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THE DYNAMICS BEHIND INTEREST RATE ADJUSTMENT: EVIDENCE FROM BAYESIAN MODEL AVERAGING

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Abstract. *This study investigates the speed of interest rate pass-through using a uniquely compiled dataset drawn from existing empirical studies. The main objective is to identify the factors driving heterogeneity in the adjustment speed reported across the literature. To this end, the analysis employs Bayesian Model Averaging to identify the model specification that best explains the observed variation in pass-through estimates. The robustness of the results is further assessed using OLS estimation. In addition, publication selectivity is examined through basic regression models to detect potential biases arising from study design and publication characteristics. The results reveal substantial variation in the distribution of adjustment speeds across studies, driven by a wide range of methodological, publication-related, and macro-financial factors. These findings suggest that the dynamics of interest rate adjustment are highly context-dependent and sensitive to both structural and institutional conditions. Overall, the analysis contributes to the literature by providing new meta-analytical evidence on the determinants of adjustment speed within the interest rate transmission channel and highlights the need for further research incorporating additional determinants and more advanced econometric techniques.*

Keywords: *speed of adjustment, Bayesian techniques, pass-through, publication selectivity.*

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Introduction

Meltzer (2001) characterizes the transmission mechanism as the process through which monetary policy decisions generally impact the economy, with specific attention paid to their influence on the price level. The interest rate channel of monetary policy represents one of the key mechanisms of transmission through which central banks influence the real economy. Through this channel, decisions regarding changes in central bank policy rates are transmitted to bank interest rates for both lending and deposit activities. These decisions have a fundamental impact on debt servicing costs, returns on savings, asset valuations, and overall economic activity.

Since this channel operates in a two-stage framework, commercial banks set their individual interest rates based on the central bank's policy rate, but with the addition of a markup. The magnitude of this markup depends on several factors, including banks' willingness to lend, the level of credit risk, their balance sheet conditions, and the macroeconomic environment of the respective country. Given that the financial and economic conditions of banks and countries differ, these markups inevitably vary across institutions.

A highly effective transmission channel is foundational for translating monetary policy intentions into outcomes for economic agents and for securing macroeconomic targets. This smooth policy conveyance is crucial for central banks and is also essential to financial system participants who require stable and predictable economic conditions. The transmission process is typically assessed in the empirical literature through two key indicators: the degree and the speed of interest rate pass-through. The degree of pass-through reflects the extent to which changes in central bank policy rates are transmitted to commercial bank lending and deposit rates, whereas the speed of pass-through measures how quickly bank rates adjust to a new long-run equilibrium following a change in policy rates.

Empirical evidence confirms that both the pass-through and speed of adjustment indicators exhibit substantial heterogeneity, which is attributable to numerous factors. These include international and market-specific differences (Gori, 2018; Andries et al., 2025), alongside the distinct characteristics of individual banking products (Holmes et al., 2015; Stanisławska, 2015; Heckmann and Moertel, 2020). Furthermore, major external shocks, such as the global financial crisis and the ensuing zero lower bound period, have intensified these cross-country disparities. Consequently, monetary authorities require a thorough understanding of these dynamics to effectively guide economic activity.

The following chapter provides a detailed examination of the current state of research on the interest rate transmission mechanism, drawing on existing studies that directly address this channel as well as meta-analyses that have so far investigated it in a comprehensive manner. This chapter offers an in-depth analysis of the methodological approaches, analytical techniques, and empirical procedures employed in the literature, while identifying the key factors that influence the functioning and effectiveness of the transmission channel.

Literature Review

Within the literature review, we focus primarily on the technical characteristics of the individual studies, such as methodological approaches and types of data used, rather than on their empirical results. These aspects were crucial in determining the selection of variables for the meta-analytical research.

Spanning more than nine decades, the interest rate channel of monetary policy transmission remains a prominent topic in economic discourse. Mishkin (1995) emphasizes that the interest rate transmission channel is regarded as one of the most traditional mechanisms within monetary policy, with its importance having grown in recent years due to the exclusive reliance on monetary authorities for inflation stabilization. Earlier studies examined the interest rate transmission channel using relatively simple modelling approaches, with particular attention paid to external shocks that disrupted equilibrium. Cottarelli et al. (1995) confirmed that a higher level of competition increases the intensity of interest rate pass-through. Similarly, Borio and Fritz (1995) emphasized that monetary system stability and market competition are key factors contributing to the transmission process.

The global financial crisis of 2008 gave rise to a new wave of studies. Yüksel and Özcan (2012) and Ahmad et al. (2013) investigated fluctuations in the speed and degree of pass-through within the interest rate transmission channel as a result of the crisis. Liu et al. (2016) examined the impact of the global financial crisis on retail interest rate pass-through in Australia, finding that the crisis led to higher lending rate markups and a decline in both short- and long-term pass-through, as banks adjusted more slowly and asymmetrically to changes in funding costs. Darracq Pariès et al. (2014) examined the cross-country heterogeneity in retail bank lending rates in the euro area, incorporating a wide range of factors such as borrower riskiness, lender balance sheet constraints, and sovereign debt tensions affecting interest rate-setting behaviour. A common feature of these studies is their reliance on Error Correction Models (ECM), which often suffer from biased results concerning cointegration relationships due to misspecification. Consequently, several contemporary studies adopted Vector Autoregressive (VAR) models to capture dynamic interactions. For example, Gori (2018) and Papadamou and Markopoulos (2018) analysed pre- and post-crisis periods across euro area countries, both reaching similar conclusions regarding the slowdown of interest rate pass-through across different categories of loan products.

Following the introduction of low interest rates and unconventional monetary policy measures, new research integrated shadow interest rates and other indicators such as Quantitative Easing (QE) and Credit Easing (CE) into the analysis. Blot and Labondance (2022) examined the influence of unconventional monetary policy measures on retail bank interest rates in the Euro Area during periods when the policy rate reached the effective lower bound. Their study utilized a panel Error Correction Model to analyse the impact of various balance-sheet policies implemented by the ECB. The findings indicated that unconventional measures, particularly liquidity provisions and covered bond purchase programmes, affected banking interest rates beyond the traditional pass-through of current and expected policy rates. Fungáčová et al. (2023), employing panel modelling and the local projections approach, investigated both standard and non-standard monetary measures such as Targeted Longer-Term Refinancing Operations (TLTROs) and QE. Their findings suggest that pass-through was generally weakened during the prolonged period of low or even negative interest rates.

From the perspective of data type, the empirical literature can be divided into two main groups: those using micro-level bank data (e.g. Kitamura et al., 2015; Holmes et al., 2015; Basten and Mariathasan, 2023) and those using aggregated bank data (e.g. Egert et al., 2007; Şahin and Çiçek, 2018; Bernhofer and van Treeck, 2013).

Another strand of research has examined whether interbank interest rates accurately reflect banks' marginal funding costs. The global financial and sovereign debt crises led to declining trust in the banking system, increased uncertainty in interbank markets, and funding difficulties for banks, causing lending spreads to widen and no longer fully reflect movements in reference rates. As a result, studies such as Illes et al. (2019) and Varga (2021) introduced a new measure — the Weighted Average Cost of Liabilities (WACL) — to better capture banks' actual funding costs. Their findings indicate that this measure more accurately reflects the true cost of bank financing and maintains a more stable long-run relationship with commercial bank rates.

The most recent literature (Kerola et al., 2024; Beyer et al., 2024; Byrne and Foster, 2023) has sought to reassess the interest rate transmission mechanism considering recent events, including the COVID-19 crisis and the end of the zero lower bound era. These studies typically employ advanced econometric methods, large cross-country samples, and a broad set of determinants. However, many of them present results in a format unsuitable for inclusion in meta-analysis, either due to missing statistical information or incompatible data presentation.

Previous meta-analyses have partially succeeded in gathering comprehensive evidence in this area. Gregor et al. (2020) focus on the symmetric pass-through of interest rates, covering studies published up to 2017, while Iorngurum (2024) examines asymmetric pass-through degree using a Bayesian framework. Nevertheless, an important research gap remains — a lack of comprehensive investigation into the speed of adjustment coefficients within interest rate pass-through models, which have received relatively little attention in the literature. Therefore, the following section presents the entire process of data collection and analysis aimed at exploring the speed of interest rate transmission.

Methods

An essential component of any meta-analysis is the independent and systematic collection of data from relevant primary studies. To begin this process, the Google Scholar database was primarily used, as it provides extensive access to academic and scientific literature. Given that the speed of adjustment is a key parameter of the interest rate transmission channel and is typically estimated alongside the interest rate pass-through, the keywords "interest rate pass-through" and "interest rate transmission" were employed for the search. To manage the volume of articles and ensure the quality of the dataset, selected studies had to meet several specific criteria. Only studies published from 2017 onwards were considered to capture recent developments, following the scope of the previous meta-analysis by Gregor et al. (2020). Furthermore, the study was required to report the speed of adjustment to the long-run equilibrium. Crucially, the article had to provide necessary statistics, such as standard errors, to facilitate subsequent analysis of publication bias. Finally, to ensure uniformity and reduce comparison errors, estimates had to be original numerical results reported directly by the authors, avoiding replications or results cited from other sources, and all core results had to be presented as elasticities.

The final resulting dataset, after cleaning for duplicates and irrelevant studies, comprises 36 primary studies that collectively yield 459 independent estimates of the speed of adjustment coefficient. Data collection was finalized on July 8, 2024. The data were collected in collaboration between two researchers to ensure research quality and minimize potential errors. Summary statistics, including both weighted and unweighted average values of the speed of adjustment estimates, are briefly outlined in Table A1. Additionally, Figure A1 provides a forest plot diagram across all included studies. The plot illustrates the variability of the various estimates, including their corresponding confidence intervals. The distribution of these estimates emphasizes that the underlying true effect is likely heterogeneous and conditional on the specific attributes of each study. To thoroughly examine the observed heterogeneity in the reported estimates, 34 explanatory variables were compiled, falling into four main categories: data and methodological variables, estimation variables, publication variables, and macro-financial variables.

The empirical analysis was conducted in two primary stages: publication bias analysis and Bayesian Model Averaging (BMA) estimation. A critical aspect of any robust meta-analysis is addressing publication bias, a systematic issue in the academic process. This bias stems from the disparity between the originally obtained results and those results which successfully reach publication. Due to a tendency toward selective reporting, journals frequently favour outcomes demonstrating strong statistical significance or large effect magnitudes. Consequently, estimates that align with theory but exhibit weaker statistical power or smaller effect sizes are often minimized or withheld from final reports, thus contributing to the selective distortion of the literature. Such selective practices frequently incentivize researchers to align their reported results with existing conventional findings in the literature. Existing meta-studies, such as those by Gregor et al. (2020) and Iornguruma (2024), confirm that estimates concerning the interest rate transmission channel are not exempt from this bias.

The analysis of publication bias encompasses both a graphical assessment and several fundamental empirical tests. The graphical component utilizes a funnel plot, which is presented in the Figure1 in the Results section. This plot serves as an initial visual check of a core assumption in publication bias analysis: the independence of effect size and its precision. The funnel plot is a scatter plot, which demonstrates the collected effect sizes from individual articles comparing a measure of individual study sizes (Rothstein et al, 2005). In the complete absence of publication bias, the plot should exhibit a symmetrical, inverted funnel shape. Conversely, an asymmetrical funnel plot is indicative of potential publication bias.

Regarding the empirical assessment, several regression-based tests are utilised, which rely on the same core assumption as the graphical analysis: the independence of the effect size and the standard error. The first approach involves the Precision Effect Test and Funnel Asymmetry Test (FAT-PET) framework. This model allows for the detection of publication bias, where an absolute value greater than 2 is typically interpreted as indicating significant bias, while lower values suggest only minor distortion. Additionally, the Precision Effect Estimate with Standard Error (PEESE) test is included, which is distinct from the FAT-PET model as it does not assume a linear relationship between the estimated effect and its precision. Furthermore, the Weighted Average of Adequate Power (WAAP) test proposed by Ioannidis et al. (2017) is applied. This test minimizes the influence of less precise studies by calculating a weighted average of results, thereby mitigating potential reporting bias effects. In line with the recommendations of Iornguruma (2024) and Irsova et al. (2023), the tests are estimated using instrumental variables. These instruments are constructed from the inverse of the sample size used in the original studies. This instrumental variable approach is implemented to reduce the issue of precision hacking and, consequently, to enhance the robustness of the resulting estimates.

The reasons for the variation in effect sizes across individual studies are analysed using Bayesian Model Averaging (BMA). BMA is a robust meta-regression technique that effectively addresses model uncertainty by evaluating a wide range of potential model specifications simultaneously. The estimation is based on the Markov Chain Monte Carlo (MCMC) process using the Metropolis-Hastings algorithm (Brooks et al., 2011). Using this method, the following regression equation was estimated:

$$SoA_{i,j} = \beta_0 + \beta_1 SE_{e,y} + \beta_2 Z_{e,y} + \varepsilon_{e,y} \tag{1}$$

where $SoA_{i,j}$ denotes the effect size for the e-th observation in study y, $SE_{e,y}$ demonstrates the individual standard error, $Z_{e,y}$ denotes the group of determinants, $\varepsilon_{e,y}$ represents an error term, β_1 the magnitude of publication bias, β_2 the coefficients for the study-level characteristics. The following chapter presents the findings from the BMA analysis, complemented by Ordinary Least Squares (OLS) robustness checks. The BMA results utilize two key metrics, such as the Posterior Mean and Standard Error and the Posterior Inclusion Probability (PIP). A regressor is considered inconclusive if its PIP value is less than 0.50. Evidence becomes weakly significant when the PIP falls between 0.50 and 0.75. A regressor could be categorized as substantially significant when the PIP ranges from 0.75 up to 0.95. Furthermore, a PIP value between 0.95 and 0.99 indicates the regressor is strongly significant. Finally, a regressor is deemed decisively significant when its Posterior Inclusion Probability is 0.99 or higher (Amini and Parmeter, 2011).

Results

This section outlines the graphical and empirical findings from the publication bias analysis, followed by the results of the BMA regression model and its associated robustness checks.

Figure 1 presents the funnel plot for speed of adjustment coefficients across the included studies. The black dots denote individual estimates plotted against the inverse of their standard errors, and the black vertical line represents the mean effect size. The constructed funnel plot indicates a pronounced asymmetry in the distribution of individual study estimates. Although the distribution of estimates comprises solely negative values, the absence of a clearly defined funnel shape further indicates a substantial risk of publication bias. Moreover, the asymmetric form of the funnel implies potential selective reporting practices within certain studies, leading to the publication of inflated and less precise results. Consequently, the assumption of independence between the effect size and the standard error appears to be violated. These findings are additionally verified through several empirical tests, which were mentioned in the previous section.

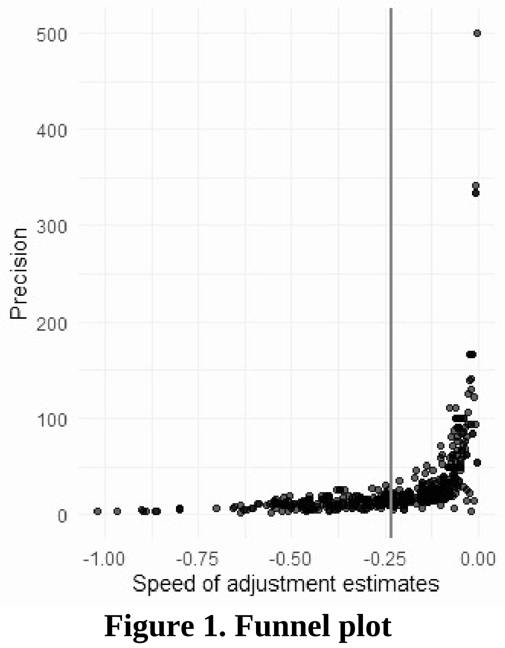

Figure 1. Funnel plot

Source: own elaboration

Results from the linear and nonlinear regression-based tests are presented in Table 1. The empirical findings are consistent with the conclusions drawn from the graphical inspection of the funnel plot. The estimated publication bias, as indicated by the FAT-PET and PEESE tests, exceeds the absolute value of 2, providing evidence of substantial publication bias. Furthermore, the effect size after correcting for potential publication bias is considerably lower for all three tests compared to the average value reported in Table A1.

Table 1. Results of the publication bias tests

Method	FAT-PET	PEESE	WAAP
Effect size	-0.085 (0.021)***	-0.189 (0.025)***	-0.084 (0.022)***
Publication bias	-2.069 (0.382)***	-4.235 (1.462)**	-

Note: *SoA denotes speed of adjustment. Standard errors are clustered at study level. Effect size means the values of the effect size after checking for publication bias. Standard errors are presented in parentheses. ***, **, and * correspond to p-values of ≤ 0.001, ≤ 0.01, and ≤ 0.05.*

Source: own elaboration

The examination of the sources of heterogeneity included in the 34 explanatory variables is presented in Table 2. The columns PIP and BMA report the results of the BMA analysis, including Posterior Means and their standard errors, while the columns OLS and p-value display the outcomes of the robustness checks. Variables with a posterior inclusion probability exceeding 0.5 are highlighted in bold. For the best-performing model, a total of 16 significant variables were identified.

The significance of the standard error is a common finding in many meta-analyses, including Iorngurum (2024), Bajzik et al. (2023), and Ehrenbergerová et al. (2022), indicating the persistent presence of publication selectivity even after controlling for heterogeneity.

Among the category of data and methodology variables, the Panel data, Cross-country estimates, and error correction model (ECM) are found to be significant. Studies using panel data or examining several countries at once tend to publish smaller values of the speed of returning toward new equilibrium compared to single county analyses. This pattern may arise for several reasons. Studies covering multiple countries often aggregate cross-country differences, thereby smoothing out national idiosyncrasies. In addition, analyses based on panel datasets combine information across countries and over time, which can blur national characteristics and lead to less accurate estimates of how quickly rates adjust. On the other hand, the ECM variable exhibits a stronger negative effect on the estimated speed of adjustment. This finding suggests that studies employing the ECM tend to report higher adjustment speeds. However, these results should be interpreted with caution, as approximately 97 percent of the SoA estimates in our sample were obtained using the ECM approach, which may introduce bias into our findings.

Within the category of estimation variables, nearly all variables were found to be statistically significant. Studies utilizing the money market rate, NFC rate, or rate on other loans tend to report higher estimates of the SoA. However, the largest effect was observed for the variable average of all rates, where the results were approximately 33 percent higher. This outcome may be attributed to the fact that average interest rates tend to aggregate the effects of different loan-specific rates into a single composite measure, thereby losing the distinctive characteristics associated with individual interest rate categories.

Additional sources of heterogeneity were identified among the publication-related variables, specifically Journal, Central bank, and World Bank. All of these determinants exhibit small negative effects on the estimated speed of adjustment, implying that results tend to be slightly higher when the study is published in a peer-reviewed journal or when the authors are affiliated with a central bank or the World Bank.

Significant sources of heterogeneity were also identified among the macro-financial variables. While development status and inflation rate tend to increase the estimated speed of adjustment, market capitalization, exchange rate targeting, and unemployment rate are associated with lower SoA estimates.

Table 2. Results of the BMA analysis and robustness check

Categories	Variables	PIP	BMA	OLS	p-value
	Intercept	1.000	-0.001 (NA)	0.052 (0.069)	0.454
	Standard error	**1.000**	**-1.239 (0.097)**	-2.366 (0.292)	0.000
Data and methodology	Panel data	**0.914**	**0.085 (0.033)**	-0.049 (0.039)	0.217
	Micro data	0.077	0.002 (0.005)		
	Cross country estimates	**0.999**	**0.128 (0.031)**	0.050 (0.035)	0.156
	Monthly data	0.082	-0.002 (0.015)		
	System of equations	0.093	-0.001 (0.009)		
	ECM	**0.999**	**-0.235 (0.034)**	-0.093 (0.048)	0.062
	Time span	0.219	0.001 (0.002)		
Estimation	Money market rate	**0.901**	**-0.090 (0.037)**	0.016 (0.036)	0.657
	Consumer rate	0.122	0.003 (0.018)		
	NFC rate	**0.949**	**-0.069 (0.021)**	-0.064 (0.020)	0.003
	Mortgage rate	0.122	0.004 (0.017)		
	Rate on the other loans	**0.897**	**-0.045 (0.022)**	-0.084 (0.041)	0.047
	Average of all rates	**1.000**	**-0.329 (0.038)**	-0.182 (0.048)	0.001
Publication	Journal	**0.999**	**-0.146 (0.026)**	0.005 (0.031)	0.862
	Top journal	0.074	-0.001 (0.006)		
	Publication year	0.171	-0.001 (0.003)		
	University	0.119	-0.006 (0.023)		
	Bank	0.070	-0.001 (0.007)		
	Central bank	**0.981**	**-0.059 (0.016)**	0.013 (0.031)	0.862
	IMF	0.182	0.017 (0.050)		
	World bank	**0.767**	**-0.061 (0.042)**	-0.064 (0.028)	0.029
Macro-financial	Import openness	0.284	-0.046 (0.094)		
	Development status	**0.959**	**-0.157 (0.045)**	-0.058 (0.032)	0.075
	Market capitalization	**0.903**	**0.201 (0.076)**	0.054 (0.053)	0.314
	Gross domestic product	0.074	-0.007 (0.142)		
	Inflation rate	**0.962**	**-0.378 (0.130)**	-0.039 (0.304)	0.899
	Bank concentration	0.164	-0.011 (0.043)		
	Credit risk	0.270	-0.003 (0.188)		
	Inflation targeting	0.217	0.012 (0.030)		
	Exchange targeting	**0.989**	**0.263 (0.051)**	0.070 (0.033)	0.041
	Unemployment	**0.865**	**0.834 (0.409)**	-0.293 (0.479)	0.545
	CB independence	0.171	0.015 (0.049)		
	Financial depth	0.121	0.005 (0.023)		

Note: *Standard errors are presented in parentheses. Weights are defined as the inverse of the number of estimates reported per study. The unit information prior and dilution model prior were utilized. Standard errors were clustered at the study level. ECM refers to error correction models, NFC rate represents the interest rate applied to non-financial corporations, IMF stands for the International Monetary Fund.*

Source: own elaboration

The level of economic development may contribute to higher pass-through due to more advanced banking systems and financial markets. Similarly, in periods of high inflation, commercial banks tend to respond more rapidly to changing economic conditions (Taguchi and Sohn, 2014). In contrast, exchange rate volatility under floating exchange rate regimes introduces uncertainty in financial markets, prompting banks to adjust their lending rates more cautiously. High market capitalization indicates a stable and well-developed financial system in which banks face less pressure to make urgent adjustments to interest rates, reflecting greater financial stability. Overall, the results of the analysis are partially robust.

Discussion

This paper provides the first meta-analysis that specifically examines the speed at which interest rates return to a new equilibrium, offering a novel contribution to the broader understanding of interest rate transmission mechanism. It provides a new perspective on the adjustment speed parameter, which has not been systematically examined in the literature so far, by exploring the underlying heterogeneity among studies and conducting a comprehensive assessment of publication bias. The meta-analysis includes publications from 2017 onward, a period marked by the adoption of negative interest rate policies and an increasing reliance on unconventional monetary tools. By including this recent period, the study captures structural changes in the functioning of monetary transmission channels under extraordinary policy conditions.

The results suggest that the estimated speed of adjustment, reflecting how quickly lending rates return to their long-run equilibrium following a change in the policy rate, ranges between 8 and 18 percent across the examined studies. This indicates that the adjustment process tends to be gradual rather than instantaneous. Such findings may be interpreted considering the unprecedented monetary policy interventions of the past decade. Extraordinary measures undertaken by central banks, such as large-scale asset purchases, quantitative easing, credit easing, and asset purchase programmes, have likely contributed to the weakening of the interest rate pass-through mechanism by compressing market rate variability, flattening yield curves, and dampening banks' incentives to adjust retail rates promptly.

Nevertheless, some findings should be interpreted with caution. Although the analysis of publication bias revealed clear signs of asymmetry and an atypical funnel plot shape, these patterns warrant further empirical scrutiny. Future research should therefore apply more advanced statistical and econometric techniques, to verify the robustness of these results and to examine the relationship between the estimated speed of adjustment and its corresponding standard errors more directly. Furthermore, the current meta-analysis could be expanded in several directions. Future work could incorporate a richer set of explanatory variables capable of explaining the heterogeneity in adjustment speeds across studies. In particular, publication-related factors, such as the disciplinary area to which the journal belongs in major databases, may influence the reported estimates and therefore merit closer examination. Differences in estimated pass-through coefficients may arise when studies are published in journals not specifically dedicated to banking or monetary economics. Similarly, the inclusion of variables reflecting unconventional monetary policy regimes (e.g., quantitative easing, credit easing, or targeted longer-term refinancing operations) and digital transformation in financial systems could provide deeper insights into how evolving financial technologies and policy frameworks reshape the speed and effectiveness of monetary transmission.

Overall, while this study offers novel and valuable empirical evidence on the speed of interest rate pass-through, it also opens new avenues for research aimed at understanding how structural, methodological, and policy-related factors jointly determine the dynamics of interest rate adjustment in modern monetary systems.

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Appendix A

Table A1. Summary statistics

	Observations	Unweighted mean	Weighted mean
SoA estimates	459	-0.233 [-0.251; -0.216]	-0.249 [-0.274; -0.224]
SE	459	0.074 [0.066; 0.081]	-

Note: SoA denotes speed of adjustment. Each article's weight was assigned inversely proportional to the volume of estimates it provided. The 95% confidence intervals are included in brackets.
Source: own elaboration

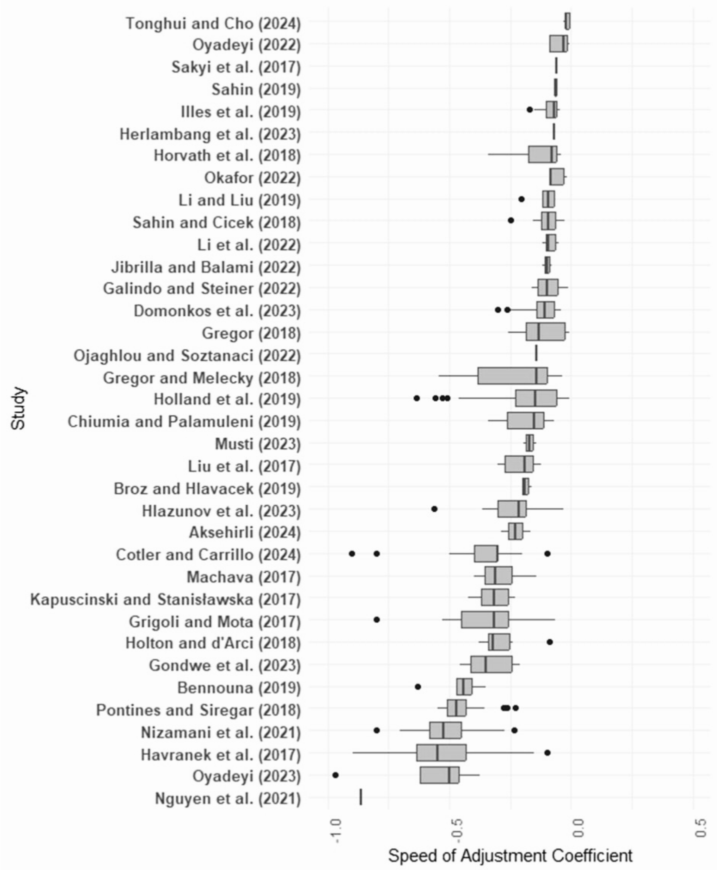

Figure A1. Forest plot

Note: Boxes represent the interquartile range (from the 25th to the 75th percentile). The horizontal line inside the box denotes the median value.
Source: own elaboration