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METHOD VERSUS CROSS-COUNTRY HETEROGENEITY IN THE EXCHANGE RATE PASS-THROUGH

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Method Versus Cross-Country Heterogeneity in the Exchange Rate Pass-Through

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Abstract:
Estimates of the exchange rate pass-through vary significantly across studies, making it difficult for policymakers and researchers to ascertain the true impact of exchange rate fluctuations on domestic prices. I conduct a meta-analysis to understand why estimates differ and provide consensus for the conflicting results. My dataset includes 32 primary studies containing 684 estimates for 108 countries. Because there are many potential causes of heterogeneity, I use Bayesian model averaging to identify the most important ones. I find that estimates vary due to differences in country-specific and methodological characteristics. The country-specific characteristics include central bank independence, inflationary environment, and economic development, while the methodological variables include data frequency, data dimension, and data time span. When I control for differences in methodology and assign greater weight to those that reflect the best practices in the literature, I find that the implied pass-through estimates remain substantial, albeit smaller than suggested in the literature. The pass-through is 6% for developed countries and 9% for developing countries.

JEL: F31, F41
Keywords: exchange rate pass-through, prices, heterogeneity, meta-analysis

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1 Introduction

Apart from policy rates, central banks occasionally manipulate foreign exchange rates in order to target inflation. In doing so, they make very explicit assumptions about how strong the policy transmission to inflation is and how long it does take (Ha et al. 2020). These assumptions are represented by the exchange rate pass-through, which describes how domestic prices respond to changes in exchange rates (Burstein & Gopinath 2014). Therefore, examining the exchange rate pass-through is crucial for policymakers and researchers, as it sheds light on how changes in exchange rates affect domestic prices, which can have significant implications for macroeconomic policies.

Despite the importance of the exchange rate pass-through, determining its precise value is challenging for researchers and policymakers. One reason for this difficulty is that estimates of the pass-through vary significantly across studies, as shown in Figure 1, possibly due to differences in methodology and country characteristics. Additionally, in empirical economics, it is often the case that not all the estimates get published, and what is left does not reflect the complete picture of what research has to offer. In meta-analysis, this phenomenon is known as publication bias (more on publication bias in Section 3).

The literature identifies several country characteristics that could potentially infuence the exchange rate pass-through. For instance, Fischer (1995) suggests that central bank independence gives policymakers the discretion to curtail currency and inflationary pressures. Taylor (2000) argues that domestic firms in a stable inflationary environment are less likely to pass on costs induced by exchange rates, as they expect price fluctuations to be only transitory. Boz et al. (2022) note that import prices respond quickly to exchange rates when a large fraction of imports is invoiced in foreign currencies. Furthermore, Ghosh (2013) states that the pass-through effect increases with trade openness.[1]

On the other hand, methodological heterogeneity is likely to occur when researchers employ different types of data and estimation techniques. Cross-sectional data represents information across individuals, time series data represents information across time, and panel data represents information across both individuals and time. Therefore, estimates based on the different types can be dissimilar. Furthermore, the statistical methods employed by researchers involve different assumptions and statistical procedures, which could yield heterogeneous results for the pass-through.

This study focuses on the pass-through from nominal effective exchange rates into consumer prices and addresses four critical questions: how do country characteristics actually affect the pass-through, how do methodological characteristics influence reported estimates, to what extent does publication bias affect reported estimates, and how big is the estimated pass-through after correcting for publication bias? I focus on this pass-through because consumer prices are more relevant for monetary policy than producer and international prices. To answer the raised questions, I employ a meta-analytic approach. I use linear and non-linear methods of testing and correcting for publication bias. I also use Bayesian model averaging to examine the causes of heterogeneity and to estimate the exchange rate pass-through while accounting for possible biases in the literature.

To date, only one meta-analysis by Velickovski & Pugh (2011) examines the exchange rate

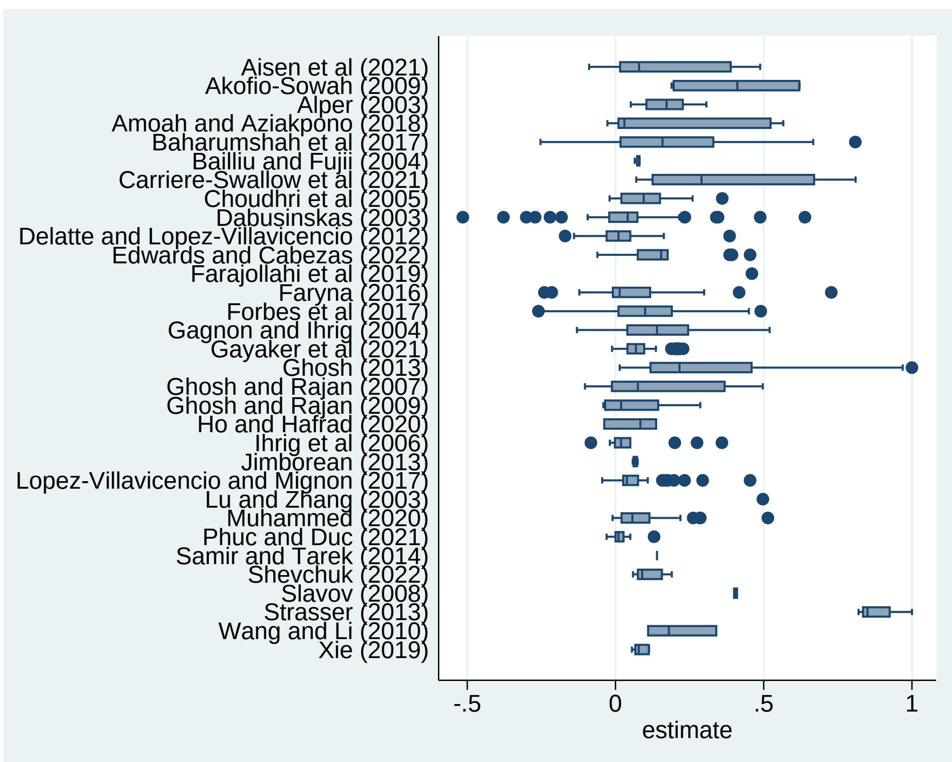
[1]The macroeconomic determinants are discussed fully in Section 4.

pass-through and documents its variation. I extend the previous meta-analysis by collecting standard errors of estimates and conducting the first formal test of publication bias on the pass-through. Furthermore, with a larger database, I enlarge the pool of explanatory variables suggestive of why results vary so much even for similar datasets.

The results reveal mild publication bias, which suggests that researchers tend to overestimate the exchange rate pass-through. Furthermore, the results reveal the methodological and country-specific determinants of pass-through heterogeneity. The methodological determinants include data frequency, data dimension, and data time span, while the country-specific determinants include economic development, inflationary environment, and central bank independence. Controlling for these factors and giving greater weight to variables that reflect the best practices in the literature, I find that the pass-through is context-dependent. Specifically, for developed and developing countries, I obtain coefficients of 6% and 9%, respectively.

The paper is structured as follows: Section 2 outlines the common approaches to estimating the exchange rate in the literature and gives an overview of previous empirical studies on the topic. Section 3 contains the empirical findings on publication bias and the exchange rate pass-through after correcting for such bias. Section 4 examines the factors contributing to heterogeneity in the literature. Finally, Section 5 offers concluding remarks. The Appendix contains additional results not reported in the main text and the list of studies included in the dataset.

Figure 1: Estimates of the pass-through vary both within and across studies



Notes: The span of each rectangular box represents the interquartile range between the 25th and 75th percentiles. The mid lines represent median values. The two whiskers represent the highest and lowest data points between the upper and lower quartiles, multiplied by a factor of 1.5.

2 The Dataset

Researchers usually derive estimates of the exchange rate pass-through from nominal effective exchange rates into consumer prices from the following basic model:

$$P_t = \hat{\alpha} + \hat{\beta} ER_t + u_t \tag{1}$$

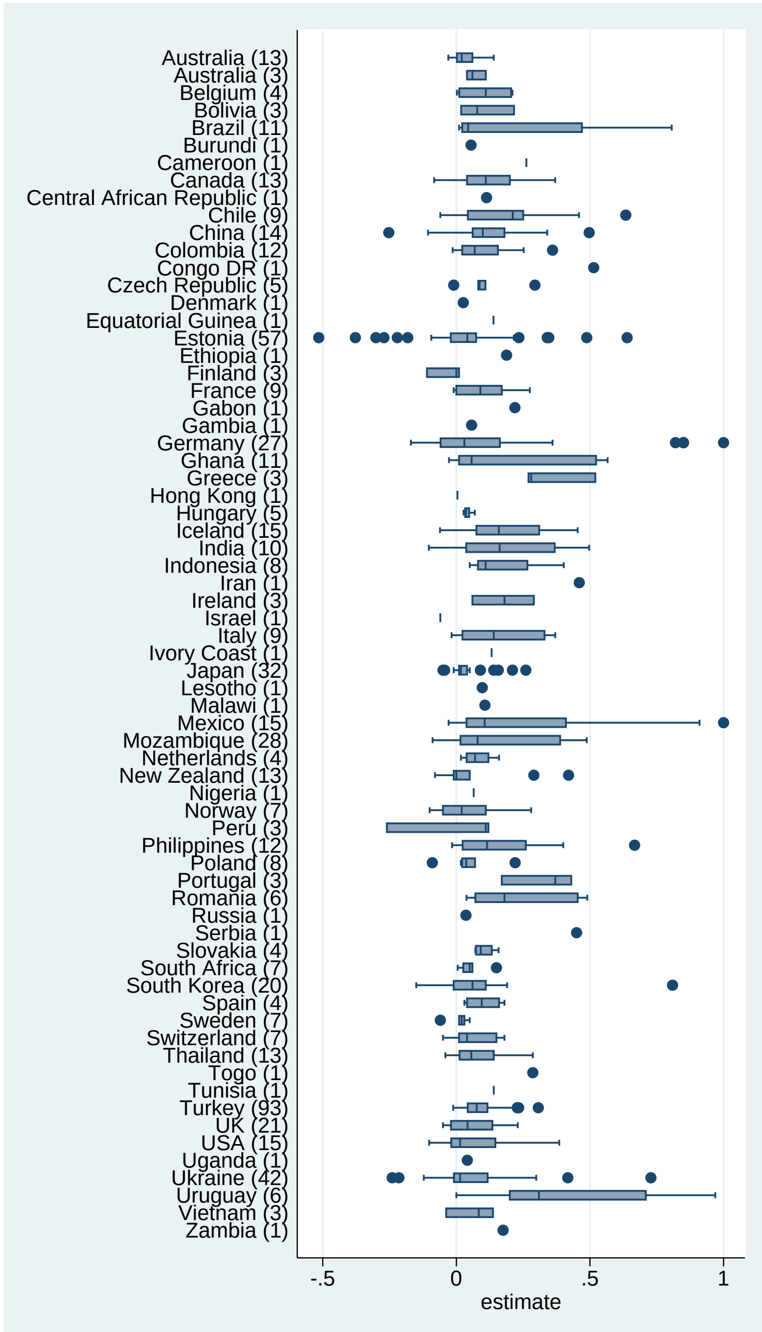
Here, P_t and ER_t denote consumer price and nominal effective exchange rate, respectively, at time t, $\hat{\beta}$ denotes the exchange rate pass-through, $\hat{\alpha}$ denotes the intercept, and u_t denotes the error term. To collect the estimates, I begin by searching for studies on the exchange rate pass-through through Google Scholar, which has extensive coverage and full-text search capabilities. Out of thousands of results, I review the first 700 studies and select those that meet specific criteria. First, the study must report estimates of the pass-through from nominal effective exchange rates to consumer prices. Second, the study must provide information about the standard errors of estimates for formal tests of publication bias. Third, the researchers must clearly describe the methodology and data used so I can extract explanatory variables that explain heterogeneity between studies. Fourth, to obtain consistent estimates, the exchange rate variable must be defined as units of domestic currency per basket of foreign currencies such that an increase (decrease) in the exchange rate implies depreciation (appreciation), and the pass-through is positive by definition. Finally, only estimates without interaction terms should be reported since studies rarely provide the necessary information to disentangle estimates from interaction terms.

Table 1: Statistical summary

		Unweighted			Weighted		
Category	Obs.	Mean	95% conf. int.		Mean	95% conf. int.	
All estimates	684	0.11	0.1006	0.1272	0.19	0.1689	0.2031
Data Characteristics							
Annual data	5	0.15	-0.0596	0.3663	0.27	0.0023	0.5344
Quarterly data	502	0.11	0.0931	0.1233	0.15	0.1355	0.1694
Monthly data	177	0.13	0.1007	0.1570	0.26	0.2129	0.2998
Panel data	38	0.30	0.2058	0.3951	0.36	0.2535	0.4591
Time series data	645	0.10	0.0899	0.1148	0.13	0.1201	0.1472
Post crisis	70	0.11	0.0919	0.1367	0.11	0.0948	0.1341
OECD data	133	0.08	0.0583	0.1048	0.09	0.0707	0.1150
Specification Characteristics							
Appreciation	26	0.04	-0.0423	0.1174	0.06	0.0055	0.1144
Depreciation	27	0.11	0.0394	0.1859	0.12	0.0421	0.2016
Estimation Characteristics							
Ordinary least squares	545	0.10	0.0832	0.1110	0.13	0.1175	0.1485
Maximum likelihood	90	0.16	0.1261	0.1928	0.30	0.2574	0.3437
Generalized method of moments	7	0.06	0.0503	0.0775	0.07	0.0602	0.0765
Publication Characteristics							
Peer reviewed journal	408	0.13	0.1136	0.1504	0.22	0.1988	0.2467
Country Characteristics							
Inflation targeting regime	83	0.10	0.0725	0.1304	0.11	0.0779	0.1349
Fixed exchange regime	54	0.18	0.1340	0.2313	0.26	0.2062	0.3091
Developed countries	237	0.09	0.0723	0.1128	0.16	0.1299	0.1971
Eurozone member	60	0.14	0.0812	0.2048	0.41	0.3080	0.5177
Forward guidance	263	0.09	0.0701	0.1029	0.13	0.1070	0.1530
Industry Characteristics							
Primary or secondary sector	70	0.12	0.0663	0.1788	0.39	0.2959	0.4877

Notes: OECD denotes Organisation for Economic Co-operation and Development; Obs denotes number of observations; conf. int. denotes confidence interval. The weights are the inverse of the number of estimates reported per study.

Figure 2a: Estimates also vary across countries



Notes: The span of each rectangular box represents the interquartile range between the 25th and 75th percentiles. The mid lines represent median values. The two whiskers represent the highest and lowest data points between the upper and lower quartiles, multiplied by a factor of 1.5. The numbers in brackets represent the number of estimates reported per country. Please see for Table D.2 for numerical details.

Altogether, I identify 32 primary studies that meet the five criteria and terminate the search on May 6, 2023. These studies contain 684 estimates and mainly consist of published articles and working papers. At this stage, I examine the studies in greater detail and identify up to 22 explanatory variables concerning study and country characteristics that can explain the heterogeneity between studies. I collect data for the variables and create at least 15,048 data points (684 x 22) for the meta-analysis. The final sample of 32 studies includes 23 peer-reviewed journal articles and grey literature, which I report in Table A.1 in the Appendices. The dataset and codes used in the meta-analysis are available on request.

The structure and size of the sample provide three main benefits: firstly, a significant proportion (72%) of the sample comprises peer-reviewed journal articles, giving greater weight to high-quality papers. Secondly, the number of observations is sufficiently large to consider several explanatory variables in the meta-regression analysis. Finally, the reported estimates concern countries relevant for world trade and a total of 108 countries: 642 country-specific estimates for 68 countries, and 42 panel estimates for 40 countries.[2] The sample covers research spanning more than five decades, with the earliest and latest years of publication being 1970 and 2021, respectively. Since all the studies report elasticities, partial correlation coefficients are not necessary, preventing information loss.

Table 1 presents the statistical summary. Apart from unweighted means, I consider weighted means because the former are easily dominated by studies reporting multiple estimates. Nonetheless, both measures show that estimates vary across subsets of the sample. For instance, panel estimates are more than twice the size of time series estimates. Importantly, the overall averages suggest a small effect size: the unweighted mean estimate is about 11 percent, while the weighted mean estimate is about 19 percent.

I illustrate the dataset in Figure 1, where the box plot shows that the estimates reported are heterogeneous across primary studies. Due to this heterogeneity, the overall averages do not accurately represent all the estimates. To address this issue, one possible solution is to identify the potential sources of heterogeneity, enabling us to account for them and model the exchange rate pass-through in different contexts.

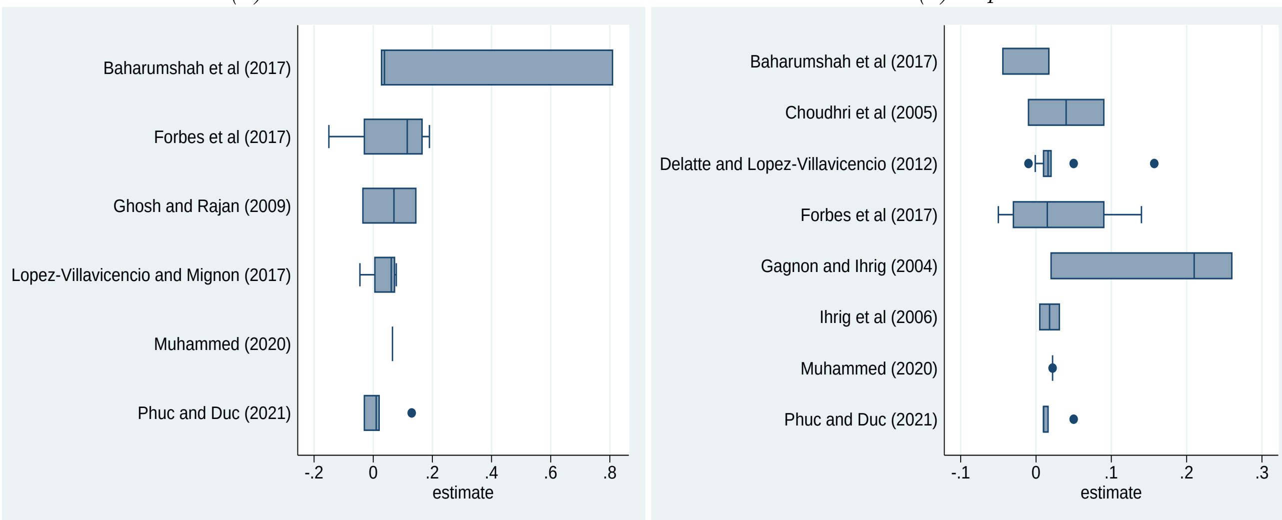
Figure 2a depicts cross country heterogeneity in the exchange rate pass-through. Such heterogeneity may arise due to variation in country characteristics. In the subsequent sections, I extensively examine the relationship between country characteristics and the exchange rate pass-through, after conducting tests for publication bias.

Heterogeneity can also arise from variations in the methods employed by researchers. Even when studying the same country, different results can be obtained. In the study sample, South Korea and Japan are two of the most frequently studied countries, and as shown in Figure 2b, primary studies report widely differing estimates. If the heterogeneity among studies were solely due to country characteristics, the estimates for each country in the box plots should be the same, but that is not the case. Hence, I also take into account methodological differences in modeling the exchange rate pass-through, in addition to controlling for country characteristics.

[2] I present data on the number of estimates reported per country and other additional statistics in Table D.2, Table D.3, and Table D.4 in the Appendices

Figure 2b: Estimates vary even for the same country

(a) South Korea *(b) Japan*



Notes: The span of each rectangular box represents the interquartile range between the 25th and 75th percentiles. The mid lines represent median values. The two whiskers represent the highest and lowest data points between the upper and lower quartiles, multiplied by a factor of 1.5.

3 Publication Bias

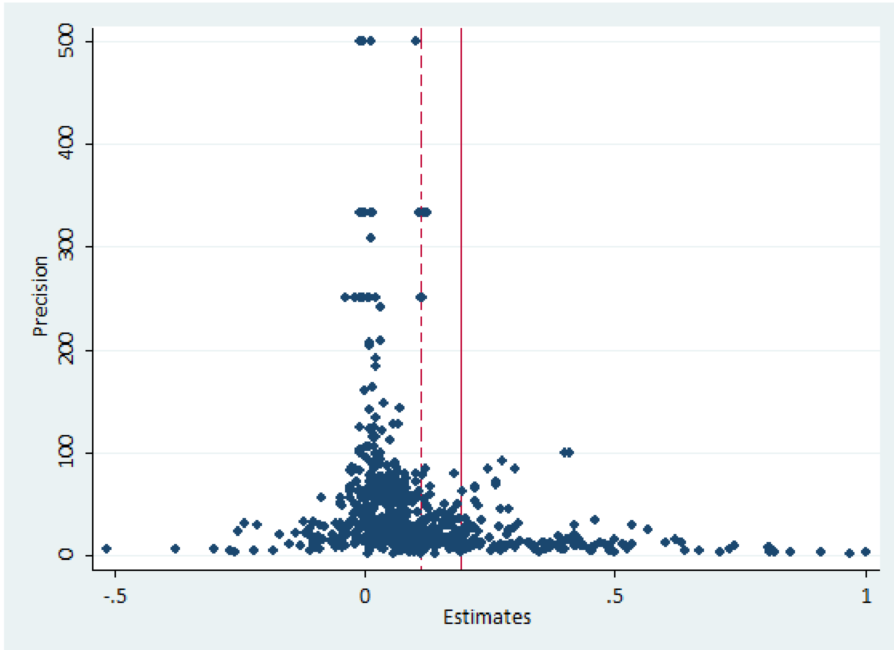
The literature dealing with publication bias is non-existent for the exchange rate pass-through into consumer prices. Therefore, even though this paper focuses mainly on heterogeneity, I begin the meta-analysis with publication bias in view.

In academic literature, researchers and editors often have a bias against results that contradict popular theories or intuition. When this bias occurs frequently in a subset of the literature, publication bias ensues. Publication bias refers to a phenomenon where authors selectively report their findings to conform to specific criteria, especially theory. For instance, most studies on money demand report positive income elasticities, as negative elasticities are deemed meaningless both theoretically and intuitively (see Knell & Stix 2005).

Selective reporting may increase the chances of passing the peer-review process, and polished results may aid in reader inference (Elminejad et al. 2022). However, publication selection bias can have serious consequences. The exclusion of unusual or unexpected results can create a false narrative in the literature, leading to the exaggeration or underestimation of the effect being researched. In economics, policies based on exaggerated findings may miss the intended policy targets. In medicine and pharmacology, treatment based on inflated results from drug trials could be fatal.

Publication bias is well-known in economics, as evidenced by numerous studies. For example, a research survey conducted by Ioannidis et al. (2017) finds widespread publication bias in economics research. Similarly, Havranek (2010) uncovers strong evidence of publication bias among primary studies examining the effects of currency unions on trade. Gechert et al. (2021) detects publication bias in studies on the Cobb-Douglas production function, while Havrankova & Reckova (2015) finds that publication bias inflates the reported effects of atmospheric carbon dioxide on global temperature. Given these findings, it is necessary to test and correct for publication bias in the literature estimating the exchange rate pass-through.

Figure 3: The funnel plot reveals mild publication bias



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

The funnel plot, introduced by Egger et al. (1997), is a useful tool in detecting publication bias. It is a scatter plot that displays estimates on the horizontal axis and precision (i.e., inverse of standard errors) on the vertical axis. If the plot is asymmetrical or denser on one side, we confirm the presence of publication bias. For the dataset, I present the funnel plot in Figure 3, which reveals slight asymmetry.[3] The right side of the plot is denser than the left, indicating mild publication bias. Nonetheless, funnel plots are limited to graphical analysis. To rigorously test and correct for publication bias, I utilize funnel asymmetry tests and non-linear techniques.

Table 2 presents the results of the funnel asymmetry tests that I perform by regressing estimates on their standard errors. If publication bias is a linear function of the standard error, the slopes would indicate the degree of publication bias, and the intercepts would show the "true" mean estimate of the exchange rate pass-through. I find evidence of publication bias using ordinary least squares (OLS), and the mean estimate of 6.1 percent is statistically significant. However, including standard errors in the regression model introduces heteroskedasticity, which cannot be addressed by OLS. Therefore, I employ least squares weighted by precision (WLS_{PREC}) to correct for heteroskedasticity and four additional estimators as robustness checks: least squares weighted by the number of observations (WLS_{NOBS}), study-level fixed-effects (FE), study-level between-effects (BE), and least squares instrumented by the number of observations (IV_{NOBS}).

Most of the additional funnel asymmetry tests reveal mild publication bias and a mean estimate of about 3 - 6 percent. Only the between-effects and instrumental variables models do not detect publication bias, and their mean estimates are close to the weighted average imposed by the literature in Table 1.

[3]This observation is more pronounced in Figure B.1 which uses a log-scaled precision funnel plot.

Table 2: The funnel asymmetry tests

	OLS	*FE*	*BE*
SE	0.805***	0.744***	0.283
(publication bias)	(0.195)	(0.119)	(0.187)
	[0.261, 1.349]		
Constant	0.061***	0.064***	0.159***
(bias corrected estimate)	(0.012)	(0.008)	(0.037)
	[0.034, 0.088]		
Observations	684	684	684
Studies	32	32	32
	$WLS_{(NOBS)}$	$WLS_{(PREC)}$	$IV_{(NOBS)}$
SE	0.577***	1.222***	-0.887
(publication bias)	(0.176)	(0.243)	(0.874)
	[0.171, 0.914]	[0.656, 1.820]	
Constant	0.057***	0.033***	0.172**
(bias corrected estimate)	(0.006)	(0.039)	(0.072)
	[0.025, 0.081]	[0.015, 0.053]	
Observations	684	684	684
Studies	32	32	32

Notes: I use different weights and methods to regress estimates of the exchange rate pass-through on their standard errors. In parentheses, I report standard errors clustered at the study-level. OLS = ordinary least squares; FE = study-level fixed effects model; BE = study-level between effects model; $WLS_{(NOBS)}$ = weighted least squares with number of observations used as weight; $WLS_{(PREC)}$ = weighted least squares with precision (1/SE) used as weights; $IV_{(NOBS)}$ = instrumental variables estimation with number of observations used as instrument for standard error. ***, **, and * denote statistical significance at 1%, 5% and 10% level respectively.

Table 3: Non-linear tests of publication bias

p-hacking tests by Elliot et al. (2022)	
Test for non-increasingness	[1.000]
Test for monotonicity and bounds	[0.916]
Observations ($p <= 0.15$)	444
Total observations	684
Studies	32

Notes: In square brackets, I report p-values.

The idea that publication bias is directly correlated with standard errors has been criticized for being too narrow in scope (see Andrews & Kasy 2019, Stanley & Doucouliagos 2014). As a result, I also employ non-linear methods to address publication bias. My approach includes the weighted average of the adequately powered estimates (WAAP) (Ioannidis et al. 2017), the stem-based method (Furukawa 2020), the selection model (Andrews & Kasy 2019), the endogenous kink (EK) model (Bom & Rachinger 2019), the p-uniform* method (van Aert & van Assen 2020), and the meta-analysis instrumental variable estimator (MAIVE) (Irsova et al. 2023). Additionally, I use two p-hacking tests developed by Elliott et al. (2022).

In Table 3, I present the results of the two p-hacking tests, both of which yield high p-values, indicating the absence of p-hacking. Since p-hacking and publication bias are conceptually similar, the results suggest that the p-hacking tests do not detect the mild publication bias.

Table 4: Non-linear corrections for publication bias

	Ioannidis et al. (2017)	Andrews & Kasy (2019)	Furukawa (2021)
Bias corrected estimate	0.024***	0.042***	0.023
	(0.006)	(0.005)	(0.054)
Observations	684	684	684
Studies	32	32	32
	Bom & Rachinger (2019)	van Aert & van Assen (2021)	MAIVE
Bias corrected estimate	0.024***	0.186***	0.022
	(0.002)	[0.001]	(0.209)
Observations	684	684	684
Studies	32	32	32

Notes: MAIVE denotes meta-analysis instrumental variables estimator applied to PET-PEESE (precision effect test and precision-effect estimate with standard errors). In parentheses, I report standard errors. In square brackets, I report p-value(s). ***, **, and * denote statistical significance at 1%, 5% and 10% level respectively.

I report results for the six non-linear correction methods in Table 4. The first method, proposed by Ioannidis et al. (2017), is the weighted average of the adequately powered estimates (WAAP), which utilizes the subset of estimates with statistical power exceeding 80% to calculate the bias-corrected mean. The second method, introduced by Andrews & Kasy (2019), is the selection model, which adjusts the weights of underrepresented effect sizes in the sample to attenuate publication bias in the mean estimate. The third is the stem-based technique by Furukawa (2020) which corrects for bias by optimizing the trade-off between bias and variance. Because imprecise estimates are usually more significant in number, their exclusion increases variance while reducing publication bias. Therefore, the algorithm of the stem-based method tries to minimize the bias and the variance jointly. The fourth method is the endogenous kink model introduced by Bom & Rachinger (2019), which assumes that the linear relationship between publication bias and standard errors exists only when precision is low, and disappears when estimates are sufficiently precise.

Apart from the selection model and the WAAP, the non-linear correction techniques discussed above use the funnel plot, assuming that there is no systematic relationship between estimates and standard errors in the absence of publication bias. However, this assumption is not always realistic and needs to be adjusted, since researchers' choices of data and methods can create a correlation between estimates and standard errors, even without publication bias. To address this issue, the p-uniform* method uses p-values instead of standard errors, relaxing the unrealistic assumption. This method assumes that the distribution of p-values should be uniform at the true effect size, and therefore calculates a mean estimate that is consistent with a uniform probability distribution.

Furthermore, the aforementioned non-linear techniques assume that the reported precision accurately reflects the true underlying precision, but this is not always the case. A study by Irsova et al. (2023) demonstrates that researchers may manipulate precision through p-hacking, and this can result in bias that exceeds publication bias. To address this issue, Irsova et al. (2023) developed the MAIVE technique, which corrects for spurious precision by replacing reported variance with the portion of variance explained by the inverse sample size used in the primary study. The MAIVE technique is applicable to all methods that rely on reported variances or standard errors. In this study, I apply the MAIVE technique to the PET-PEESE (precision effect test and precision-effect estimate with standard errors) method proposed by Stanley (2017).

The non-linear correction methods mainly indicate publication bias. Table 4 shows that most of the bias-corrected mean estimates obtained from these techniques lie within an interval of 2 - 4 percent, which is less than half the weighted mean computed from primary studies in Table 1.

4 Heterogeneity

The literature on exchange rate pass-through presents a wide range of estimates, and it is crucial to understand the reasons for such variation. There are three potential explanations: publication bias, differences in study characteristics, and differences in country characteristics. In the previous section, the application of linear and non-linear correction methods illustrated that unbiased estimates differ from biased ones. Thus, the task at hand is to clarify how dissimilarities in study and country characteristics contribute to the diversity of estimates. In this section, I identify 22 variables related to these characteristics and assess their impact on the estimates reported in the dataset. Ultimately, I control for heterogeneity and make informed projections about the true mean estimate.

4.1 Variables

The variables can be classified into six primary groups: data, specification, estimation, publication, country, and industry characteristics. In Table 5, I list the variables and present the summary statistics. I present a detailed description of the variables in Appendix D (Table D.1). Furthermore, I provide a correlation matrix in Figure C.1. The correlation matrix illustrates that there are no substantial correlations between individual variables in the baseline model, and the variance-inflation factors (Table C.4) are not up to 10.

Data characteristics: The datasets utilized in the primary studies differ in their frequency, with some researchers using annual, quarterly, or monthly data. To determine whether these disparities contribute to heterogeneity, I create two dummy variables, one for quarterly and the other for monthly data, using annual data as the reference category.[4] Additionally, I account for differences in data dimensions by incorporating a dummy variable that equals 1 for panel data and 0 for time series data.

Another potential cause of heterogeneity is the time frame used for investigation. Some studies cover several decades, while others span only a few years. Therefore, following the standard established by previous meta-analyses, I add a variable representing the number of years studied. I also add a dummy variable to capture the effects of the 2008 global financial crises. Finally, I hypothesize that the data source could influence the results, given that statistical authorities use varying data-gathering techniques and guidelines. As a substantial number of studies in the sample employ OECD data, I include a binary dummy variable to reflect this.

Specification characteristics Following Coughlin & Pollard (2000), a handful of studies ac-

[4] Because the two dummy variables are highly correlated, I include only the dummy for monthly data in the baseline regression. In the appendices, I present a robustness check in Table C.2 using the dummy for quarterly data and find that the regression results are similar.

Table 5: Summary statistics

Variable	Obs	Mean	95% conf. int.	
Estimate	684	0.1860	0.1689	0.2031
Standard error	684	0.1056	0.0920	0.1193
Data Characteristics				
Annual data (used as reference category)	684	0.0632	0.0449	0.0814
Quarterly data	684	0.6842	0.6493	0.7191
Monthly data	684	0.2526	0.2200	0.2853
Panel data	684	0.1891	0.1596	0.2185
Time series data (used as reference category)	684	0.7794	0.7482	0.8105
Time span	684	19.1026	18.3891	19.8160
Post crises	684	0.0427	0.0275	0.0579
OECD data	684	0.1375	0.1116	0.1633
Specification Characteristics				
Appreciation	684	0.0442	0.0287	0.0596
Depreciation	684	0.0505	0.0340	0.0669
Horizon	684	1.1059	0.8108	1.4010
Estimation Characteristics				
Ordinary least squares	684	0.6423	0.6063	0.6783
Maximum likelihood estimator	684	0.1737	0.1452	0.2021
Generalized method of moments (used as reference category)	684	0.0479	0.0319	0.0640
Publication Characteristics				
Peer reviewed journal	684	0.7158	0.6819	0.7497
Impact factor	684	0.2921	0.2507	0.3334
Country Characteristics				
Trade openess	683	0.6590	0.6352	0.6828
Inflationary environment	683	0.2050	0.1515	0.2586
Inflation targetting regime	684	0.0903	0.0688	0.1118
Fixed exchange regime	684	0.2801	0.2463	0.3138
Central bank independence	665	0.5283	0.5117	0.5449
Developed country	684	0.3143	0.2794	0.3492
Eurozone membership	684	0.0776	0.0575	0.0977
Forward guidance	684	0.2490	0.2165	0.2815
Industry Characteristics				
Primary or secondary sector	684	0.0846	0.0637	0.1056

Notes: OECD denotes Organisation for Economic Co-operation and Development; Mean denotes mean weighted by inverse of number of estimates reported per study; Obs denotes number of observations; conf. int. denotes confidence interval.

count for exchange rate pass-through asymmetry. These studies show that prices respond unevenly to exchange rate appreciation and depreciation. Because I wish to verify that some heterogeneity arises from the asymmetry, I create two dummy variables to capture responsiveness to appreciation and depreciation separately.

Furthermore, I include the time horizon used for estimation as it may help explain heterogeneity within and across studies. For instance, in impulse response functions, the responsiveness of prices to exchange rate shocks typically dwindles as we move from contemporaneous shocks toward lagged shocks.

Estimation characteristics The three main estimation methods employed by authors include ordinary least squares (OLS), maximum likelihood estimation (MLE), and generalized method of moments (GMM). These methods involve different assumptions and statistical procedures, which could yield heterogeneous study outcomes. So I codify two binary dummies for OLS and MLE, using GMM as the reference category. Even though I collected data for other estimation methods like instrumental variables (IV) and seemingly unrelated regression (SUR), I did not include them because their variation is very low and might not help explain why estimates differ.

Publication characteristics Apart from differences in methods and country charateristics, publication characteristics might influence the reported estimates. Following Havranek & Irsova (2011), I include two variables to control for study quality: a dummy for publication in peer-reviewed journals and a continuous variable for the RePEc recursive impact factor of the publication.

Country characteristics First, I consider openness. If international trade constitutes a significant fraction of domestic economic activity, I can expect domestic prices to change more quickly in response to nominal exchange rate movements (Ghosh 2013). In addition, because openness often implies less competition from domestic firms, exporters may pass exchange rate fluctuations more quickly to importers and consumers in open economies (An & Wang 2012, Soto & Selaive 2003). To measure openness, I use the ratio of trade to gross domestic product (GDP).

Second, I consider the inflationary environment. Taylor (2000) explains how the inflationary environment affects the exchange rate pass-through. First, for domestic firms, the expected persistence of inflation decreases when the inflationary environment becomes stable. Furthermore, as the expected persistence of inflation decreases, domestic firms become less responsive to costs induced by the exchange rate and other prices. Therefore, in this model, the exchange rate pass-through declines when prices are relatively stable. I use the rate of inflation as a proxy for the inflationary environment.

Gagnon & Ihrig (2004) attribute changes in the magnitude of the exchange rate pass-through to increased emphasis on inflation targetting. A central bank might take aggressive steps to stabilize domestic inflation by tightening policy to offset inflationary pressure from rising import prices. When firms understand the central bank's policy stance, they are less likely to adjust prices in response to cost increment, including those arising from exchange rate depreciation. Therefore, I codify a binary variable that takes on values of 1 only if a country's central bank uses inflation targeting. This includes inflation targeting countries with a strict or dual mandate and inflation targeting countries like Switzerland, who use exchange rate as an instrument under unconventional circumstances.

Campa & Goldberg (2005) state that countries with less volatile exchange rate rates are more likely to have their currencies chosen for transaction invoicing. For this reason, countries with less volatile exchange rates would also be those with lower exchange rate pass-through factors. I include a dummy for a fixed exchange rate regime to serve as a proxy for low exchange rate variability. This proxy allows us to retain many observations in the dataset because, for many countries, data on exchange rate volatility is non-existent in some years.

Cross-country variation in central bank independence might help explain some heterogeneity. For instance, Fischer (1995) and Ha et al. (2020) opine that financial independence gives a central bank more discretion in tightening policy to curtail currency and inflationary pressures. Should this opinion be factual, economies with higher levels of central bank independence would have weaker pass-through into prices. I use the Garriga (2016) index to indicate the extent of central bank independence.

Furthermore, after the global financial crisis in 2008, the central banks of many countries in the study sample adopted forward guidance as a monetary policy strategy. Under forward guidance, the pass-through to domestic prices might be low because economic agents expect inflation to match the central banks' targets regardless of exchange rate fluctuations. Therefore, I include a dummy variable for the use of forward guidance.

Following the introduction of the Euro in 1999, many European countries became members of the Eurozone, giving up monetary policy autonomy to the European Central Bank. To assess the effect of these changes on the exchange rate pass-through, I include a dummy for Eurozone membership.

Finally, because developing countries have less developed financial markets and limited instruments for currency hedging (Bird & Rajan 2001), I wish to verify whether exchange rates affect prices on a greater scale in developing countries. Therefore, I include a binary dummy variable for level of economic development.

Altogether, I have eight economic characteristics that might lead to cross-country heterogeneity: openness, inflationary environment, monetary policy framework, exchange rate regime, central bank independence, forward guidance, Eurozone membership, and economic development. Data for the corresponding variables come from multiple sources. The World Bank's World Development Indicators provide statistics on openness and inflation. I turn to the Bank of England's Centre for Central Banking Studies for data on monetary policy frameworks and the IMF's annual reports on exchange arrangements and restrictions for data on exchange rate regimes. Data on central bank independence comes from Garriga (2016). Data on forward guidance comes from multiple web sources as there is no database for this variable. Data on Eurozone membership comes from the European Commission (europa.eu). And lastly, data on economic development comes from the IMF's World Economic Outlook Database.

Industry characteristics Some of the primary studies report different pass-through estimates for different products. The products fall under three broad economic industries: primary, secondary, and tertiary. Because I observe that researchers usually lump primary and secondary products together in estimating the pass-through, I create a dummy that equals one for primary and secondary products and equals 0 otherwise.

4.2 Estimation

To explain the variation across studies, I use the following baseline regression model:

$$\hat{\beta}_{is} = \gamma_0 + \gamma_1 SE_{is} + \gamma_2 X_{is} + \epsilon_{is} \tag{2}$$

Here, $\hat{\beta}_{is}$ represents the ith exchange rate pass-through estimate from the sth study, SE_{is} denotes the corresponding standard error, X_{is} denotes the explanatory variables, including study and country characteristics, and ϵ_{is} denotes the error term. The intercept γ_0 reflects the mean pass-through estimate corrected for publication bias conditional on the covariates, and the coefficient γ_1 measures the degree of publication bias, albeit linearly.

I have many variables related to study design and country characteristics that can explain the variation observed in the empirical literature. While I want to control for these variables, the problem is that it is not possible to quickly determine the essential variables to include in the baseline model. This situation of model uncertainty calls for model averaging methods that formally address model uncertainty in meta-analysis. I employ the Bayesian model averaging (BMA) method developed by Raftery et al. (1997).

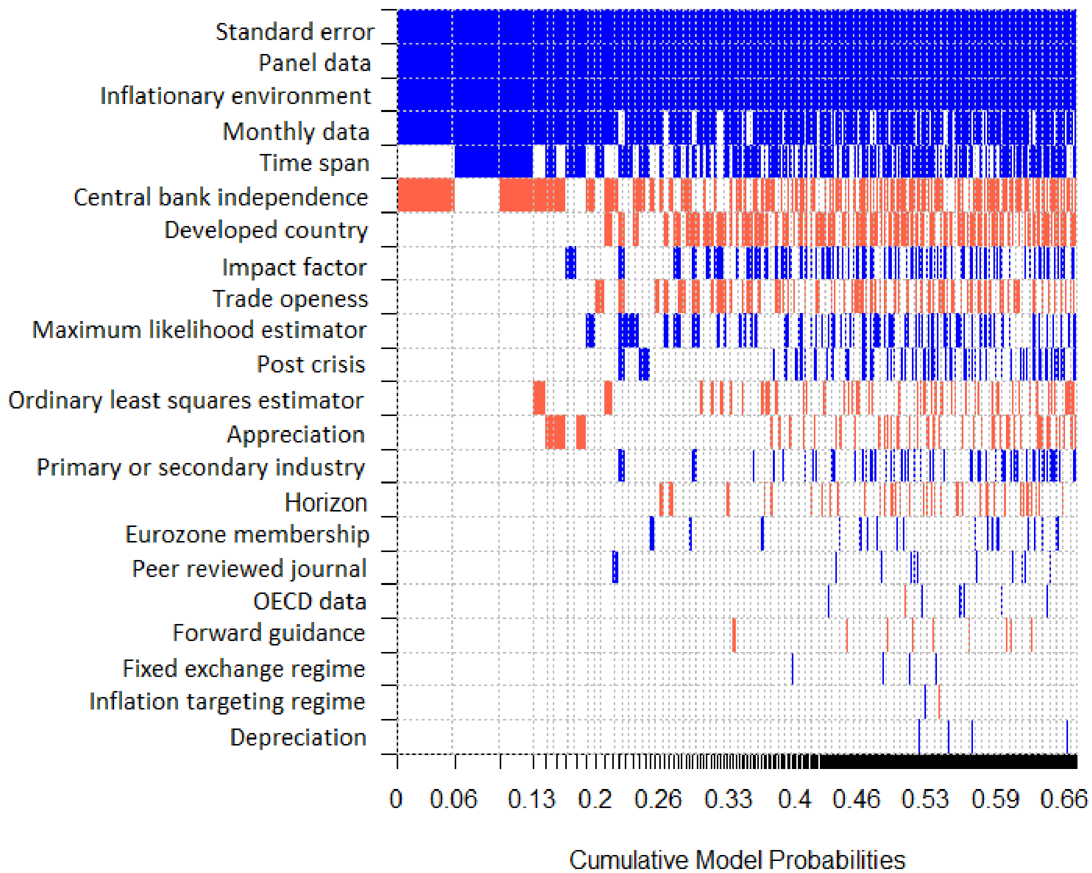
Bayesian model averaging allows us to estimate the probability that a given explanatory variable matters in the regression model explaining heterogeneity. It does this by estimating variants of the regression model with various combinations of the explanatory variables. It then uses goodness of fit and parsimony to weight the individual models. Because there are 21 explanatory variables in the baseline model, including the standard error, the Bayesian model averaging method will have to compute 2^{21} regressions. I simplify this cumbersome task using the Metropolis-Hastings algorithm provided in the `bms` package written by Zeugner & Feldkircher (2015) in the R programming language. This algorithm achieves brevity by walking only through the most likely models. Furthermore, to minimize the effects of collinearity among the explanatory variables, I employ the dilution prior developed by George (2010). I refer the reader to Raftery et al. (1997) for an exhaustive discussion on Bayesian model averaging.

I report four vital statistics in the Bayesian model averaging framework: posterior model probability, posterior mean, posterior standard deviation, and posterior inclusion probability. The posterior model probability of each model indicates its likelihood. On the other hand, the posterior mean represents the estimated coefficients weighted by posterior model probability, and the posterior standard deviation represents the uncertainty component attached to the posterior mean. I interpret these two parameters similarly to coefficients and their standard errors in ordinary regression settings. The posterior inclusion probability is the sum of posterior model probabilities for all models containing a given explanatory variable. To interpret this parameter, I follow Jeffreys (1961): the effect of an explanatory variable is 'weak' for a probability value between 0.5 and 0.75, 'substantial' for a probability value between 0.75 and 0.95, 'strong' for a probability value between 0.95 and 0.99, and 'decisive' for a probability value greater than 0.99.

4.3 Results

Figure 4 illustrates the baseline BMA results. On the vertical axis, the explanatory variables stand in descending order according to their posterior inclusion probabilities. This ranking places the most important variables at the top of the figure. On the horizontal axis, from left to right, the individual models stand in descending order according to their posterior model

Figure 4: Model inclusion in Bayesian model averaging



Notes: The figure illustrates the benchmark Bayesian model reported in Table 6. For estimation, I use the unit information g-prior recommended by Eicher et al. (2011) and the dilution prior suggested by George (2010), which accounts for the effects of collinearity. 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. A detailed decription of the variables is in Table D.1.

probabilities, such that the best models lie on the left. The color scheme indicates the direction and importance of the variables. A white-colored cell signals the exclusion of the corresponding variable from the model, a blue-colored cell (darker in grayscale) signifies a positive coefficient for the corresponding variable, and a red-colored cell (lighter in grayscale) signifies a negative coefficient.

Following the plot, I identify the essential variables. The top 6 include *Panel data*, *Inflationary environment*, *Monthly data*, *Time span*, *Central bank independence*, and *Developed country.* Figure C.4 in the Appendices details the posterior coefficient distributions for these variables.

I provide numerical estimates for the baseline BMA model on the left of Table 6. On the right, I report results using OLS as a robustness check. The topmost variables in the plot have the highest posterior inclusion probabilities, and the posterior inclusion probabilities are greater than 0.5. I observe that the standard error is statistically significant, indicating publication bias. Similarly, the results show that the constant matters in the regression model. Its magnitude of 0.0553 represents the mean estimate corrected for publication bias conditional on the covariates. Henceforth, I discuss numerical results for all the explanatory variables comprising the dataset's six categories.

Data characteristics In this category, the BMA results show that data frequency, dimension, and time span matter for the reported estimates. Primary studies that employ monthly and panel data report relatively large estimates. Also, the magnitude of the reported estimate increases marginally if the data covers a longer time span.

On the other hand, the post-crisis dummy's insignificance suggests no heterogeneity due to the 2008 global financial crisis. It also does not matter if a primary study used data from the OECD's database.

Country characteristics Three country characteristics explain why estimates differ across studies. Ranking the variables according to their posterior inclusion probabilities shows that the inflationary environment is the most important, followed by central bank independence and development. The pass-through to domestic prices is relatively strong in countries with high inflationary environments and relatively weak in countries with high levels of central bank independence and developed countries. Interestingly, these results remain consistent in the frequentist check using ordinary least squares.

Other study characteristics The remaining study characteristics are less important in explaining why estimates differ. Nonetheless, two essential conclusions follow from this result. First, the limited explanatory power of the two dummies for pass-through asymmetry indicates that the pass-through to domestic prices is likely to be symmetrical, which contradicts the belief that prices respond asymmetrically to exchange rate appreciation and depreciation. Second, the fact that time horizon does not matter for the estimates suggests that pass-through in the short-term does not differ in the long-term.

4.4 Implied Estimates of the Exchange Rate Pass-through

In the final stage of the meta-analysis, I compute the exchange rate pass-through implied by the literature under various contexts after correcting for publication bias. This process involves estimating values of the pass-through using the benchmark BMA model. I review the literature,

Table 6: Why do estimates of the exchange rate pass-through differ?

Response variable: Estimated beta:	Bayesian model averaging (baseline model)			OLS (frequentist check)		
	P. Mean	P. SD.	PIP	Coeff.	SE	p-val.
Constant	0.0553	NA	**1.0000**	0.0525*	0.0277	0.0580
Standard error	0.8047	0.0747	**1.0000**	0.8424***	0.0639	0.0000
Data Characteristics						
Monthly data	0.0571	0.0277	**0.8790**	0.0662***	0.0156	0.0000
Panel data	0.1536	0.0285	**1.0000**	0.1597***	0.0256	0.0000
Time span	0.0016	0.0014	**0.6391**	0.0021***	0.0007	0.0040
Post crisis	0.0138	0.0275	0.2406			
OECD data	0.0019	0.0097	0.0683			
Specification Characteristics						
Appreciation	-0.0129	0.0298	0.1949			
Depreciation	0.0008	0.0072	0.0357			
Horizon	-0.0005	0.0014	0.1501			
Estimation Characteristics						
Ordinary least squares estimator	-0.0075	0.0180	0.1851			
Maximum likelihood estimator	0.0159	0.0274	0.2971			
Publication Characteristics						
Peer reviewed journal	0.0017	0.0074	0.0763			
Impact factor	0.0183	0.0282	0.3444			
Country Characteristics						
Trade openess	-0.0185	0.0300	0.3244			
Inflationary environment	0.0344	0.0091	**0.9896**	0.0330***	0.0081	0.0000
Inflation targetting regime	0.0006	0.0052	0.0376			
Fixed exchange regime	0.0017	0.0087	0.0575			
Central bank independence	-0.0565	0.0543	**0.5859**	-0.0894***	0.0290	0.0020
Developed country	-0.0275	0.0306	**0.5140**	-0.0262*	0.0135	0.0540
Forward guidance	-0.0012	0.0063	0.0592			
Eurozone membership	0.0056	0.0181	0.1192			
Industry Characteristics						
Primary or secondary sector	0.0122	0.0260	0.2200			
Observations	663			663		
Studies	32			32		

Notes: The left panel reports BMA results based on the unit information g-prior and the dilution model prior (see Eicher et al. 2011, George 2010). The right panel reports a frequentist check using ordinary least squares for PIPs > 0.5. OECD denotes Organisation for Economic Co-operation and Development; P. Mean denotes posterior mean; P. SD. denotes posterior standard deviation; PIP denotes posterior inclusion probability; Coeff. denotes regression coefficient; SE denotes standard error; p-val. denotes probability value. I report PIPs > 0.5 in bold. ***, **, and * denote statistical significance at 1%, 5% and 10% level respectively.

identify the best practices commonly employed by researchers, and attempt to replicate them by assigning appropriate values to the BMA model's explanatory variables.

First, I plug in zero for the standard error because I want to correct for publication bias. I plug in sample maxima for the two variables representing study quality: peer-reviewed journal publication and impact factor. Similarly, I plug in sample maxima for the use of OECD data due to transparency and quality concerns. I prefer annual and time series data because the BMA results suggest that monthly and panel data inflate the estimates. To derive the immediate response of consumer price to exchange rate movement, I plug in sample minima (zero) for time horizon. To derive estimates for developed countries, I plug in sample maxima for the development dummy. Alternatively, I plug in sample minima to derive estimates for developing countries. Finally, I set all other variables to their sample means.

Table 7: Implied estimates of the exchange rate pass-through

	Mean estimate	Confidence interval
Developed countries	0.06	[-0.1085, 0.3371]
Developing countries	0.09	[-0.0325, 0.4292]

Notes: In this table, I present the mean estimates implied by the benchmark BMA model, giving consideration to the best practices in the literature. The confidence intervals are approximate and constructed using OLS with the standard errors clustered at the study level.

Table 7 shows the implied mean estimates for two contexts: developed and developing countries. The results are consistent with expectations from the literature: the pass-through for developed countries is lower than the pass-through for developing countries.

5 Concluding Remarks

This study provides a quantitative survey of methodological and cross-country heterogeneity in the exchange rate pass-through into consumer prices. I begin by collecting 684 estimates reported in 32 studies to test and correct for publication bias. The findings reveal mild publication bias. Once corrected, I see that the pass-through becomes much smaller than previously reported in the literature.

Furthermore, I investigate why estimates vary across studies. For this task, I consider 22 different variables that are related to both the methodology used and the characteristics of the country being studied. With so many variables to consider and little guidance on the most important variables to choose, model uncertainty arises, so I employ Bayesian model averaging. Among the methodological variables, I find that the reported magnitude of the exchange rate pass-through depends on data frequency, data dimension, and data time span. Among the country variables, I find that the magnitude depends on the level of central bank independence, inflation, and economic development. Specifically, developed countries and those with high levels of central bank independence tend to experience lower levels of exchange rate pass-through. On the other hand, countries with high inflation rates tend to experience higher levels of exchange rate pass-through.

The Bayesian model averaging results allow us to compute the implied exchange rate pass-through for various subgroups, based on the best practices in the literature. For developed countries, I obtain 6%, while for developing countries, I obtain 9%. I hope that these findings will be valuable for readers interested in understanding the impact of exchange rate fluctuations on consumer prices.

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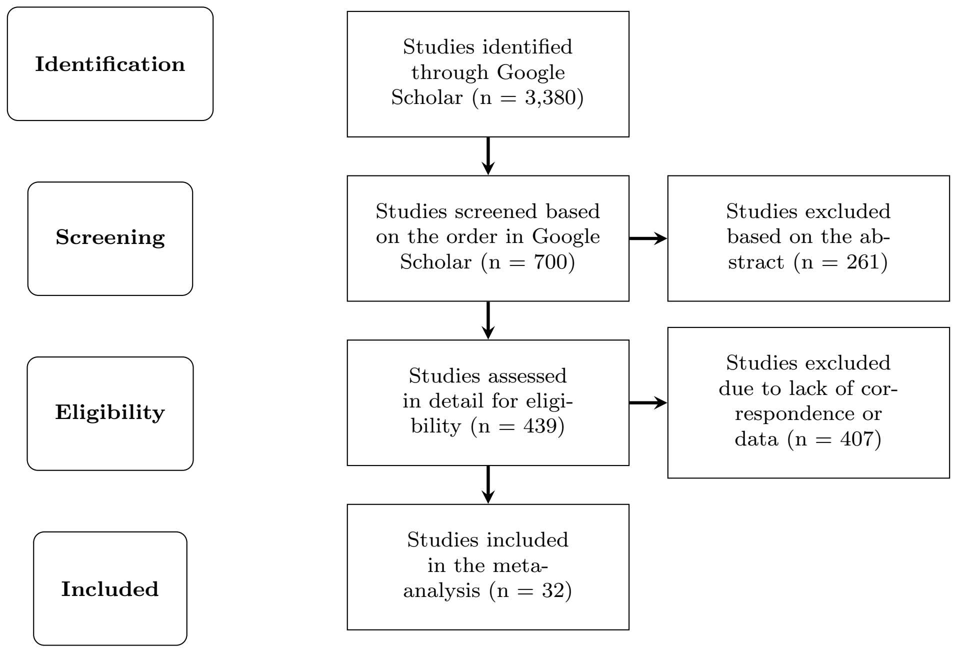
Appendices

A Details of Literature Search

Figure A.1: PRISMA Flow Diagram



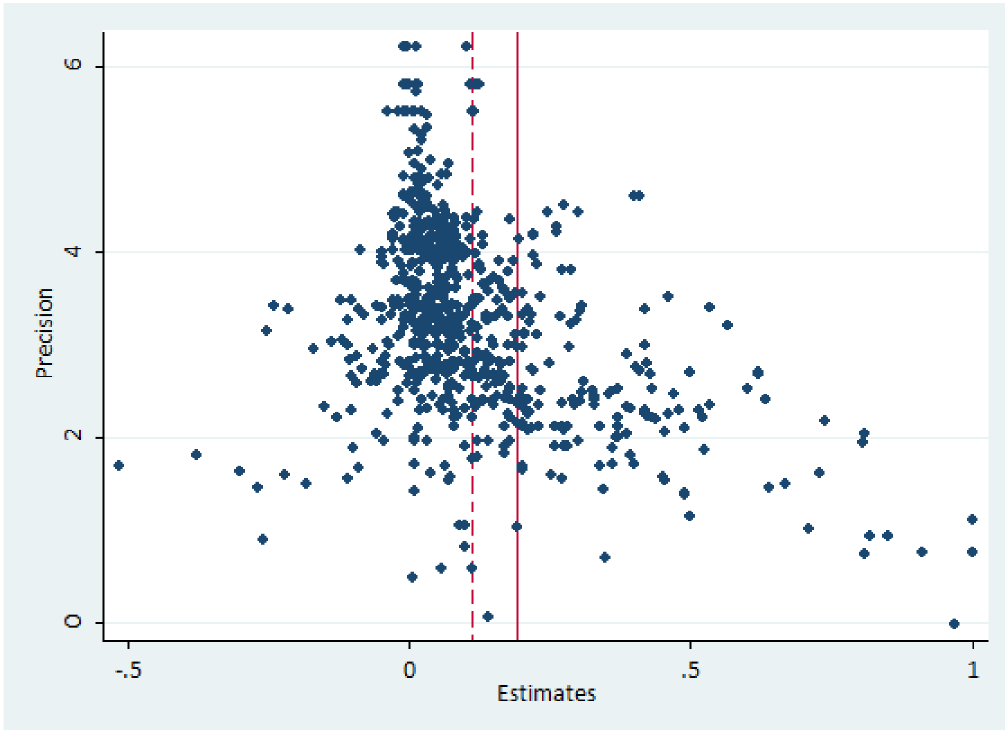
Notes: PRISMA stands for Preferred Reporting Items for Systematic Reviews and Meta-Analyses. Exhaustive details on PRISMA and related reporting standards of meta-analysis are provided by Havranek et al. (2020).

Table A.1: The 32 studies used in the meta-analysis

Serial	Author(s) (year)	Serial	Author(s) (year)
1	Aisen et al (2021)	17	Ghosh (2013)
2	Akofio-Sowah (2009)	18	Ghosh and Rajan (2007)
3	Alper (2003)	19	Ghosh and Rajan (2009)
4	Amoah and Aziakpono (2018)	20	Ho and Hafrad (2020)
5	Baharumshah et al (2017)	21	Ihrig et al (2006)
6	Bailliu and Fujii (2004)	22	Jimborean (2013)
7	Carriere-Swallow et al (2021)	23	Lopez-Villavicencio and Mignon (2017)
8	Choudhri et al (2005)	24	Lu and Zhang (2003)
9	Dabusinskas (2003)	25	Muhammed (2020)
10	Delatte and Lopez-Villavicencio (2012)	26	Phuc and Duc (2021)
11	Edwards and Cabezas (2022)	27	Samir and Tarek (2014)
12	Farajollahi et al (2019)	28	Shevchuk (2022)
13	Faryna (2016)	29	Slavov (2008)
14	Forbes et al (2017)	30	Strasser (2013)
15	Gagnon and Ihrig (2004)	31	Wang and Li (2010)
16	Gayaker et al (2021)	32	Xie (2019)

B Additional Figure for Publication Bias Tests

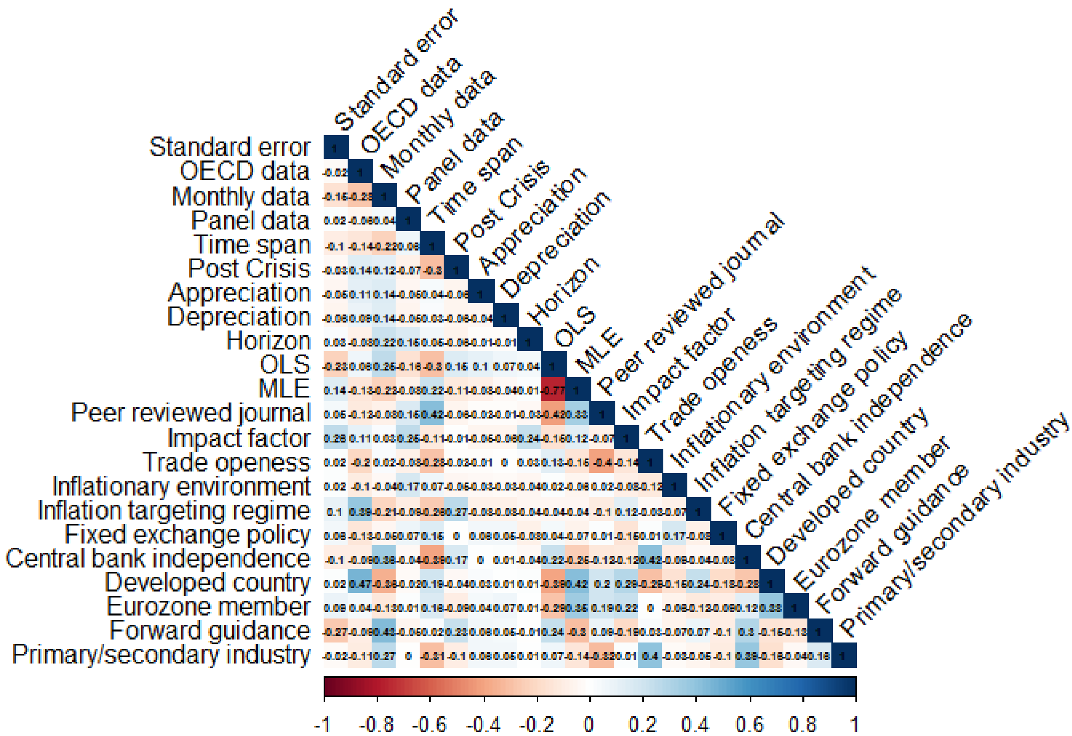
Figure B.1: Log-scaled funnel plot reveals mild publication bias



Notes: The solid vertical line represents the weighted mean, and the dashed vertical line the weighted median. Precision is log-scaled.

C Additional Results for BMA Models

Figure C.1: Explanatory variables in benchmark model are not strongly correlated



Notes: The figure shows correlation coefficients (Pearson) for the explanatory variables summarized in Table 5.

Table C.1: Summary of the benchline BMA estimation

Mean no. regressors	*Draws*	*Burn-ins*	*Time No.*	*models visited*
8.0177	2×10^6	1×10^6	5.3922 mins	682,652
Modelspace	*Models visited*	*Topmodels*	*Corr. PMP*	*No. Obs.*
4.194×10^6	16%	67	0.9997	663
Model prior	*g-prior*	*Shrinkage-stats*		
dilut/ 15	UIP	Av=0.9985		

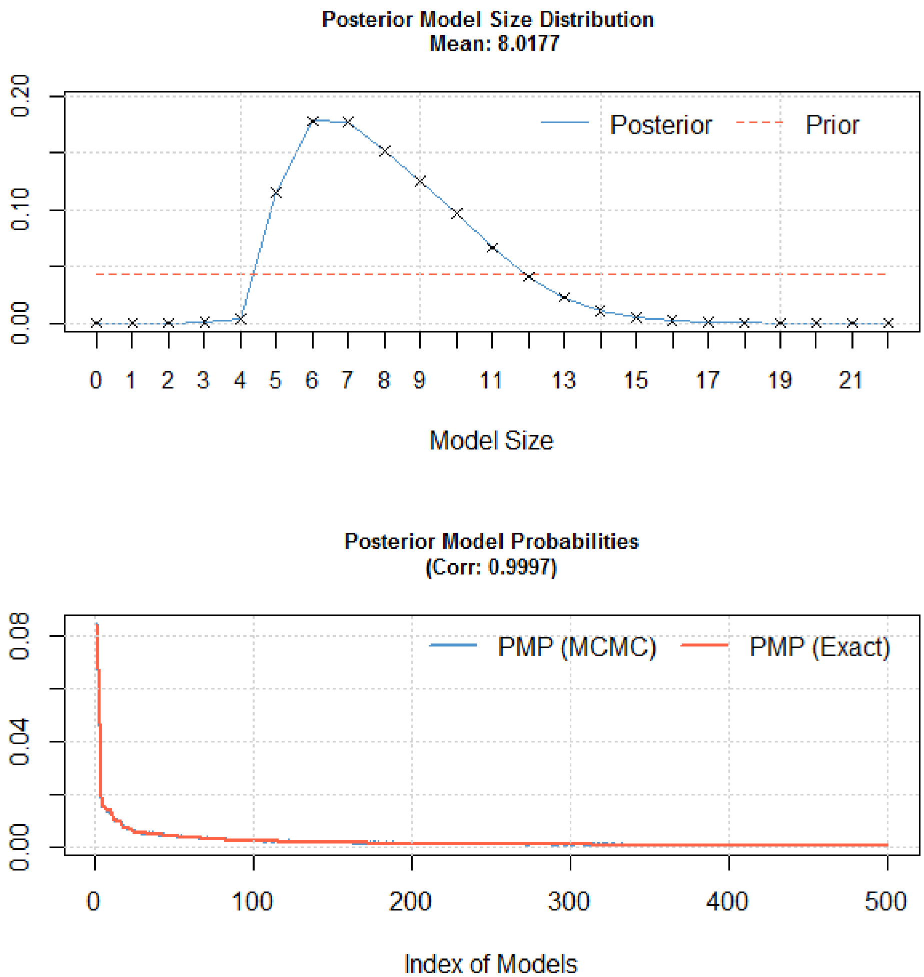
Notes: Model summary of benchline BMA model estimated with the unit information g-prior and the dilution model prior (see Eicher et al. 2011, George 2010). Benchline BMA model is presented in Table 6.

Table C.2: Robustness check with quarterly data dummy

Response variable: Estimated beta:	Bayesian model averaging (baseline model)		
	P. Mean	P. SD.	PIP
Constant	0.1051	NA	**1.0000**
Standard error	0.7927	0.0758	**1.0000**
Data Characteristics			
Quarterly data	-0.0420	0.0298	**0.7372**
Panel data	0.1472	0.0292	**0.9997**
Time span	0.0015	0.0014	**0.6146**
Post crisis	0.0153	0.0289	0.2606
OECD data	0.0012	0.0077	0.0563
Specification Characteristics			
Appreciation	-0.0092	0.0251	0.1504
Depreciation	0.0011	0.0084	0.0411
Horizon	-0.0003	0.0011	0.1079
Estimation Characteristics			
Ordinary least squares estimator	-0.0084	0.0191	0.2014
Maximum likelihood estimator	0.0188	0.0290	0.3437
Publication Characteristics			
Peer reviewed journal	0.0022	0.0086	0.0905
Impact factor	0.0246	0.0310	0.4418
Country Characteristics			
Trade openess	-0.0289	0.0349	0.4654
Inflationary environment	0.0337	0.0095	**0.9848**
Inflation targetting regime	0.0005	0.0049	0.0353
Fixed exchange regime	0.0016	0.0085	0.0558
Central bank independence	-0.0453	0.0527	0.4854
Developed country	-0.0379	0.0317	**0.6584**
Forward guidance	-0.0006	0.0046	0.0439
Eurozone membership	0.0056	0.0181	0.1192
Industry Characteristics			
Primary or secondary sector	0.0168	0.0299	0.2841
Observations	663		
Studies	32		

Notes: The table reports BMA results based on the unit information g-prior and the dilution model prior (see Eicher et al. 2011, George 2010). OECD denotes Organisation for Economic Co-operation and Development; P. Mean denotes posterior mean; P. SD. denotes posterior standard deviation; PIP denotes posterior inclusion probability; I report PIPs > 0.5 in bold.

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



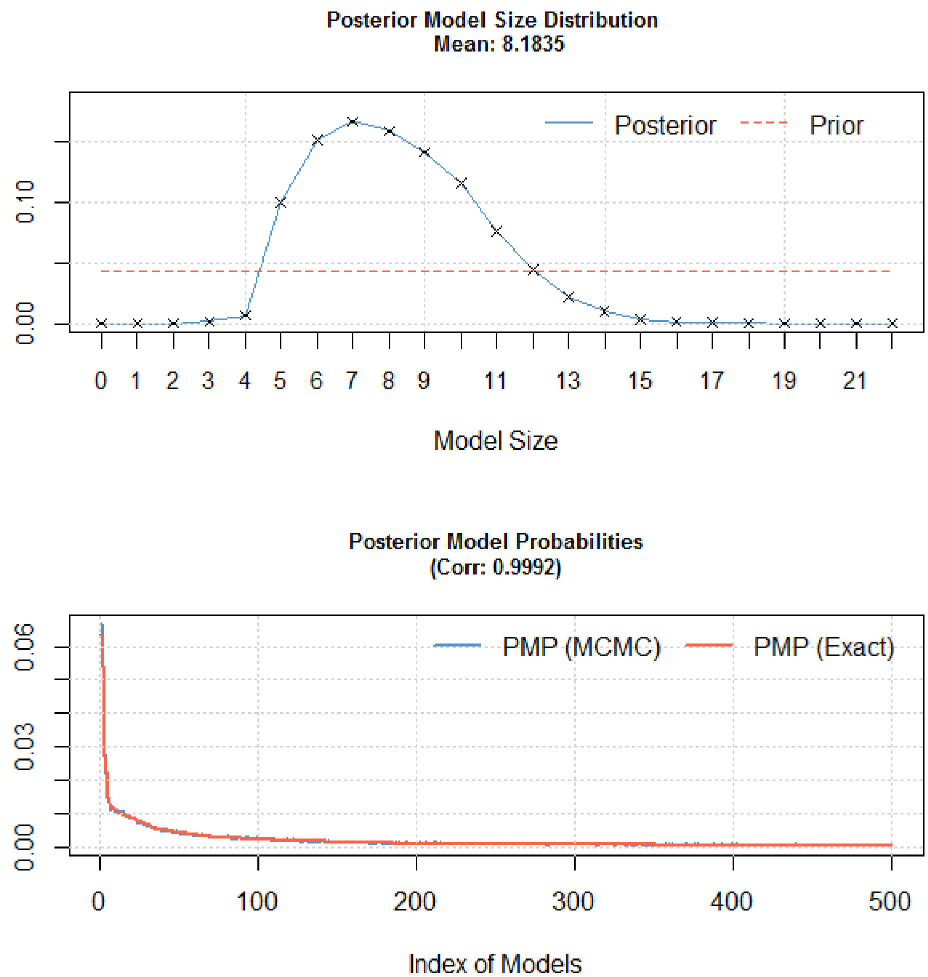
Notes: The figure shows the posterior model size distribution and the posterior model probabilities of the benchline BMA model reported in Table 6.

Table C.3: Summary of robustness check BMA model

Mean no. regressors	*Draws*	*Burn-ins*	*Time No.*	*models visited*
8.1835	2×10^6	1×10^6	5.2060 mins	687,163
Modelspace	*Models visited*	*Topmodels*	*Corr. PMP*	*No. Obs.*
4.1943×10^6	16%	66	0.9992	663
Model prior	*g-prior*	*Shrinkage-stats*		
random/ 15	BRIC	Av=0.9985		

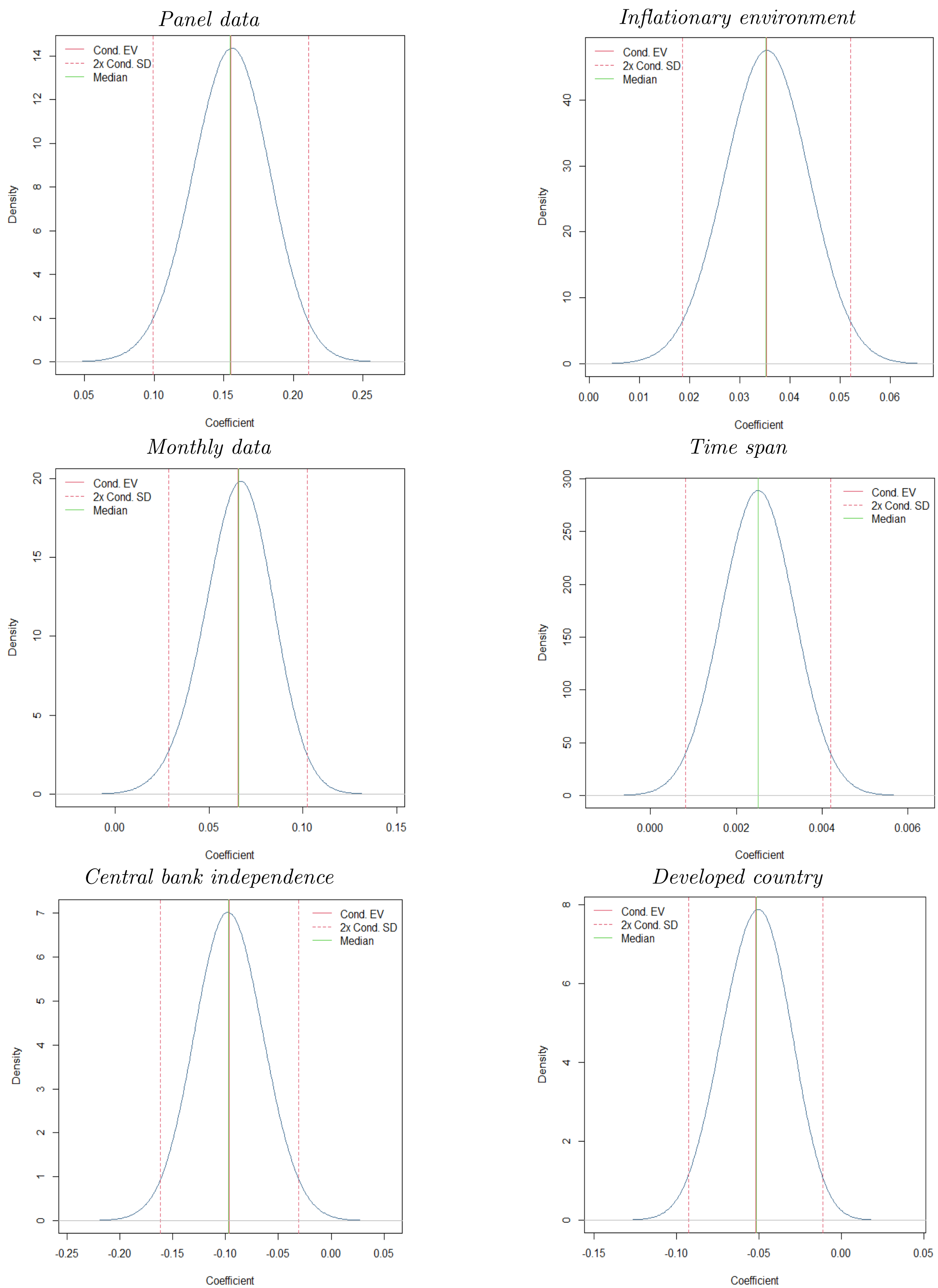
Notes: Model summary of robustness check BMA model estimated with the unit information g-prior and the dilution model prior (see Eicher et al. 2011, George 2010)..

Figure C.3: Model size and convergence for robustness check BMA model



Notes: The figure shows the posterior model size distribution and the posterior model probabilities of the BMA model reported in Table C.2.

Figure C.4: Posterior coefficient distributions for selected explanatory variables



Notes: The figure shows the posterior coefficient distributions of the regression coefficients corresponding to selected explanatory variables in the baseline BMA model.

Table C.4: Variance inflation factors for baseline BMA

	VIF	1/VIF
Standard error	1.28	0.78
Data Characteristics		
Monthly data	2.16	0.46
Panel data	1.40	0.71
Time span	2.14	0.47
Post crisis	1.33	0.75
OECD data	2.05	0.49
Specification Characteristics		
Appreciation	1.13	0.88
Depreciation	1.11	0.90
Horizon	1.22	0.82
Estimation Characteristics		
Ordinary least squares estimator	3.63	0.28
Maximum likelihood estimator	3.69	0.27
Publication Characteristics		
Peer reviewed journal	1.91	0.52
Impact factor	1.60	0.63
Country Characteristics		
Trade openess	1.88	0.53
Inflationary environment	1.14	0.88
Inflation targetting regime	1.58	0.63
Fixed exchange regime	1.18	0.85
Central bank independence	2.00	0.50
Developed country	2.47	0.40
Forward guidance	1.83	0.55
Eurozone membership	1.59	0.63
Industry Characteristics		
Primary or secondary sector	1.59	0.63
Mean VIF	1.81	

Notes: The table reports variance inflation factors (VIFs) for the regressors used in the baseline BMA model. VIFs were obtained using ordinary least squares.

D Description of Variables and Additional Statistics

Table D.1: Definition of variables used in the study

Variable	Description
Estimate	= Estimate of the pass-through from NEER into consumer prices
Standard error	= Standard error of the pass-through estimate
Data Characteristics	
Annual data	= 1 if annual data was used for estimation
Quarterly data	= 1 if quarterly data was used for estimation (reference category: annual data)
Monthly data	= 1 if monthly data was used for estimation (reference category: annual data)
Time series data	= 1 if time series data was used for estimation
Panel data	= 1 if panel data was used for estimation (reference category: time series data)
Time span	= Number of years in dataset used to estimate the pass-through
Post crisis	= 1 if estimation period occured after the 2008 global financial crisis
OECD data	= 1 if data from the OECD's database was used
Specification Characteristics:	
Dependent Variable	
Appreciation	= 1 if pass-through measures responsiveness to exchange rate appreciation only
Depreciation	= 1 if pass-through measures responsiveness to exchange rate depreciation only
Horizon	= Number of time lags (or leads) used to estimate the pass-through
Estimation Characteristics	
Generalized method of moments (GMM)	= 1 for estimation with generalized method of moments estimator
Ordinary least squares estimator	= 1 for estimation with OLS estimator (reference category: GMM)
Maximum likelihood estimator	= 1 for estimation with maximum likelihood estimator (reference category: GMM)
Publication Characteristics	
Peer reviewed journal	= 1 for publication in peer-reviewed journal
Impact factor	= Recursive impact factor of the publication outlet from IDEAS REPEC
Country Characteristics	
Trade openess	= Trade as a percentage of GDP
Inflationary environment	= Level of inflation
Inflation targetting (IT)	= 1 if IT of any form was adopted during most (at least 50%) of the estimation period
Fixed exchange regime	= 1 if country's de jure exchange rate regime was fixed or managed during most (at least 50%) of the estimation period
Central bank independence	= Central bank independence index from Garriga (2016)
Developed country	= 1 if country was developed throughout the estimation period
Guidance	= 1 if a country adopted forward guidance during most (at least 50%) of the estimation period
Eurozone membership	= 1 if country was (or became) a member of the Eurozone during the estimation period
Industry Characteristics	
Primary or secondary sector	= 1 for primary or secondary sector

Notes: *SD* denotes standard deviation; OECD denotes Organization for Economic Co-operation and Development; OLS denotes ordinary least squares; GDP denotes Gross Domestic Product; NEER denotes nominal effective exchange rate.

Table D.2: Number of estimates reported per country/region

Serial	Country	Obs.	Serial	Country	Obs.
1	Australia	13	36	Japan	32
2	Austria	3	37	Lesotho	1
3	Belgium	4	38	Malawi	1
4	Bolivia	3	39	Mexico	15
5	Brazil	11	40	Mozambique	28
6	Burundi	1	41	Netherlands	4
7	Cameroon	1	42	New Zealand	13
8	Canada	13	43	Nigeria	1
9	Central African Republic	1	44	Norway	7
10	Chile	9	45	Peru	3
11	China	14	46	Philippines	12
12	Colombia	12	47	Poland	8
13	Congo DR	1	48	Portugal	3
14	Czech Republic	5	49	Romania	6
15	Denmark	1	50	Russia	1
16	Equatorial Guinea	1	51	Serbia	1
17	Estonia	57	52	Slovakia	4
18	Ethiopia	1	53	South Africa	7
19	Finland	3	54	South Korea	20
20	France	9	55	Spain	4
21	Gabon	1	56	Sweden	7
22	Gambia	1	57	Switzerland	7
23	Germany	27	58	Thailand	13
24	Ghana	11	59	Togo	1
25	Greece	3	60	Tunisia	1
26	Hong Kong	1	61	Turkey	93
27	Hungary	5	62	Uganda	1
28	Iceland	15	63	UK	21
29	India	10	64	Ukraine	42
30	Indonesia	8	65	Uruguay	6
31	Iran	1	66	USA	15
32	Ireland	3	67	Vietnam	3
33	Israel	1	68	Zambia	1
34	Italy	9	69	Panel estimates	42
35	Ivory Coast	1	70	Total	684

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

Table D.3: Number of countries per category in the dataset

Serial	Country	Obs.
1.	Developed countries	26
2.	Developing countries	42
3.	Inflation targeters	30
4.	Non-inflation targeters	38
5.	Fixed or managed exchange rate regime	28
6.	Float exchange rate regime	40
7.	Officially declared independent central bank	58
8.	Dependent central bank	10

Notes: Obs. denotes number of countries/region per category.

Table D.4: Distribution of the panel estimates

Serial	Countries	Obs.
1	Australia, Belgium, Canada, Denmark, Finland, France, Italy, Netherlands, Spain, UK, USA	4
2	Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, Slovenia	4
3	Bolivia, Brazil, Chile, Colombia, Mexico, Uruguay	10
4	Czech Republic, Hungary, Poland, Romania	2
5	Albania, Croatia, Serbia	2
6	Bulgaria, North Macedonia, Slovakia, Slovenia	2
7	Estonia, Latvia, Lithuania	2
8	Brazil, Colombia, Czech Republic, Hungary, Indonesia, South Korea, Mexico, Philippines, Poland, Romania, Slovakia, South Africa, Thailand, Turkey	2
9	Austria, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong S.A.R., Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, New Zealand, Norway, Portugal, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, The Netherlands, UK, USA	4
10	Bolivia, Bolivia, Brazil, Bulgaria, Chile, China, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Honduras, Hungary, India, Indonesia, Malaysia, Mexico, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Romania, Russia, South Africa, Thailand, Turkey, Ukraine, Uruguay	4
11	Burundi, Cameroon, Central African Republic, Congo DR, Ivory Coast, Gabon, Gambia, Ghana, Lesotho, Malawi, Nigeria, Sierra Leone, South Africa, Togo, Uganda	2
12	Argentina, Bolivia, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Nicaragua, Panama, Paraguay, Uruguay, Venezuela	2
13	Antigua and Barbuda, Argentina, Armenia, Australia, Austria, Bahamas, Bahrain, Belgium, Belize, Bolivia, Brazil, Bulgaria, Burundi, Cameroon, Canada, Central African Republic, Chile, China, Colombia, Congo DR, Costa Rica, Croatia, Cyprus, Czech Republic, Denmark, Dominica, Dominican Republic, Ecuador, Equatorial Guinea, Estonia, Fiji, Finland, France, Gabon, Gambia, Germany, Ghana, Greece, Grenada, Guyana, Hong Kong, Hungary, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Ivory Coast, Japan, Korea, Latvia, Lesotho, Lithuania, Luxembourg, Malawi, Malaysia, Malta, Mexico, Moldova, Morocco, Netherlands, New Zealand, Nicaragua, Nigeria, North Macedonia, Norway, Pakistan, Papua New Guinea, Paraguay, Philippines, Poland, Portugal, Romania, Russia, Samoa, Saudi Arabia, Sierra Leone, Slovakia, Slovenia, Solomon Islands, South Africa, Spain, St Kitts and Nevis, St Vincent and the Grenadines, StLucia, Sweden, Switzerland, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, Uganda, Ukraine, United Kingdom, United States, Uruguay, Venezuela, Zambia	2
14	Total	42

Notes: Obs. denotes number of estimates per panel group.

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