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Long-Run Transition vs. Short-Run Adjustment: Modeling Slovakia's Macroprudential Policy Path

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Abstract

The global financial and sovereign debt crises prompted policymakers to prioritise systemic risk and financial stability. Since then, the use of borrower-based measures in macroprudential policy has become central to managing credit booms and housing market imbalances. However, evidence on the formal and rule-based implementation of this policy remains limited, particularly in small open economies that are prone to financial imbalances. Using a vector error correction model (VECM), this paper estimates Slovakia's long-run macroprudential rule and its short-run asymmetric adjustment. The results indicate a transition from a passive, procyclical stance to an active, countercyclical framework between 2009 and 2014. In the short run, most of the tightening occurs when conditions are excessively loose, consistent with a strong initial move towards a tighter borrower-based framework. These findings contribute to the empirical evidence on both the long-run macroprudential rule and the asymmetric short-run responses that influence policy transmission.

Keywords: Macroprudential policy, vector error correction model, structural break, policy transmission, credit conditions.

JEL Codes: C32, C51, E61

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Non-technical summary

Motivation: This paper examines how macroprudential policy in Slovakia evolved from a largely passive pre-global-financial-crisis setting into an active borrower-based framework aimed at containing risks associated with household indebtedness and the mortgage market. Slovakia provides a useful case study because it is a small open euro area economy with a rapidly expanding mortgage market, a prolonged period of low interest rates, and strong competition among banks. These conditions supported credit growth and rising house prices, but they also increased the risk that financial imbalances could build up too quickly.

Research question: This paper focuses on the tightening of borrower-based measures, captured by a cumulative indicator of banks' lending standards that reflects the overall degree of mortgage credit tightness. It studies two policy-relevant questions. First, what long-run relationship links credit standards, house prices, and household indebtedness? We interpret this relationship as a macroprudentially consistent policy stance rather than as a mechanical rule for a single instrument, which makes it useful for policymakers because it captures the combined effect of policy and market forces. Second, how do credit standards adjust in the short run when financing conditions become too loose or too tight?

Key long-run finding: The main finding is that Slovakia underwent a clear regime shift. Before the crisis-related transition, credit conditions behaved in a more passive and at times procyclical way. After the transition, tighter borrower-based measures were reflected in systematically tighter credit standards that moved closely with rising household indebtedness and house prices. This is consistent with a more active and countercyclical macroprudential framework. We date this shift to around 2011, more broadly within the 2009–2014 transition period, in line with the wider institutional strengthening of macroprudential policy in Slovakia and across Europe after the crisis.

Long-run policy implications: A key policy implication is that macroprudential policy should take into account both sides of the household balance sheet. On the liability side, household indebtedness matters because it captures leverage and households' vulnerability to income and interest-rate shocks. On the asset side, house prices matter because they signal overheating, valuation pressures, and collateral-related risks. The results therefore support a dual-risk perspective: effective policy should account for both debt accumulation and housing-market pressures rather than focusing on a single indicator.

Short-run findings and policy implications: The paper also shows that short-run adjustment is asymmetric. Credit conditions and the macro-financial stance tighten more strongly when they are excessively loose than they ease when they are excessively tight. For policymakers, this suggests that macroprudential policy may need to respond more forcefully during periods of loose financing conditions and overheating. At the same time, the results are also consistent with a practical reading of Slovakia's experience: the introduction of borrower-based measures produced an initial structural tightening, followed by a more cautious wait-and-see phase as the framework matured.

Takeaway for policymakers: Overall, the paper shows that Slovakia's macroprudential framework evolved into a more systematic and countercyclical regime. The main lesson for policymakers is that financial stability is better protected when policy responds to both rising household leverage and housing-market overheating, and when it is willing to tighten decisively during periods of excessively loose credit conditions. The paper therefore offers a practical benchmark for assessing whether credit conditions remain broadly aligned with financial stability objectives.

1. Introduction

The global financial crisis significantly reshaped the policy landscape, bringing systemic risk and financial stability to the forefront of the policy agenda. In this paper, we focus on borrower-based measures of macroprudential policy, which has emerged as a key instrument for curbing excessive credit growth, housing market imbalances and asset price bubbles. Slovakia is a particularly instructive case of an economy prone to shocks that fuel financial imbalances. As a small, open economy with a rapidly developing mortgage market, it has experienced interest rate convergence and entry into the monetary union. This was followed by an extended period of ultra-low interest rates, driven by common ECB monetary policy and intensified bank competition. This combination provides a compelling setting for examining macroprudential policy. Today, Slovakia ranks among the most proactive users of macroprudential tools in the European Union.

Existing empirical work on macroprudential policy often does not separate short-run adjustment from long-run equilibrium. Many studies average policy effects across time and across regimes, which masks how macroprudential tools operate in tightening and loosening phases (e.g. Cerutti et al., 2017; Alam et al., 2025). Measurement is another limitation, because macroprudential policy is frequently proxied by binary indicators, intensity scores, or composite indexes, which reduces comparability across countries and over time. These choices help explain the wide variation in estimated effects documented by Araujo et al. (2024) and motivate a framework that models an explicit macroprudential rule and its state-dependent adjustment.

These gaps are important for Central and Eastern Europe, where macroprudential frameworks have undergone a structural shift. Countries such as Slovakia moved from having almost no macroprudential policy before the global crisis to operating a persistently tight and active regime afterward (see Eller et al. (2020)). Existing empirical strategies do not capture this transition. This paper fills this gap by estimating both the long-run macroprudential rule and the asymmetric short-run adjustment that characterize the region's, and specifically Slovakia's, structural tightening path.

This paper employs a vector error correction model (VECM) to estimate Slovakia's long-run macroprudential rule, accounting for regime shifts in the relationship between credit conditions, house prices, and household indebtedness. It further documents an asymmetric short-run adjustment of macroprudential policy, characterized by a stronger response when credit conditions are excessively loose.

This paper makes three main contributions to the macroprudential policy literature. First, it distinguishes between the long-run equilibrium and the short-run asymmetric adjustment of macroprudential policy. Second, it develops and estimates a long-run macroprudential rule that captures Slovakia's transition from a passive, procyclical regime to an active, countercyclical policy regime. The identified structural break in 2011 aligns with institutional developments and supporting empirical evidence. Third, it shows that most of the tightening occurs when conditions are excessively loose, consistent with a strong initial move towards a tighter borrower-based framework followed by a more "wait-and-see" regime, reflecting a targeted reaction to financial overheating.

The structure of the paper is as follows. Section 2 reviews the related literature. Section 3 outlines the underlying economic framework, describes the dataset, discusses the institutional context of Slovak macroprudential policy, and presents the VECM methodology. Section 4 reports the empirical results, including the cointegration analysis and the estimated long-run relationships for the macroprudential policy rule and house prices. It also examines the short-run asymmetric adjustment. The final section concludes.

2. Related Literature

This paper relates to three strands of research: (i) empirical models of house prices and housing fundamentals, (ii) the role of credit constraints and lending standards in housing and credit cycles, and (iii) macroprudential policy design, including evidence on the effectiveness of borrower-based instruments and the case for systematic policy adjustment over the financial cycle.

A large empirical literature estimates long-run relationships between house prices and fundamental drivers, often alongside credit or leverage variables that capture the financial cycle (Anundsen and Jansen, 2013; Turk, 2015; Cavalleri et al., 2019; Valderrama et al., 2023). These studies typically build on life-cycle and user-cost frameworks (Meen and Andrew, 1998; Meen, 2002), in which households choose housing and asset holdings subject to budget constraints and borrowing conditions. Observed house prices can then be evaluated relative to fundamentals to identify persistent misalignments.

A closely related strand emphasises that borrowing constraints affect housing demand through a shadow value of credit frictions. Ermisch (1984) and Meen and Andrew (1998) show that when housing choices are constrained by loan limits tied to current income, the housing optimality condition includes a shadow price of the constraint. Despite its theoretical relevance, this component is often approximated in empirical work. For instance, Turk (2015) abstracts from it, while Anundsen and Jansen (2013) uses household debt as a proxy. Duca et al. (2011), by contrast, employs the loan-to-value (LTV) ratio for first-time buyers as a proxy for the shadow price of credit constraints. Following this logic, we proxy the evolution of credit constraints using Bank Lending Survey (BLS) indicators of credit conditions for household housing loans (Köhler-Ulbrich et al., 2016). As highlighted by Tressel and Zhang (2016), BLS measures are informative for macroprudential transmission because they capture shifts in credit supply conditions in a timely way, particularly in the post-crisis period.

The paper also connects to the empirical literature on the effectiveness of macroprudential tools in mitigating systemic risk. A broad set of studies finds that borrower-based and capital-based measures reduce excessive credit growth and help contain housing market imbalances (Claessens et al., 2013; Vandenbussche et al., 2015; Kuttner and Shim, 2016; Akinci and Olmstead-Rumsey, 2018; Richter et al., 2019), while Araujo et al. (2024) provide meta-analytic evidence of robust credit effects and more muted, though still negative, effects on house prices. For Slovakia, borrower-based macroprudential indices have been constructed (Jurca et al., 2020; Cesnak et al., 2021; Klacso, 2022; Klacso and Martin, 2024), and similar indices exist for CESEE more broadly (Eller et al., 2020). However, these indices often face limited coverage, infrequent updates, or structural inconsistencies across time. In this context, BLS credit-conditions indicators offer longer coverage and regular updates, while also reflecting credit-market outcomes that are tightly linked to policy actions and banks' behaviour.

Beyond estimating average effects, there is growing recognition that macroprudential instruments should be adjusted systematically in response to evolving financial vulnerabilities (Borio, 2003; Cerutti et al., 2017; International Monetary Fund, 2014). In line with this perspective, we use the long-run relationship normalised on the BLS-based stance measure to characterise a *macroprudentially consistent macro-financial stance relation* that links credit conditions to key systemic indicators such as house prices and the household indebtedness. This framing is consistent with the idea that macroprudential policy aims to anchor financial risks over the medium run, while allowing for temporary deviations in response to shocks and frictions. Related theoretical work formalises such behaviour in "Taylor-type" macroprudential rules. For example, Rubio and Carrasco-Gallego (2015) study a DSGE economy with collateral-constrained borrowers and an LTV-based macroprudential instrument, and show that macroprudential feedback rules that respond sufficiently strongly to systemic-risk indicators can improve stabilisation and welfare.

Finally, most empirical applications in this area assume symmetric adjustment back to long-run equilibria (Anundsen and Jansen, 2013; Turk, 2015; Cavalleri et al., 2019; Valderrama et al., 2023), while a separate literature documents state-dependent adjustment in housing and credit markets. Threshold and regime-switching cointegration models allow equilibrium correction to differ by the sign or size of deviations (Enders and Siklos, 2001; Balke and Fomby, 1997; Hansen and Seo, 2002), and asymmetric ARDL models capture uneven short-run pass-through (Shin et al., 2014). In macro-financial settings, both policy and market responses can be stronger when vulnerabilities intensify (Smets, 2018; Martin et al., 2021). Motivated by this evidence, we allow the short-run adjustment dynamics to depend on the state of the system.

3. Economic Theory, Methodology, and Data

3.1. Economic Theory

The model incorporates two long-run relationships: one grounded in a life-cycle framework for housing fundamentals (e.g., Anundsen and Jansen (2013)), and another derived from the literature on systematic macroprudential policy responses to financial vulnerabilities in credit and housing markets.

Housing Market Fundamentals

To understand the fundamental determinants of house prices, we must consider both demand-side and supply-side factors. A commonly used framework for modeling house prices is the life-cycle model (see Meen and Andrew (1998); Meen (2002)), and its recent applications in Anundsen and Jansen (2013); Turk (2015); Cavalleri et al. (2019); Valderrama et al. (2023). The maximization of lifetime utility subject to a budget constraint, housing, and asset formation equations yields the following marginal rate of substitution (MRS) between housing (marginal utility of housing–μ_h) and a composite consumption good (marginal utility of consumption–μ_c), as derived in Meen and Andrew (1998):

$$\mu_h/\mu_c = MRS = HP_t\left[(1-\tau_t)i_t - \pi_t + \delta_t - \dot{HP}_t^e/HP_t + \lambda_t/\mu_c\right] \tag{1}$$

where HP_t denotes real house prices, τ_t the household marginal tax rate, i_t the nominal market interest rate, π_t is the annual inflation rate, δ_t the depreciation rate of housing, $\frac{\dot{HP}_t^e}{HP_t}$ the expected real capital gain (house price appreciation), and $\frac{\lambda_t}{\mu_c}$ the shadow price of the credit constraint relative to the marginal utility of consumption. Eq. (1) represents the real housing user cost of capital (net of expected capital gains) augmented by credit constraints. Market efficiency requires the following no-arbitrage condition, where Q_t represents the quality-adjusted rental price of housing services consistent with the life-cycle model:

$$HP_t = Q_t/\left[(1-\tau_t)i_t - \pi_t + \delta_t - \dot{HP}_t^e/HP_t + \lambda_t/\mu_c\right] \tag{2}$$

While this no-arbitrage condition does not hold at every point in time, it is expected to hold in the long run. Turk (2015) and Cavalleri et al. (2019) interpret this as the discounted value of the future stream of real imputed rental income, with the real user cost of capital serving as the discount rate.

Since Q_t is not observed directly at quarterly frequency with a long sample, it is replaced with proxies for its demand- and supply-side determinants ($Q_t^{D,S}$) as it represents the market clearing price of housing services. Following Poterba (1984) and others, this yields an inverted demand function[1]:

$$HP_t = f^* \left(Q_t^{D,S}, r_t, \dot{HP}_t^e / HP_t, \lambda_t / \mu_c \right) \tag{3}$$

where $r_t = i_t - \pi_t$ is the real interest rate. We follow Anundsen and Jansen (2013); Turk (2015) and include as determinants: real household disposable income (DI_t), real net financial assets of households ($NETFA_t$), housing stock (HS_t), and working-age population ($POP_{25-44,t}$).

The real user cost component can be divided into two parts. The first part is related to the real direct user cost, i.e., $i_t - \pi_t = r_t$. In the long run, we use the real 10-year government bond rate or the mortgage rate. In the short-run dynamics, we also use the real or nominal versions of these interest rates. Due to data availability, we abstract from the household marginal tax rate. The second part relates to the expected real housing price appreciation. In this paper, we only use the first measure because the second measure only enters the short-run dynamics. We follow Anundsen and Jansen (2013) who argues that housing price appreciation does not have a permanent effect, but rather builds momentum, or the ”bubble builder” effect.

Ermisch (1984) shows that when households face an income constraint on borrowing for a house purchase (e.g., banks set the maximum loan as a multiple of current income), the optimality condition for housing should contain the shadow price of the credit constraint, λ_t/μ_c (see Eqs. 1–3). The literature treats this term heterogeneously. Turk (2015) completely omits this term in their long equation for house prices. Anundsen and Jansen (2013) use household debt as a proxy for this term and studies the long-run relationship between house prices and household debt. Finally, Duca et al. (2011) uses the loan-to-value (LTV) ratio for first-time homebuyers as a proxy for the shadow price of the credit constraint. Based on these studies, we use the results of the Bank Lending Survey on credit conditions for households for house purchases. Macroprudential policy — implicitly stated in Ermisch (1984) and Duca et al. (2011) but not emphasized in this context — has the biggest influence on these conditions. We use this as a measure of credit constraint: $MAP_t^{BLS,HH}$. Market-clearing house prices at any given level of the housing stock are therefore given by:

$$HP_t = f \left(Q_t^{D,S}, r_t, MAP_t^{BLS,HH} \right) \tag{4}$$

Modelling the Long-run Macroprudential Policy Rule

Much of the existing literature focuses on the effects of macroprudential policies on credit dynamics and housing markets. Studies such as Claessens et al. (2013); Vandenbussche et al. (2015); Kuttner and Shim (2016); Akinci and Olmstead-Rumsey (2018); Richter et al. (2019) provide empirical evidence on the effectiveness of macroprudential policy tools for curbing credit expansions, excessive house price growth, and related indicators of systemic risk. In their comprehensive meta-study, Araujo et al. (2024) find statistically significant negative effects of macroprudential policy tightening on credit, as well as weaker and more imprecise negative effects on house prices.

More importantly, macroprudential authorities do not set policy tools arbitrarily. Rather, they adjust the stance of macroprudential instruments, such as DSTI, DTI, LTV, and capital buffers, in response to excessive credit or house price dynamics. The key feature of this paper is the

[1] Similar to Turk (2015) and Cavalleri et al. (2019), we ignore the depreciation rate in our formulation. For comparison, Anundsen and Jansen (2013) used a small, constant value of 0.004.

construction and empirical estimation of a long-run macroprudential policy rule that systematically links macroprudential settings to developments in the housing market and credit. Borio and Lowe (2002); Borio (2003) advocate linking macroprudential policy settings to deviations of credit and asset prices from their long-term trends. Claessens et al. (2013); Cerutti et al. (2017); International Monetary Fund (2014) empirically document that macroprudential tightening is typically preceded by excessive credit growth and housing market booms. This logic forms the basis of early warning systems and the design of countercyclical macroprudential policies.

Beyond the academic literature, policy institutions such as the ESRB, the ECB, and national macroprudential authorities emphasise the importance of the residential real estate sector for financial and macroeconomic stability, reflecting their mandate to help prevent the build-up of housing market vulnerabilities across Europe (ESRB, 2016, 2022). In particular, the ESRB can issue warnings to flag emerging vulnerabilities and adverse trends and, if warranted, follow up with recommendations that specify the necessary remedial actions.

We specify a long-run macroprudential policy rule in which the macroprudential stance (proxied by credit conditions, $MAP_t^{BLS,HH}$) is modeled as a function of real house prices (HP_t) and the household indebtedness (HHD_t/GDP_t):

$$MAP_t^{BLS,HH} = g\left(HP_t, HHD_t/GDP_t\right) \tag{5}$$

This formulation acknowledges that, in the long term, macroprudential policies must align with systemic risk indicators, such as house prices and credit. Macroprudential authorities cannot ease credit conditions indefinitely while house prices rise or debt accumulates rapidly without risking financial imbalances. Likewise, they should avoid maintaining excessively tight conditions during periods of housing or credit correction. Therefore, we posit that, in the long run, macroprudential policy settings, household indebtedness, and house prices should co-move, with misalignments gradually being corrected through policy responses or market adjustments.

In empirical work, it is not feasible to cleanly separate an ideal instrument-level macroprudential policy rule from the macro-financial stance that can be identified using the BLS measure. Nevertheless, our identification strategy is supported by two key facts. First, the BLS series comoves closely with borrower-based measure indices after 2014, when the toolkit became more active and systematic. Second, the data exhibit a structural break over 2009–2014 that aligns with the documented institutional shift from a largely passive to a more active macroprudential regime.

3.2. Methodology

We employ a vector error correction model (VECM) to analyze the short-run dynamics and long-run relationships among key macro-financial variables. This framework is particularly well-suited for economic systems characterized by persistent trends and equilibrium relationships (Johansen, 1988, 1995). In our context, variables such as house prices, household credit, and macroprudential policy measures often exhibit non-stationary behavior while being jointly influenced by economic fundamentals.

Economically, this framework captures two essential features of macroprudential policy transmission. First, it acknowledges that macro-financial variables may diverge temporarily due to shocks or frictions but are ultimately anchored by long-run equilibrium forces, such as valuation fundamentals or credit constraints (Anundsen and Jansen, 2013). Second, it accommodates asymmetric and delayed short-run adjustments, reflecting real-world frictions like implementation lags, imperfect signal extraction, and institutional inertia (Duca et al., 2011; Araujo et al., 2024).

We use a general VARX(p, q) model in which some of the system's variables are treated as weakly exogenous. Furthermore, we adopt the approach proposed by Harbo et al. (1998) for partial systems and constrain a deterministic trend to enter the cointegrating space, following recommendations by Johansen (1995) and Gonzalo (1994). The VECM(p, q) representation of the VARX(p, q) forms the basis for our econometric analysis:

$$\Delta \mathbf{X}_t = \tilde{\Pi}\tilde{\mathbf{Y}}_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta \mathbf{X}_{t-i} + \sum_{i=0}^{q-1} \Psi_i \Delta \mathbf{Z}_{t-i} + \tilde{\Phi}\tilde{\mathbf{D}}_t + \varepsilon_t \tag{6}$$

where $\mathbf{X}_t$ denotes the vector of endogenous variables, $\mathbf{Z}_t$ contains weakly exogenous variables, and $\tilde{\mathbf{Y}}_{t-1} = (\mathbf{X}'_{t-1}, \mathbf{Z}'_{t-1}, t)'$ includes a restricted linear trend. The matrix $\tilde{\Pi} = \alpha\beta'$ captures the cointegrating relationships, where β are the long-run coefficients and α are the adjustment speeds. The deterministic components $\tilde{\mathbf{D}}_t$ include constants and outlier dummies[2].

The rank of the matrix $\tilde{\Pi}$, which determines the number of cointegrating vectors r, is tested using the Johansen trace test (Johansen, 1988). This step is crucial in identifying both the equilibrium housing market condition and the macroprudential policy rule.

Model estimation proceeds by selecting optimal lag lengths, conducting cointegration tests, and estimating the parameters. To validate the model, we perform diagnostic tests for autocorrelation, heteroskedasticity, and residual normality. Model stability is ensured by verifying that all eigenvalues of the companion matrix lie inside the unit circle. Additionally, we test the stationarity of the estimated error correction terms to confirm reversion to equilibrium. This approach provides a coherent framework for evaluating the effectiveness and consistency of macroprudential policy in stabilizing the housing market over time.

3.3. Data

In summary, the following variables were suggested by Anundsen and Jansen (2013); Turk (2015); Akinci and Olmstead-Rumsey (2018); Cavalleri et al. (2019); Richter et al. (2019); Valderrama et al. (2023) and others to study the relationships between the housing market, household debt, and macroprudential policy: house prices, household indebtedness, macroprudential policy indices, housing stock, household income, real and nominal interest rates (market mortgage rate or long-run government bond rate), financial assets of households, and demographic indicators. By embedding the macroprudential rule as a cointegrating vector, we capture the systematic, long-run policy feedback mechanism in response to evolving vulnerabilities in housing and credit markets.

We linearize the theoretical formulations in Eqs. (4)-(5) using a semi-logarithmic transformation. Lowercase letters denote variables expressed in natural logarithms (except interest rates). The empirical analysis includes four endogenous variables: real house prices, the household indebtedness, the BLS-based macroprudential stance, and real disposable income. The specification aims to keep the system parsimonious while retaining key informational content. The

[2]For clarity, we explicitly define the variable blocks in equation (6). The vector of endogenous $I(1)$ variables is $X_t = \big(hp_t,\ hhd_t/gdp_t,\ map_t^{bls},\ di_t\big)'$, comprising (in order) real house prices, the household indebtedness, the cumulative BLS-based credit-conditions (stance) measure, and real disposable income. The vector of weakly exogenous controls is $Z_t = \big(hs_t,\ rb_t,\ pop_{25\text{–}44,t},\ netfa_t\big)'$, including the housing stock, the real (nominal) bond rate (or, alternatively, the real (nominal) mortgage rate), working-age population, and real wealth. Finally, D_t collects deterministic components and indicator variables, namely the included constant and trend terms, regime dummies reflecting the structural-break specification, and outlier dummies.

dataset comprises quarterly observations from 2000Q4 to 2024Q4 (97 in total). After accounting for lag length selection, the effective sample spans 2001Q4 to 2024Q4 (93 observations). Table 4 and Figure 4 in Appendix A provide details on data sources, variable transformations, and original sample coverage.

Real House Prices (hp_t): In the macroprudential rule, the Bratislava regional house price index plays a role similar to core inflation in a Taylor rule, since it provides a cleaner and more macro sensitive signal than the national index. Bratislava is the largest and most liquid housing market in Slovakia, closely aligned with national business cycle conditions, interest rate developments, and macroprudential policy actions. It is also more sensitive to speculative demand and less influenced by region-specific shocks that may distort national aggregates. It also exhibits fewer measurement errors and do not need as many outlier dummies to pass diagnostics (Figure 6 in Appendix F.3). Nevertheless, it remains highly correlated with the national house price index (denoted hp_t^{SK}), with correlations above 0.85 for quarterly growth rates.

Household Debt-to-GDP (hhd_t/gdp_t): The household debt-to-GDP ratio is one of the main indicators of macroprudential policy due to its systemic relevance, responsiveness to policy changes, and strong long-term signaling properties. It captures the cumulative leverage of the household sector and is widely used by the National Bank of Slovakia (NBS) and international institutions to guide borrower-based macroprudential interventions.

Real Disposable Income (di_t): This is the key macroeconomic determinant of housing demand. It captures the real income effect—reflecting the state of the real economy (e.g., business cycle conditions, long-term growth, unemployment, and inflation)—and influences borrower eligibility under macroprudential regulations.

Other macroeconomic variables relevant to the housing market and macroprudential policy are treated as exogenous or control variables. *Housing stock* reflects the supply side of the market. Nominal or real *interest rates* represent the cost of borrowing. *Population aged 25–44* captures demographic pressures on housing demand. *Real net financial assets* proxy for household wealth and buffer capacity[3].

Unit root tests, with greater emphasis placed on the ADF and PP tests, confirm that all series are integrated of order one, I(1), except for the population variable, where the evidence is mixed (Table 5 in Appendix B). Additional tests were conducted to verify that the variables hhd_t/gdp_t and hs_t are stationary in first differences. We will take this into consideration in further modeling.

3.3.1. *BLS-Based Macroprudential Stance* (map_t^{bls})

Originally, positive values in the Bank Lending Survey (BLS) for household housing loans indicate a net tightening of credit standards, whereas negative values reflect easing. By cumulating this series, we approximate a stock measure of overall macroprudential credit tightness[4]. The

[3]Ideally, one would complement the analysis with a long quarterly series of debt-service or payment-to-income measures to capture borrower vulnerability more directly. In practice, the available series are either too short or exhibit structural breaks and definition changes within our sample, which would undermine the cointegration analysis. We therefore proxy household vulnerability using the household debt-to-GDP ratio together with disposable income and interest-rate measures, which jointly capture leverage, repayment capacity, and financing conditions. Nevertheless, the resulting dataset remains aligned with standard practice in the relevant literature.

[4]We use the log of the cumulative BLS index to dampen extremes and interpret the resulting series as a semi-elasticity. Because the quarterly BLS series contains both tightening and easing signals, its cumulative sum falls below zero in the early years of the sample, when no structural macroprudential tightening had yet taken place. A logarithmic transformation therefore requires a level shift. We add a constant of 4.3, the smallest value that ensures strictly positive observations throughout the sample while preserving dynamics and keeping the relative variability of the transformed series comparable to other macroeconomic variables. This shift is monotonic and does not affect identification, cointegration properties, or the estimated long-run relationships. For 2001–2005, when BLS data are

BLS-based stance captures housing-related borrower-based macroprudential tightening, but does not directly reflect capital-based or liquidity-based macroprudential tools.

This transformation allows us to distinguish two economic dimensions of the series. The long-run component, visible in the upward trend (see Figure 1), captures the structural tightening of macroprudential policy observed in Slovakia and across CESEE economies, as documented by Eller et al. (2020). Over the main tightening period (2014Q4–2020Q3), its correlation with the borrower-based measures (BBM) index of Klacso (2022) exceeds 0.9 in levels. The short-run component reflects business-cycle dynamics and quarterly adjustments in BLS credit standards. During the same tightening period, its correlation with first differences of the BBM index exceeds 0.5.[5] These short-run movements respond not only to macroprudential actions but also to broader market forces, including changes in economic activity, housing market expectations, borrower creditworthiness, banks' risk tolerance, competition, and funding costs.

The National Bank of Slovakia has published extensively on macroprudential policy indices, particularly those based on borrower-based measures such as LTV, DTI, and DSTI (e.g. Jurca et al., 2020; Cesnak et al., 2021; Klacso, 2022; Klacso and Martin, 2024). Similarly, Eller et al. (2020) constructs broad macroprudential indices for CESEE economies and evaluates their macroeconomic effects. However, these indices have several limitations for our purposes: limited sample coverage (2014–2020 in Klacso (2022)), the absence of systematic updates (Eller et al. (2020)), and inconsistent volatility, with very low variation before 2014 and substantially higher variation thereafter. The cumulative BLS measure of credit conditions for housing loans overcomes these limitations and offers several advantages. First, credit conditions function as an intermediate target in the macroprudential transmission mechanism. Second, the measure closely co-moves with synthetic macroprudential indices after 2014. Third, it provides a longer and more stable time series suitable for econometric modelling.

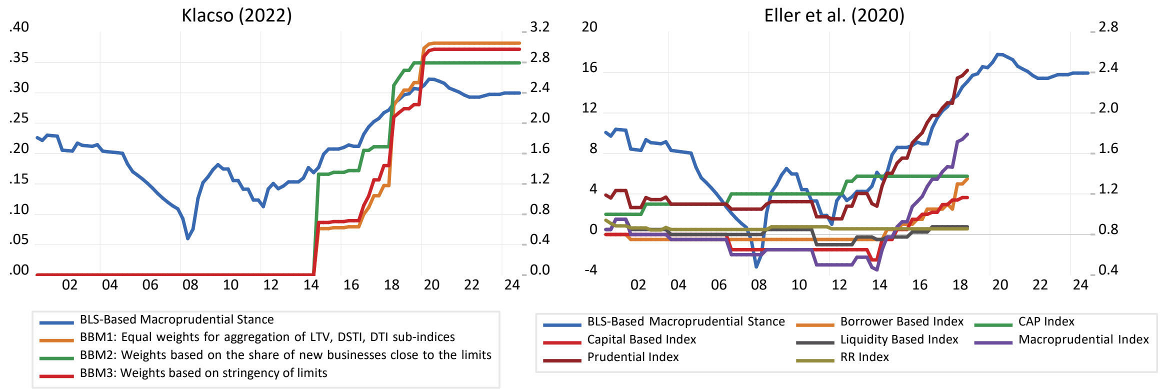
Interpreting the second cointegration relation as a pure policy rule is a substantial simplification. It is more accurate to view it as a macroprudentially consistent macro-financial stance rule. In particular, the trend component of the cumulative BLS series captures the structural tightening path associated with borrower-based macroprudential policy, whereas the cyclical component reflects a mixture of macroprudential actions and endogenous bank behaviour, including shifts in risk tolerance, competitive pressures, and funding conditions. Accordingly, when we refer to a macroprudential rule, we do so for simplicity and we mean this broader macroprudentially consistent macro-financial stance rule.

In our framework, the BLS credit-conditions indicator plays two related roles. Firstly, in the house price equation, it acts as a proxy for the shadow value of credit constraints, as discussed in the housing demand literature (Ermisch, 1984; Duca et al., 2011). Second, when the second cointegrating relation is normalised on the cumulative BLS measure, its low-frequency trend is interpreted as a proxy for the medium-term tightening path in credit supply conditions, which moves in line with the macroprudential policy environment.

unavailable, the pre-cumulation series is extended using the standardized prudential index of Eller et al. (2020), which is highly correlated with BLS over 2005Q1–2008Q4 (0.8 in levels and 0.6 in differences). The extension is rescaled (using the mean and variance of BLS) to ensure continuity and consistency with post-2005 BLS dynamics. Results are qualitatively similar when using the non-logged cumulative index, with the expected exception that the absolute level of the long-run coefficient differs.

[5] Correlation diagnostics show a clear comovement between quarterly changes in the BBM index and the BLS-based macroprudential stance. The centered Pearson correlation is modest ($r \approx 0.3$), while the uncentered Pearson and Spearman rank correlations are stronger ($r \approx 0.5^{***}$-0.6^{***}). Overall, tightening of borrower-based measures coincides with tighter bank lending standards during 2014Q4–2020Q3.

Figure 1: A Comparison of Pure Macroprudential BBM Indices and the BLS-based Macroprudential Stance.



Sources: Klacso (2022) (left panel), Eller et al. (2020) (right panel), ECB, NBS, and author's calculations.

3.3.2. Macroprudential Policy and Institutional Changes in Slovakia

Slovakia provides a clear example of an economy vulnerable to shocks that amplify financial imbalances. Since the early 2000s, it has experienced major restructuring and privatization of the banking sector, rapid mortgage market expansion, and significant financial deepening. EU accession in 2004 brought swift interest rate convergence, and euro adoption in 2009 eliminated monetary policy autonomy. The 2010s were marked by ultra-low interest rates under ECB policy and intensified banking competition, interrupted only by the COVID-19 and energy shocks.

Following the global financial crisis, the National Bank of Slovakia (NBS) increased its efforts to safeguard financial stability. Recognising the limitations of monetary policy in addressing sector-specific risks, the NBS established the institutional and legal foundations for a macroprudential policy framework. The European sovereign debt crisis (2011–2013) emphasised the importance of national measures for mitigating systemic risks in small open economies within a monetary union. From 2014 onwards, the NBS became one of the EU's most proactive central banks in applying borrower-based macroprudential instruments. This included introducing, calibrating and gradually tightening measures such as loan-to-value (LTV) limits, debt-to-income (DTI) caps and debt-service-to-income (DSTI) limits, in order to restrain excessive credit growth, reduce household leverage and enhance the resilience of the financial system. These domestic developments coincided with broader institutional reforms at the European level. In 2010 the European Systemic Risk Board (ESRB) was established as the EU's macroprudential oversight body, responsible for identifying and mitigating systemic risks across member states[6].

The period 2009–2014 marks a phase of major structural transformation in Slovakia's macroprudential policy framework. Evidence from the single-equation structural break tests for the debt coefficient (Table 6 in Appendix C) supports this conclusion. The global Bai and Perron (1998) test identifies 2011Q3 as the main break date, corresponding to the institutional shift from a passive to an active macroprudential regime in Slovakia and across Europe. The sequential version of the test indicates two breaks in 2008Q4 and 2014Q3, which separate the passive regime, the transition period, and the full activation of macroprudential policy. We

[6]The 2011 'Six-Pack' legislation strengthened the surveillance of macroeconomic and fiscal policies, including monitoring credit booms and house price inflation. Meanwhile, the 2013 'Two-Pack' legislation further enhanced fiscal governance and macroeconomic coordination within the eurozone.

adopt the global test results as the baseline while retaining all transition period break dates for robustness analysis.

The schematic in Figure 5 in Appendix D illustrates the model's structure. NBS, as the macroprudential authority, sets policy by assessing the evolution of credit conditions (intermediate target), the housing market, and overall financial stability (final target). Macroprudential actions (implicit before the 2009-2014 transition period) influence credit conditions through their interaction with broader, and often conflicting, market forces such as the economic outlook, housing market expectations, borrower creditworthiness, bank risk tolerance, competition, and funding costs. In the full structural framework, credit conditions and the housing market jointly shape the evolution of financial stability.

4. Results

4.1. Cointegration analysis

The cointegration analysis begins with selecting an appropriate lag structure for the VARX model. The full system, as defined in Eqs. (4)-(5), includes four endogenous variables: real house prices (hp_t), household indebtedness (hhd_t/gdp_t), the BLS-based macroprudential stance (map_t^{bls}), and real disposable income (di_t). The exogenous variables consist of two dummies ($dum_{\geq 11Q3}$ and its interaction term $dum_{\geq 11Q3} \times (hhd_t/gdp_t)$) in addition to housing stock (hs_t), the real mortgage rate (rr_t), working-age population ($pop_{25\text{–}44,t}$), and real net financial assets ($netfa_t$). Based on the Akaike Information Criterion (AIC), we select two lags for the endogenous variables, assuming a maximum of four and initially including only the dummies as exogenous regressors. With this lag length fixed, the AIC also suggests two lags for the exogenous variables. Final verification confirms that a VARX(2,2) specification is well suited for the subsequent analysis.

Table 1: Johansen Cointegration Test Results[a]

Rank Hypothesis	Model with a Structural Break[b]		
	Trace Stat.	1%/5% Crit.[c]	**Rank**
$H_0 : r = 0, H_A : r \geq 1$	134.15	91.10 / 82.50	
$H_0 : r \leq 1, H_A : r \geq 2$	64.82	64.66 / 57.32	2
$H_0 : r \leq 2, H_A : r \geq 3$	34.70	42.00 / 35.96	
VARX(2,2) Diagnostics			
Stability (roots <1)	Yes		
VAR AR 1-4 LM Test (p-value)	0.37		
VAR JB Normality Test (p-value)	0.09		
VAR Hetero. Test (p-value)	0.75		
Sample: 2001Q4-2024Q4 (93 obs.)			

[a] Endogenous variables: real house prices (hp_t), household indebtedness (hhd_t/gdp_t), the BLS-based macroprudential stance (map_t^{bls}), and real disposable income (di_t). Restricted variables: $dum_{\geq 11Q3}$, $dum_{\geq 11Q3} \times (hhd_t/gdp_t)$ and trend (t). In the robustness analysis rotating through the following restricted variables: housing stock (hs_t), real mortgage rate (rr_t), working-age population ($pop_{25\text{–}44,t}$), and real net financial assets ($netfa_t$). Unrestricted variables: Δrr_t, Δrr_{t-1}, $\Delta netfa_t$, $\Delta netfa_{t-1}$, quarterly dummies for 2008Q2, 2010Q1, and 2012Q2 to control for outliers, and a constant
[b] The structural break is captured via a post-2011Q3 level shift dummy and a slope dummy for debt.
[c] Critical values are obtained from Table 13 in Doornik (2003) - with 4 endogenous variables and 2 exogenous variables.
Sources: Author's computation.

We test for the existence of two cointegrating vectors in the system that includes the four endogenous variables, two restricted exogenous dummies, and a deterministic trend to account for omitted long-run factors. The unrestricted part of the model includes a constant, dummy variables capturing outliers[7], and fast-moving exogenous variables in first differences, such as the real interest rate and net financial assets. Other long-run exogenous variables are retained for robustness checks. Residual diagnostics indicate that there are no significant issues with autocorrelation, heteroskedasticity or normality. As shown in Table 1, two cointegrating relationships are identified.

The existence of two cointegrating vectors is robust across various specifications. They are consistently identified regardless of whether outliers are controlled for, the number of lags on endogenous variables (1 to 4), or the inclusion of a deterministic trend (t). The result holds when rotating through alternative restricted (long-run) exogenous variables (hs_t, rr_t, $pop_{25–44,t}$, $netfa_t$) and when varying the lags (0 to 4) of unrestricted (short-run) exogenous variables (Δrr_t, $\Delta netfa_t$). Moreover, the finding remains stable across different break dates within the 2009–2014 window. In contrast, models without a structural break fail diagnostic tests and produce inconsistent identification of the second cointegrating vector. These results confirm that the system with a structural break robustly supports two cointegrating relationships.

4.2. Long-Run System: Housing Fundamentals and a Macroprudentially Consistent Macro-Financial Stance

We summarise the identification of the two long-run relations in five steps. We begin with an unrestricted empirical baseline and impose only the minimal restrictions needed for exact identification. We then add an economically motivated dual-risk restriction with estimated long-run coefficients, consider a policy-calibration scenario and evaluate it via sensitivity analysis, and finally re-estimate the full system to confirm that the cointegration rank, regime shift, and key long-run elasticities are robust to richer specifications

Step 1: Unrestricted empirical baseline and minimal identifying restrictions

We identify two cointegrating vectors in a system comprising four endogenous variables and two exogenous dummy variables (see Table 1). The first vector, normalized on house prices, captures the fundamental long-run relationship in the housing market. The second cointegration relation, normalised on the BLS-based stance measure, is best interpreted as a macroprudentially consistent macro-financial stance rule. Given the presence of two cointegrating vectors, we impose one identifying restriction per equation to achieve exact identification (see either column (1) of Table 2 for condensed results, or column (1) of Table 7 in Appendix E for full results). Specifically, we exclude household indebtedness from the house price equation as it is proxied by credit conditions (we use Duca et al. (2011) approach instead of Anundsen and Jansen (2013)) and real disposable income from the macroprudential policy rule as the policy authority responds primarily to housing related imbalances. Table 2 also shows a statistically significant post-2011 shift in the long-run debt coefficient consistent with Slovakia's institutional transition. The long-run disposable income coefficient is both statistically significant and economically consistent (≈ 1.5–1.7), reflecting the expected affordability relationship between income and house prices.

Step 2: Dual-risk restriction with estimated long-run coefficients

We assume that from 2011 onward the macroprudential authority assigns equal weight to house prices and household indebtedness, capturing risks on both the asset and liability sides of the household balance sheet (the "dual-risk" channel; see column (2) of Table 2). This choice

[7] Outlier dummies are included for 2008Q2 and 2012Q2 to account for volatility in the Bank Lending Survey (BLS) during the Global Financial Crisis and the European sovereign debt crisis, and for 2010Q1 to capture the post-GFC contraction in activity linked to hhd_t/gdp_t. Another suspected outlier is 2021Q4, which is associated with the house price series and likely reflects measurement error during the COVID-19 pandemic.

Table 2: Estimated VECM Results with Two Cointegrating Relationships and Long-Run Exogenous Variables

	(1)		(2)		(3)		(4)		(5)	
Cointegrating Restriction Test (LR)										
Gradually inserted and tested restrictions	Baseline structural Identification		MaP rule: Dual Risk Channel		MaP rule: Policy calib.		MaP rule: Policy calib. (validation)		Robustness of the MaP rule: All restrictions imposed	
	$\beta_{1,hp} = 1$	$\beta_{2,map} = 1$	$\beta_{2,hp} = \beta_{2,hhd/gdp}$		$\beta_{2,hp} = 1.5$		$\beta_{1,d11Q3*hhd/gdp}$			
	$\beta_{1,hhd/gdp} = 0$	$\beta_{2,di} = 0$	$+\beta_{2,d11Q3*hhd/gdp}$				$= 0$			
			$\chi^2(1) = 0.276$		$\chi^2(2) = 0.410$		$\chi^2(3) = 0.429$		$\chi^2(3) = 2.826$	
			p-value = 0.60		p-value = 0.82		p-value = 0.93		p-value = 0.42	
Cointegrating Equations (β)										
hp_t (norm.)	1.000	0.755***	1.000	1.562***	1.000	1.500	1.000	1.500	1.000	1.500
	–	(0.172)	–	(0.140)	–	–	–	–	–	–
hhd_t/gdp_t	0.000	-0.611***	0.000	-0.818***	0.000	-0.816***	0.000	-0.806***	0.000	-1.628***
	–	(0.086)	–	(0.110)	–	(0.108)	–	(0.103)	–	(0.170)
map_t^{bls} (norm.)	0.119***	1.000	0.025	1.000	0.026	1.000	0.034**	1.000	-0.055***	1.000
	(0.030)	–	(0.025)	–	(0.025)	–	(0.016)	–	(0.019)	–
di_t	1.703***	0.000	1.486***	0.000	1.507***	0.000	1.510***	0.000	1.754***	0.000
	(0.160)	–	(0.129)	–	(0.125)	–	(0.089)	–	(0.242)	–
$dum_{\geq 11Q3}$ (exog.)	1.012**	-8.953***	-0.177	-7.412***	-0.230	-7.185***	-0.147***	-7.153***	-0.030	-10.466***
	(0.485)	(1.012)	(0.386)	(0.621)	(0.332)	(0.315)	(0.032)	(0.302)	(0.044)	(0.626)
$dum_{\geq 11Q3} \times$	-0.346***	2.786***	0.011	2.381***	0.025	2.316***	0.000	2.306***	0.000	3.128***
hhd_t/gdp_t (exog.)	(0.141)	(0.288)	(0.113)	(0.181)	(0.099)	(0.108)	–	(0.103)	–	(0.170)
hs_t (exog.), rb_t (exog.), $pop_{25-44,t}$ (exog.), $netfa_t$ (exog.)									Y	Y
Adjustment Coefficients ($\alpha_{11,ECT1}, \alpha_{23,ECT2}$)										
$ECT1_{t-1}$, $ECT2_{t-1}$	-0.128***	-0.337***	-0.126***	-0.275***	-0.124***	-0.282***	-0.125***	-0.285***	-0.142***	-0.226***
	(0.037)	(0.062)	(0.042)	(0.051)	(0.042)	(0.051)	(0.042)	(0.053)	(0.036)	(0.029)
Short-Run Dynamics (Δ)	Δhp_{t-1}, $\Delta hhd_{t-1}/gdp_{t-1}$, Δmap_{t-1}^{bls}, Δdi_{t-1}; Δrr_t, Δrr_{t-1}, $\Delta netfa_t$, $\Delta netfa_{t-1}$; $dum_{=08Q2}$, $dum_{=10Q1}$, $dum_{=12Q2}$, $dum_{=21Q4}$, constant (exog.)									
Model Fit										
LogL	948.1876		948.0495		947.9830		947.9733		962.4557	
VECM(1,1) Residual Diagnostics (based on AIC): Stability; ADF (AIC) Test for (t-Stat) EC; VAR AR 1-4 LM Test; VAR JB Normality Test; VAR Hetero. Test	✓		✓		✓		✓		✓	
Sample: 2001Q4-2024Q4 (93 obs.)										

Notes: The VECM (1)–(4) includes four endogenous variables and two long-run exogenous dummy variables. In addition, the VECM (5) includes four long-run exogenous variables. Standard errors are in parentheses. Asterisks $^{***}/^{**}/^{*}$ denote statistical significance at the $1\%/5\%/10\%$ level. For ease of interpretation, (norm.) denotes the variable used for normalisation (the left-hand-side variable), all other variables are reported on the right-hand side with signs adjusted accordingly.
Sources: Author's calculations.

is supported by a large literature documenting tight long-run comovement between house prices, credit, and fundamentals (e.g. Anundsen and Jansen, 2013; Turk, 2015). The restriction of equal long-run weights is not rejected by the data ($p = 0.55$), and the log-likelihood remains effectively unchanged. The LR coefficient on house prices (≈ 1.6) indicates a stable countercyclical response, treating prices as an early warning signal analogous to inflation in a Taylor rule. In contrast, the pre-2011 negative long-run debt coefficient (about -0.8) suggests procyclical credit conditions in the absence of an active borrower-based toolkit, consistent with low household leverage before the transition period (2009–2014) and limited perceived need for intervention. After 2011, the debt semi-elasticity becomes countercyclical ($-0.8 + 2.4 \approx 1.6$), reflecting the institutional shift towards an active borrower-based framework[8]. However, in practice, and unlike in the simplified model specification used here, macroprudential policy in Slovakia also responds to additional variables, such as credit growth and debt-servicing capacity, particularly in more recent and shorter samples where more data are available.

Step 3: Policy-calibration scenario for the long-run stance coefficients

Supported by empirical evidence, theory, and ESRB policy guidance, we calibrate the long-run stance coefficients to 1.5 on house prices and, after 2011, on household indebtedness (column (3) of Table 2). Several considerations motivate this choice. First, cross-country studies show that borrower-based measures significantly restrain mortgage credit and house price growth, which implies that policy must respond by more than one-for-one to emerging imbalances in order to be effective (Kuttner and Shim, 2016; Ampudia et al., 2021). Second, in DSGE models with collateral constraints, Taylor-type macroprudential rules require coefficients above unity on the key systemic-risk indicator to deliver determinacy and improved stabilisation (Rubio and Carrasco-Gallego, 2015). Third, micro evidence indicates that property values are about 1.5 times as sensitive to credit availability (Kelly et al., 2018), which provides a natural benchmark for calibration. Fourth, ESRB guidance stresses the need for early, forward-looking, and substantial action when collateral valuations become stretched. Empirically, the value of 1.5 is not rejected by the data ($p = 0.78$), and the log-likelihood remains effectively unchanged; sensitivity analysis supports a range between 1.2 and 2.1 (LR $p = 0.12$–0.14). Column (4) of Table 2 confirms the economic and statistical consistency of this restriction.

Step 4: Scenario and sensitivity analysis of the calibrated coefficients

We evaluate the calibrated coefficients using scenario and sensitivity analysis during the tightening phase (2014Q4–2020Q3). Specifically, we simulate paths of $ECT2_t$, $\Delta(hhd_t/gdp_t)$, and Δhp_t, and compare their volatility across alternative coefficient settings. This provides a practical design criterion, since policymakers typically prefer smooth adjustment and stable outcomes. As shown in Table 9 in Appendix C, small coefficients generate high volatility in $ECT2_t$ and muted short-run adjustment, while very large coefficients compress $ECT2_t$ but amplify volatility in house prices and debt growth. Values around 1.4–1.6 strike a prudent balance between policy activism and outcome stability, which supports our baseline calibration.

Step 5: System-level robustness

To assess robustness at the system level, we re-estimate the model using the full structural specification (column (5) of Table 2). The house-price cointegrating relation remains close to the single-cointegration benchmark (Table 10 in Appendix F.2), confirming the stability of the

[8] The robustness of these economic restrictions is confirmed under alternative break dates within the 2009–2014 transition period (see Table 8 in Appendix F.1). Across these specifications, the long-run restrictions are rarely rejected and the key coefficients remain stable, particularly from 2013 onward. Standard diagnostics show no residual autocorrelation and only minor deviations from normality at the sample boundaries. Considering statistical evidence, model fit criteria, and the timing of institutional changes in Slovakia and the EU, we adopt 2011Q3 as the preferred break date.

housing-fundamentals relationship. Two minor and expected differences emerge. First, once the full system is estimated jointly and the second long-run relation is imposed, the coefficient on map_t^{bls} in the house-price relation becomes less precisely estimated and sensitive to specification, so we refrain from giving it a strong economic interpretation. For this reason, we also report a separate fundamentals-only system in which the sign is negative and the estimate is more stable. Second, when long-run exogenous controls are excluded, the structural dummy in the house-price equation becomes statistically significant, consistent with it absorbing omitted regime-related shifts. Importantly, the cointegration rank, the post-2011 regime shift in long-run coefficients, and the qualitative signs and magnitudes of the key long-run elasticities are preserved under the full specification, indicating that the main conclusions are not driven by the parsimonious baseline.

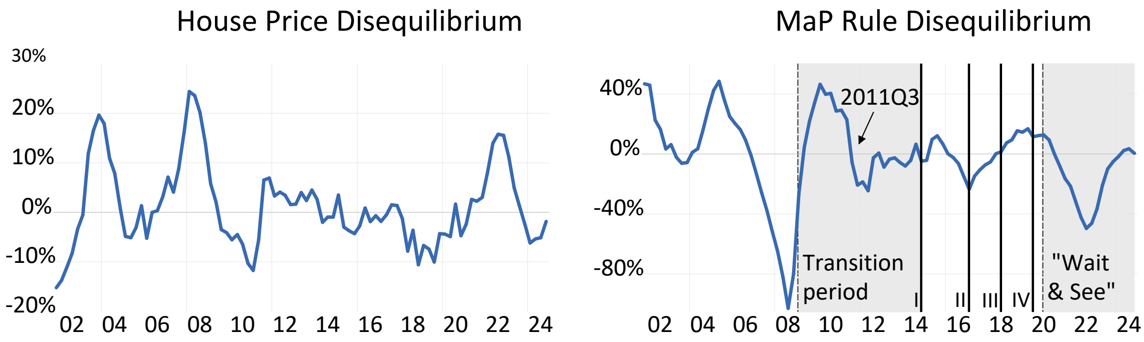
Once the stance relation is augmented with the full set of long-run exogenous controls, it should no longer be interpreted as a stance rule in a strict instrument-level sense. Instead, it is best viewed as a broader reduced-form long-run equilibrium relation that conditions on additional macro-financial determinants. The key point of this exercise is that, even under this richer specification, the economically motivated restrictions introduced earlier (including the dual-risk restriction and the calibrated policy-scenario coefficients) remain empirically admissible and leave the qualitative long-run interpretation unchanged.

Figure 2 displays deviations from equilibrium for both cointegrating vectors. For house prices, three distinct periods of positive disequilibrium—2003, 2008, and 2022—are followed by correction phases in 2004–2005, 2009–2011, and 2023. The period from 2012 to 2018 appears relatively stable, with only minor fluctuations. In the macroprudentially consistent macro-financial stance relation, the error correction term trajectories differ clearly across phases. Positive values indicate tighter-than-benchmark credit conditions, while negative values indicate looser-than-benchmark conditions. The series exhibits large and persistent deviations in the pre-transition period, including the 2005–2008 easing cycle associated with the convergence phase and the abrupt tightening in 2009–2010. Importantly, the subsequent reduction in volatility appears to be gradual and concentrated over the 2009–2014 transition window, rather than mechanically tied to a single break date, consistent with an evolving shift from a largely passive to a more systematic macroprudential framework. We highlight the transition period, the starting points of the four tightening episodes identified in the BBM index of Klacso (2022), and the subsequent wait-and-see phase. The 2020–2024 divergence episode illustrates why the BLS-based macro-financial stance should be interpreted as a time-varying, broad measure of realised credit conditions rather than as a pure macroprudential policy index.

4.2.1. National House Price Index and Additional Robustness Checks

Using the national house price index produces qualitatively similar results. The main difference is the substantial measurement noise present in the national series during the period leading up to the Global Financial Crisis (2006–2007) and the COVID-19 period (2020–2022). This required the implementation of extensive outlier controls to mitigate residual non-normality (see Figure 6). Nevertheless, the presence of two cointegrating relations is confirmed (Table 11). Robustness checks are analogous to those in Table 1. The structural break separating passive and active macroprudential regimes remains economically and statistically significant (column (1) of Table 12). A dual-risk specification that places equal long-run weights on house prices and debt is consistent with the data (column (2) of Table 12). However, due to higher noise levels and reliance on outlier controls, the estimated long-run coefficient on house prices is smaller (≈ 1.2 versus 1.5) and the adjustment loading is also smaller (0.05 versus ≈ 0.13) and marginally insignificant. In this setting, a specification that gives relatively more weight to debt than prices (see columns (3)–(4) of Table 12) is preferable. The over-identifying restrictions are not rejected and imply a rule that reacts one-for-one to house prices, while the long-run co-

Figure 2: Error Correction Terms: House Price Disequilibrium and MaP Rule Disequilibrium.



Notes: The shaded areas mark the macroprudential transition period (2009Q1–2014Q4) and the "wait-and-see" phase (2020Q4–2021Q4), during which the macroprudential authority primarily assessed the effects of previous structural tightening. The vertical line at 2011Q3 indicates the structural break when policy shifted from a passive to an active stance. Labels I–IV denote the starting points of the main tightening phases (2014Q4, 2017Q1, 2018Q3, and 2020Q1) as classified in the index of borrower-based measures by Klacso (2022).
Sources: Author's calculations and Klacso (2022).

efficient on debt is approximately 1.5, yielding a calibration that is both policy plausible and empirically supported.

The results in this section are supported by several robustness checks. Firstly, in the estimated system, the long-run house price equation remains consistent in both its baseline and extended forms with the standalone, fundamentals-based specification that excludes the second cointegrating relation. Secondly, the findings are not dependent on the specific break date. The main results remain unchanged when the break is placed anywhere within the 2009–2014 transition period. Third, long-run coefficients in the range of 1.4–1.6 provide a stable balance between volatility in the rule and volatility in the outcome variables. Fourth, despite the elevated volatility in the national house price index, the results remain broadly similar once this is at least partially accounted for.

4.3. Short-Run Adjustment: Stronger Leaning Against the Wind

This section studies how the system adjusts in the short run when it deviates from the two long-run relations. We start from the symmetric VECM and interpret the adjustment coefficients on the two error-correction terms. We then allow for state dependence by splitting each error-correction term into positive and negative components, which captures potentially different dynamics during easing versus tightening phases. Finally, we summarise the main economic messages and illustrate them with the counterfactual simulation.

$ECT1_t$ measures the deviation of real house prices from the housing-fundamentals relation. A positive $ECT1_t$ indicates that house prices are above the level implied by fundamentals (overvaluation), while a negative value indicates undervaluation. $ECT2_t$ measures the deviation from the long-run macroprudentially consistent macro-financial stance relation (normalised on the BLS-based stance measure). Under our normalisation, a positive $ECT2_t$ corresponds to tighter-than-benchmark credit conditions, whereas a negative value corresponds to looser-than-benchmark conditions.

Symmetrical adjustment

The estimated VECM adjustment coefficients point to two opposing forces that shape short-run movements in credit conditions (Table 3, symmetric adjustment). On the one hand, credit conditions respond procyclically to the housing cycle: relative to the housing-fundamentals relation, $\Delta map^{bls}t$ loads negatively ($\alpha 13, ECT1! \approx ! - 0.68$), so positive house-price gaps are followed by an easing of credit conditions, which tends to amplify booms. The procyclical response estimated by the model is likely driven by endogenous bank behaviour. On the other hand, credit conditions also exhibit a stabilising force relative to the long-run stance benchmark: adjustment to the macroprudentially consistent stance relation is countercyclical, so when conditions are tighter (looser) than implied by the benchmark they subsequently ease (tighten) ($\alpha_{23,ECT2}! \approx ! - 0.28$).

House prices adjust only gradually toward equilibrium ($\alpha_{11,ECT1} \approx -0.13$), while household indebtedness rises in response to disequilibria ($\alpha_{12,ECT1} \approx 0.14$), confirming leverage procyclicality. Disposable income appears weakly exogenous, showing no systematic response to either long-run relation (LR test: $\chi^2(5) = 1.79$, $p = 0.88$). Overall, the short-run stance of credit conditions depends on the balance between market and policy forces, making $\alpha_{23,ECT2}$ a key parameter for financial stability.

Asymmetrical adjustment

The baseline VECM assumes symmetric adjustment to disequilibria, but both theory and evidence point to state-dependent, nonlinear adjustment in housing and credit markets. Threshold and regime-switching cointegration models show that deviations from equilibrium correct asymmetrically depending on the sign and size of the gap (Enders and Siklos, 2001; Balke and Fomby, 1997; Hansen and Seo, 2002). In macro-financial settings, policy and market behavior can differ across booms and busts, motivating stronger reactions when risks build up (Smets, 2018; Martin et al., 2021). Consistent with this literature, we split the error-correction terms into positive and negative components. This specification complements cross-country evidence on the intensity of macroprudential actions (Cerutti et al., 2017) by estimating asymmetric adjustment within a structural VECM for Slovakia.

Table 3: Adjustment Coefficients

α	(1) Δhp_t	(2) $\Delta hhd_t/gdp_t$	(3) Δmap_t^{bls}	(4) Δdi_t
		Panel A Symmetrical adjustment to House Price Gap		
$ECT1_{t-1}$	-0.125***	0.137***	-0.682***	0.049
	(0.041)	(0.033)	(0.178)	(0.050)
		Asymmetrical adjustment to House Price Gap		
$ECT1^+_{t-1}$			-1.106***	
			(0.131)	
$ECT1^+_{t-2}$	-0.153***	0.179***		
	(0.026)	(0.035)		Exo.
$ECT1^-_{t-5}$	0.163*			
	(0.062)			
$ECT1^-_{t-6}$	-0.184**			
	(0.058)			
		Panel B Symmetrical adjustment to MaP Rule Gap		
$ECT2_{t-1}$	-0.005	0.034***	-0.284***	0.009
	0.012	(0.010)	(0.053)	(0.015)
		Asymmetrical adjustment to MaP Rule Gap		
$ECT2^+_{t-2}$			-0.121**	
			(0.051)	
$ECT2^+_{t-4}$		-0.033**		
		(0.011		
$ECT2^-_{t-1}$		0.044***		Exo.
		(0.011)		
$ECT2^-_{t-1}$ $\times dum_{\geq 11Q3}$		0.042**		
		(0.014)		
$ECT2^-_{t-2}$			-0.415***	
			(0.051)	
Sample: 2001Q4-2024Q4 (93 obs.)				

Notes: Adjustment coefficients are from column (4) of Table 2, and from columns (1), (2), and (4) of Table 13. Standard errors are in parentheses. Asterisks $^{***}/^{**}/^{*}$ denote statistical significance at the 1%/5%/10% level. Shaded coefficients and $^{***}/^{**}/^{*}$ reflect post-selection adjusted p-values following Benjamini and Yekutieli (2005).
Sources: Author's computation.

To generate empirically realistic short-run dynamics, three modified equations are estimated using automated model selection procedures (AutoGets and Swapwise) applied to a broad set of potential regressors. Given the limited sample and large candidate sets, the aim is to characterise overall short-run patterns rather than to interpret individual coefficients. Model selection is guided by the Schwarz information criterion, and resulting p-values are adjusted using the Benjamini and Yekutieli (2005) procedure to minimise the risk of spurious findings. Since Δmap_t^{bls} serves as an intermediate target influenced by both policy and market forces, the specification remains parsimonious but always includes (i) asymmetric error-correction terms from the long-run macroprudential rule ($ECT2^+$, $ECT2^-$) at two lags and (ii) the housing overvaluation uncertainty measure[9]. The latter captures episodes when housing market overvaluation and financial volatility jointly trigger credit tightening, reflecting heightened caution by the macroprudential authority or by banks' own risk management[10].

[9]For Δhp_t and $\Delta(hhd/gdp)_t$, the candidate set includes $\{ECT1^+_{t-j}, ECT1^-_{t-j}, ECT2^+_{t-j}, ECT2^-_{t-j}\}_{j=1}^6$, $\{\Delta hp_{t-j}\}_{j=1}^6$, $\{\Delta(hhd/gdp)_{tj}\}_{j=1}^6$, $\{\Delta map_{t-j}^{bls}\}_{j=1}^6$, $\{\Delta di_{t-j}\}_{j=0}^4$, $\{\Delta rr_{t-j}\}_{j=0}^4$, and $\{\Delta netfa_{t-j}\}_{j=0}^4$, along with interaction terms between the ECT components and endogenous variables and a post-2011Q3 slope dummy. This yields roughly 100 potential regressors. For Δmap_t^{bls}, an analogous specification (excluding the always-included regressors discussed in the text) produces 76 candidate variables. A constant and outlier-control dummies are always included in both specifications.

[10]The housing overvaluation uncertainty measure is the average of three normalized components: the 8-quarter

Credit conditions adjust asymmetrically to housing and policy imbalances, reflecting the interplay between market forces and macroprudential control (column (3) of Table 3). When house prices exceed fundamentals, credit conditions ease sharply, with the estimated response around -1.1, indicating procyclical behavior that amplifies housing booms. Macroprudential adjustment is countercyclical and asymmetric, as policy reacts more forcefully when credit is looser than fundamentals (around -0.4) than when it is overly tight (around -0.1). This asymmetry highlights a stronger policy response to excessively loose credit conditions. Credit conditions (column (4) of Table 13 in Appendix G) also display persistence, likely reflecting institutional decision lags that became more evident after 2011. Rising housing-overvaluation uncertainty tightens lending standards (around 1.1), effectively offsetting procyclical pressures during periods of overvaluation and volatility. The response to debt is cyclical, while higher real mortgage rates are associated with a temporary easing of lending conditions, suggesting that banks offset rising borrowing costs by loosening non-price terms.

An alternative explanation, which is also consistent with the data, is that borrower-based measures were introduced when credit conditions were already loose. Because no comparable measures existed earlier, the initial implementation likely had a strong perceived impact and showed up as a structural or cumulative tightening in credit conditions. This was then followed by a more cautious wait-and-see approach (see Figure 2). Looking ahead, adjustments in borrower-based measures may become more cyclical and less structural as the framework matures. House prices exhibit partial mean reversion but remain highly sensitive to financial conditions, with faster corrections during booms than in downturns (column (1) of Table 3). Overvaluations are corrected relatively quickly, with an estimated adjustment of around -0.15, while undervaluations adjust more slowly through a delayed rebound, beginning with a temporary increase of about 0.16 followed by a correction of about -0.18. This asymmetry points to price stickiness and slower recovery in downturns, consistent with credit frictions and seller inertia. House price growth (column (1) of Table 13 in Appendix G) is highly persistent, and past household indebtedness growth further boosts prices, confirming the amplifying role of credit. Changes in mortgage rates are positively associated with house price growth, reflecting strong co-movement between credit conditions and housing demand.

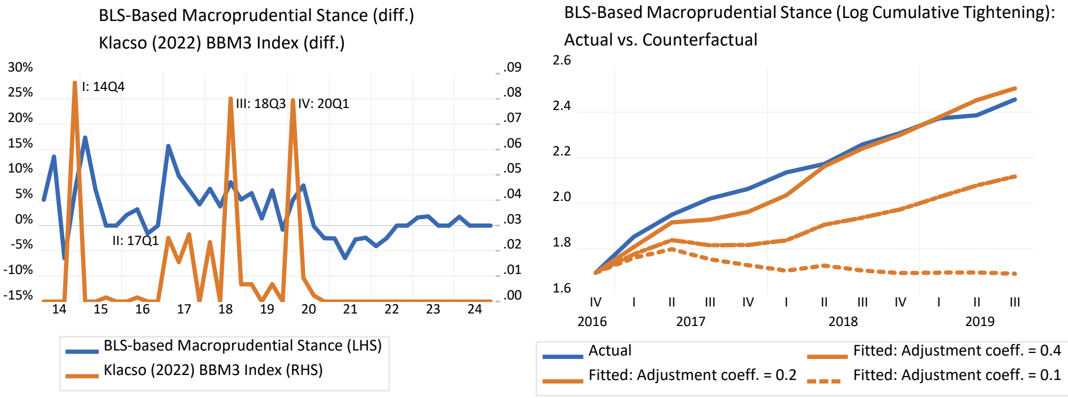
Household indebtedness is highly persistent and procyclical, with policy adjustments providing only partial moderation (column (2) of Table 3). When housing is overvalued, borrowing increases, with an estimated response of around 0.18, reinforcing the link between asset prices and credit expansion. Adjustment to the macroprudential rule is moderate, as borrowing reacts only mildly to deviations from fundamental credit conditions. Higher mortgage rates curb debt growth, with an estimated effect of about -0.7, underscoring the sensitivity of household borrowing to financing costs (column (2) of Table 13 in Appendix G).

Policy counterfactual

To assess the policy relevance of the estimated dynamics, a counterfactual simulation is conducted using the three short-run equations for house prices, household indebtedness, and credit conditions. The exercise examines how weaker adjustment in the credit-conditions equation would affect policy transmission. Specifically, the response coefficient on $ECT2^{-}_{t-2}$ in the short-run Δmap^{bls}_t equation, which is estimated at about -0.4, is mechanically reduced by 50% and 75% to match the magnitude of the symmetric and positive adjustment terms. The analysis focuses on Slovakia's main macroprudential tightening phase between 2017Q1 and

moving standard deviation of house price growth, household indebtedness growth, and the spread between the mortgage rate and the 10-year government bond yield, each scaled to $(0, 1)$ using min–max normalization. To capture how uncertainty amplifies tightening during booms, we interact this index with the positive house price gap ($ECT1^{+}_t$). As this term is highly correlated with $ECT1^{+}_t$, we use its orthogonalized residuals in the final BLS equation. The positive and significant coefficient indicates that periods of higher uncertainty and rapid price growth, lead to stronger credit tightening by regulators (or banks) as a risk management response.

Figure 3: Counterfactual credit conditions under different adjustment coefficients



Sources: Author's calculations.

2019Q3 (Phases II and III in the left panel of Figure 3 and the right panel of Figure 2). Phases I and IV were short-lived and shaped by elevated volatility. The first phase reflected uncertainty around the announcement and implementation of new measures, while the fourth phase coincided with the COVID-19 period, during which macro-financial variables were exceptionally volatile.

The right panel of Figure 3 shows that a weaker adjustment, whether due to policy hesitation or stronger market forces, would have substantially muted the intended tightening of credit conditions. In reality, the Slovak macroprudential authority acted decisively, tightening credit conditions persistently and asymmetrically to curb excessive credit growth and support financial stability.

Conclusion

This paper provides empirical evidence of how macroprudential policy operates in Slovakia through borrower-based measures, a country that moved from virtually no macroprudential framework before the global financial crisis to one of the most active regimes in the European Union. By estimating a vector error correction model, we establish a macroprudentially consistent macro-financial stance rule that links credit conditions to house prices (whether measured nationally or using the Bratislava region index, which reflects the largest and most liquid segment of the market) and to household indebtedness. We also identify a structural shift around 2011 that marks the transition from a largely passive, procyclical regime to an active, more countercyclical one.

The short-run dynamics reveal that macroprudential policy does not adjust symmetrically. Credit conditions respond more forcefully when they are excessively loose, which indicates that authorities act more decisively in periods of overheating. Or similarly, this may largely reflect an initial, structural tightening when borrower-based measures were first introduced during a period of loose credit, followed by a more cautious "wait-and-see" phase as the framework matured. This asymmetric adjustment strengthens the stabilising role of macroprudential policy and counteracts the strong procyclical pressures that arise from housing and credit markets. A key policy contribution of this paper is the estimation of an operational macroprudential rule that provides a transparent benchmark for assessing policy actions.

These findings highlight the importance of analysing macroprudential policy through both long-run relationships and short-run adjustment paths. Evaluations that focus only on long-run targets overlook the state dependence and transitional dynamics that shape policy effectiveness. The framework developed in this paper can be in future research applied to other Central and Eastern European economies that experienced similar structural shifts.

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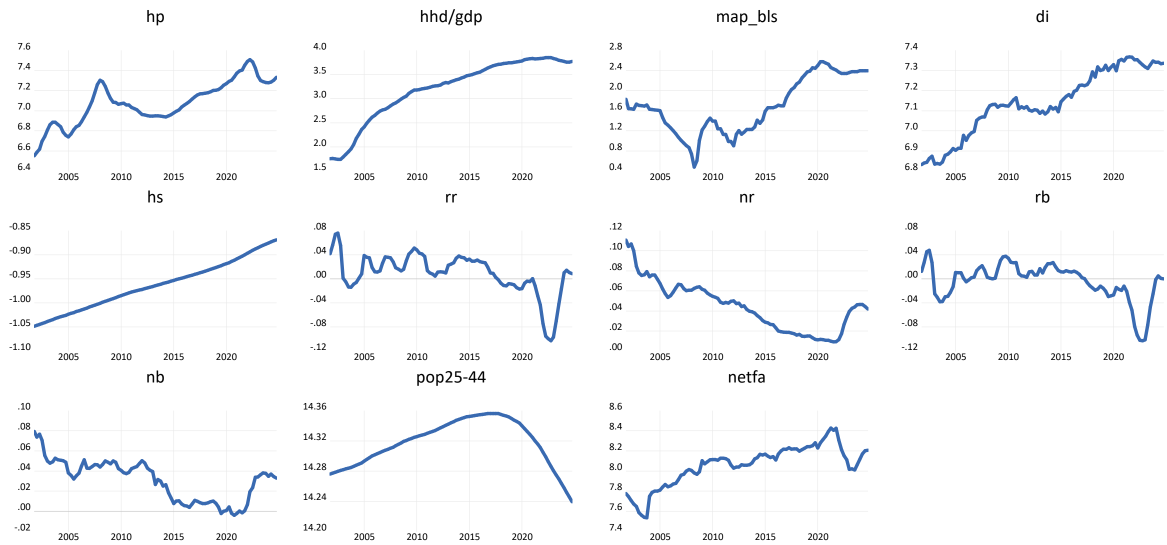
A. Data Description

Table 4: Summary of Time Series Variables Used in the Estimation

Variable	Description	Source	Sample	Transformation
hp_t	Real House Price Index Bratislava Region, EUR/m^2	NBS	2000Q4–2024Q4	SA, real, PC, log
hp_t^{SK}	Real House Price Index National, EUR/m^2	NBS	2000Q4–2024Q4	SA, real, PC, log
hhd_t/gdp_t	Household Debt to GDP Ratio	NBS, Eurostat	1995Q1–2024Q4	log ratio
map_t^{bls}	BLS-based macroprudential stance	NBS, ECB	1997Q2–2024Q4	log index
di_t	Real Disposable Income	SOSR	1995Q1–2024Q4	SA, real, PC, log
hs_t	Housing stock is the cumulative total of completed dwellings	SOSR	1996Q1–2024Q4	SA, real, PC, log
rr_t	Real Mortgage Interest Rate on New Loans	NBS	2004Q1–2023Q4	Percentage
nr_t	Nominal Mortgage Interest Rate on New Loans	NBS	2004Q1–2023Q4	Percentage
rb_t	Real government 10-year bond	Eurostat	2000Q4–2023Q4	Percentage
nb_t	Nominal government 10-year bond	Eurostat	2000Q4–2023Q4	Percentage
$pop_{25-44,t}$	Working age population	Eurostat	1991Q1–2023Q4	log number
$pop_{45-69,t}$	45-69 age cohort	Eurostat	1991Q1–2023Q4	log number
$netfa_t$	Real Net Financial Assets of Households	Eurostat	1995Q4–2023Q4	SA, real, PC, log

Notes: All series are quarterly. Transformations are applied to ensure stationarity and comparability. The seasonally adjusted (SA) series uses the JDemetra+ method. All variables are in real terms, having been deflated by the CPI and expressed as per capita (PC), divided by the total population, except for ratios, indices, and interest rates. Yearly time series were used to extend quarterly time series if available.
Sources: National Bank of Slovakia (NBS), Eurostat, Slovak Statistical Office (SOSR), European Central Bank (ECB), and author's calculations.

Figure 4: Variables Used in Estimation.



Sources: National Bank of Slovakia (NBS), Eurostat, Slovak Statistical Office (SOSR), European Central Bank (ECB), and author's calculations.

B. Unit Root Tests

Table 5: Unit Root Tests (Levels with Trend, First Differences with Intercept)

Variable	Levels (Trend + Int.)			First Diff. (Int.)			Conclusion
	ADF	PP	KPSS	ADF	PP	KPSS	
hp_t	-3.26*	-2.47	0.11	-4.61***	-3.93***	0.14	I(1)
hp_t^{SK}	-2.87	-2.36	0.13*	-4.38***	-4.35***	0.18	I(1)
hhd_t/gdp_t	-0.88	-1.28	0.30***	-0.59	-2.98**	1.02***	I(1)
map_t^{bls}	-1.94	-1.83	0.27***	-6.66***	-6.67***	0.31	I(1)
di_t	-2.26	-1.58	0.12*	-12.43***	-12.31***	0.20	I(1)
hs_t	-3.44*	-0.18	0.17**	-1.88	-2.94**	0.38*	I(1)
rr_t	-2.57	-2.94	0.15**	-4.17***	-5.27***	0.04	I(1)
nr_t	-0.30	-1.04	0.20**	-3.48**	-5.22***	0.54**	I(1)
rb_t	-2.51	-2.79	0.20**	-3.94***	-5.48***	0.04	I(1)
nb_t	-1.60	-1.45	0.14*	-7.37***	-7.43***	0.31	I(1)
$pop_{25-44,t}$	-0.86	5.27	0.29***	0.05	0.07	0.88***	mixed
$pop_{45-69,t}$	3.24*	-2.09	0.31***	-0.92	-0.92	1.07***	mixed
$netfa_t$	-2.90	-2.28	0.18**	-7.11***	-7.21***	0.06	I(1)

Panel Unit Root Test Summary (without hp_t^{SK}, nr_t, rb_t, nb_t, $pop_{45-69,t}$)

Levels (with trend and intercept):		
H0: Unit root (assumes common unit root process):		
Levin, Lin and Chu t* (p-value)	0.64	*(The null cannot be rejected)*
Breitung t-stat (p-value)	0.91	*(The null cannot be rejected)*
H0: Unit root (assumes individual unit root process):		
Im, Pesaran and Shin W-stat (p-value)	0.32	*(The null cannot be rejected)*
ADF - Fisher Chi-square (p-value)	0.23	*(The null cannot be rejected)*
PP - Fisher Chi-square (p-value)	0.91	*(The null cannot be rejected)*
First Differences (with intercept only):		
H0: Unit root (assumes common unit root process):		
Levin, Lin and Chu t* (p-value)	0.00	*(Reject the null)*
Breitung t-stat (p-value)	0.00	*(Reject the null)*
H0: Unit root (assumes individual unit root process):		
Im, Pesaran and Shin W-stat (p-value)	0.00	*(Reject the null)*
ADF - Fisher Chi-square (p-value)	0.00	*(Reject the null)*
PP - Fisher Chi-square (p-value)	0.00	*(Reject the null)*

Notes: ADF = Augmented Dickey-Fuller; PP = Phillips-Perron; KPSS = Kwiatkowski-Phillips-Schmidt-Shin. All level tests include trend and intercept; first differences include intercept only. KPSS null: stationarity; others: unit root. Panel unit root tests assume cross-sectional independence. Asterisks denote: *** 1%, ** 5%, * 10% significance levels.
Sources: Author's calculations based on data from Table 4.

C. Structural Break

To formally test for a structural break in the macroprudential policy equation, we apply the $l+1$ versus l test procedure proposed by Bai and Perron (1998), which integrates both global and sequential testing strategies. This approach first identifies the existence of structural break(s) globally and then estimates their number and precise timing. The test also corrects for potential serial correlation and heteroskedasticity in the residuals. Since we aim to identify a structural break(s) in the long-run macroprudential policy rule, only a few breaks are expected. We therefore allow for a maximum of two breaks and impose a 25% trimming parameter (approximately 23 quarters per regime) to ensure sufficient observations for stable estimation. The significance level is set at 1%, so only large and robust shifts are detected. In the test equation, the BLS-based macroprudential stance is regressed on household indebtedness, house prices, a linear trend, and a constant. The coefficient on house prices is assumed stable, reflecting its role as a long-run early-warning indicator, while the intercept and the debt coefficient are allowed to shift across regimes, consistent with the view that macroprudential tools target credit and leverage rather than prices.

Table 6: Structural Break Detection in the Macroprudential Policy Rule

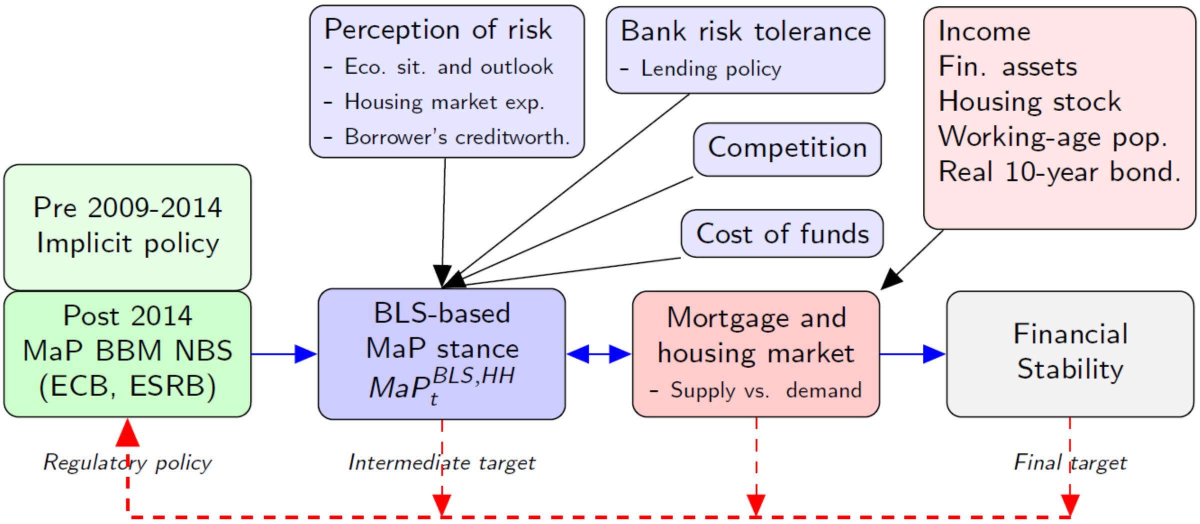
	Global tests				
Dependent variable: map_t^{bls} Regressors:	**Break Date(s)**	**UDmax**	**UDmax 1% Crit**	**WDmax**	**WDmax 1% Crit**
Breaking: $const, hhd_t/gdp_t$ Non breaking: $trend, hp_t$	2011Q3	283.32	14.34	283.32	15.41
Breaking: $const, hhd_t/gdp_t$ Non breaking: $trend, hp_t^{SK}$	2011Q3	270.77		270.77	

	Sequential tests		
Dependent variable: map_t^{bls} Regressors:	**Break Date(s)**	**F-stat**	**F-stat 1% Crit**
Breaking: $const, hhd_t/gdp_t$	2011Q3	141.66	14.34
Non breaking: $trend, hp_t$	2008Q4, 2014Q3	96.39	10.30
Breaking: $const, hhd_t/gdp_t$	2011Q3	135.38	14.34
Non breaking: $trend, hp_t^{SK}$	2008Q4, 2014Q3	84.97	10.30
Sample: 2001Q4-2024Q4 (93 obs.)			

Notes: Bai and Perron (1998) tests are based on the UDmax (WDmax) statistic and sequential F-statistics setting trimming value of 0.25, 1% significance level, and maximum number of two breaks. Break dates are reported when structural changes are statistically significant.
Sources: Author's computation.

D. Model Structure

Figure 5: Model Structure.



Sources: Author.

E. Complete Results: Long Run System

Table 7: Estimated VECM Results with Two Cointegrating Relationships and Long-Run Exogenous Variables

	(1)		(2)		(3)		(4)		(5)	
Cointegrating Restriction Test (LR)										
Gradually inserted and tested restrictions	Structural Identification		MaP rule: Dual Risk Channel		MaP rule: Policy calib.		MaP rule: Policy calib. (validation)		Robustness of the MaP rule: All restrictions imposed	
	$\beta_{1,hp} = 1$	$\beta_{2,map} = 1$	$\beta_{2,hp} = \beta_{2,hhd/gdp}$ $+\beta_{2,d11Q3*hhd/gdp}$		$\beta_{2,hp} = 1.5$		$\beta_{1,d11Q3*hhd/gdp}$ $= 0$			
	$\beta_{1,hhd/gdp} = 0$	$\beta_{2,di} = 0$	$\chi^2(1) = 0.276$		$\chi^2(2) = 0.410$		$\chi^2(3) = 0.429$		$\chi^2(3) = 2.826$	
			p-value = 0.60		p-value = 0.82		p-value = 0.93		p-value = 0.42	
Cointegrating Equations (β)										
hp_t (norm.)	1.000	0.755***	1.000	1.562***	1.000	1.500	1.000	1.500	1.000	1.500
	–	(0.172)	–	(0.140)	–	–	–	–	–	–
hhd_t/gdp_t	0.000	-0.611***	0.000	-0.818***	0.000	-0.816***	0.000	-0.806***	0.000	-1.628***
	–	(0.086)	–	(0.110)	–	(0.108)	–	(0.103)	–	(0.170)
map_t^{bls} (norm.)	0.119***	1.000	0.025	1.000	0.026	1.000	0.034**	1.000	-0.055***	1.000
	(0.030)	–	(0.025)	–	(0.025)	–	(0.016)	–	(0.019)	–
di_t	1.703***	0.000	1.486***	0.000	1.507***	0.000	1.510***	0.000	1.754***	0.000
	(0.160)	–	(0.129)	–	(0.125)	–	(0.089)	–	(0.242)	–
$dum_{\geq 11Q3}$ (exog.)	1.012**	-8.953***	-0.177	-7.412***	-0.230	-7.185***	-0.147***	-7.153***	-0.030	-10.466***
	(0.485)	(1.012)	(0.386)	(0.621)	(0.332)	(0.315)	(0.032)	(0.302)	(0.044)	(0.626)
$dum_{\geq 11Q3}\times$	-0.346***	2.786***	0.011	2.381***	0.025	2.316***	0.000	2.306***	0.000	3.128***
hhd_t/gdp_t (exog.)	(0.141)	(0.288)	(0.113)	(0.181)	(0.099)	(0.108)	–	(0.103)	–	(0.170)
hs_t (exog.)									-1.935**	18.345***
									(0.928)	(3.372)
rb_t (exog.)									-1.165***	7.927***
									(0.400)	(1.665)
$pop_{25-44,t}$ (exog.)									-2.240***	13.790***
									(0.544)	(2.638)
$netfa_t$ (exog.)									0.275**	-1.236**
									(0.138)	(0.528)
Adjustment Coefficients ($\alpha_{11,ECT1}, \alpha_{23,ECT2}$)										
$ECT1_{t-1}$, $ECT2_{t-1}$	-0.128***	-0.337***	-0.126***	-0.275***	-0.124***	-0.282***	-0.125***	-0.285***	-0.142***	-0.226***
	(0.037)	(0.062)	(0.042)	(0.051)	(0.042)	(0.051)	(0.042)	(0.053)	(0.036)	(0.029)
Short-Run Dynamics (Δ)										
	Δhp_{t-1}, $\Delta hhd_{t-1}/gdp_{t-1}$, Δmap_{t-1}^{bls}, Δdi_{t-1}									
	Δrr_t, Δrr_{t-1}, $\Delta netfa_t$, $\Delta netfa_{t-1}$, $dum_{=08Q2}$, $dum_{=10Q1}$, $dum_{=12Q2}$, $dum_{=21Q4}$, constant (exog.)									
Model Fit										
LogL	948.1876		948.0495		947.9830		947.9733		962.4557	
AIC	-18.8427		-18.8398		-18.8383		-18.8381		-18.9775	
VECM(1,1) Residual Diagnostics (based on AIC)										
Stability (next AR root), 2 AR roots=1	0.912		0.925		0.926		0.924		0.938	
ADF (AIC) Test for (t-Stat)										
$ECT1_t$	-4.680		-4.751		-4.505		-4.527		-3.505	
$ECT2_t$	-4.474		-4.357		-4.489		-4.461		-3.470	
VAR AR 1-4 LM Test (p-value)	0.30		0.30		0.29		0.30		0.56	
VAR JB Normality Test (p-value)	0.25		0.18		0.18		0.17		0.14	
VAR Hetero. Test (p-value)	0.19		0.21		0.20		0.20		0.28	
Sample: 2001Q4-2024Q4 (93 obs.)										

Notes: The VECM (1)–(4) includes four endogenous variables and two long-run exogenous dummy variables. In addition, the VECM (5) includes four long-run exogenous variables. Standard errors are in parentheses. Asterisks $^{***}/^{**}/^{*}$ denote statistical significance at the 1%/5%/10% level. For ease of interpretation, (norm.) denotes the variable used for normalisation (the left-hand-side variable), all other variables are reported on the right-hand side with signs adjusted accordingly.
Sources: Author's calculations.

F. Robustness Checks

F.1. Robustness of the Macroprudential Policy Rule

Table 8: Robustness of the Structural Break Date in the Macroprudential Policy Rule

Break Date	2009Q1	2009Q2	2009Q3	2009Q4	2010Q1	2010Q2	2010Q3	2010Q4
LR test (p-value)	0.35	0.39	0.26	0.02	0.15	0.15	0.92	0.67
Equal β coeff.	-1.53	-1.53	-1.53	-1.53	-1.57	-1.57	-1.61	-1.61
AR(1–4)	0.83	0.72	0.80	0.80	0.62	0.62	0.56	0.58
Normality	0.00	0.01	0.01	0.01	0.02	0.02	0.04	0.08
LogL	945.8546	947.6265	945.5135	948.9360	946.6000	946.6000	947.6523	943.6779
AIC	-18.7926	-18.8307	-18.7852	-18.8588	-18.8086	-18.8086	-18.8312	-18.7458
Break Date	2011Q1	2011Q2	2011Q3	2011Q4	2012Q1	2012Q2	2012Q3	2012Q4
LR test (p-value)	0.03	0.43	0.60	0.58	0.90	0.24	0.24	0.37
Equal β coeff.	-1.60	-1.59	-1.56	-1.48	-1.48	-1.36	-1.36	-1.37
AR(1–4)	0.40	0.35	0.30	0.45	0.56	0.57	0.57	0.68
Normality	0.08	0.15	0.18	0.18	0.20	0.25	0.25	0.22
LogL	948.1745	945.9478	948.0495	947.5793	945.7242	946.7429	946.7429	946.2332
AIC	-18.8425	-18.7946	-18.8398	-18.8297	-18.7898	-18.8117	-18.8117	-18.8007
Break Date	2013Q1	2013Q2	2013Q3	2013Q4	2014Q1	2014Q2	2014Q3	2014Q4
LR test (p-value)	0.15	0.24	0.82	0.92	0.97	0.88	0.60	0.68
Equal β coeff.	-1.26	-1.16	-1.24	-1.14	-1.03	-1.01	-1.26	-0.71
AR(1–4)	0.73	0.74	0.84	0.77	0.72	0.64	0.62	0.18
Normality	0.19	0.19	0.19	0.13	0.08	0.08	0.02	0.03
LogL	948.3991	946.4815	943.7887	943.6738	943.2859	940.9154	938.2956	941.3882
AIC	-18.8473	-18.8061	-18.7481	-18.7457	-18.7373	-18.6864	-18.6300	-18.6965

Notes: Same estimation specification as in column (2) of Table 2, with varying break dates.
Sources: Author's computation.

Table 9: LR Coefficients (β) in the Macroprudential Policy Rule and Their Associated Volatility During the Tightening Period (2014Q4–2020Q3)

Std. dev.		$\beta_{2,hhd/gdp}$				
		1.2	1.4	1.6	1.8	2.0
		$ECT2_t$				
$\beta_{2,hp}$	1.2	↑ **10.083**	7.628	5.151	↓ **3.358**	↓ **3.850**
	1.4	↑ **9.323**	6.840	4.655	↓ **3.773**	5.006
	1.6	↑ **8.642**	6.260	4.611	↓ **4.553**	6.087
	1.8	↑ **8.107**	6.024	4.938	5.423	7.039
	2.0	7.749	6.030	5.484	6.285	7.855
		$\Delta hhd_t/gdp_t$				
$\beta_{2,hp}$	1.2	↓ **0.557**	↓ **0.574**	0.598	0.625	↑ **0.648**
	1.4	↓ **0.566**	0.588	0.612	0.635	↑ **0.652**
	1.6	↓ **0.579**	0.601	0.622	0.64	↑ **0.651**
	1.8	0.591	0.611	0.628	0.64	↑ **0.645**
	2.0	0.600	0.616	0.628	0.635	0.637
		Δhp_t				
$\beta_{2,hp}$	1.2	↓ **0.240**	↓ **0.238**	0.317	0.448	0.599
	1.4	↓ **0.240**	0.304	0.424	0.567	0.716
	1.6	↓ **0.295**	0.402	0.537	0.679	↑ **0.817**
	1.8	0.384	0.508	0.643	0.777	↑ **0.900**
	2.0	0.482	0.608	0.736	↑ **0.858**	↑ **0.967**

Notes: Same estimation specification as in column (3) of Table 2, with varying LR coefficients (β) in the Macroprudential policy rule. The four largest (smallest) values are highlighted.
Sources: Author's computation.

F.2. Pure Fundamentals House Price Equation

In this section, we estimate the long-run relationship for house prices based exclusively on economic fundamentals, abstracting from financial variables such as household debt. Following the approach of Valderrama et al. (2023), Turk (2015), and Meen (2002), we model house prices as a function of structural and demographic factors. This contrasts with studies such as Anundsen and Jansen (2013), which emphasize the interaction between house prices and credit. The objective is to establish a baseline consistency check for the full system presented in other sections.

The VECM specification includes three endogenous variables: real house prices (hp_t), the BLS-based macroprudential stance (map_t^{bls}), and real disposable income (di_t). It also includes four long-run exogenous variables: the housing stock (hs_t), the real mortgage rate (rr_t) or, alternatively, the real ten-year government bond rate (rb_t), the working-age population aged 25 to 44 ($pop_{25\text{–}44,t}$), and real net financial assets ($netfa_t$). One cointegrating relationship is robustly detected. The short-run dynamics include exogenous controls such as first differences of real interest rates, changes in net financial assets, and dummy variables capturing crisis-related outliers (2008Q2, 2008Q4, 2012Q2) and two outliers related to disposable income series (2005Q4, 2018Q1).

Demographic variables are very persistent and standard unit root tests do not clearly separate I(1) from I(2) behaviour. For this reason we treat the log of the 25–44 cohort as a slow moving exogenous driver in the long run house price equation. We use this variable both in levels and in first differences.

The estimation results (see Table 10) align with theoretical expectations and remain robust across alternative specifications of long-run interest rates and short-run controls. Real disposable income and financial wealth put upward pressure on house prices by supporting housing demand. A larger housing stock is associated with lower house prices because it reflects greater supply. Higher real mortgage rates and tighter credit conditions, proxied by the BLS-based macroprudential stance, also reduce house prices. The estimated effect of macroprudential policy is relatively modest. This is expected, since structural supply-side factors, such as the physical housing stock, have a more persistent and dominant influence on house price dynamics.

The long-run income coefficient exceeds unity, which would imply an upward drift in the price-to-income ratio if income were the only determinant. Over our sample, however, financial deepening and declining real interest rates can shift the equilibrium price-to-income ratio upward, so it need not be stationary. Moreover, the cointegrating relation conditions on other slow-moving fundamentals (such as housing supply and demographics), so the price-to-income ratio alone is not the stationary object. This pattern is consistent with closely related European housing studies (Anundsen and Jansen, 2013; Turk, 2015).

In the baseline specification in column (1) of Table 10, both the size of the prime age population and the long term real interest rate enter the cointegrating relation in levels. This is consistent with the channel in Piergallini (2020). A 1% decline in the 25–44 cohort is associated with a 2.8% increase in the long run level of real house prices. Lower birth rates, slower growth in the 25–44 population, and higher life expectancy contribute to disinflation and lower real interest rates. These conditions support higher real house prices in the long run. The population variable may also capture the broader regime of low growth, low inflation, and low interest rates that characterises Slovakia and similar economies.

Adding an additional demographic variable, the population aged 45–69 as a proxy for repeat homebuyers, does not improve the model specification. While a larger cohort in this age group is plausibly associated with higher house prices through stronger housing demand, including another slow-moving demographic series materially affects the estimates of other slow-moving fundamentals. In particular, the coefficient on the BLS-based stance measure becomes unstable and can change sign, while the estimated effects of housing stock, the real bond rate, and the baseline demographic control shift in magnitude. This sensitivity is consistent with multicollinearity among highly persistent variables, which makes the long-run coefficients less precisely identified. For this reason, we exclude the 45–69 population variable from the preferred specifications.

Replacing the cohort level with its growth rate (column (2a) of Table 10), the demographic variable remains strongly significant and has the expected sign. A 0.1 percentage point decline in population growth is associated with an increase of about 4.2% in the long run level of real house prices. The long run real rate is no longer significant. This reflects the high correlation between demographic growth and real yields ($\rho \approx 0.7$). Both variables capture the same structural forces of lower potential growth and a lower natural real rate. In these specifications the demographic term absorbs the long run effect of interest rates on house prices, while interest rates still affect housing dynamics in the short run. When the long run real rate is removed from the cointegrating relation (column (2b) of Table 10), the results are very similar.

We decompose long term real interest rates into a demographic component and a non demographic residual.[11] In the long run house price equation in column (3) of Table 10, lower demographic growth significantly raises the equilibrium level of real house prices. This is consistent with the general equilibrium mechanism in Piergallini (2020). After we control for demographics, unusually low non demographic long run real rates are also associated with higher equilibrium house prices, although this effect is estimated with less precision. Taken together, these

[11]The ten year real bond yield is regressed on the growth rate of the 25–44 age cohort and the residual from this regression is taken as the non demographic component.

results support the view that demographic forces and non demographic financial conditions jointly shape the structural level of house prices.

When we use the national house price index in column (4) of Table 10, the results are consistent with the results for the Bratislava region. The main difference is data quality. The national series likely contains more measurement error and we could not control for outliers in the same way as in the regional model. In the residual diagnostics only the normality test is violated, while the other tests are satisfactory. Since the national index is highly correlated with the Bratislava index, the long run results remain very similar.

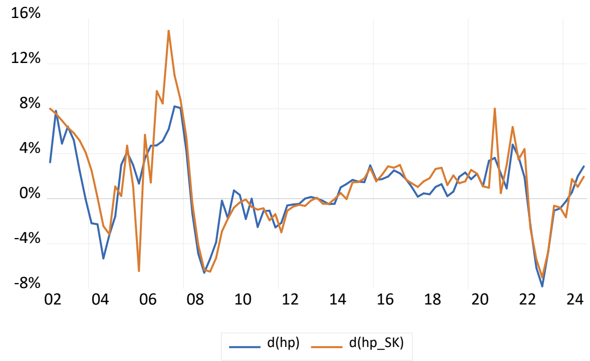
Table 10: Estimated VECM Results with One Cointegrating Relationship - Pure Fundamentals House Price Equation

	Dem. levels (1)	Dem. levels add. 45–69 (1a)	Dem. diffs. (2a)	Dem. diffs. wo LR IR (2b)	Dem. diffs. LR IR non dem. (3)	National Index (4)
Cointegrating Equation (β)						
hp_t (norm.)	1.000	1.000	1.000	1.000	1.000	
	–	–	–	–	–	
hp_t^{SK} (norm.)						1.000
						–
map_t^{bls}	-0.080***	0.114**	-0.092*	-0.087*	-0.149***	-0.134***
	(0.025)	(0.056)	(0.050)	(0.050)	(0.041)	(0.049)
di_t	1.927***	1.458***	2.072***	2.095***	2.163***	2.494***
	(0.266)	(0.293)	(0.419)	(0.419)	(0.365)	(0.459)
hs_t (exog.)	-2.879***	-26.243***	-3.434***	-3.435***	-3.682***	-3.363***
	(0.657)	(5.092)	(1.075)	(1.102)	(0.901)	(1.126)
rb_t (exog.)	-1.719***	-2.879***	-0.160			-2.146**
	(0.458)	(0.486)	(0.744)			(0.934)
rb_t^{nd} (exog.)					-0.845	
					(0.626))	
$pop_{25-44,t}$ (exog.)	-2.840***	-9.450***				-4.111***
	(0.455)	(1.392)				(0.792)
$d(pop_{25-44})_t$ (exog.)			-41.742***	-41.870***	-57.426***	
			(13.663)	(13.683)	(12.443)	
$pop_{45-69,t}$ (exog.)		16.567***				
		(3.603)				
$netfa_t$ (exog.)	0.212	0.160	-0.238	-0.256	-0.295	0.430
	(0.158)	(0.185)	(0.209)	(0.197)	(0.185)	(0.275)
Adjustment Coefficients ($\alpha_{1,ECT}$)						
ECT_{t-1}	-0.153***	-0.057**	-0.118***	-0.116***	-0.083**	-0.144***
	(0.032)	(0.027)	(0.027)	(0.026)	(0.034)	(0.032)
Short-Run Dynamics (Δ)						
	Δhp_{t-1}, Δmap_{t-1}^{bls}, Δdi_{t-1}					
	Δrr_t, Δrr_{t-1}, $\Delta netfa_t$, $\Delta netfa_{t-1}$ (exog.)					
	$dum_{=05Q4}$, $dum_{=08Q2}$, $dum_{=08Q4}$, $dum_{=12Q2}$, $dum_{=18Q1}$, constant (exog.)					
Model Fit						
LogL	655.2270	658.7610	647.0308	647.0207	643.4536	607.1601
AIC	-13.0371	-13.0916	-12.8609	-12.8822	-12.7840	-12.0034
VECM(1,1) Residual Diagnostics (based on AIC)						
Stability (next AR root), 2 AR roots=1	0.901	0.892	0.871	0.868	0.868	0.832
ADF (AIC) Test for ECT_t (t-Stat)	-4.308	-2.611	-4.899	-4.806	-5.837	-4.758
VAR AR 1-4 LM Test (p-value)	0.55	0.77	0.66	0.67	0.57	0.07
VAR JB Normality Test (p-value)	0.13	0.14	0.07	0.07	0.11	0.00
VAR Hetero. Test (p-value)	0.41	0.92	0.27	0.28	0.12	0.54
Sample: 2001Q4-2024Q4 (93 obs.)						

Notes: Standard errors are in parentheses. Asterisks ***, ** and * denote statistical significance at the 1%, 5% and 10% levels. rb_t^{nd} denotes the non demographic component of the ten year real interest rate. For ease of interpretation, (norm.) denotes the variable used for normalisation (the left-hand-side variable), all other variables are reported on the right-hand side with signs adjusted accordingly.
Sources: Author's calculations.

F.3. National House Price Index

Figure 6: Real House Price Index Bratislava Region vs. National (QoQ)



Sources: National Bank of Slovakia (NBS).

Table 11: Johansen Cointegration Test Results[a] - National House Price Index

Rank Hypothesis	Model with a Structural Break[b] Trace Stat.	1%/5% Crit.[c]	Rank
$H_0 : r = 0, H_A : r \geq 1$	139.83	91.10 / 82.50	
$H_0 : r \leq 1, H_A : r \geq 2$	79.27	64.66 / 57.32	2
$H_0 : r \leq 2, H_A : r \geq 3$	39.51	42.00 / 35.96	
VARX(2,2) Diagnostics			
Stability (roots <1)	Yes		
VAR AR 1-4 LM Test (p-value)	0.06		
VAR JB Normality Test (p-value)	0.01		
VAR Hetero. Test (p-value)	0.82		
Sample: 2001Q4-2024Q4 (93 obs.)			

[a] Endogenous variables: national real house prices (hp_t^{SK}), household indebtedness (hhd_t/gdp_t), the BLS-based macroprudential stance (map_t^{bls}), and real disposable income (di_t). Restricted variables: $dum_{\geq 11Q3}$, $dum_{\geq 11Q3} \times (hhd_t/gdp_t)$ and trend (t). In the robustness analysis rotating through the following restricted variables: housing stock (hs_t), real mortgage rate (rr_t), working-age population ($pop_{25-44,t}$), and real net financial assets ($netfa_t$). Unrestricted variables: Δrr_t, Δrr_{t-1}, $\Delta netfa_t$, $\Delta netfa_{t-1}$, quarterly dummies to control for outliers (06Q1, 06Q2, 06Q4, 07Q2, 08Q2, 10Q1, 21Q1, 21Q2, 22Q3), and a constant
[b] The structural break is captured via a post-2011Q3 level shift dummy and a slope dummy for debt.
[c] Critical values are obtained from Table 13 in Doornik (2003) - with 4 endogenous variables and 2 exogenous variables.
Sources: Author's computation.

Table 12: Estimated VECM Results with Two Cointegrating Relationships - National House Prices Index

	(1)		(2)		(3)		(4)	
Cointegrating Restriction Test (LR)								
Gradually inserted and tested restrictions in column (3) and (4)	Structural Identification		MaP rule: Dual Risk Channel		MaP rule: Policy calib. debt emphasis		MaP rule: Policy calib. (validation)	
	$\beta_{1,hp} = 1$ $\beta_{1,hhd/gdp} = 0$	$\beta_{2,map} = 1$ $\beta_{2,di} = 0$	$\beta_{2,hp} = \beta_{2,hhd/gdp}$ $+\beta_{2,d11Q3*hhd/gdp}$		$\beta_{2,hhd/gdp} + \beta_{2,d11Q3*hhd/gdp}$ $= 1.5 * \beta_{2,hp}$		$\beta_{1,d11Q3*hhd/gdp}$ $= 0$	
			$\chi^2(1) = 1.046$		$\chi^2(1) = 0.630$		$\chi^2(2) = 0.652$	
			p-value = 0.31		p-value = 0.43		p-value = 0.72	
Cointegrating Equations (β)								
hp_t^{SK} (norm.)	1.000	0.460***	1.000	1.208***	1.000	0.982	1.000	0.981
	–	(0.117)	–	(0.112)	–	(0.087)	–	(0.080
hhd_t/gdp_t	0.000	-0.476***	0.000	-0.759***	0.000	-0.676***	0.000	-0.686***
	–	(0.082)	–	(0.117)	–	(0.104)	–	(0.102)
map_t^{bls} (norm.)	0.300***	1.000	0.017	1.000	0.070	1.000	0.050*	1.000
	(0.056)	–	(0.047)	–	(0.048)	–	(0.030)	–
di_t	2.519***	0.000	2.060***	0.000	2.151***	0.000	2.146***	0.000
	(0.276)	–	(0.221)	–	(0.227)	–	(0.184)	–
$dum_{\geq 11Q3}$ (exog.)	2.677***	-8.339***	-0.535	-6.191***	0.081	-6.853***	-0.112**	-6.875***
	(0.865)	(0.799)	(0.677)	(0.589)	(0.710)	(0.608)	(0.054)	(0.554)
$dum_{\geq 11Q3}\times$	-0.834***	2.557***	0.127	1.967***	-0.057	2.149***	0.000	2.157***
hhd_t/gdp_t (exog.)	(0.254)	(0.229)	(0.200)	(0.178)	(0.209)	(0.181)	–	(0.165)
Adjustment Coefficients ($\alpha_{11,ECT1}, \alpha_{23,ECT2}$)								
$ECT1_{t-1}$, $ECT2_{t-1}$	-0.063**	-0.389***	-0.046	-0.275***	-0.051*	-0.303***	-0.050*	-0.295***
	(0.026)	(0.076)	(0.029)	(0.049)	(0.028)	(0.055)	(0.028)	(0.053)
Short-Run Dynamics (Δ)								
	Δhp_{t-1}^{SK}, $\Delta hhd_{t-1}/gdp_{t-1}$, Δmap_{t-1}^{bls}, Δdi_{t-1}							
	Δrr_t, Δrr_{t-1}, $\Delta netfa_t$, $\Delta netfa_{t-1}$, constant (exog.)							
	$dum_{=06Q1}$, $dum_{=06Q2}$, $dum_{=06Q4}$, $dum_{=07Q2}$, $dum_{=08Q2}$, $dum_{=10Q1}$, $dum_{=21Q1}$, $dum_{=22Q2}$, $dum_{=22Q3}$ (exog.)							
Model Fit								
LogL	946.8340		946.3109		946.5193		946.5080	
AIC	-18.3835		-18.3723		-18.3768		-18.37685	
VECM(1,1) Residual Diagnostics (based on AIC)								
Stability (next AR root), 2 AR roots=1	0.881		0.883		0.879		0.878	
ADF (AIC) Test for (t-Stat)								
$ECT1_t$	-3.857		-3.628		-3.646		-3.609	
$ECT2_t$	-4.235		-4.178		-4.063		-4.077	
VAR AR 1-4 LM Test (p-value)	0.25		0.22		0.22		0.22	
VAR JB Normality Test (p-value)	0.02		0.02		0.02		0.02	
VAR Hetero. Test (p-value)	0.22		0.12		0.13		0.13	
Sample: 2001Q4-2024Q4 (93 obs.)								

Notes: The VECM (1)–(4) includes four endogenous variables and two long-run exogenous dummy variables. Standard errors are in parentheses. Asterisks $^{***}/^{**}/^{*}$ denote statistical significance at the $1\%/5\%/10\%$ level. For ease of interpretation, (norm.) denotes the variable used for normalisation (the left-hand-side variable), all other variables are reported on the right-hand side with signs adjusted accordingly.
Sources: Author's calculations.

G. Short Run Dynamics

Short-run regressors were selected using the AutoGets procedure, which applies an automated general-to-specific (GETS) reduction based on Hendry and Nielsen (2012). Starting from a general model, statistically insignificant variables are iteratively removed while maintaining diagnostic validity. Model selection is guided by the Schwarz information criterion (SIC) to ensure parsimony. The use of four selection blocks (three for $\Delta map_t^{\mathrm{BLS}}$) indicates that the regressors were evaluated in sequential subsets to enhance search efficiency and model stability (see columns (1)–(3) of Table 13). As a robustness check for the short-run $\Delta map_t^{\mathrm{BLS}}$ equation, the Swapwise algorithm with the "minimum R^2 increment" criterion was also employed, iteratively adding and swapping regressors to minimize redundant explanatory power and identify a globally optimal specification with the most efficient variable set (see column (4) of Table 13) until an insignificant regressor was added.

The short-run equations are estimated individually rather than system-wide. Once the long-run cointegration structure has been imposed, the VECM framework ensures system coherence while enabling the short-run dynamics to be consistently estimated on an equation-by-equation basis. As all endogenous variables only enter through their lagged differences, feedback between equations is limited contemporaneously, making separate estimation statistically consistent and practically efficient. System-wide estimation would only offer marginal efficiency gains, but would substantially increase complexity given the heterogeneous regressor sets and automatic model selection procedures applied.

Table 13: Short-Run Dynamics

	(1)	(2)	(3)	(4)
Cointegrating Equations (β)				
$ECT1^{+}/^{-}$: Pos. / Neg. House Price Gap $ECT2^{+}/^{-}$: Pos. / Neg. Long-Run MaP Rule Gap				
Variable selection method	AutoGets Δhp_t	AutoGets $\Delta hhd_t/gdp_t$	AutoGets Δmap_t^{bls}	Swapwise Δmap_t^{bls}
Adjustment Coefficients (α)				
$ECT1^{+}_{t-1}$			-0.934***	-1.106***
			(0.135)	(0.131)
$ECT1^{+}_{t-2}$	-0.153***	0.179***		
	(0.026)	(0.035)		
$ECT1^{-}_{t-5}$	0.163*			
	(0.062)			
$ECT1^{-}_{t-6}$	-0.184**			
	(0.058)			
$ECT2^{+}_{t-2}$			-0.049	-0.121**
			(0.059)	(0.051)
$ECT2^{+}_{t-4}$		-0.033**		
		(0.011)		
$ECT2^{-}_{t-1}$		0.044***		
		(0.011)		
$ECT2^{-}_{t-1} \times dum_{\geq 11Q3}$		0.042**		
		(0.014)		
$ECT2^{-}_{t-2}$			-0.408***	-0.415***
			(0.037)	(0.035)
Short-Run Dynamics (Δ)				
$Uncertainty_{t-2}$			1.142**	1.128**
			(0.469)	(0.453)
Δhp_{t-1}	0.769***			
	(0.051)			
$\Delta hhd_{t-1}/gdp_{t-1}$		0.612***	1.374***	1.285***
		(0.065)	(0.325)	(0.306)
$\Delta hhd_{t-4}/gdp_{t-4}$		0.155		
		(0.065)		
$\Delta hhd_{t-5}/gdp_{t-5}$			-1.518***	-1.990***
			(0.319)	(0.370)
$\Delta hhd_{t-6}/gdp_{t-6}$	0.115			0.866*
	(0.052)			(0.318)
$\Delta hhd_{t-6}/gdp_{t-6} \times dum_{\geq 11Q3}$			1.701*	
			(0.593)	
$\Delta map^{bls}_{t-3} \times dum_{\geq 11Q3}$				0.257
				(0.099)
Δmap^{bls}_{t-4}			0.257***	0.308***
			(0.064)	(0.059)
Δrr_t		-0.726***		
		(0.115)		
Δrr_{t-1}	0.421**			
	(0.125)			
Δrr_{t-3}				-1.371**
				(0.469)
constant (exog.)	0.003	0.008***	-0.005	0.006
	(0.002)	(0.002)	(0.012)	(0.009)
Quarterly dummies	$dum_{=08Q2}$, $dum_{=10Q1}$, $dum_{=12Q2}$, $dum_{=21Q4}$			
Model Fit				
Adj.R^2	0.837	0.802	0.725	0.760
LogL	274.1921	287.9842	150.7733	157.8899
AIC	-5.7844	-5.9351	-3.1672	-3.2848
Residual Diagnostics				
Serial Corr. 1-4 LM Test (p-value)	0.15	0.53	0.25	0.86
JB Normality Test (p-value)	0.97	0.66	0.58	0.88
White Hetero. Test (p-value)	0.41	0.47	0.47	0.49
VIF (max value)	3.55	2.98	2.90	4.21
T (Obs.)	91	93	87	87
Original Sample:	2001Q4-2024Q4 (93 obs.)			

Notes: Standard errors are in parentheses. Asterisks ***/**/* denote statistical significance at the 1%/5%/10% level. Shaded coefficients and ***/**/* reflect post-selection adjusted p-values following Benjamini and Yekutieli (2005).
Sources: Author's calculations.