eur.

Figure 13: Comparison of gaps against other methods

Panel (a): Housing market   Panel (b): Credit market



Notes: a gap is expressed as a per cent deviation from the fundamental values. Panel (a) compares house price gaps from the joint disequilibrium model with other methods used to estimate fundamental house prices: one-sided HP filter with $\lambda = 400\,000$ on nominal and real house prices, long-term cumulative average of house price to net earnings (price-to-income) ratio, long-term cumulative average of house price to rent price ratio, and cointegrating equation, regressing house prices on construction costs, GDP per capita, population and credit stock. Panel (b) compares credit flow gaps estimated by the joint disequilibrium model with credit stock gaps estimated using forecast-augmented (4 last quarter weighted average) one-sided HP filter with $\lambda = 400\,000$ on the mortgage credit stock to GDP ratio.

also be inflated as investors demand a higher return on investment. Lastly, our estimated gap on the basis of the two-market disequilibrium model shows similar results to that of Naruševičius et al. (2019, Fig. 6.)

Panel (b) in Figure 13 compares the credit flow gap estimated by the two-market disequilibrium model with the mortgage credit stock gap, estimated as the deviation of the credit-to-GDP ratio from the forecast-augmented HP filtered trend, using the method of Gerdrup et al. (2013) and Geršl and Mitterling (2021). The figure suggests that the joint disequilibrium model signalled excessive lending during the boom, similarly to the results of Valinskytė and Rupeika (2015) and Reichenbachas and Naruševičius (2018). Interestingly, throughout the 2000s, the disequilibrium-based credit market gap showed imbalances accumulating much earlier than the slow-moving credit-stock-to-GDP gap. In recent times, around 2021, we can see that both gap measures are signalling mortgage credit overflow.

All in all, we show that our gap estimates for Lithuania are broadly in line with the results, using other methods from the literature. In addition to that, our two-market disequilibrium framework can be used for rich housing and credit market analysis, beyond the measurement of misalignments.

5 Conclusions

In this paper, we proposed a novel approach to analyse housing and credit markets and their interdependencies. Our two-market disequilibrium model proves to be a rich setting for identifying market demand and supply, as well as finding the historical drivers of quantity and price variables. The paper contributes to the financial stability literature, as the presented framework can be used for joint measurement of housing and credit misalignments, as well as identification of their origins, at policy-making institutions.

We estimated the model using Lithuanian data and identified the historical demand and supply series for housing and mortgage markets, along with their determinants. The computed historical house price and credit flow misalignments, or gaps, can be used as an early warning tool for detection of market overvaluation. Our main modelling findings about Lithuanian housing and credit dynamics can be grouped into three episodes.

During the boom of 2006-2008 Lithuania experienced a dramatic increase in house prices and mortgage credit, which can be linked to high economic growth, including the deepening of the financial sector and positive expectations, as well as expansionary bank lending, coupled with loose lending standards. During this period, the mortgage market experienced an excess supply of credit, which contributed to relatively low interest rates. In contrast, the housing market could be characterised by a shortage of housing supply, spurring the high growth in home prices. Both markets experienced a bubble with house prices being overvalued and credit flow above its fundamentals, which was fuelled mainly by low credit standards, excessive macroeconomic growth and an optimistic outlook.

The bust of 2009 and the aftermath saw a sharp reversal of past economic trends, causing a large fall in demand for both housing and credit. As banks significantly tightened their lending practices, due to realisation of risk, the credit market experienced supply shortages and an increase in lending margins. The housing market supply hardly moved, leading to an excess of housing that in turn caused a collapse in house prices. The aftermath of the crisis saw a creditless economic recovery, as the two markets were subdued for around 7 years, until house price and credit flow gaps were closed.

In recent years, or around the COVID-19 pandemic, the markets started booming again, with home prices and volume of transactions reaching new record highs. In spite of the short curfew episode at the beginning of 2020, the housing market is experiencing an excess demand, which is causing a double-digit growth in house prices. Just before the pandemic, the mortgage market experienced a temporary lack of supply with rising lending margins, with the latter trend being reversed after the beginning of COVID-19. The two-market expansion has been enabled by the low interest rate environment and driven mostly by favourable economic conditions and demographics and strong expectations, as well as a spur in lockdown-induced household savings. The recent spike in construction and material costs constrained housing supply and put upward pressure on home prices. According to the two-market disequilibrium model, by mid-2021 house prices were overvalued by around 16%, and credit 20% above its fundamentals. However, one must bear in mind that these estimates are specific to this particular framework, as other approaches suggest a more modest level of misalignments.

Interestingly, we find that our historical measurements of the two market misalignments are concordant 87% of the time. That is, if there is a credit overflow, it is usually coupled with overvalued house prices, and vice versa. In fact, cross-correlation analysis shows that the credit gap estimate leads the house price gap by approximately 1-2 quarters. While correlation does not imply causation, in practice, due to confounding factors behind misalignments, one may expect house prices to become overvalued after a positive credit gap emerges. What is more, from the historical perspective, overvalued house prices were mostly associated with and preceded by a housing supply shortage, whereas positive credit flow gaps often appeared when there was or had been excess mortgage supply.

Although there is uncertainty around the level of housing and credit fundamentals and the associated gaps, our historical estimates for Lithuania largely coincide with results from other approaches, based on Valinskytė and Rupeika (2015), Kulikauskas (2016), Reichenbachas and Naruševičius (2018) or Naruševičius et al. (2019). As the magnitude of the more recent market misalignments to some extent depends on assumptions about the sustainability of the macroeconomic environment and assessment of expectations, the model could be even expanded to endogenise these factors for more accurate measurements.

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A Appendix

A.1 Two-market disequilibrium model matrices

Regime-invariant matrix:

$$A_0 := \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

Regime I matrices

$$A_1^I := \begin{pmatrix} 0 & \alpha_1^C & \alpha_3^C & \alpha_2^C \\ 0 & \gamma^C \left(\alpha_1^C - \beta_1^C\right) & \gamma^C \left(\alpha_3^C - \beta_3^C\right) & \gamma^C \left(\alpha_2^C - \beta_2^C\right) \\ \alpha_3^H & \alpha_2^H & 0 & \alpha_1^H \\ \gamma^H \left(\alpha_3^H - \beta_3^H\right) & \gamma^H \left(\alpha_2^H - \beta_2^H\right) & 0 & \gamma^H \left(\alpha_1^H - \beta_1^H\right) \end{pmatrix}$$

$$A_2^I := \begin{pmatrix} \alpha_0^C & 0 & 0 & 0 \\ \gamma^C \alpha_0^C & -\gamma^C \beta_0^C & 0 & 0 \\ 0 & 0 & \alpha_0^H & 0 \\ 0 & 0 & \gamma^H \alpha_0^H & -\gamma^H \beta_0^H \end{pmatrix}, \qquad A_3^I := \begin{pmatrix} 1 & 0 & 0 & 0 \\ \gamma^C & -\gamma^C & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & \gamma^H & -\gamma^H \end{pmatrix}$$

Regime II matrices

$$A_1^{II} := \begin{pmatrix} 0 & \beta_1^C & \beta_3^C & \beta_2^C \\ 0 & \gamma^C \left(\alpha_1^C - \beta_1^C\right) & \gamma^C \left(\alpha_3^C - \beta_3^C\right) & \gamma^C \left(\alpha_2^C - \beta_2^C\right) \\ \beta_3^H & \beta_2^H & 0 & \beta_1^H \\ \gamma^H \left(\alpha_3^H - \beta_3^H\right) & \gamma^H \left(\alpha_2^H - \beta_2^H\right) & 0 & \gamma^H \left(\alpha_1^H - \beta_1^H\right) \end{pmatrix}$$

$$A_2^{II} := \begin{pmatrix} 0 & \beta_0^C & 0 & 0 \\ \gamma^C \alpha_0^C & -\gamma^C \beta_0^C & 0 & 0 \\ 0 & 0 & 0 & \beta_0^H \\ 0 & 0 & \gamma^H \alpha_0^H & -\gamma^H \beta_0^H \end{pmatrix}, \qquad A_3^{II} := \begin{pmatrix} 0 & 1 & 0 & 0 \\ \gamma^C & -\gamma^C & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & \gamma^H & -\gamma^H \end{pmatrix}$$

Regime III matrices

$$A_1^{III} := \begin{pmatrix} 0 & \alpha_1^C & \alpha_3^C & \alpha_2^C \\ 0 & \gamma^C \left(\alpha_1^C - \beta_1^C\right) & \gamma^C \left(\alpha_3^C - \beta_3^C\right) & \gamma^C \left(\alpha_2^C - \beta_2^C\right) \\ \beta_3^H & \beta_2^H & 0 & \beta_1^H \\ \gamma^H \left(\alpha_3^H - \beta_3^H\right) & \gamma^H \left(\alpha_2^H - \beta_2^H\right) & 0 & \gamma^H \left(\alpha_1^H - \beta_1^H\right) \end{pmatrix}$$

$$A_2^{III} := \begin{pmatrix} \alpha_0^C & 0 & 0 & 0 \\ \gamma^C \alpha_0^C & -\gamma^C \beta_0^C & 0 & 0 \\ 0 & 0 & 0 & \beta_0^H \\ 0 & 0 & \gamma^H \alpha_0^H & -\gamma^H \beta_0^H \end{pmatrix}, \qquad A_3^{III} := \begin{pmatrix} 1 & 0 & 0 & 0 \\ \gamma^C & -\gamma^C & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & \gamma^H & -\gamma^H \end{pmatrix}$$

Regime IV matrices

$$A_1^{IV} := \begin{pmatrix} 0 & \beta_1^C & \beta_3^C & \beta_2^C \\ 0 & \gamma^C \left(\alpha_1^C - \beta_1^C\right) & \gamma^C \left(\alpha_3^C - \beta_3^C\right) & \gamma^C \left(\alpha_2^C - \beta_2^C\right) \\ \alpha_3^H & \alpha_2^H & 0 & \alpha_1^H \\ \gamma^H \left(\alpha_3^H - \beta_3^H\right) & \gamma^H \left(\alpha_2^H - \beta_2^H\right) & 0 & \gamma^H \left(\alpha_1^H - \beta_1^H\right) \end{pmatrix}$$

$$A_2^{IV} := \begin{pmatrix} 0 & \beta_0^C & 0 & 0 \\ \gamma^C \alpha_0^C & -\gamma^C \beta_0^C & 0 & 0 \\ 0 & 0 & \alpha_0^H & 0 \\ 0 & 0 & \gamma^H \alpha_0^H & -\gamma^H \beta_0^H \end{pmatrix}, \qquad A_3^{IV} := \begin{pmatrix} 0 & 1 & 0 & 0 \\ \gamma^C & -\gamma^C & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & \gamma^H & -\gamma^H \end{pmatrix}$$

A.2 Tables

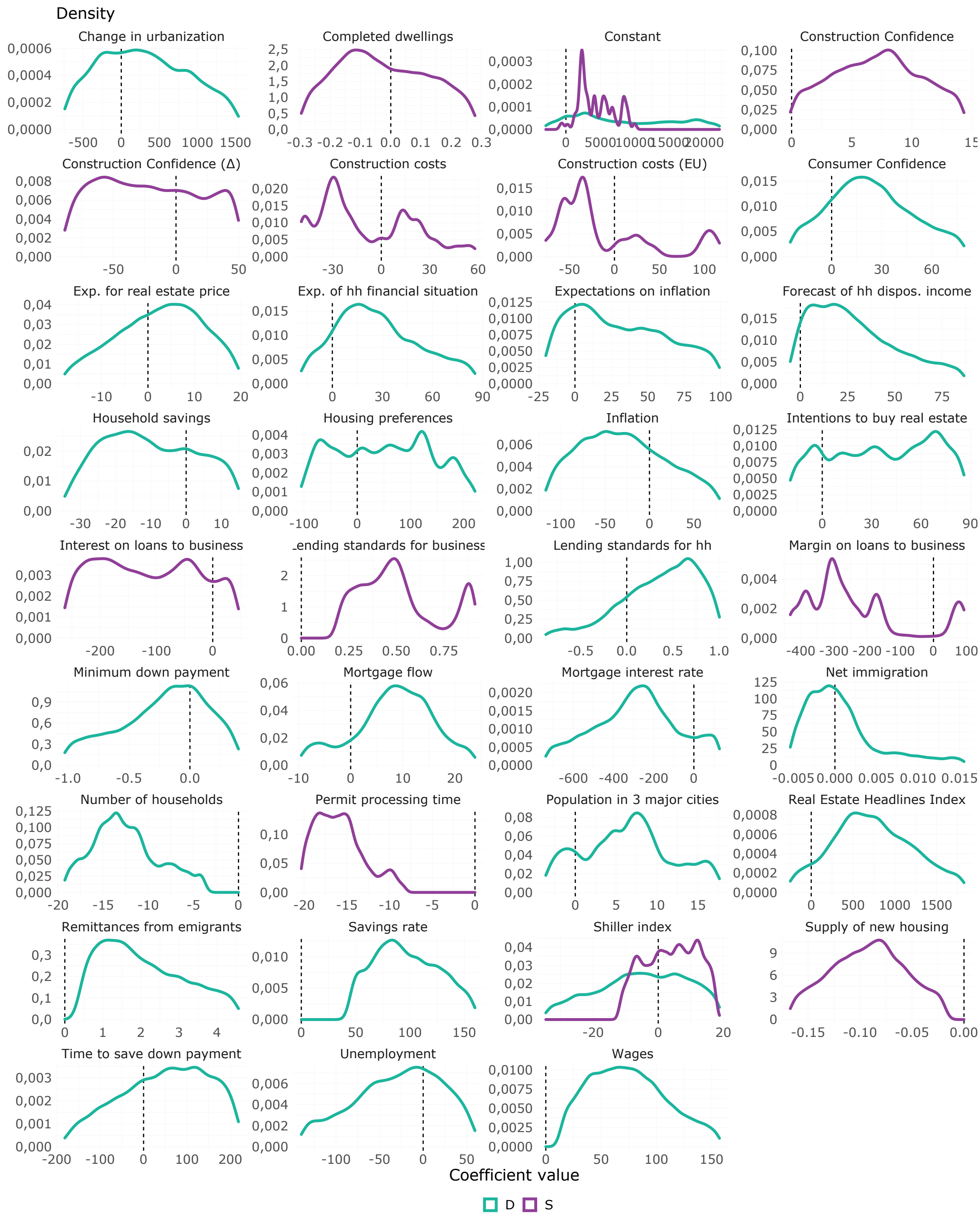
Table 2: List of all explanatory variables

Market	Equation	Group	Variable	D	S	Source
C	D	House price	**Shiller index**	+		BoL
C	D	Apartments	Number of housing transactions	+		CR
C	D	Deposits	Change in deposits to GDP ratio	+		BoL/SL
C	D	Economy	Unemployment	-		SL
C	D	Economy	GDP growth	+		SL
C	D	Expectations	Consumer Confidence Index	+		SL
C	D	Expectations	Forecast of housing prices	+		BoL
C	D	Expectations	Real Estate Headlines Index	+		BoL
C	D	Income	Change in wages	+		SL
C	D	Indebtedness	Indebtedness of households	-		BoL
C	D	Inflation	Inflation expectations	+		EC
C	S	Credit risk	**Non-performing loans**		-	BoL
C	S	Concentration	Concentration (HHI)		-	BoL
C	S	Economy	GDP growth		+	SL
C	S	Expectations	Forecast of hh' financial situation		+	SL
C	S	Funding costs	Avibor		-	BoL
C	S	House price	Shiller index		+	BoL
C	S	Income	Change in compensation per employee		+	SL
C	S	Lending standards	Minimum down payment		-	BoL
H	D	Interest rate	**Mortgage interest rate**	-		BoL
H	D	Income	**Change in wages**	+		SL
H	D	Income	**Growth in real disposable income**	+		BoL
H	D	Expectations	**Consumer Confidence Index**	+		SL
H	D	Expectations	**Forecast of housing prices**	+		BoL
H	D	Expectations	**Real Estate Headlines Index**	+		BoL
H	D	Expectations	**Inflation expectations**	+		EC
H	D	Expectations	**Forecast of hh' financial situation**	+		SL
H	D	Expectations	**Intention to buy real estate**	+		SL
H	D	Demographics	**Number of households**	+		SL
H	D	Demographics	**Net immigration**	+		SL
H	D	Demographics	**Change in urbanization**	+		SL
H	D	Demographics	**Population in 3 major cities**	+		SL
H	D	Credit	Mortgage flow	+		BoL
H	D	Economy	Unemployment	-		SL
H	D	Economy	Inflation	+		SL
H	D	Lending standards	Minimum down payment	-		BoL
H	D	Lending standards	Lending standards for households	+		BoL
H	D	Quality	Housing preferences	+		CR
H	D	Remittances	Remittances from emigrants	+		BoL
H	D	Saving	Time to save down payment	-		BoL
H	D	Saving	Likelihood of saving money	+		SL
H	D	Saving	Change in deposits to GDP ratio	+		BoL/SL
H	S	Funding costs	**Interest rate on loans to business**		-	BoL
H	S	Funding costs	**Margin on loans to business**		-	BoL
H	S	Funding costs	**Lending standards for business**		+	BoL
H	S	Construction costs	**Construction input price index**		-	SL
H	S	Construction costs	**Construction input price index, EU**		-	Eurostat
H	S	Construction costs	**Change in construction input price**		-	SL
H	S	Stock	**Supply of new housing**		+	SL
H	S	Stock	**Completed dwellings**		+	SL
H	S	Construction conditions	Permit processing time		-	WB
H	S	Construction expectations	Construction Confidence Indicator		+	SL

Notes: column names are the following – Market denotes Credit (C) or Housing (H), Equation denotes Demand (D) or Supply (S), Coef. denotes the expected sign of the attached coefficient.

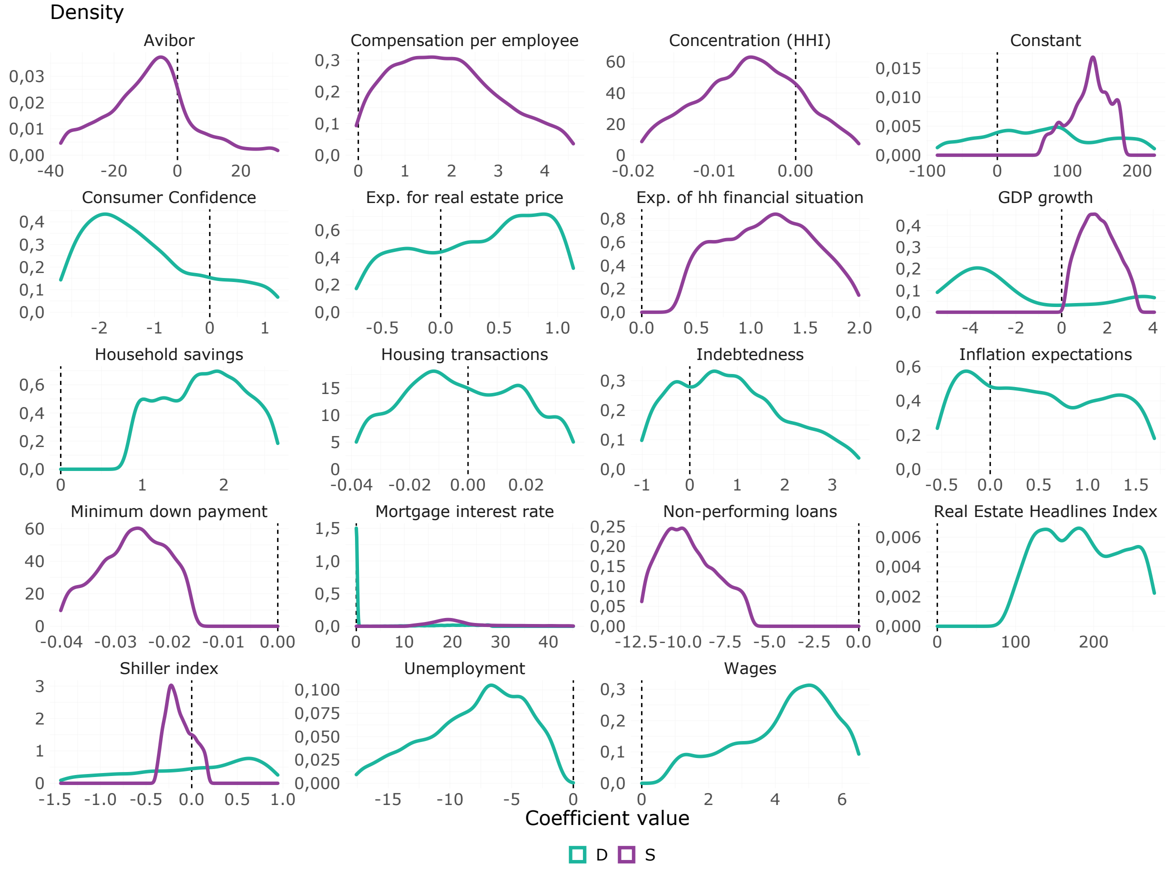
A.3 Figures

Figure 14: Densities of housing single-market equation coefficients



Notes: the green lines show densities of the coefficients in the housing market demand equation (D) and the purple lines show densities of the coefficients in the supply equation (S). The figure displays densities of coefficients of 176 256 housing model specifications obtained in the first stage of the estimation procedure explained in Section 3.2.

Figure 15: Densities of credit single-market equation coefficients



Notes: the green lines show densities of the coefficients in the credit market demand equation (D) and the purple lines show densities of the coefficients in the supply equation (S). The figure displays the densities of coefficients of 52 962 credit model specifications obtained in the first stage of the estimation procedure explained in Section 3.2.

Figure 16: Estimated demand and supply for 56 models

Panel (a): Demand fits

Panel (b): Supply fits

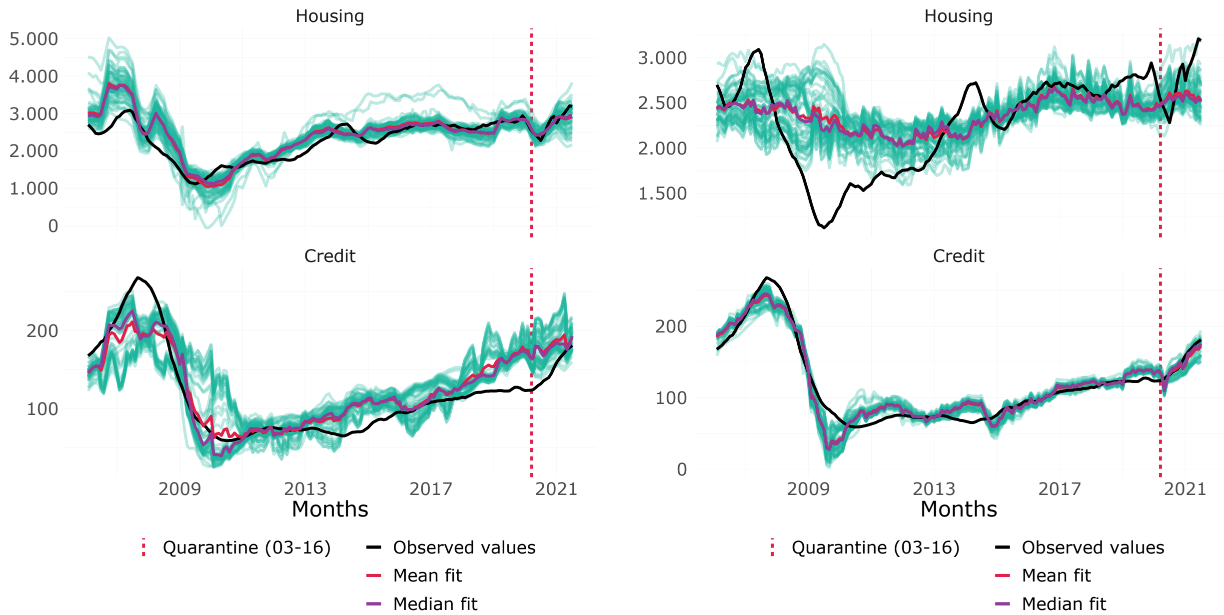
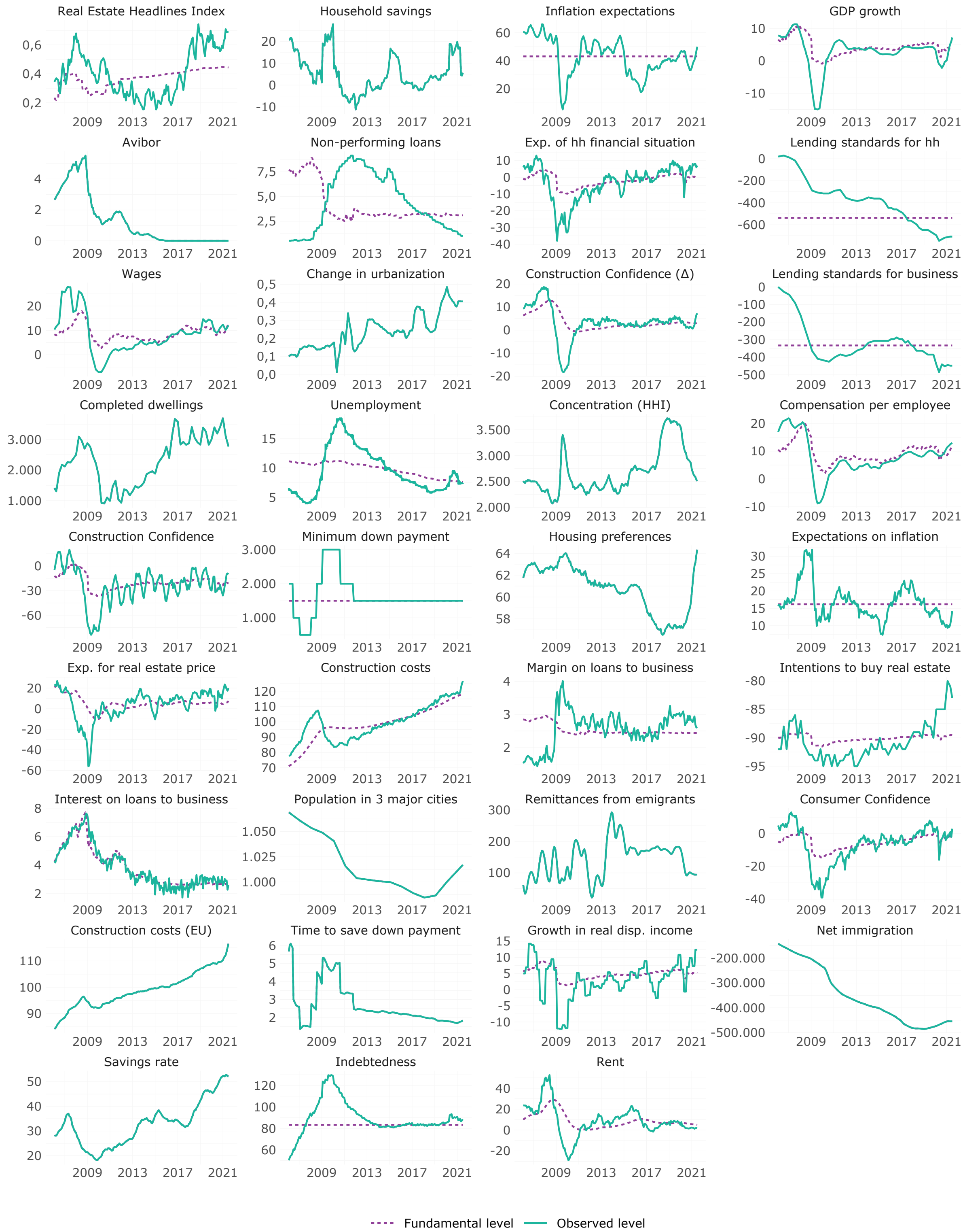


Figure 17: The fundamental series for each explanatory variable



Notes: the fundamental values are obtained using assumptions explained in Section 4.1.

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