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INTEREST RATE PASS-THROUGH ASYMMETRY: A META-ANALYTICAL APPROACH

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Interest Rate Pass-Through Asymmetry: A Meta-Analytical Approach

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Abstract:
The interest rate pass-through represents a vital transmission mechanism between the financial sector and the real economy. Nonetheless, the empirical literature offers no consensus regarding the direction and extent of asymmetry in this pass-through. In this paper, I systematically review the empirical literature using various contemporary meta-analytic techniques to test for publication bias and establish consensus for the conflicting study outcomes. I find evidence of publication bias. Beyond publication bias, the magnitude of the reported pass-through declines relative to the simple literature average, but substantial asymmetry remains. Precisely, bank lending rates appear to be a lot more responsive to increases than decreases in monetary policy interest rates. Furthermore, I identify the factors responsible for diverse study outcomes. These include study characteristics, asymmetry, and macrofinancial variables. Concerning study characteristics, results differ due to differences in data frequency, data source, the researched period, study quality, author affiliation, and estimation context. Concerning macrofinancial factors, results differ due to differences in openness to foreign direct investment inflows, openness to trade, the inflationary environment, and economic development status. The pass-through is particularly strong in countries more open to foreign direct investment inflows and developed economies but relatively weak for countries more open to import trade and countries with a high inflationary environment. Finally, I model the interest rate pass-through based on the best practices in the literature. On average, the short-run pass-through to bank lending rates is about 49.7% for a policy rate hike and about 29.7% for a policy rate cut. On the other hand, the long-run pass-throughs are about 69.6% and 46.6%, respectively.

JEL: E43
Keywords: Interest rate pass-through, asymmetry, meta-analysis

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1 Introduction

The interest rate pass-through depicts how banks adjust their lending rates relative to a reference rate, usually the monetary policy rate (Havranek et al. 2016). Its relevance for monetary policy cannot be overemphasized, as changes in bank lending rates are likely to influence aggregate demand and inflation, at least to some extent (Marotta 2009). In the literature, the typical rationale for examining the interest rate pass-through is to empirically verify its magnitude, which could be indicative of monetary policy efficacy and feasibility.

Several studies have investigated asymmetry in the interest rate pass-through. A common conclusion is that lending rates respond differently to increases and decreases in monetary policy rates. Asymmetric behavior, if substantial, implies that monetary tightening and easing could have unequal effects on the economy (Gambacorta & Iannotti 2007). Suppose, for instance, that lending rates respond more quickly to monetary policy rate increments than decrements. A policy-induced increase in lending rates via monetary policy rates would impact output or prices more substantially than a policy-induced decrease. For ease of reference, the literature distinguishes between an "upward pass-through" and a "downward pass-through". The former refers to the pass-through effect due to increased monetary policy rates, while the latter refers to the pass-through effect due to decreased monetary policy rates. I use both terms in this paper extensively in discussing the interest rate pass-through.

Despite the policy relevance of the interest rate pass-through, previous research lacks consensus regarding the direction and degree of its asymmetry. Authors differ on whether the upward pass-through is more pronounced than the downward pass-through and whether differences due to asymmetry are substantial or negligible. Furthermore, the likelihood of publication bias complicates inference about the true magnitude of the pass-through (more on publication in Section 4). This paper's main objective is to resolve the issues mentioned above. To this end, I conduct a literature search, construct a meta-dataset comprising dozens of empirical studies, and systematically review the literature using meta-analytical techniques.

In the meta-analysis, I focus on studies examining the pass-through from discount and interbank monetary policy rates to bank lending rates. Two reasons guide this choice. To begin with, commercial banks borrow primarily from the central bank and the interbank market, making discount and interbank rates the primary determinants of bank lending rates. Secondly, studies on asymmetry in the pass-through from discount and interbank rates greatly outnumber those considering other policy-relevant rates.

This study is not the first systematic review of the interest rate pass-through literature. A meta-study by Gregor et al. (2021) examines the interest rate pass-through using a sample of 54 studies containing 1,098 estimates. Nonetheless, while the study by Gregor et al. (2021) focuses on symmetric pass-through estimates, I consider the body of research on pass-through asymmetry. Research in this area is relatively new, as evidenced by the publication year of the earliest study in the meta-analysis sample: 1997. I pose three essential questions. Does publication bias affect the literature? Does asymmetry remain substantial after correcting for publication bias? Why do results vary widely across the literature? To find answers to these questions, I employ linear and state-of-the-art non-linear methods to detect and correct for publication bias. In explaining why results differ, I employ Bayesian model averaging. As far as I know, this is the first meta-analytic study on interest rate pass-through asymmetry.

The results indicate publication bias. But even after correcting for publication bias, asymmetry in the interest rate pass-through remains. The upward pass-through is noticeably larger than the downward pass-through, confirming widely held speculations that bank lending rates are more responsive to increases than decreases in monetary policy rates. Furthermore, using the Bayesian model averaging method, I find that results differ by study characteristics, namely, data frequency, data source, the researched period, study quality, author affiliation, and estimation context. Besides study characteristics, results differ by macrofinancial characteristics, namely, openness to foreign direct investment inflows, openness to trade, the inflationary environment, and economic development status. Precisely, the pass-through is relatively strong in countries more open to foreign direct investment inflows and countries with developed economies. On the other hand, the pass-through is relatively weak in countries more open to import trade and countries with a high inflationary environment.

Finally, the Bayesian model averaging exercise provides a framework for modeling asymmetry in the interest rate pass-through based on the best practices in the literature. This approach suggests that the short-run upward pass-through is about 49.7%, while the short-run downward pass-through is about 29.7%. On the other hand, long-run upward and downward pass-throughs are about 69.6% and 46.6%, respectively.

The remainder of this paper consists of five parts. Section 2 discusses the various theoretical perspectives on asymmetry; Section 3 describes the meta-dataset; Section 4 addresses publication bias; Section 5 addresses heterogeneity; and Section 6 contains the conclusion.

2 Theoretical Perspectives on Asymmetry

This section summarizes the main theoretical viewpoints related to asymmetry in the interest rate pass-through to bank lending rates. Stiglitz & Weiss (1981) propose a model involving adverse selection in credit markets. In this model, banks operate amidst a pool of borrowers categorized as "good" and "bad." While good borrowers consistently repay their loans, bad borrowers default on their obligations. To distinguish between the two groups, banks utilize the lending rate as a screening tool. The "bad" borrowers, perceiving their lower probability of repayment, are willing to accept loans at higher interest rates. Consequently, if banks raise their lending rates, the average risk profile of borrowers also increases, potentially impacting profits. The possibility of facing defaults dissuades banks from significantly increasing lending rates, even if faced with elevated funding costs.

On the other hand, if all banks are earning positive economic profits, banks will tend to lower prices swiftly. Reducing the lending rate not only attracts more customers but also attracts better-quality customers. As a result, the Stiglitz-Weiss model predicts that banks increase lending rates gradually in response to rising costs while promptly lowering lending rates when costs decrease.

Ausubel (1991) proposes an alternative adverse selection theory and criticizes the Stiglitz-Weiss model for misrepresenting real-world credit markets: in reality, bank lending rates are quicker to move upward in response to increases in the costs of funds than to move downward in response to decreases in the costs of funds. Therefore, unlike the Stiglitz-Weiss model, the Ausubel model suggests "downward stickiness" in interest rates.

The model focuses on the credit card market and posits three classes of consumers. Consumers in the first class are cautious of the exorbitant costs of credit card loans, so they borrow only under unanticipated or unplanned circumstances. Banks prefer consumers in this class because they eventually repay their loans and are less likely to be responsive to any interest rate cut, as they do not intend to borrow at the outset.

Consumers in the second class fully intend to take credit card loans at the outset. These consumers are bad credit risks and borrow on their credit cards only because they lack cheap alternatives. From a bank's perspective, consumers in the second class are not ideal, as they borrow large sums but often default. Consumers in the third class can be described as "convenience" users: they only use credit cards as a convenient payment medium to settle transactions. These consumers do not matter for the discussion because they never borrow and are unresponsive to changes in interest rates.

Given this environment of consumers, Ausubel (1991) argues that banks will be hesitant to cut lending rates. The rationale is highly intuitive: a lower price on credit will disproportionately attract the class of consumers who intend to utilize their credit lines.

Models involving search costs, such as the Diamond model (Diamond 1971), offer additional insights into the possible causes of asymmetry. The logic here is that, if borrowers face substantial search costs in locating or switching to lower-priced lenders, then higher-priced lenders can hold on to many of their captive customers despite their high prices. Competing lenders may try to win over new customers by offering sign-up bonuses. Still, because such strategies are often ineffective and impractical, banks will maintain wide profit margins, and lending rates will remain rigid downward.

The "trigger price" model by Green & Porter (1984) offers an alternative explanation for downward price rigidity in oligopolistic credit markets. In this model, firms collude to keep output below competitive levels as long as prices remain above a threshold termed the "trigger price." A negative cost shock does not end the collusion but provides the opportunity to make excess profit. Therefore, output remains below equilibrium levels, and prices do not drop following a negative cost shock. Nonetheless, a positive cost shock elicits a swift price increase. Firms increase prices quickly to reverse the encroachment on their profit margins.

The "trigger sales" model by Tirole (1988) is a variant of the "trigger price" model. The model predicts that when input prices fall, an oligopolistic firm will choose to maintain the old output price if sales remain above a predetermined threshold level. This behavior allows the firm to earn supernormal profit in the short term. Only a decrease in sales would compel the firm to reduce prices promptly because such a decrease would signal competitive price cuts by rival firms. Lowering prices would then be considered the most effective competitive strategy. On the other hand, an increase in input prices would always trigger price increases; otherwise, retail margins could become negative.

Overall, the literature presents cogent arguments in favor of asymmetry. However, the conclusions are diverse. The Stiglitz-Weiss model suggests that prices are more sensitive to decreasing costs, while the other four theories suggest that prices are more sensitive to increasing costs. Perhaps a meta-analysis can help us decide which theories best explain the asymmetry in the pass-through.

3 The Meta-Dataset

The focal parameter is the pass-through from monetary policy to bank lending rates. Asymmetry in this pass-through is typically computed from the following non-linear regression model:

$$\Delta LR = \hat{\alpha} + \hat{\beta}^{+} G_t \Delta IR + \hat{\beta}^{-}(1 - G_t)\Delta IR + \hat{\gamma} X_t + u_t$$

$$G_t = \begin{cases} 1 & if\ \Delta IR > 0 \\ 0 & if\ \Delta IR < 0 \end{cases}$$

Here, LR_t denotes the lending rate, IR_t denotes the monetary policy reference rate, $\hat{\beta}^{+}$ denotes the pass-through corresponding to an increase in the monetary policy reference rate, $\hat{\beta}^{-}$ denotes the pass-through corresponding to a decrease in the monetary policy reference rate, G_t denotes a dummy that takes on values of 1 if the monetary policy reference rate increases, and 0 otherwise, X_t and $\hat{\gamma}$ denote vectors of explanatory variables and coefficients, respectively, $\hat{\alpha}$ denotes the intercept, and u_t denotes the error term.

I use Google Scholar to search for empirical studies containing estimates of the pass-through. Google Scholar is ideal because of its extensive coverage and full-text search capabilities. I query the search engine using the following keywords as search terms: `("interest rate pass-through" OR "interest rate channel" OR "monetary transmission mechanism") AND ("asymmetry" OR "non-linear")`. The search produces thousands of results, so I examine the studies and select only those that satisfy the following conditions. First, the study must report standard errors or information that can be used to conduct formal tests of publication bias. Second, the study must report asymmetric estimates of the pass-through from interbank or discount policy rates to bank lending rates. Thirdly, the study must report numerical results because data collection from figures like impulse response functions and graphs might lead to a systematic measurement error and loss of accuracy. Lastly, the study should report pass-through estimates in the form of an elasticity to ensure that all effect sizes in the sample are directly comparable.

Because the empirical literature on interest rate pass-through asymmetry is relatively new and still growing, I identify only 40 primary studies that meet all four criteria after screening. The search ends on March 15, 2024.[1] The final sample of 40 studies listed in Table A.1 consists of 30 peer-reviewed journal articles, nine working papers, and one proceedings paper. The selected studies collectively provide 1,054 asymmetric estimates of the pass-through into bank lending rates.[2] I examine these studies in-depth and discover at least 40 key explanatory variables related to study and country characteristics, which can potentially explain the variation observed between primary studies. I manually gather data for these variables and create a dataset comprising at least 42,160 data points (1,054 multiplied by 40) for the meta-regression analysis.

[1]Details of the literature search can be found in the PRISMA diagram in Figure A.1 (Appendix A). I refer the reader to the guidelines by Havranek et al. (2020) for further information on PRISMA and related reporting standards in meta-analysis.

[2]The 40 studies contain about 1,100 estimates which, however, include several outliers. Trimming reduces the size of the dataset to 1054 observations but mitigates the influence of outliers on the results of the meta-regression analyses. On the other hand, winsorization leads to incoherent results.

The dataset enhances the meta-regression analysis in five key areas. First, a substantial part (75%) of the sample consists of peer-reviewed journal articles, ensuring that high-quality research papers are adequately represented in the study sample. This enhances the reliability and credibility of the findings. Secondly, the sample size is sufficiently large for the inclusion of several explanatory variables in the meta-regression analysis. This enables a more comprehensive exploration of factors that may contribute to the observed variation between studies. Thirdly, the reported estimates in the sample pertain to countries that matter for global output and banking. This ensures that the findings have broad economic relevance and implications. Fourthly, the sample spans nearly three decades of research, ranging from the earliest publication in 1997 to the latest in 2024. Finally, because the estimates are all elasticities, there is no need for conversion to partial correlation coefficients. This eliminates the risk of information loss during conversion and maintains the accuracy and originality of the data.

Table B.1 summarizes the pass-through estimates numerically. Apart from simple means, I use weighted means to give each study in the sample equal weight. Both statistical summaries highlight notable differences between upward and downward pass-through estimates. Precisely, the overall mean estimates are substantially larger for the upward pass-through than the downward pass-through, which can be interpreted as preliminary evidence of "downward rigidity." Furthermore, the estimates exhibit consistent variation across specific subgroups of the literature, suggesting systematic heterogeneity, which I later confirm in the meta-regression analysis. For instance, ordinary least squares estimates are larger than estimates obtained using the Johansen cointegration method. Similarly, the pass-through effect is more pronounced for pre-GFC estimates than post-GFC estimates.[3]

Lastly, I provide illustrations of the dataset in Figures B.1 and B.2, where the box plots reveal the extent of heterogeneity across and within the 40 primary studies. The results are quite diverse for both upward and downward pass-through estimates. Table B.1 suggests preliminarily that this diversity might be systematically related to differences in study characteristics. Furthermore, because of the heterogeneity, overall averages are likely not representative of some subsets in the literature. To address this issue, a plausible solution researchers often use in meta-analysis is to identify the potential sources of heterogeneity, enabling us to account for these variations and model asymmetry in the interest rate pass-through more accurately for different contexts. In the subsequent sections, I examine heterogeneity in greater detail after conducting tests of publication bias.

4 Publication Bias

In economics, as in other disciplines, our expectations about certain phenomena are influenced by conventional views. As a result, research findings that contradict these views are often disregarded in favor of "consistent" results. In meta-analysis, this preferential reporting of results on the basis of the direction or statistical significance of findings is called publication bias. Publication bias usually takes on two forms. Firstly, researchers may manipulate their econometric models or methodologies to obtain statistically significant effect sizes bearing the expected sign. Alternatively, editors and reviewers may be predisposed to rejecting insignificant results that contradict the predictions of established theories. While publication bias does not

[3]GFC represents the 2008 to 2012 global financial crisis.

necessarily involve sinister motives from the researchers or publishers, its consequence is that larger, more significant effect sizes will be overrepresented in the literature.

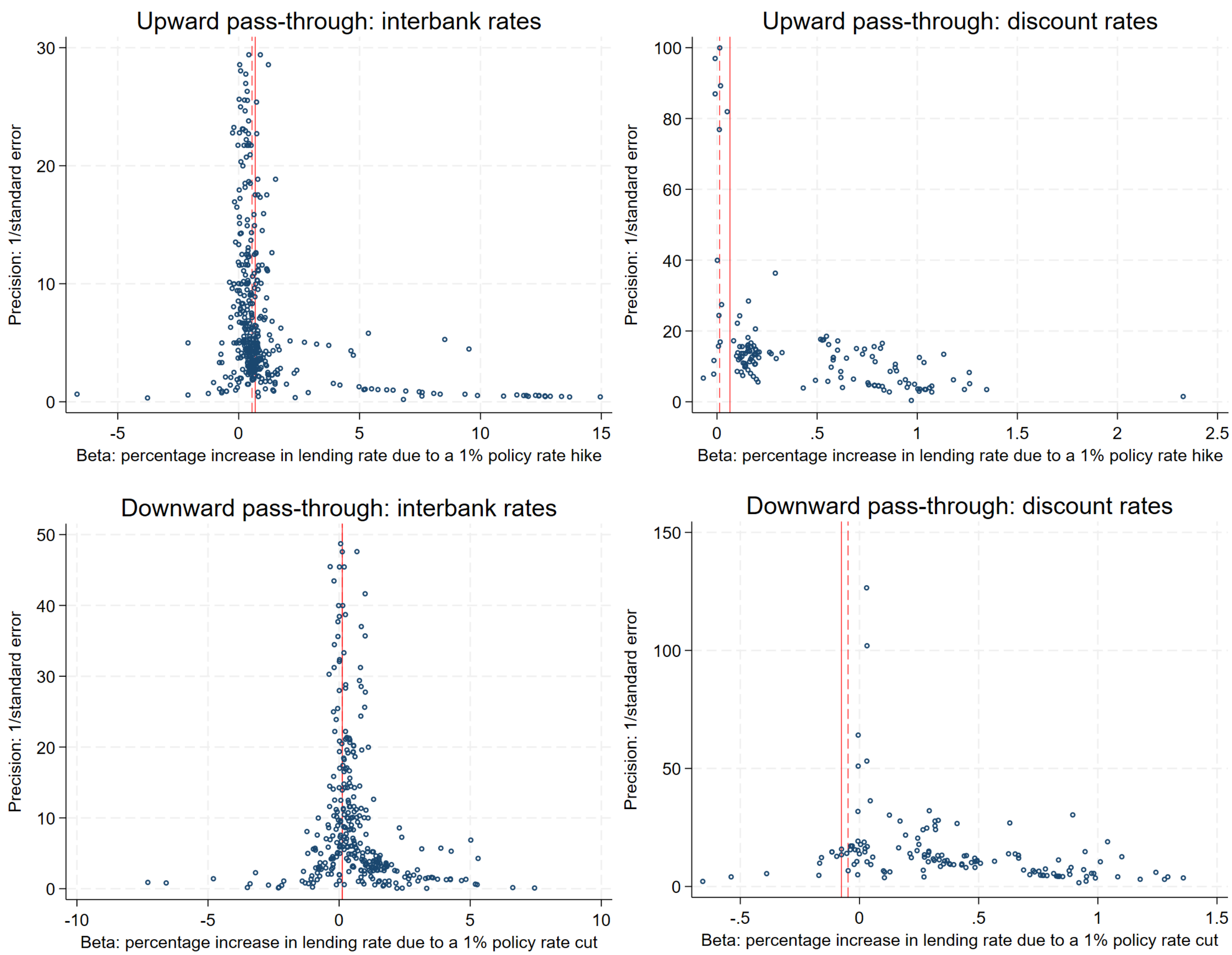
The meta-analytic literature offers quantitative and graphical methods of detecting and correcting for publication bias. For this study, I employ both. I start with the funnel plot developed by Egger et al. (1997) which provides a visual method of detecting publication bias. The funnel plot is a scatter diagram with estimates on the horizontal axis and precision (inverse of the standard errors) on the vertical axis. If there is no systematic heterogeneity and all estimates have equal chances of publication such that there is no publication bias, the more precise estimates would be closer to the mean and the less precise estimates would be farther. In this case, the distribution would resemble a symmetrically inverted funnel (Cala et al. 2022). However, if results are published selectively such that there is substantial publication bias, the missing estimates would make the inverted funnel look asymmetrical. Therefore, assuming there is no systematic heterogeneity, asymmetry can be interpreted as evidence of publication bias. I present funnel plots for the dataset in Figure 1. Apart from the funnel plot illustrating the downward pass-through from interbank policy rates, all funnel plots exhibit varying degrees of asymmetry, suggesting publication bias in the pass-through literature.

To quantitatively test for publication bias, I employ linear and non-linear methods. First, I regress estimates on their standard errors. The logic is that if authors inflate their estimates to overshadow large standard errors, publication bias should be a linear increasing function of the standard errors. Therefore, the slope of the regression indicates the degree of publication bias, while the intercept indicates the effect size corrected for publication bias. Formally, a test for the statistical significance of the intercept is called the precision effect test (PET), while a test for the statistical significance of the slope is called the funnel asymmetry test (FAT). Apart from being statistically significant, the slope should be greater than 2 in absolute value if there is strong publication bias, and less if the bias is mild.

In regressing estimates on their standard errors, the underlying assumption is that publication bias is linearly related to the standard errors. However, there is no guarantee that this assumption holds in all cases. For instance, if effect sizes are statistically significant despite large standard errors, authors will have no incentive to search for larger estimates, and publication bias will be linearly correlated with standard errors only when results are statistically insignificant. Due to this limitation, I consider three non-linear approaches to testing and correcting for publication bias: the weighted average of the adequately powered (WAAP) by Ioannidis et al. (2017), the selection model by Andrews & Kasy (2019), and the p-hacking tests by Elliott et al. (2022).

The WAAP calculates the bias-corrected mean by taking the weighted average of estimates with at least 80% statistical power. The selection model assumes that biased effect sizes are overrepresented in the sample. Therefore, it gives greater weight to underrepresented effect sizes in the sample, aiming to reduce publication bias in the mean estimate. The two histogram-based tests developed by Elliott et al. (2022) detect p-hacking (or publication bias) using the Cox-Shi conditional chi-squared test (Cox & Shi 2022). Elliott et al. (2022) state that the density function of the p-curve should be monotone and non-increasing if there is no hacking of probability values. Therefore, the first test checks the monotonicity of the density function, while the second test checks the non-increasingness of the density function. In contrast to the FAT-PET, WAAP, and selection model, which assume that reported estimates are independent of their standard errors when there is no publication bias, these two histogram-based p-hacking

Figure 1: Funnel plots



Notes: The solid vertical line represents the weighted mean, and the dashed vertical line, the weighted median.

Table 1: Testing and correcting for publication bias

	Upward pass-though			Downward pass-though		
All estimates:	FAT-PET	WAAP	Selection	FAT-PET	WAAP	Selection
Bias-corrected mean	0.400***	0.443***	0.420***	0.229***	0.202*	0.304***
	(0.117)	(0.105)	(0.030)	(0.088)	(0.110)	(0.038)
	[0.183, 0.707]			[0.079, 0.439]		
Publication bias	1.598***			1.173***		
	(0.143)			(0.567)		
	[0.214, 4.800]			[0.154, 2.796]		
Observations	582	582	582	472	472	472
Total studies	35	35	35	38	38	38

	Upward pass-though			Downward pass-though		
Interbank policy rates:	FAT-PET	WAAP	Selection	FAT-PET	WAAP	Selection
Bias-corrected mean	0.483***	0.461***	0.448***	0.464**	NA	0.300***
	(0.172)	(0.129)	(0.027)	(0.173)	(.)	(0.059)
	[0.069, 0.904]			[-0.163, 0.838]		
Publication bias	1.611***			1.570*		
	(0.230)			(0.774)		
	[1.375, 5.444]			[0.096, 3.136]		
Observations	440	440	440	330	330	330
Total studies	26	26	26	30	30	30

	Upward pass-though			Downward pass-though		
Discount policy rates:	FAT-PET	WAAP	Selection	FAT-PET	WAAP	Selection
Bias-corrected mean	0.372***	0.372***	0.444***	0.215*	0.212*	0.383***
	(0.083)	(0.079)	(0.033)	(0.117)	(0.116)	(0.031)
	[-0.027, 0.617]			[-0.099, 0.496]		
Publication bias	0.789			1.703		
	(1.112)			(0.951)		
	[0.233, 4.249]			[-1.363, 4.206]		
Observations	142	142	142	142	142	142
Total studies	11	11	11	10	10	10

Notes: I report standard errors clustered at the study level except for the selection model; in square brackets, I report 95% confidence intervals from wild bootstrap (Roodman et al. 2019). FAT-PET = funnel asymmetry and precision effect tests weighted by MAIVE-adjusted precision (Irsova et al. 2023); WAAP = weighted average of the adequately powered method by Ioannidis et al. (2017); Selection = selection model by Andrews & Kasy (2019). ***, **, and * denote statistical significance at the 1%, 5% and 10% levels respectively.

tests relax the independence assumption. The independence assumption needs to be relaxed because method choices can affect both the reported estimates and their standard errors and make them correlated even when there is no publication bias (Matousek et al. 2022).

One important problem that is often overlooked while testing for publication bias is spurious precision. Methods like the FAT-PET and WAAP rely on precision-weighting, but researchers may manipulate precision and, by doing so, introduce a bias that obscures inference about the true mean effect. To prevent spurious precision-weighting in the FAT-PET and WAAP, I employ the meta-analysis instrumental variable estimator (MAIVE) (Irsova et al. 2023). This technique

Table 2: P-hacking tests by Elliott et al. (2022)

	All estimates	Interbank policy rates	Discount policy rates
Upward pass-through			
Test for monotonicity and bounds	0.015	0.013	0.003
Test for non-increasingness	0.019	0.013	0.003
Bins	15	5	5
Observations ($p \leq 0.15$)	227	178	339
Total studies	35	26	11
Downward pass-through			
Test for monotonicity and bounds	0.053	0.027	0.034
Test for non-increasingness	0.095	0.027	0.034
Bins	15	5	5
Observations ($p \leq 0.15$)	191	53	44
Total studies	38	30	10

Notes: The table reports p-values for the two histogram-based tests for p-hacking by Elliott et al. (2022) using the de-rounding procedure in Brodeur et al. (2016).

corrects for precision hacking by replacing reported variance with instrumental variables constructed from the inverse of the sample size used in the primary study.

I present the main results in Table 1 and the p-hacking tests in Table 2. The FAT-PET detects publication bias in the full sample of upward and downward pass-through estimates. In the subsamples, it only detects publication bias among interbank policy rate pass-through estimates, which is rather surprising because discount policy rate pass-through estimates exhibit stronger asymmetry in the funnel plots. On the other hand, the two histogram-based p-hacking tests detect publication bias in all samples.

The overall bias-corrected mean estimates for the upward and downward pass-throughs are approximately 40 – 44 percent and 20 – 30 percent, respectively. These results show that asymmetry remains after correcting for publication bias and corroborate the views of Ausubel (1991), Diamond (1971), Green & Porter (1984), and Tirole (1988) on downward rigidity in the interest rate pass-through. Evidence of asymmetry also persists in the subsamples. For interbank policy rates, the upward and downward pass-through estimates are about 45 – 48 percent and 30 – 46 percent, respectively, while for discount policy rates, the upward and downward pass-through estimates are about 37 – 44 percent and 21 – 38 percent, respectively.

5 Heterogeneity

Estimates of the interest rate pass-through differ substantially, and it is essential to know why. In this section, I check whether the observed heterogeneity can be explained systematically by differences in the contexts in which researchers obtain estimates. The foremost factor that comes to mind is asymmetry. If the interest rate pass-through exhibits asymmetry as suggested by the bias-corrected mean estimates, results will differ according to the direction of asymmetry reported by the researcher. Furthermore, we can expect some diversity due to differences in loan characteristics, research methodology, and macrofinancial variables.

After examining the primary studies in the sample closely, I identify 40 key variables (including the standard errors) capable of capturing the various contexts. In what follows, I discuss these variables and the rationales for choosing them.

5.1 Variables

The variables fall under six main categories: asymmetry variables, data variables, estimation variables, publication variables, loan variables, and macrofinancial variables. Table B.2 lists the variables along with their corresponding summary statistics. A comprehensive description of these variables is available in Appendix D (Table D.2). Furthermore, I present a correlation matrix in Figures C.1 to demonstrate that there are only minimal correlations between the variables.

Asymmetry variables The inclusion of asymmetry-related variables allows for the verification of heterogeneity due to asymmetry. Accordingly, I code a binary variable that takes on values of 1 and 0 for upward and downward pass-through estimates, respectively.

Data variables I include 10 variables related to data characteristics. First, I introduce variables to control for the frequency and dimension of the employed dataset. Most of the primary studies in the sample use quarterly, monthly, and weekly data. Therefore, these studies capture interest rate adjustments across different time intervals. To confirm that results vary due to differences in data frequency, I create three matching dummies for quarterly, monthly, and weekly data. On the other hand, I control for data dimension by incorporating a dummy variable that equals 1 for time series data and 0 for panel data. Results might differ between time series and panel data because time series data captures interest rate adjustments across time only, while panel data captures interest rate adjustments across time and cross-sections.

Next, I control for the time span covered in each primary study. The rationale: studies covering many years should have sufficient observations and be more accurate than those covering only a few years. I also control for the three main data sources employed namely, the IMF, the ECB, and national databases. Given the differences in data collection methodologies and reporting standards among statistical agencies, results may exhibit systematic variations based on the chosen database. Finally, to capture changes in the interest rate pass-through due to the 2008-2012 global financial crisis (GFC), I include dummies for pre-GFC and post-GFC data.

Estimation variables Besides data characteristics, heterogeneity in estimates may arise from differences in the estimation context. Authors typically distinguish between long-run and short-run pass-through estimates when estimating interest rate pass-through. Long-run estimates often derive from cointegrating equations, while short-run estimates typically stem from differenced equations and error correction models. To examine how these distinctions contribute to heterogeneity, I introduce two dummy variables: one for long-run estimates and another for short-run estimates.

Next, I consider the lag length applied to the monetary policy rate variable. Accounting for lag length helps determine whether past realizations of monetary policy rates influence current bank lending rates. I also address potential simultaneity bias caused by endogenous explanatory variables. In macroeconomics, interest rates influence aggregate demand and prices. Consequently, reverse causality from bank lending rates to inflation may introduce simultaneity bias in primary studies that use inflation as an explanatory variable for modeling the interest rate pass-through. To control for simultaneity bias, I include a variable for studies that control for inflation without instrumental variables or other techniques capable of preventing reverse causality.

Lastly, I control for differences in estimation methods and the monetary policy rate used in pass-through estimation. Authors often employ ordinary least squares and the Johansen maximum likelihood-based cointegration method (Johansen 1991). Thus, I include two variables corresponding to these techniques. As for the monetary policy rate, the meta-dataset only contains estimates for interbank and discount policy rates. Therefore, I code a dummy for interbank policy rates, with discount policy rates serving as the reference category.

Publication variables I consider five variables related to publication characteristics that possibly influence reported findings on the pass-through. The first is the year of publication. Because recent studies might capitalize on advances in investigative methods and produce better results than old studies, I expect estimates to vary with the year of publication. The second is the author's affiliation. Authors affiliated with central banks might report inflated pass-through estimates due to vested interests. The remaining three variables include the primary study's annual citation count, type of publication outlet, and impact factor. These variables might influence empirical results systematically because they mainly reflect the quality of the author's work.

Loan variables The literature investigates three main loan types: business loans, consumer loans, and mortgage loans. To determine whether interest rates on these loan types respond differently to monetary policy rates, I code three dummies, one for each loan type. Furthermore, I control for loan maturity by introducing two dummies for short- and long-term loans.

Macrofinancial variables Because empirical studies focus on different countries, differences in macrofinancial conditions may have a role in explaining the diversity of results. I consider 11 macrofinancial variables, namely, openness to trade, openness to foreign direct investment (FDI) inflows, economic development status, market capitalization, inflationary environment, economic growth rate, stock turnover ratio, central bank independence, inflation targeting, exchange rate regime, and monetary integration (Euro Area membership). In assigning values to these macrofinancial variables, I use the average of the sample period in the primary study. For instance, if a primary study uses data from 2010 to 2020, I use data averaged from 2010 to 2020 to measure the macrofinancial variables for that study.

Openness to trade and foreign direct investment inflows I anticipate an ambiguous effect from openness to trade or FDI inflows. On the one hand, openness exposes domestic banks and firms to foreign lenders, thereby weakening the effects of domestic monetary policy rates on bank lending rates. On the other hand, openness can also promote domestic competition, which can lead to a more substantial pass-through (Do & Levchenko 2004, Huang & Temple 2005, Law 2009).

Economic development status I anticipate a positive relationship between economic development status and the strength of the interest rate pass-through. The intuition is that developed economies have larger, more efficient, and competitive financial markets (Greenwood & Smith 1997) that allow for the proper functioning of monetary transmission mechanisms.

Market capitalization and stock turnover ratio I anticipate a positive relationship between the interest rate pass-through and the two financial market size indicators: stock market turnover ratio and capital market depth proxied by market capitalization. An increase in financial market size implies increased competition from rival lenders in credit and capital markets which would compel banks to adjust lending rates quickly to retain customers and maintain market share Badinger (2007).

Inflationary environment and inflation targeting I anticipate a more pronounced pass-through in countries where central banks pursue inflation targeting or maintain stable prices. One potential explanation for this is that a central bank dedicated to price stability utilizes the interest rate mechanism to manage inflation effectively. Consequently, such a commitment prompts the central bank to allocate its resources and regulatory efforts towards strengthening the interest rate pass-through.

Economic growth In a growing economy, the demand for loans is likely to be less elastic to interest rates (Gigineishvili 2011). Therefore, I anticipate a positive relationship between economic growth and the magnitude of the interest rate pass-through.

Central bank independence I expect central bank independence to positively affect the magnitude of the interest rate pass-through. Central banks might be predisposed to clearing bottlenecks or implementing policies to strengthen the interest rate channel, as this channel transmits policy to the real economy. On the other hand, central bank independence gives central banks greater autonomy to carry out their objectives.

Exchange rate regime Concerning exchange rate flexibility, I refer to the Mundell–Fleming trilemma model (Fleming 1962, Mundell 1963). This model suggests that a central bank can only keep the exchange rate fixed in an open economy with free capital flows by forfeiting monetary policy sovereignty. Forfeiting monetary policy sovereignty implies that domestic interest rates respond to international conditions instead of domestic monetary policy and policy-controlled interest rates. On the other hand, a flexible exchange rate regime allows the central bank to maintain its monetary policy sovereignty and, by implication, its influence on domestic interest rates.

Euro Area membership Euro Area monetary integration might strengthen the pass-through by exposing financial markets in member states to regional capital inflows and regional competition. Therefore, I anticipate a positive relationship between Euro Area membership and the magnitude of the pass-through.

In gathering data for the macrofinancial variables, I use multiple sources. Data on openness to trade, openness to FDI inflows, market capitalization, inflation, economic growth, and stock market turnover ratio come from the World Bank's World Development Indicators database. Data on monetary policy frameworks and exchange rate regimes come from the Bank of England's Centre for Central Banking Studies and the IMF's annual reports on exchange arrangements and restrictions, respectively. Data on economic development status come from the IMF's World Economic Outlook Database. Data on Euro Area membership come from the European Commission's website (europa.eu). Lastly, data on central bank independence come from Romelli (2022).

5.2 Estimation

To model heterogeneity in the interest rate pass-through, I use the following regression model:

$$\hat{\beta}_{it} = \hat{\gamma}_0 + \hat{\gamma}_1 SE_{it} + \hat{\gamma}_2 X_{it} + \epsilon_{it}$$

Here, $\hat{\beta}_{is}$ represents the ith estimate extracted from the sth study, SE_{is} denotes the corresponding standard error, X_{is} denotes the vector of potential explanatory variables, and ϵ_{is} denotes the stochastic term. The estimated slope γ_1 reveals the degree of publication bias, and the estimated vector γ_2 provides coefficients corresponding to the vector X_{is}.

When estimating the specified regression model with non-Bayesian methods, it is crucial to include only the essential explanatory variables. Including all 40 explanatory variables could lead to problems such as overfitting and multicollinearity, which can obscure statistical inference. One useful approach to mitigating these issues is to exclude some explanatory variables from the baseline regression model. However, this approach carries the risk of omitting relevant regressors and is also subject to manipulation by researchers. An alternative solution is the Bayesian model averaging method (Raftery et al. 1997) which tackles the challenge of model uncertainty and addresses multicollinearity using the dilution prior proposed by George (2010).

To optimize model estimation, the Bayesian method considers several potential models and decides on the most plausible set of explanatory variables. This computationally intensive exercise is simplified using the Metropolis-Hastings algorithm, provided in the `bms` package in R by Zeugner & Feldkircher (2015). The algorithm achieves computational tractability by considering only the likely models out of the vast number (2^{40}) of candidate regression models.

In interpreting the Bayesian model averaging results, I use the posterior means and inclusion probabilities. The posterior mean of each regressor reveals the direction and scale of its overall impact in the baseline model. On the other hand, the corresponding posterior inclusion probability indicates the significance of the regressor: the regressor is 'insignificant' if its inclusion probability falls below 0.5; 'weakly significant' if its inclusion probability falls between 0.5 and 0.75; 'substantially significant' if its inclusion probability falls between 0.75 and 0.95; 'strongly significant' if its inclusion probability falls between 0.95 and 0.99; and 'decisively significant' if its inclusion probability exceeds 0.99 (Jeffreys 1961).

5.3 Results

The model inclusion graph in Figures C.8 summarizes the Bayesian model averaging exercise. The figure orders the regressors on the vertical axis according to posterior inclusion probability from top to bottom. On the horizontal axis, it ranks the candidate models according to posterior model probability, such that the most plausible model lies on the extreme left. The coloring scheme reflects the direction of an explanatory variable's impact on the pass-through: blue (darker in grayscale) indicates a positive effect; red (lighter in grayscale) indicates a negative effect; and a blank cell signifies zero or exclusion.

We can observe that the best model contains only fifteen explanatory variables, which cut across five categories of the dataset: asymmetry, data, estimation, publication, and macrofinancial variables. I refer to the main Bayesian model averaging results reported in Table 3 to elaborate on how these variables contribute to heterogeneity. On the left, the posterior mean of each regressor captures the direction and magnitude of its influence, while the posterior inclusion probability indicates its statistical significance. Furthermore, the OLS model on the right side acts as a frequentist check.

Publication bias Before delving into context-specific results, I wish to touch on publication bias, a focal issue in this study. In Table 3, the standard error is highly significant in the Bayesian model and the frequentist check. This implies that publication bias remains even after controlling for heterogeneity, strongly corroborating the initial findings in Section 4.

Asymmetry variable(s) The asymmetry dummy crosses the benchmark for statistical significance. Its posterior mean suggests that, on average, the upward pass-through is about 23%

larger than the downward pass-through. This finding confirms downward rigidity in the interest rate pass-through as predicted by Ausubel (1991), Diamond (1971), Green & Porter (1984), and Tirole (1988) in their various theories. The result also implies that changes in monetary policy rates may have a stronger impact on inflation and other real economic variables during phases of policy rate hikes than during phases of policy rate cuts.

Data variables Among the data characteristics, the determinants of heterogeneity include data frequency, data source, and the period covered in the author's dataset (i.e. pre-GFC or post-GFC). More precisely, estimation with quarterly data tends to yield larger effect sizes compared to monthly and weekly data. This observation is not surprising because quarterly data captures the pass-through over a longer time interval than the other data frequencies. Similarly, there is a noticeable effect regarding IMF data. Studies utilizing IMF data are more inclined to report larger estimates compared to those using ECB data or data from national databases. Lastly, the pass-through appears to be approximately 18% larger when estimated with pre-GFC data, suggesting a stronger interest rate pass-through before the onset of the global financial crisis.

Estimation variables Sizeable differences exist between long-run and short-run estimates. On average, based on the posterior means, long-run estimates are about 20% larger than short-run estimates. This supports the conclusions of numerous empirical studies that the long-run pass-through is more substantial than the short-run pass-through. Notable differences are also apparent between estimates obtained via ordinary least squares (OLS) and the Johansen maximum likelihood-based method. Researchers employing OLS tend to report larger estimates compared to those utilizing the Johansen method. One potential explanation for this variation lies in the underlying econometric procedures. The Johansen method addresses spurious relationships by testing for cointegration. In addition, it employs maximum likelihood estimation, which differs from OLS when the classical OLS assumptions are violated.

On the other hand, the dummy for interbank policy rates does not matter for heterogeneity. This suggests that bank lending rates respond the same way to interbank and discount monetary policy rates.

Publication variables In this category, I find that results vary with the primary study's annual citation score. Frequently-cited studies report smaller pass-through estimates than rarely-cited studies. Because the annual citation score is an indicator of study quality, this finding implies that high-quality studies are less likely to exaggerate the magnitude of the interest rate pass-through than low-quality studies. Another important determinant is the author's affiliation. Authors affiliated with central banks tend to report larger estimates. This confirms prior speculations that central bank authors may have vested interests.

Loan variables Among the loan variables, the short-term loan dummy carries the largest posterior inclusion probability: 0.3788. However, based on the criteria by Jeffreys (1961), this posterior inclusion probability does not meet the benchmark for statistical significance. Therefore, the BMA results suggest that the magnitude of the interest rate pass-through does not significantly depend on loan characteristics.

Macrofinancial variables The magnitude of the interest rate pass-through depends on four macrofinancial variables, namely, openness to trade, openness to FDI inflows, economic development status, and the inflationary environment. The effects of trade openness and the inflationary environment are negative. Based on prior speculations, trade openness might decrease the pass-through by exposing domestic banks and firms to foreign lenders, while a central bank

Table 3: Asymmetry contributes to heterogeneity in the interest rate pass-through

Response variable: Beta estimate	Baseline Bayesian model			Frequentist check (OLS)		
	P. Mean	P. SD.	PIP	Coefficient	Standard error	p-value.
Constant	0.0158	NA	**1.0000**	0.1297	0.2610	0.6220
Standard error	0.5186	0.0487	**1.0000**	0.6327	0.2179	0.0060
Asymmetry variable						
Upward pass-through	0.2297	0.0410	**0.9997**	0.2791	0.0672	0.0000
Data variables						
Quarterly data	1.5006	0.1187	**1.0000**	0.9055	0.7080	0.2090
Monthly data	0.0005	0.0147	0.0046			
Weekly data	0.0008	0.0190	0.0108			
Time span	0.0000	0.0005	0.0048			
IMF data	-0.3591	0.1291	**0.9399**	-0.4342	0.3371	0.2060
ECB data	0.0012	0.0163	0.0172			
National database	0.0068	0.0424	0.0295			
Time series	0.0000	0.0042	0.0027			
Pre-GFC data	0.1806	0.1058	**0.7943**	0.1266	0.1330	0.3470
Post-GFC data	-0.0030	0.0234	0.0228			
Estimation variables						
Long-run	-1.1116	0.1071	**1.0000**	-1.2594	0.6562	0.0630
Short-run	-1.3105	0.1061	**1.0000**	-1.6442	0.6426	0.0150
Lag length	-0.0064	0.0202	0.1069			
Simultaneity bias	0.0027	0.0251	0.0265			
Ordinary least squares	1.7151	0.1266	**1.0000**	1.5720	0.6635	0.0230
Johansen method	1.5772	0.1570	**1.0000**	1.4521	0.6252	0.0260
Interbank reference rate	0.0001	0.0045	0.0033			
Publication variables						
Publication year	0.0000	0.0004	0.0038			
Annual citation score	-0.0549	0.0133	**0.9888**	-0.0412	0.0220	0.0690
Peer-reviewed journal	-0.0049	0.0247	0.0472			
Impact factor	-0.0010	0.0342	0.0165			
Central bank author	0.4157	0.0549	**0.9999**	0.3710	0.0900	0.0000
Loan variables						
Business loan	0.0087	0.0360	0.0753			
Consumer loan	-0.0039	0.0278	0.0338			
Mortgage loan	0.0092	0.0429	0.0703			
Short-term loan	0.0748	0.1047	0.3788			
Long-term loan	0.0035	0.0253	0.0509			
Macrofinancial variables						
Trade openness	-3.3729	0.2510	**1.0000**	-2.8758	0.7694	0.0010
FDI inflows to GDP ratio	19.5262	1.5533	**1.0000**	18.5753	3.9231	0.0000
Developed economy	0.2544	0.0494	**0.9998**	0.4392	0.0885	0.0000
Market capitalization	-0.0177	0.0557	0.1059			
Inflationary environment	-1.4911	0.2650	**1.0000**	-0.9072	0.5976	0.1380
Economic growth rate	-0.0080	0.1760	0.0045			
Stock turnover ratio	0.0001	0.0031	0.0069			
Central bank independence	-0.0005	0.0149	0.0037			
Inflation targeter	-0.0009	0.0115	0.0125			
Floating exchange rate regime	0.0006	0.0104	0.0057			
Euro Area	0.0017	0.0181	0.0123			
Observations/Studies	980/38			1,026/38		

Notes: BMA model weighted by the inverse number of estimates reported per study, estimated with the unit information g-prior and the dilution model prior (see Eicher et al. 2011, George 2010). Study-level clustered standard errors in the frequentist check. P. Mean denotes posterior mean; P. SD. denotes posterior standard deviation; PIP denotes posterior inclusion probability; p-value denotes probability value; PIPs > 0.5 in bold.

committed to a low inflationary environment (with a monetary or inflation targeting framework) might allocate its resources and regulatory efforts toward strengthening the interest rate channel.

On the other hand, the effects of openness to FDI inflows and economic development status are positive. According to prior speculations, openness to FDI inflows might positively affect the pass-through by promoting competition in domestic financial markets (Do & Levchenko 2004, Huang & Temple 2005, Law 2009) and also by boosting domestic economic activity. Similarly, economic development status might correlate positively with the magnitude of the pass-through because developed economies have larger, more efficient, and competitive financial markets compared to developing countries (Greenwood & Smith 1997).

5.4 Best Practice Modelled Estimates

Apart from explaining heterogeneity, I use the baseline Bayesian model to estimate the interest rate pass-through based on the "best practice" approach. In the "best practice" approach, the researcher uses the explanatory regression model to estimate the parameter of interest by mimicking the "perfect" study or a hypothetical study possessing the ideal characteristics. For this exercise, I assign values of zero to the standard error and simultaneity bias dummy to mimic a study that is free from publication and simultaneity biases. I also assign a value of zero to the central bank author dummy to mimic a study published by an author without vested interests.

Next, I use sample maxima for the annual citation score to mimic a high-quality study. I choose the Johansen method instead of OLS because the former prevents spurious relationships. For estimation, I prefer quarterly data because it amplifies the pass-through more strongly than monthly and weekly data in the BMA model. I also prefer post-GFC datasets to pre-GFC datasets because the former provide more up-to-date results.

To incorporate asymmetry into the pass-through, the asymmetry variable alternates between 1 and 0 to capture the upward and downward pass-throughs, respectively. On the other hand, because we have two separate dummies for the long-run pass-through and the short-run pass-through, I use only one variable at a time. Precisely, for the long-run pass-through, the long-run dummy takes on a value of 1, and the short-run dummy remains at zero, while for the short-run pass-through, the short-run dummy takes on a value of 1, and the long-run dummy remains at zero. Lastly, all the macrofinancial variables and insignificant regressors take on their sample means.

I report the modeled estimates in Table 4. The estimates are noticeably larger when monetary policy rates increase than when they decrease. Concerning the overall mean estimates, the best practice approach suggests 49.7% for the short-run upward pass-through and 26.7% for the short-run downward pass-through. On the other hand, it suggests 69.6% for the long-run upward pass-through and 46.6% for the long-run downward pass-through.

I also report estimates for developed and developing economies. To distinguish between the two categories, the development dummy alternates between 1 and 0, while other variables remain as previously defined. For developed economies, the short-run estimates are 61.9% and 38.9%, respectively, for the upward and downward pass-throughs, while the long-run estimates are 81.8% and 58.8%, respectively. On the other hand, for developing economies, the short-run estimates are 36.5% and 13.5%, while the long-run estimates are 56.3% and 33.4%, respectively.

In summary, the modeled estimates highlight the direction of asymmetry in the interest rate

Table 4: Modelled estimates

	Overall	Developed	Developing
Short-run			
Upward pass-through	0.497	0.619	0.365
	[0.203, 3.228]	[0.386, 3.732]	[-0.068, 2.752]
Downward pass-through	0.267	0.389	0.135
	[0.0149, 2.457]	[0.213, 2.947]	[-0.294, 2.020]
Long-run			
Upward pass-through	0.696	0.818	0.563
	[0.538, 3.888]	[0.631, 4.482]	[0.396, 3.283]
Downward pass-through	0.466	0.588	0.334
	[0.320, 3.148]	[0.415, 3.741]	[0.168, 2.554]

Note(s): Credible intervals approximated using OLS in square brackets.

pass-through. Precisely, the fact that the upward pass-through is larger than the downward pass-through in all contexts suggests that commercial banks are more likely to adjust lending rates when monetary policy rates rise than when they fall. Another important observation is that the pass-through seems to be stronger in developed economies than in developing economies.

6 Conclusion

This study uses a meta-analytical approach to examine asymmetry in the pass-through from monetary policy rates to bank lending rates. First, I test and correct for publication bias using linear and recently developed non-linear techniques. I detect publication bias, but evidence of asymmetry remains after bias correction. Precisely, the bias-corrected estimates are more substantial for the upward than the downward pass-through, confirming the view that bank lending rates are more sensitive to increases than decreases in monetary policy rates.

Furthermore, I examine the role played by asymmetry in explaining heterogeneity in the interest rate pass-through. I also examine the roles played by several macrofinancial factors and study characteristics. Because these potential determinants of heterogeneity are large in number, I employ Bayesian model averaging to identify the most significant ones. The results show that asymmetry significantly influences the magnitude of the interest rate pass-through. In addition, results vary due to differences in study characteristics and macrofinancial factors. Regarding study characteristics, I find that heterogeneity depends on data frequency, data source, the researched period, study quality, author affiliation, and estimation context. On the other hand, concerning macrofinancial variables, I find that heterogeneity depends on openness to foreign direct investment inflows, openness to trade, economic development status, and the inflationary environment. Precisely, openness to foreign direct investment inflows and economic development status positively affect the magnitude of the pass-through, while openness to import trade and inflation correlate negatively with the magnitude of the pass-through.

Lastly, I use the Bayesian model averaging results to model the interest rate pass-through based on some of the best practices in the literature. This approach yields a mean estimate of 49.7% for the short-run upward pass-through and 29.7% for the short-run downward pass-through. On the other hand, it yields 69.6% for the long-run upward pass-through and 46.6% for the long-run downward pass-through. In conclusion, these findings provide some consensus for the diverse views and results on asymmetry in the interest rate pass-through. Furthermore, they suggest that changes in monetary policy rates may have a more pronounced impact on prices and consumption during phases of monetary tightening compared to phases of monetary easing.

References

Andrews, I. & Kasy, M. (2019), 'Identification of and correction for publication bias', *American Economic Review* **109**(8), 2766–2794.

Ausubel, L. (1991), 'The failure of competition in the credit card market', *The American Economic Review* **81**(1), 50–81.

Badinger, H. (2007), 'Market size, trade, competition and productivity: Evidence from OECD manufacturing industries', *Applied Economics* **39**(17), 2143–2157.

Brodeur, A., Le, M., Sangnier, M. & Zylberberg, Y. (2016), 'Star wars: The empirics strike back.', *American Economic Journal: Applied Economics* **8**(1), 1–32.

Cala, P., Havranek, T., Irsova, Z., Matousek, J. & Novak, J. (2022), Financial incentives and performance: A meta-analysis of economics evidence., Working paper 27/2022, Institute of Economic Studies, Charles University.

Cox, G. & Shi, X. (2022), 'Simple adaptive size-exact testing for full-vector and subvector inference in moment inequality models.', *Review of Economic Studies* **90**(1), 201–228.

Diamond, P. (1971), 'A model of price adjustment', *Journal of economic theory* **3**(2), 156–168.

Do, Q. T. & Levchenko, A. A. (2004), Trade and Financial Development, Working Paper Series 3347, World Bank Policy Research.

Egger, M., Smith, G. D., Schneider, M. & Minder, C. (1997), 'Bias in meta-analysis detected by a simple, graphical test', *BMJ* **315**(7109), 629–634.

Eicher, T. S., Papageorgiou, C. & Raftery, A. E. (2011), 'Default priors and predictive performance in Bayesian model averaging, with application to growth determinants', *Journal of Applied Econometrics* **26**(1), 30–55.
URL: *http://dx.doi.org/10.1002/jae.1112*

Elliott, G., Kudrin, N. & Wuthrich, K. (2022), 'Detecting p-hacking.', *Econometrica* **90**(1), 887–906.

Fleming, M. J. (1962), 'Domestic Financial Policies under Fixed and under Floating Exchange Rates', *Staff Papers-International Monetary Fund* **9**(3), 369–380.

Gambacorta, L. & Iannotti, S. (2007), 'Are there asymmetries in the response of bank interest rates to monetary shocks?', *Applied Economics* **39**(19), 2503–2517.

George, E. I. (2010), Dilution priors: Compensating for model space redundancy, *in* 'IMS Collections Borrowing Strength: Theory Powering Applications - A Festschrift for Lawrence D. Brown', Vol. 6, Institute of Mathematical Statistics, pp. 158–165.

Gigineishvili, N. (2011), Determinants of interest rate pass-through: Do macroeconomic conditions and financial market structure matter?., Working paper 11/176, International Monetary Fund.

Green, E. & Porter, R. (1984), 'Noncooperative collusion under imperfect price information', *Econometrica: Journal of the Econometric Society* **52**(1), 87–100.

Greenwood, J. & Smith, B. D. (1997), 'Financial markets in development, and the development of financial markets', *Journal of Economic dynamics and control* **21**(1), 145–181.

Gregor, J., Melecký, A. & Melecký, M. (2021), 'Interest rate pass-through: A meta-analysis of the literature', *Journal of Economic Surveys* **35**(1), 141–191.

Havranek, T., Irsova, Z. & Lesanovska, J. (2016), 'Bank efficiency and interest rate pass-through: Evidence from Czech loan products', *Economic Modelling* **54**(2016), 153–169.

Havranek, T., Stanley, T. D., Doucouliagos, H., Bom, P., Geyer-Klingeberg, J., Iwasaki, I., Reed, W. R., Rost, K. & van Aert, R. C. M. (2020), 'Reporting Guidelines for Meta-Analysis in Economics', *Journal of Economic Surveys* **34**(3), 469–475.

Huang, Y. & Temple, J. (2005), Does external trade promote financial development?, Discussion paper 5150, CEPR.

Ioannidis, J. P., Stanley, T. D. & Doucouliagos, H. (2017), 'The Power of Bias in Economics Research', *The Economic Journal* **127**(605), F236–F265.

Irsova, Z., Bom, P., Havranek, T. & Rachinger, H. (2023), Spurious precision in meta-analysis, Working paper 2023/05, Charles University Prague, Faculty of Social Sciences, Institute of Economic Studies.

Jeffreys, H. (1961), *Theory of Probability*, Oxford Classic Texts in the Physical Sciences, third edn, Oxford: Oxford University Press.

Johansen, S. (1991), 'Estimation and hypothesis testing of cointegration vectors in gaussian vector autoregressive models', *Econometrica* **59**(1), 1551–1580.

Law, S. H. (2009), 'Trade openness, capital flows and financial development in developing economies', *International Economic Journal* **23**(3), 409–426.

Marotta, G. (2009), 'Structural breaks in the lending interest rate pass-through and the euro', *Economic Modelling* **26**(1), 191–205.

Matousek, J., Havranek, T. & Irsova, Z. (2022), 'Individual discount rates: a meta-analysis of experimental evidence.', *Experimental Economics* **25**(1), 318–358.

Mundell, R. A. (1963), 'Capital mobility and stabilization policy under fixed and flexible exchange rates', *Canadian Journal of Economics and Political Science* **29**(4), 475–485.

Raftery, A. E., Madigan, D. & Hoeting, J. (1997), 'Bayesian model averaging for linear regression models', *Journal of the American Statistical Association* **92**(437), 179–191.

Romelli, D. (2022), 'The political economy of reforms in central bank design: Evidence from a new dataset.', *American Economic Review* **37**(112), 641–688.

Roodman, D., MacKinnon, J. G., Nielsen, M. O. & Webb, M. D. (2019), 'Fast and wild: Bootstrap inference in Stata using boottest.', *The Stata Journal* **19**(1), 4–60.

Stiglitz, J. & Weiss, A. (1981), 'Credit rationing in markets with imperfect information', *The American economic review* **71**(3), 393–410.

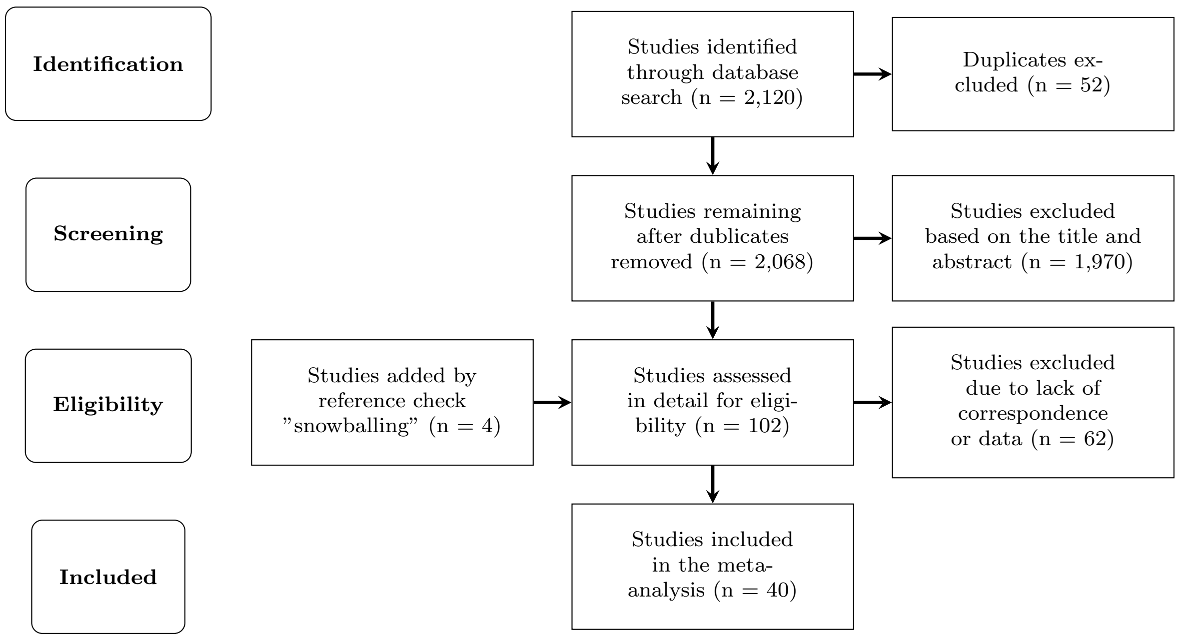
Tirole, J. (1988), *The theory of industrial organization*, MIT press, Massachusetts, United States.

Zeugner, S. & Feldkircher, M. (2015), 'Bayesian model averaging employing fixed and flexible priors: The BMS package for R', *Journal of Statistical Software* **68**(4), 1–37.

Appendices

A Details of Literature Search

Figure A.1: PRISMA Flow Diagram



Notes: PRISMA stands for Preferred Reporting Items for Systematic Reviews and Meta-Analyses. For further details on PRISMA and related reporting standards in meta-analysis, I refer the reader to Havranek et al. (2020).

Table A.1: The primary studies used in the meta-analysis

Serial	Author(s) (year)	Serial	Author(s) (year)
1	Kondorfer (1997)	21	Apergis and Cooray (2015)
2	Marotta (2009)	22	Marcal et al (2020)
3	Gambacorta and Iannotti (2007)	23	Herlambang et al (2023)
4	Kwapil and Scharler (2010)	24	Valadkhani and Bollen (2013)
5	Greenwood-Nimmo et al (2010)	25	Divino and Haraguchi (2022)
6	Castro and Mello (2012)	26	Karagiannis et al (2014)
7	Valadkhani and Anwar (2012)	27	Li et al (2021)
8	Sander and Kleimeier (2004)	28	Pederson (2018)
9	Karagiannis et al (2010)	29	Panagopoulos and Spiliotis (2015)
10	Bogoev and Sergi (2012)	30	Yu et al (2013)
11	Espinosa-Vega and Rebucci (2004)	31	Valadkhani et al (2014b)
12	Roelands (2012)	32	Cotler and Carrillo (2024)
13	Cecchin (2011)	33	Tonghui and Cho (2023)
14	Valadkhani et al (2014)	34	Musti (2023)
15	Machava (2017)	35	Kashyap et al (2023)
16	Liu et al (2016)	36	Gregor (2018)
17	Belke et al (2013)	37	Bao and Nhut (2013)
18	Mihaylov (2016)	38	Galindo and Steiner (2022)
19	Holland et al (2020)	39	Mangwengwende et al (2011)
20	Sahin and Cicek (2018)	40	Martinez et al (2022)

B Summary Statistics and Related Figures

Table B.1: Mean estimates by subsets of the dataset

		Weighted			Unweighted		
Category	Obs.	Mean	95% conf. int.		Mean	95% conf. int.	
All estimates	1,054	0.1966	0.1594	0.2338	0.8117	0.6954	0.9279
Asymmetry variables							
Upward pass-through	582	0.3677	0.3030	0.4323	1.0175	0.8312	1.2037
Downward pass-through (reference category)	472	0.1064	0.0637	0.1492	0.5579	0.4399	0.6760
Data variables							
Quarterly data	89	0.1554	-0.0134	0.3241	3.8803	2.9688	4.7917
Monthly data	792	0.3139	0.2794	0.3484	0.5105	0.4434	0.5776
Weekly data	127	-0.2699	-0.3526	-0.1873	0.8712	0.5742	1.1681
IMF data	134	0.3950	0.2673	0.5227	0.5453	0.3990	0.6917
ECB data	285	0.4892	0.4592	0.5192	0.3300	0.2313	0.4287
National database	597	0.1345	0.0859	0.1831	1.1159	0.9223	1.3095
Time series	757	0.1901	0.1466	0.2336	0.8641	0.7102	1.0180
Panel data (reference category)	297	0.3072	0.2266	0.3878	0.6779	0.5496	0.8063
Pre-GFC data	335	0.2727	0.2233	0.3222	0.6508	0.5425	0.7592
Post-GFC data	32	-0.1558	-0.2320	-0.0796	0.4454	0.2451	0.6458
Estimation variables							
Long-run	390	0.1702	0.1109	0.2295	0.8016	0.6504	0.9529
Short-run	608	0.1731	0.1334	0.2128	0.5008	0.4024	0.5992
Simultaneity bias	106	1.0132	0.8453	1.1811	1.0561	0.6635	1.4487
Ordinary least squares	769	0.2501	0.1966	0.3036	0.9722	0.8175	1.1269
Johansen method	198	0.1761	0.1284	0.2237	0.3843	0.2661	0.5024
Interbank reference rate	770	0.2432	0.1955	0.2910	0.9463	0.7890	1.1035
Discount reference rate (reference category)	284	0.0348	0.0016	0.0681	0.4467	0.3992	0.4942
Publication variables							
Peer-reviewed journal	713	0.1613	0.1156	0.2069	0.8949	0.7312	1.0587
Central bank author	240	0.1441	0.0902	0.1981	0.7403	0.5818	0.8987
Loan variables							
Business loan	288	0.4637	0.4064	0.5210	0.7538	0.5882	0.9194
Consumer loan	215	0.3676	0.2706	0.4645	0.4646	0.2442	0.6849
Mortgage loan	167	0.5389	0.4888	0.5891	0.3866	0.3074	0.4659
Short-term loan	282	0.2889	0.2376	0.3402	0.5871	0.4308	0.7434
Long-term loan	181	0.5617	0.4908	0.6326	0.4082	0.2739	0.5425
Macrofinancial variables							
Developed economy	570	0.2888	0.2409	0.3368	1.0443	0.8540	1.2347
Inflation targeter	466	0.3050	0.2549	0.3551	0.7749	0.6144	0.9355
Floating exchange rate regime	900	0.2976	0.2564	0.3387	0.8940	0.7591	1.0290
Euro Area	174	0.1954	0.1537	0.2372	0.1926	0.0372	0.3480

Notes: GFC denotes global financial crisis; IMF denotes International Monetary Fund; ECB denotes European Central Bank; Obs. denotes number of observations; conf. int. denotes confidence interval. The weights are the reciprocals of the number of estimates reported per study.

Table B.2: Summary statistics

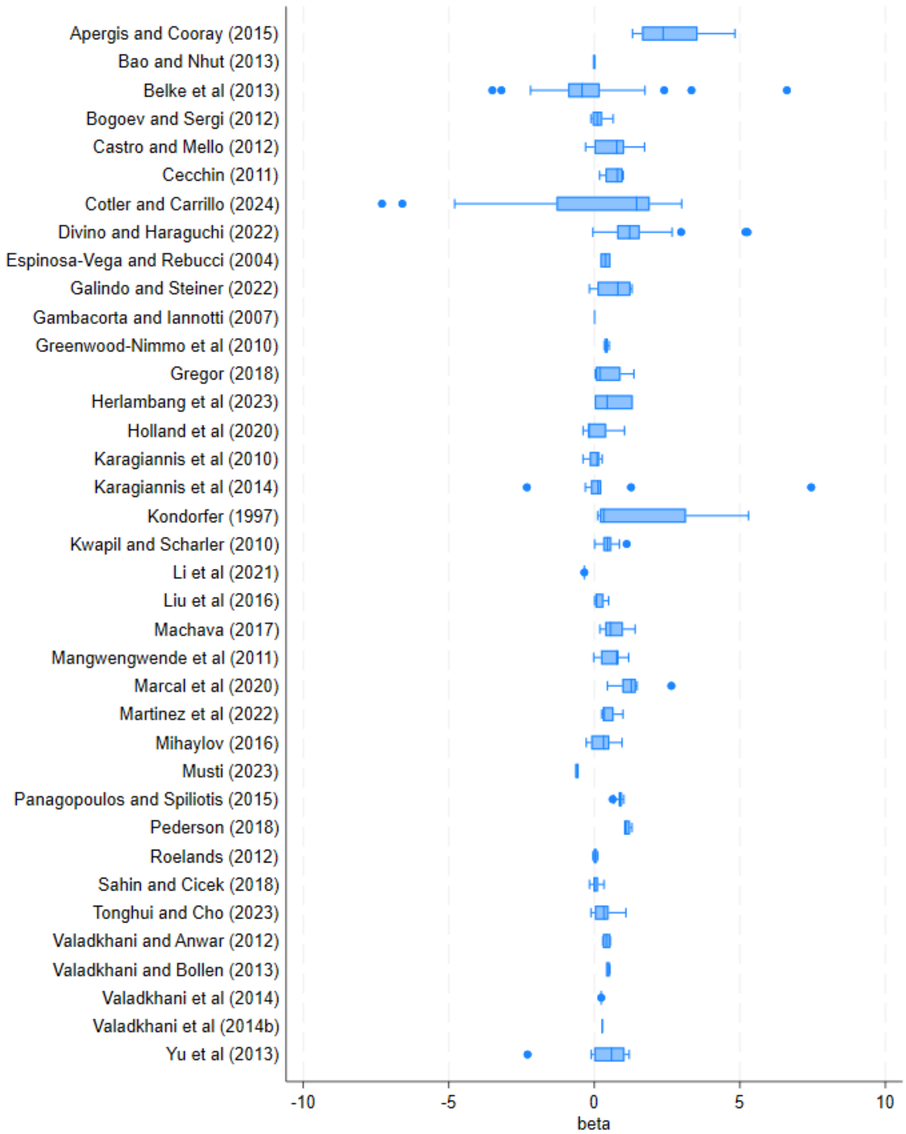
Variable	Obs	Mean	95% conf. int.	
Beta	1,054	0.1966	0.1594	0.2338
Standard error	1,054	0.0882	0.0703	0.1061
Asymmetry variables				
Upward pass-through	1,054	0.3453	0.3165	0.3740
Downward pass-through (reference category)	1,054	0.6547	0.6260	0.6835
Data variables				
Quarterly data	1,054	0.2206	0.1955	0.2456
Monthly data	1,054	0.6376	0.6085	0.6666
Weekly data	1,054	0.1390	0.1181	0.1600
Time span	1,054	12.0446	11.6051	12.4840
IMF data	1,054	0.0796	0.0632	0.0960
ECB data	1,054	0.0835	0.0668	0.1002
National database	1,054	0.8249	0.8019	0.8479
Time series	1,054	0.9446	0.9308	0.9584
Panel data (reference category)	1,054	0.0554	0.0416	0.0692
Pre-GFC data	1,054	0.2903	0.2628	0.3177
Post-GFC data	1,054	0.2630	0.2364	0.2896
Estimation variables				
Long-run	1,054	0.2590	0.2326	0.2855
Short-run	1,054	0.7137	0.6864	0.7410
Lag length	1,054	0.6275	0.5608	0.6943
Simultaneity bias	1,054	0.0435	0.0311	0.0558
Ordinary least squares	1,054	0.6018	0.5722	0.6314
Johansen method	1,054	0.2296	0.2042	0.2550
Interbank reference rate	1,054	0.7763	0.7511	0.8015
Discount reference rate (reference category)	1,054	0.2237	0.1985	0.2489
Publication variables				
Publication year	1,054	19.1277	18.7652	19.4902
Annual citation score	1,054	2.7316	2.5475	2.9158
Peer-reviewed journal	1,054	0.8332	0.8107	0.8558
Impact factor	1,054	0.0756	0.0695	0.0817
Central bank author	1,054	0.3156	0.2875	0.3437
Loan variables				
Business loan	1,054	0.2697	0.2429	0.2966
Consumer loan	1,054	0.0877	0.0706	0.1048
Mortgage loan	1,054	0.0572	0.0431	0.0712
Short-term loan	1,054	0.3047	0.2769	0.3325
Long-term loan	1,054	0.0685	0.0532	0.0838
Macrofinancial variables				
Trade openness	1,026	0.2473	0.2393	0.2553
FDI inflows to GDP ratio	1,054	0.0272	0.0257	0.0287
Developed economy	1,054	0.5203	0.4901	0.5506
Market capitalization	1,004	0.7019	0.6788	0.7249
Inflationary environment	1,054	0.0538	0.0473	0.0603
Economic growth rate	1,054	0.0396	0.0385	0.0408
Stock turnover ratio	1,000	0.9999	0.9493	1.0506
Central bank independence	1,046	0.5569	0.5460	0.5678
Inflation targeter	1,054	0.4508	0.4208	0.4809
Floating exchange rate regime	1,054	0.7669	0.7413	0.7924
Euro Area	1,054	0.2124	0.1877	0.2372

Notes: Mean denotes mean weighted by the inverse of the number of estimates reported per study; Obs denotes number of observations; conf. int. denotes confidence interval.

Figure B.1: Heterogeneity conceals the true upward pass-through

Notes: Each box represents the distribution between the 25th and 75th percentiles. The midlines represent median values. The two whiskers represent the highest and lowest observations between the 25th and 75th percentiles, multiplied by a factor of 1.5.

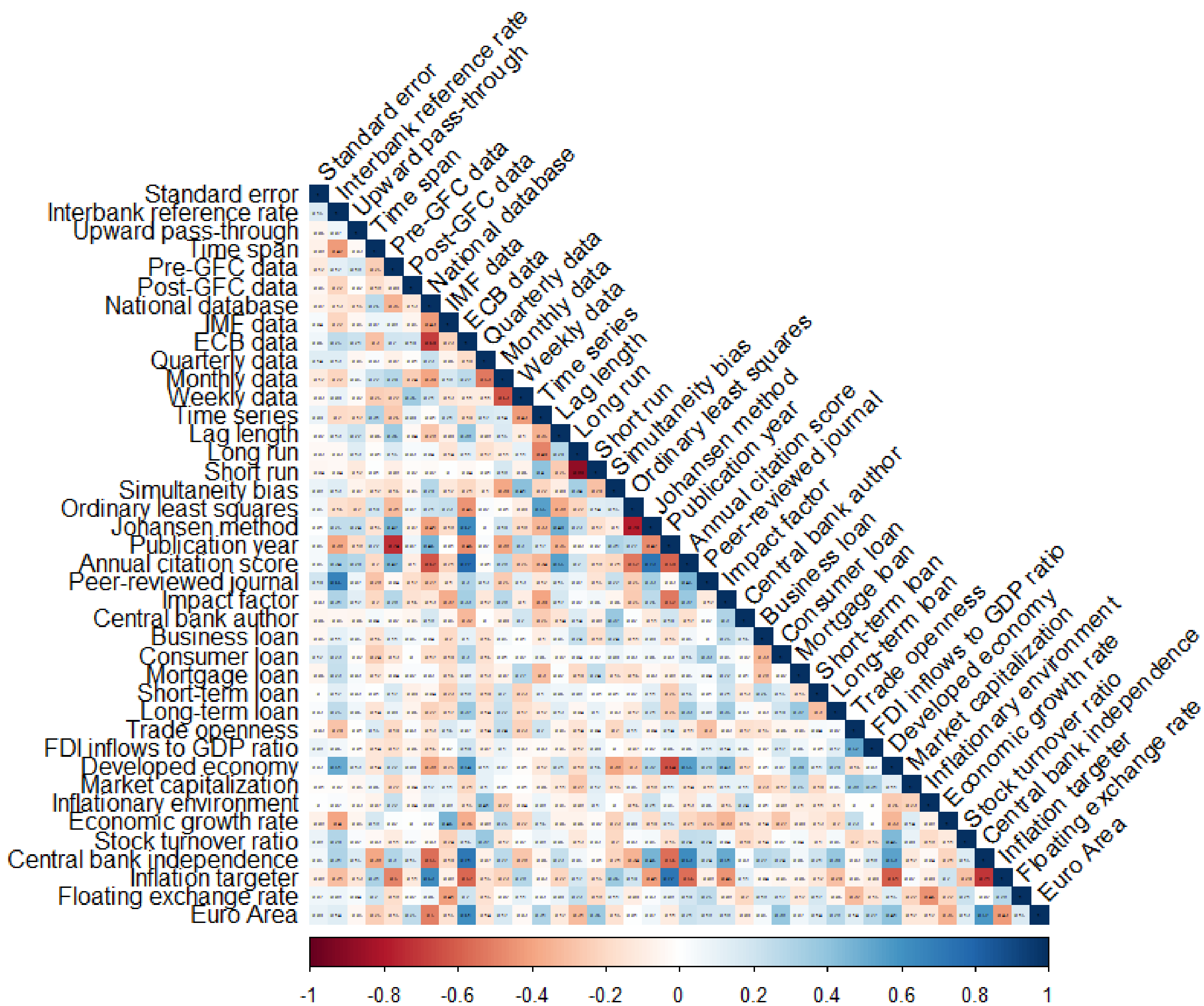
Figure B.2: Heterogeneity also conceals the true downward pass-through



Notes: Each box represents the distribution between the 25th and 75th percentiles. The midlines represent median values. The two whiskers represent the highest and lowest observations between the 25th and 75th percentiles, multiplied by a factor of 1.5.

C Diagnostics for the Baseline BMA Model

Figure C.1: Correlation plot for the baseline BMA model



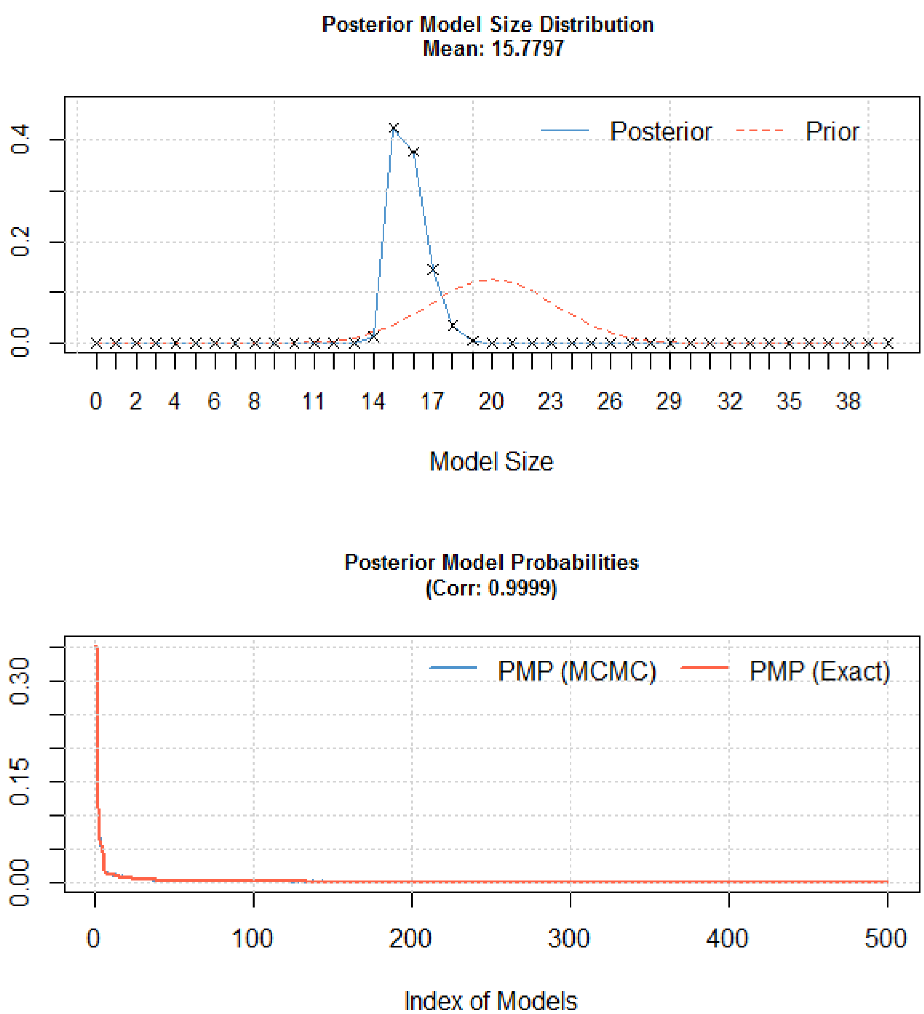
Notes: The figure shows Pearson correlation coefficients for the explanatory variables in the baseline BMA model.

Table C.1: Summary of the baseline BMA estimation

Mean no. regressors	*Draws*	*Burn-ins*	*Time No.*	*models visited*
15.7797	2×10^6	1×10^6	32.7912 mins	144,727
Modelspace	*Models visited*	*Topmodels*	*Corr. PMP*	*No. Obs.*
1.1000×10^{12}	1.3×10^{-5}%	97	0.9999	980
Model prior	*g-prior*	*Shrinkage-stats*		
dilut/ 20	UIP	Av=0.9990		

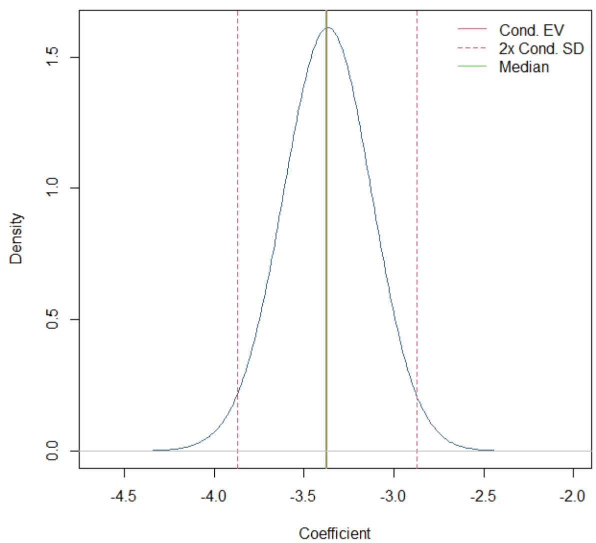
Notes: Model summary of baseline BMA model estimated with the unit information g-prior and the dilution model prior (see Eicher et al. 2011, George 2010).

Figure C.2: Model size and convergence for the baseline BMA model



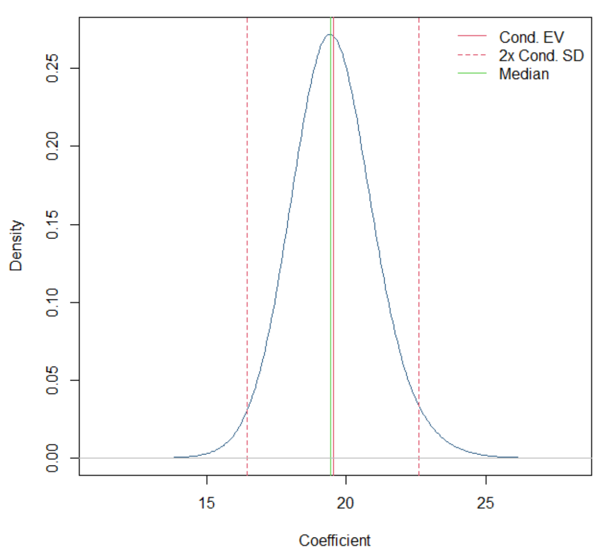
Notes: The figure shows the posterior model size distribution and the posterior model probabilities of the baseline BMA model.

Figure C.3: Posterior coefficient distribution: *Trade openness*



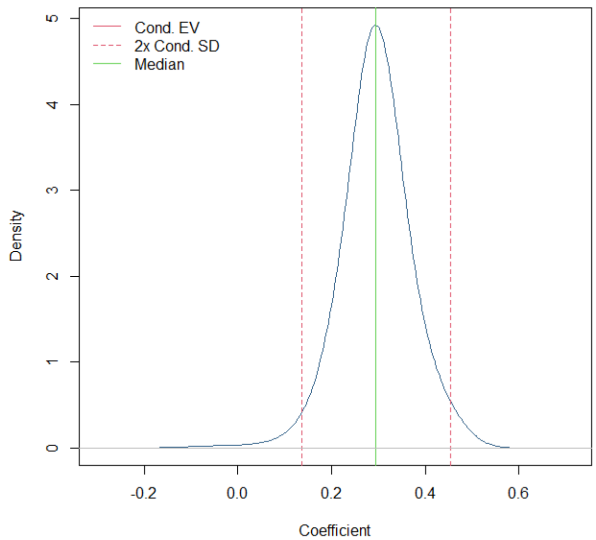
Notes: Posterior coefficient distribution for *Trade openness* in the baseline BMA model.

Figure C.4: Posterior coefficient distribution: *FDI inflows to GDP ratio*



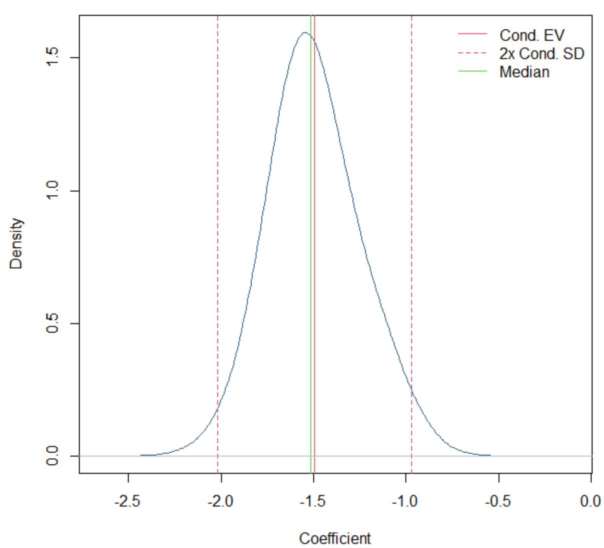
Notes: Posterior coefficient distribution for *FDI inflows to GDP ratio* in the baseline BMA model.

Figure C.5: Posterior coefficient distribution: *Developed economy*



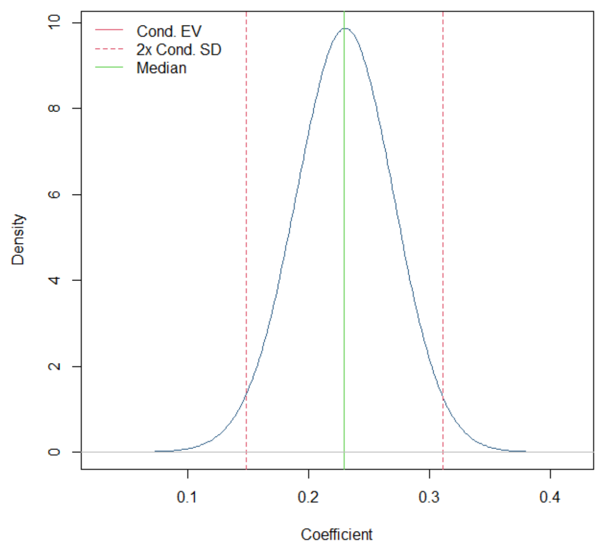
Notes: Posterior coefficient distribution for *Developed economy* in the baseline BMA model.

Figure C.6: Posterior coefficient distribution: *Inflationary environment*



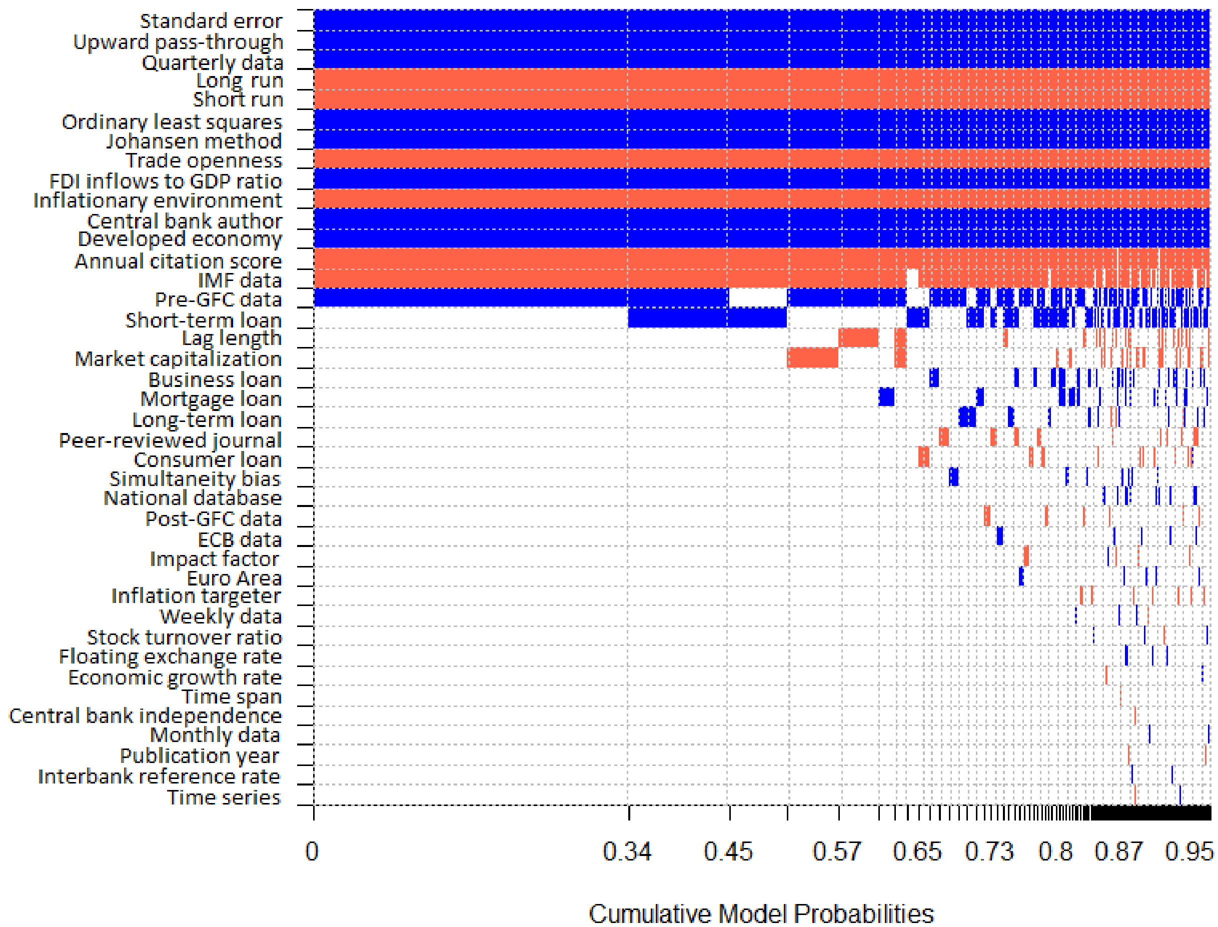
Notes: Posterior coefficient distribution for *Inflationary environment* in the baseline BMA model.

Figure C.7: Posterior coefficient distribution: *Upward pass-through*



Notes: Posterior coefficient distribution for *Upward pass-through* in the baseline BMA model.

Figure C.8: Model inclusion graph for the baseline BMA model



Notes: The columns denote individual models; the explanatory variables are ranked in descending order according to their posterior inclusion probabilities. The horizontal axis shows cumulative posterior model probabilities. Blue color (darker in grayscale) = the estimated coefficient of the explanatory variable is positive. Red color (lighter in grayscale) = the estimated coefficient of the explanatory variable is negative. No color = the variable is excluded from the estimated model.

D Description of Variables and Additional Statistics

Table D.1: Number of estimates reported per country/region

Serial	Country	Obs.	Serial	Country	Obs.
1	Australia	95	23	Luxembourg	4
2	Austria	14	24	Malaysia	4
3	Belgium	8	25	Mexico	46
4	Botswana	16	26	Mozambique	8
5	Brazil	94	27	The Netherlands	12
6	Bulgaria	16	28	Nigeria	20
7	Canada	4	29	North Macedonia	28
8	Chile	44	30	The Philippines	4
9	China	5	31	Portugal	6
10	Colombia	20	32	Russia	2
11	The Czech Republic	14	33	Singapore	4
12	Euro Area	150	34	South Africa	16
13	Finland	10	35	South Korea	4
14	France	19	36	Spain	18
15	Germany	70	37	Switzerland	29
16	Greece	10	38	Thailand	112
17	Hong Kong	4	39	Turkey	15
18	India	5	40	The United Kingdom	4
19	Indonesia	5	41	The United States of America	75
20	Ireland	4	42	Vietnam	4
21	Italy	13	43	Zambia	16
22	Japan	3	44	Total	1,054

Notes: The table reports the distribution of estimates by country or region. Obs. denotes number of estimates reported per country or region.

Table D.2: Definition of variables used in the study

Variable	Description
Beta	= Interest rate pass-through estimate
Standard error	= Standard error of the pass-through estimate
Asymmetry variables	
Upward pass-through	= 1 if the pass-through represents the effect of an increase in the policy reference rate
Downward pass-through (reference category)	= 1 if the pass-through represents the effect of a decrease in the policy reference rate
Data variables	
Quarterly data	= 1 if quarterly data is used for estimation
Monthly data	= 1 if monthly data is used for estimation
Weekly data	= 1 if weekly data is used for estimation
Time span	= Number of years in dataset used to estimate the pass-through
IMF data	= 1 if data used for estimation is from the International Financial Statistics database
ECB data	= 1 if data used for estimation is from the European Central Bank
National database	= 1 if data used for estimation is from a national database
Time series	= 1 if time series is used for estimation
Panel data (reference category)	= 1 if panel data is used for estimation
Pre-GFC data	= 1 if data covers the period before the 2008-2012 global financial crisis
Post-GFC data	= 1 if data covers the period after the 2008-2012 global financial crisis
Estimation variables	
Long-run	= 1 for long-run pass-through
Short-run	= 1 for short-run pass-through
Lag length	= lag length of the policy rate variable
Simultaneity bias	= 1 if estimation controls for inflation rate without instrumental variables or lags
Ordinary least squares	= 1 if ordinary least squares is used for estimation
Johansen method	= 1 if Johansen cointegration method is used for estimation
Interbank reference rate	= 1 if policy reference rate is an interbank rate
Discount reference rate (reference category)	= 1 if policy reference rate is a discount rate
Publication variables	
Publication year	= Year of publication of the primary study
Annual citation score	= Annual citations of the primary study
Peer-reviewed journal	= 1 if primary study is published in a peer-reviewed journal
Impact factor	= Impact factor of periodical
Central bank author	= 1 if author or co-author is a central banker
Loan variables	
Business loan	= 1 for pass-through to business loan rate
Consumer loan	= 1 for pass-through to consumer loan rate
Mortgage loan	= 1 for pass-through to mortgage loan rate
Short-term loan	= 1 for loans maturing within 1 year
Long-term loan	= 1 for loans maturing after 1 year
Macrofinancial variables	
Trade openness	= Country's imports as a percentage of GDP
FDI inflows to GDP ratio	= Country's FDI inflows as a percentage of GDP
Developed economy	= 1 if country is developed for most (at least half) of the study period, 0 otherwise
Market capitalization	= Country's market capitalization of listed domestic companies
Inflationary environment	= Country's inflation rate
Economic growth rate	= Country's economic growth rate
Stock turnover ratio	= Country's stock market turnover ratio
Central bank independence	= Country's central bank independence index
Inflation targeter	= 1 if country's is an inflation targeter for most (at least half) of the study period, 0 otherwise
Floating exchange rate regime	= 1 if country freely floats its currency for most (at least half) of the study period, 0 otherwise
Euro Area	= 1 if country is a Euro Area member for most (at least half) of the study period

Notes: IMF International Monetary Fund; ECB denotes European Central Bank; GDP denotes gross domestic product; GFC denotes global financial crisis.

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