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Google Search in Exchange Rate Models: Hype or Hope?

Bodo Herzog [1,2,3,*] and Lana dos Santos [1]

1 Economics Department, ESB Business School, Reutlingen University, 72762 Reutlingen, Germany; lana.dossantos@reutlingen-university.de
2 RRI Reutlingen Research Institute, Reutlingen University, 72762 Reutlingen, Germany
3 IFE Institute of Finance and Economics, Reutlingen University, 72762 Reutlingen, Germany
* Correspondence: Bodo.Herzog@Reutlingen-University.de

Abstract: This paper studies the power of online search intensity metrics, measured by Google, for examining and forecasting exchange rates. We use panel data consisting of quarterly time series from 2004 to 2018 and ten international countries with the highest currency trading volume. Newly, we include various Google search intensity metrics to our panel data. We find that online search improves the overall econometric models and fits. First, four out of ten search variables are robustly significant at one percent and enhance the macroeconomic exchange rate models. Second, country regressions corroborate the panel results, yet the predictive power of search intensity with regard to exchange rates vary by country. Third, we find higher prediction performance for our exchange rate models with search intensity, particularly in regard to the direction of the exchange rate. Overall, our approach reveals a value-added of search intensity in exchange rate models.

Keywords: exchange rate; Google search; big data; AI; information inattention

JEL Classification: D82; D87

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1. Introduction

Google processes over three billion queries per day and retains over sixty percent share in the web search market (Desjardins 2018). In 2004, the company launched Google Trends, a free internet facility where the search volume of keywords can be accessed by the public (Helft 2009). This new big data analytics tool is free, user-friendly, and offers data in nearly real time. As official records are published belatedly, online search data appears to be an attractive and timely source of information and opens the gate to new opportunities in empirical research.

The high and growing number of online users indicates that search intensity does reflect individual intentions and expectations (Ginsberg et al. 2009). Recent research papers prove the application of search data to be incrementally broad. For instance, Askitas and Zimmermann (2009) use Google data to forecast unemployment rates. Choi and Varian (2012) use web data to improve the forecast of automobile sales and Vaughan and Chen (2015) use it to identify business cycle turning points. Different in scope and methodology but related to our research is the work by Bulut (2017) and Chai et al. (2018).

In this research, we generalize the exchange rate model by Dornbush (1976) with online search intensity metrics and study the predictive power of online data and exchange rates. We utilize search intensity in order to exhibit the expectation channel of exchange rate movements. Our theoretical approach is based on the well-known (augmented-)overshooting model in the exchange rate literature, which relies on different macroeconomic fundamentals among the most relevant interest rates and inflation (Dornbush 1976). Subsequently, we extend the macroeconomic benchmark model by new online-search intensity metrics and examine the role of online data on exchange rate dynamics. Search intensity variables are generated by specific keywords which bear a certain relation to the macroeconomic variables and exchange rates. Thereafter, we evaluate the performance of the different models in regard to the prediction and forecasting performance. The panel regression consists of ten countries and quarterly data from 2004 to 2018. The main research question is whether search intensity improves the models' performance.

The results reveal that online search intensity variables increase the model's significance by lowering their standard errors. A single online search variable does add little, except for the following keywords: (a) Inflation, (b) GDP, (c) CPI, (d) job openings, and (e) (currency) exchange rate. Those search intensity variables are significant at 0.1 percent. Noteworthy, the keyword 'interest rate' is highly significant when estimating the models with raw data only. The country specific regressions reveal that merely the keyword 'currency+exchange rate' denotes robustness across all countries.

Looking to the macroeconomic variables, we find strong significance for inflation, interest rate, money supply, relative price of non-tradable goods, debt-to-GDP and terms of trade. This is similar in the country specific regression exercise. The value-added of including online-search keywords is revealed by the outperforming nature of the search intensity-models in general. Nonetheless, conducting research with search data is bound by the quality of the keywords (Lazer et al. 2014). For instance, there could be more searches for the name 'Apple' because the word in themselves stands for the fruit and the name of the company.

Overall, there are three major contributions of this research work. First, we demonstrate that search intensity enhances exchange rate models in general, including the prediction and forecasting performance (Tables 6 and 7). Second, broadly defined search indices do not provide a value-added because keyword aggregation eliminates the singularity of the information and narrows the variance (Tables 6 and 7). Third, integrating search intensity in macroeconomic models positively affects the direction of in-sample forecasting (Table 8). On a side note, we corroborate empirical findings in the literature when focusing on the macroeconomic variables alone.

This paper unveils novel insights into the challenging realm of exchange rate economics. Understanding exchange rates is a critical issue in understanding the interplay of the financial and real economy. Hence, this subject is of paramount relevance not only for central banks and governments, but also for businesses and financial investors.

This paper is structured as follows. In Section 2, we review the literature on exchange rates as well as on online data. The data and methodology are prescribed in Section 3. In a series of subsections, we explain the design of different search indices, the different regression models as well as the findings of pre-testing in regard to our panel data. Section 4 contains the main findings. We discuss the results and analyse the policy implications, including limitations. Finally, Section 5 concludes the paper.

2. Literature Review

The dynamic movement of a currency is a spinal question in international economics. In the past decades, economists have examined exchange rate behavior from partly orthogonal angles utilizing either a theoretical or empirical approach.

2.1. Exchange Rate Literature

Theoretical exchange rate models date back to the classical and keynesian schools of thought (Cassel 1918; Dornbusch 1976; Dornbusch and Krugman 1976; Mundell 1968). Due to fixed exchange rates during the Gold Standard and the Bretton Woods System, most empirical research started after the 1970s (Clark and MacDonald 1998).

For the first time, our empirical study aims to address the complexity of the stochastic nature of exchange rate dynamics by introducing a new determining behavioral variable: Online search intensity. The following literature review highlights work closely related to ours. Note, there are already seminal papers and good reviews in that field (Berkowitz and Giorgianni 2001; Clarida and Gali 1995; Mark 1995; Rogoff 1995; Rossi 2013).

A seminal work on exchange rates is the approach by Mundell and Fleming devised around the 1960s. The Mundell-Fleming model describes the relationship between a country's exchange rate, its output, and interest rate in an open economy. Mundell (1963) states that the behavior of the exchange rate depends crucially on the economy and vice versa.

Intuitively, when money supply increases or equivalently interest rates decline, we expect a special transition process. On the one hand, a monetary expansion increases the output. Ceteris paribus, high GDP growth renders a country´s currency more attractive and leads to an appreciation. On the other hand, a monetary expansion causes capital outflows due to lower interest rates, as investments abroad become relatively more appealing. With a lower supply of foreign exchange, the home currency depreciates. This depreciation makes exports relatively cheap, which increases net exports, and, in turn, increases the total domestic output. This represents the impact of monetary policy under floating exchange rates while assuming perfect capital mobility.

The Mundell-Fleming approach, however, fails to explain the performance of major currencies. The model assumes the purchasing power parity (PPP), which proves to be wrong under certain circumstances, such as in the short term. The PPP assumption implies constant exchange rates when, to all intents and purposes, market participants experience rather high volatilities (Brissimis et al. 2005; Liang 1998; Rogoff 1995). The inconclusiveness led to the development of other models, such as the exchange rate overshooting model by Dornbush (1976).

This model is based on a slow adjustment of prices and consistent expectations. In the end, the model captures the phenomena of short term overshooting of exchange rates above their long-run equilibrium. Thus, the exchange rate volatility is partly attributed to market inefficiencies. Dornbush (1976) maintains that volatility is intrinsic to the market as the exchange rate responds to changes in monetary policy disproportionally to compensate for slow-adjusting prices. Hence, an expansionary monetary policy leads to lower interest rates and an exchange rate movement. In the short term, we expect an depreciation of the exchange rate. However, in the long-run, we expect a appreciation due to further stimulus or, in other words, the first-order effect overshoots only in the short-run. In Rogoff (2002) words, the "initial excess depreciation leaves room for the ensuing appreciation needed to simultaneously clear the bond and money markets". Our intention when utilizing online search intensity, is to attain a better understanding of the role of expectations on the exchange rate dynamics as well as the interplay to both the goods and money market.

As with every theoretical approach, the overshooting model is not a complete picture of reality. Hooper and Morton (1982), Driskill (1981) and Buiter and Miller (1981), for instance, extended the model to overcome some of its restrictions, such as allowing for changes in the long-run real exchange rate, imperfect substitutability between domestic and foreign assets, and non-zero inflation. Moreover, contemporary theoretical research by Gray (1976) and Fischer (1977) study the idea of sticky-price open economy models in order to explain the exchange rate dynamics. Frankel (1979) developed a similar model and, as a consequence, the overshooting model is sometimes described as the Dornbusch-Frankel model. A difference between the two is that Frankel (1979) argues that exchange rates are driven by their real interest rate differentials and not their nominal. In our paper, we estimate an overshooting model and an augmented-overshooting model including search intensity.

The theoretical exchange rate models' often display weak or inconclusive empirical performance. For instance, Meese and Rogoff (1983) compare in a seminal article the out-of-sample forecasting accuracy of various structural models. They find that all, including the overshooting model, perform rather poorly in comparison to the simple random walk model—termed naive forecast. Their results constitute what is known as the "disconnecting puzzle" in international finance. Indeed, their modeling exercises fail to establish a significant link between real exchange rates and economic fundamentals. A later study finds similar results when analyzing modern models under certain horizons for certain criteria (Cheung et al. 2005). The results from Meese and Rogoff (1983) demonstrate that market expectations of exchange rates are relevant, however, expectations are difficult to measure. The timely availability of search intensity, however, gives the measurement of expectations in this literature a new lease of life.

Molodtsova and Papell (2009) show that exchange rate models can beat a random walk in an out-of-sample forecasting exercise. Sarno and Schmeling (2014) document that fundamental exchange rate models have predictive power, but their performance relies heavily on the currency and forecast horizon. Kouwenberg et al. (2017) develop a model of selected fundamentals regardless it only works for 5 out of 10 currencies, implying that it does not beat a random walk. An approved notion is that fundamentals matter in the long-run but not in the short-run (Mark 1995; Mark and Sul 2001). Engel and West (2005) state that the expectations about future macroeconomic fundamentals drive exchange rates much more than lagged fundamentals do. Their findings relate to research of Andersen et al. (2003) that find strong evidence of exchange rates reacting to news. The results support the fact that exchange rates are conditioned by both macroeconomic fundamentals on the one hand and market expectations on the other.

The disparity in ideas surrounding empirical exchange rate research can be traced back to the limitation of the studies. Indeed, the context of foreign exchange markets is challenging, especially given their high interconnectedness in globalized and interconnected markets as well as the multidimensionality and stochastic nature of exchange rates. Understanding or predicting the behavior of exchange rates still represents a tall order up until today. The literature suggest that there are other—partly hidden— forces at work. Those forces are either not adequately considered or measured within the existing empirical models. On that extent, this paper aims to contribute to the literature by including a factor which thus far has been turned a blind eye to: The people´s attention measured through online-search intensity. We reveal that macroeconomic fundamentals and search intensity are significant drivers alike.

2.2. Literature on Search Data

There is strong evidence on the usefulness of online search data. Shim et al. (2001) find that consumer's online search patterns predict their posterior purchases. Thus, information seeking behavior measures expectations and the potential demand of customers. Google data, as the world's leading search engine, particularly provide search intensity data via the tool of Google Trends (Choi and Varian 2012). Since 2004, Google publishes search data on every keyword instantaneously. Several papers have demonstrated the usefulness of search data successfully. Firstly, there is a seminal study that accounts for the power of search data by predicting flu dynamics (Ginsberg et al. 2009). Since then, the number of publications using search data is flourishing (Jun et al. 2017).

Online search data has been proven to be useful in a whole raft of different fields. For instance Vaughan and Romero-Frias (2013) find a significant correlation between search volume of a university's name and its academic reputation. Althouse et al. (2011) show that search queries predict dengue incidences, such as other influenza-like diseases (Ginsberg et al. 2009). In economics, Ettredge et al. (2005) examine U.S. unemployment trends and establish a significant correlation between job search data and unemployment. Da et al. (2011) propose a new method of capturing investor interest using search frequency, and Jun et al. (2017) demonstrate how Google Trends helps companies discover the perceptions consumers have about brands.

Yet, there is only one paper related to our work on the entwinement of search intensity and exchange rates. Bulut (2017) finds that Google Trends surpass structural models in predicting the direction of exchange rates. He concludes that the out-of-sample forecast of Google models offers better predictions for five currency pairs when compared to structural models. However, when compared to the random walk, neither Google models nor structural models perform to a similar extent. Our research differs from Bulut's in several aspects. First, our data has more currencies and a longer time period. Hence, our panel is significantly larger and thus permits to draw a more complete picture. Second, we investigate the impact of a large sample of different search keywords and even integrate newly computed aggregate search intensity indices. Third, we utilize two well-established exchange rate models, such as the overshooting model and the augmented-overshooting model with and without search intensity. Fourth, our paper estimates the models and studies their prediction as well as the forecasting performances. Furthermore, and in contrast to Bulut (2017), our work does not rely on the PPP assumption and includes more elaborated search metrics. Last but not least, we study the exchange rate determination first and not merely the forecasting power.

Yet, research with search intensity is not free from limitations. Goel et al. (2010) claim, for instance, that there is little gain in prediction when the tool is used in forecasting. Vaughan and Chen (2015) are comparing Google Trends with the Baidu Index and find that Google data verges on futility if the number of people is relatively reduced in a certain territory. Lazer et al. (2014) raise questions about the nature of predictions and argue that web search is not reliable to replace traditional methods. While not all studies have significant results, Jun et al. (2017) stress that online search has advantages in terms of immediacy and objectivity. All in all, much of the quality of search data depends on the research question and methodology.

3. Data and Methodology

We utilize a strongly balanced panel to estimate different models over a quarterly time series which begins in 2004, the earliest year Google Trends data is available, and extends until 2018. The panel consists of the following ten countries: Australia, Canada, China, Germany, Japan, Mexico, Sweden, Switzerland, United Kingdom (UK) and United States (US). The sample represents ten of the twenty most traded currencies in the world (BIS 2016). Germany represents the major economy for the Euro currency. Integrating all Eurozone countries would be more appropriate to better capture the Euro exchange, yet, we leave this task partially to future research.

For each country, we analyze the following macroeconomic variables: Real exchange rate (RRT); money supply (MM); gross domestic product (GDP); interest rate (IR); consumer price index (CPI); relative price of non-tradable goods (PNT); government debt-to-GDP (DBT); terms of trade (TOT) and net foreign assets (NFA). The debt-to-GDP and money supply data is from the OECD database (OECD 2018). All other variables are gathered from the International Monetary Fund financial statistics (IMF 2018). Because debt-to-GDP is only available annually, we conduct a cubic spline interpolation in order to disaggregate the observations into a higher frequency. As data availability differs across countries and time, some missing data points are present.[1]

3.1. Measuring Search Intensity

This paper includes online search intensity (SI), streamed from Google Trends. Search data is a proxy for measuring attention on exchange rates or related variables respectively. Google provides information on the search volume for any specific search term. The data represent the ratio of online searches made for a specific keyword in a given geographical region within a specific period to the total number of online searches made under the same specifications. The resulting time series of search intensity is scaled in the range of 0 to 100. Each search index number represents the relative popularity of a keyword (Google 2018). One of the difficulties of working with search data is selecting the appropriate set of keywords. Naccarato et al. (2018) state that a selection based on an objective and adequate method delivers useful results. Our keyword selection criteria are: (i) Keywords have to represent the major macroeconomic fundamentals of exchange rates; (ii) keywords coincide with search terms suggested by Google's algorithm; and (iii) keywords are representative to similar studies in this literature.

Table 1 contains the list with all search keywords utilised in our study. These terms were selected using the aforementioned parameters and directly or indirectly affect the macroeconomic fundamentals and hence the exchange rate.

Table 1. Google Trends Keyword Selection.

English	Germany	Japanese	French	Chinese	Swedish	Spanish
inflation	Inflation	インフレーション	inflation	通貨膨脹	inflation	inflación
CPI	VPI	消費者物価指数	IPC	消費者物價指數	KPI	IPC
GDP	BIP	国内生产总值	PIB	國內生產總值	BNP	PIB
interest rate	Zinssatz	利率	taux d'intérêt	利率	räntesats	tasa de interés
loan	Kredit	クレジット	crédit	借款	kredit	crédito
ATM	Geldautomat	現金自動支払機	Distribute-ur de billets	自動提款機	bankomat	cajero
job opening	Stellenangebot	求人	Offre d'emploi	職缺	lediga jobb	oferta de trabajo
vacation	Urlaub	休暇	vacance	假期	ferie	vacacionas
shopping	einkaufen	ショッピング	shopping	購物	shopping	compras
exchange rate	Wechselkurs	為替相場	taux de change	汇率	växelkurs	tipo de cambio
appreciation	Aufwertung	再評価	réévaluation	重估	omvärdering	revaluación

After gathering the search intensity variables, we obtain for each keyword, i, a time-series $SI_{i,t}$ over time t. One way to incorporate the search intensity to the model is by adding each single search term. This is labelled the sum of search intensity (SI_t^{Σ}). A second way is to include aggregate search indices, for instance the mean of certain search terms $(SI_t^{\overline{CAT}})$. Among others, we include the mean of all inflation query data $(\overline{IN})$, the average of interest rate queries $(\overline{IR})$, and the mean of consumption queries $(\overline{CON})$. Hence, we first obtain two trivial search intensity variables:

$$SI_t^{\Sigma} = SI_t^{INF} + SI_t^{GDP} + SI_t^{CPI} + SI_t^{IR} + SI_t^{LOAN} + SI_t^{ATM} + SI_t^{JO} + SI^{VC} + SI_t^{SHOP} + SI_t^{ExR} \tag{1}$$

$$SI_t^{\overline{CAT}} = SI_t^{\overline{INF}} + SI_t^{\overline{IR}} + SI_t^{\overline{CON}}, \tag{2}$$

where the acronyms denote the following search keywords: Search intensity of inflation (SI-INF), search intensity of gross domestic product (SI-GDP), search intensity of consumer price index (SI-CPI), search intensity of interest rate (SI-IR), search intensity of loan (SI-LOAN), search intensity of automated teller machine (SI-ATM), search intensity of job opening (SI-JO), search intensity of vacation (SI-VC), search intensity of shopping (SI-SHOP), and search intensity of exchange rate (SI-ExR). Both aggregate measures are based on disaggregated search queries over time.

Nonetheless, we design four more sophisticated online search intensity indices. First, we follow Chen et al. (2001) and define an abnormal average change in $SI_{i,t}$, computed by

$$ACSI_{i,t} = \frac{SI_{i,t} - AVSI_{i|t-4,t-1}}{SDAVSI_{i|t-4,t-1}}, \tag{3}$$

where $AVSI_{i|t-4,t-1}$ and $SDAVSI_{i|t-4,t-1}$ are the mean and standard deviation of SI for series i over the past 4 quarters, respectively. An ACSI search index, that measures the relative search to the average of the past 4-quarters, signifies an abnormally high (low) attention on the respective search expression.

Second, we follow the seminal paper by Da et al. (2011) and define:

$$LASI_{i,t} = \log(SI_{i,t}) - \log(Median(SI_{i|t-4,t})). \tag{4}$$

In short, $LASI_{i,t}$ measures the logarithmic value of search intensity (SI) of a search expression i minus the logarithmic value of the median of search intensity during the previous quarter.

Third, we follow a related idea in the seminal work by Baker et al. (2016). We compute an aggregate search intensity index (SII) that is standardized and normalized in a range of 0 to 100. In the first step, we divide the $SI_{i,t}$ by the time-series standard deviation σ_i for all search terms for all t. This creates a new time-series labeled $SS_{i,t}$. Secondly, we compute for each search term and time the normalized time-series according to

$$NSS_{i,t} = \frac{(SS_{i,t} - \min SS_{i,t}) \times 100}{(\max SS_{i,t} - \min SS_{i,t})}. \quad (5)$$

Next, we compute the mean over all $NSS_{i,t}$ in each quarter in order to obtain the aggregate search intensity index SII_t.

Fourth, we compute our own aggregate search index labelled average standardized search intensity $(ASSI_{i,t})$. In a first step, we compute the quarterly means, defined as $\overline{SS}_{i,t}$, of the standardized search $(SS_{i,t})$. Second, we compute the difference of the search volume variables divided by the standard deviation — with the formula: $ASSI_{i,t} = (SI_{i,t} - \overline{SS}_{i,t})/\sigma_i$.

We utilize the following six search indices $SIndex_{i,t}^{M1-M6}$ in our econometric models: (M1) SI_t^{Σ}, (M2) $SI_t^{\overline{CAT}}$, (M3) $ACSI_{i,t}$, (M4) $LASI_{i,t}$, (M5) SII_t, and (M6) $ASSI_{i,t}$. All search indices are based on search data and represent an attention measure for the macroeconomic drivers of the exchange rate. We include these indices as control variables in our two macroeconomic exchange rate models. Thus, we regress the exchange rate in a panel set, consisting of countries i over time t in respect to two different models ($Model_{i,t}^{type}$) and the set of six search indices ($SIndex_{i,t}^{M1-M6}$). The model is specified as follows

$$ExchangRate_{i,t} = \alpha_{i,t} + \beta_1 Model_{i,t}^{type} + \beta_2 SIndex_{i,t}^{M1-M6} + \epsilon_{i,t}, \quad (6)$$

where we assume i.i.d. for the error term $\epsilon_{i,t}$. All abbreviations and variables names are listed at the end of the paper.

3.2. Econometric Methodology

Next, we describe the two types of exchange rate models in more detail. The macroeconomic fundamentals of the overshooting model are the price level, output, money supply, and interest rate (Dornbush 1976). Our regression of the overshooting model is similar to Cheung et al. (2005), where the variables are as previously described. The term ϵ_t is the standard error and is normally distributed $\mathcal{N}(0, \sigma_\epsilon^2)$.

The 'Overshooting Model' (OM) captures the overshooting channel via $IR_{i,t}$ and assumes that PPP holds merely in the long run. Our econometric equation follows this idea but incorporates the exchange rate equilibrium relationship as described by Clark and MacDonald (1998) or in work by Ewards (1989):

$$Model_{i,t}^{OM} := \eta^M MM_{i,t} + \eta^G GDP_{i,t} + \eta^I IR_{i,t} + \eta^C CPI_{i,t}, \quad (7)$$

The second econometric model is an augmented-overshooting model. We define the regression equation of the 'Augmented Model' (AM) as follows

$$Model_{i,t}^{AM} := Model_{i,t}^{OM} + \beta PNT_{i,t} + \gamma DBT_{i,t} + \rho TOT_{i,t} + \zeta NFA_{i,t}. \quad (8)$$

Equation (8) incorporates the Balassa-Samuelson effect via PNT_t and the portfolio balance effect via DBT_t and NFA_t.[2]

Whether a country's currency appreciates or depreciates depends ultimately on the perceived desirability of holding that currency. Therefore, one can conceive the variables in Equations (7) and (8) as the major macroeconomic exchange rate determinants. If a nation's inflation or debt levels are considerably high, the desirability for that currency will be low, or, in other words, there is a tendency of a weak currency. The relative price of non-tradable goods, the terms of trade, and net foreign assets reflect the country's productivity, economic health, and demand for the country's goods and services. All of this influences the country's currency demand. Everything else constant, the better the productivity and economic situation, the higher the desirability for holding the currency.

As a measure of market expectations, we include search intensity as described previously. The idea that web search represents collective attention is established by recent research, among others by Ettredge et al. (2005), Ginsberg et al. (2009) and Da et al. (2011).

Ultimately, we describe the fourteen variants of our econometric regression models. Firstly, we distinguish between the two benchmark models, consisting of the 'Overshooting Model' (OM) in Equation (7) and the 'Augmented Model' (AM) in Equation (8). In order to simplify the terminology, we re-label $X_{i,t}^{j} := Model_{i,t}^{j}$, where j denotes either the OM- or AM-model. Both benchmark models capture the pure macroeconomic fundamentals, as denoted in Equation (9). Secondly, we estimate an extended model and include our six search indices. Equation (10) denotes the models with search intensity metrics (M1) SI_t^{Σ}, (M2) $SI_t^{\overline{CAT}}$, (M3) $ACSI_{i,t}$, (M4) $LASI_{i,t}$, (M5) SII_t, and (M6) $ASSI_{i,t}$. Thus, we obtain two regression equations based on either the pure macroeconomic models or the extended models by six search indices,

$$ExR_{i,t}^{X_{i,t}^{j}} = \alpha + \beta_1 X_{i,t}^{j} + \epsilon_{i,t} \tag{9}$$

$$ExR_{i,t}^{X_{i,t}^{j,M1-M6}} = \alpha + \beta_1 X_{i,t}^{j} + \beta_2 SIndex_{i,t}^{M1-M6} + \epsilon_{i,t}, \tag{10}$$

where $ExR_{i,t}$ denotes the respective exchange rate, $X_{i,t}^{j}$ denotes the macroeconomic $OM-$ or $AM-$model, and $SIndex$ represents the six search indices for each country i over time t. We test the hypothesis whether search intensity enhances the models.

3.3. Prediction and Forecasting Methodology

A rigorous evaluation of the prediction and forecasting performance of our model reveals a final insight about the use and quality of online search data. First, we evaluate the prediction of our two best models with search data in comparison to the economic benchmark models. We run the prediction by utilizing the estimated coefficients from above and compute the confidence intervals of 95%. In the end, we compare the real exchange rate with the performance of the model prediction:

$$ExR_{pre}^{X_{i,t}^{j}} = \widehat{\alpha} + \widehat{\beta_1} X_{i,t}^{j} + \epsilon_{i,t} \tag{11}$$

$$ExR_{pre}^{X_{i,t}^{j,M1,M6}} = \widehat{\alpha} + \widehat{\beta_1} X_{i,t}^{j} + \widehat{\beta_2} SIndex_{i,t}^{M1,M6} + \epsilon_{i,t} \tag{12}$$

where $X_{i,t}^{j}$ is always the AM-model because it is outperforming the narrow OM-model.

Second, we compute an in-sample forecast of the exchange rate over four quarters. In the forecasting exercise, we compare the forecasting of our benchmark model and the models with search intensity as well as a specified ARIMA-Model and the naive forecast of a random walk. According to standard lag-tests, we use an ARIMA(2,0,1) model. The forecasting equations are:

$$\begin{aligned}
ExR_{i,t+1}^{Xj} &= \widehat{\alpha} + \widehat{\beta_1} X_{i,t}^{j} + \epsilon_{i,t}, && \text{Basic forecast} \\
ExR_{i,t+1}^{Xj,M1,M6} &= \widehat{\alpha} + \widehat{\beta_1} X_{i,t}^{j} + \widehat{\beta_2} SIndex_{i,t}^{M1,M6} + \epsilon_{i,t}, && \text{SI forecast} \\
ExR_{i,t+1}^{Xj} &= \rho ExR_t^{Xj} + \rho^2 ExRate_{t-1}^{Xj} + \epsilon_{i,t} + \nu \epsilon_{i,t-1}, && \text{ARIMA forecast} \\
ExR_{i,t+1}^{Xj} &= ExRate_{i,t}^{Xj}, && \text{Naive forecast.}
\end{aligned}$$

In order to evaluate the forecasting performance, we compute the square errors of each forecast $\Pi_{i,t} = [ExR_{i,t}^{forecast} - ExR_{i,t}]^2$ and the sum of square errors $\Pi_i^{\Sigma} = \sum_t [ExR_{i,t}^{forecast} - ExR_{i,t}]^2$. We evaluate the forecasting performance by testing the null-hypothesis of $\Pi_{i,t}$ and Π_i^{Σ} to be zero. A rejection of the null-hypothesis in regard to a zero mean-square error identifies the models with insufficient forecasting performance.

3.4. Panel Regression Pre-Testing

Our econometric approach utilizes a large panel such as those applied in the empirical exchange rate literature by Sarno and Schmeling (2014) or Mark and Sul (2001). Nevertheless, before estimating our fourteen models, we apply several pre-tests for multi-collinearity, heteroscedasticity, autocorrelation, omitted variables, and stationarity.[3]

First, by looking to the time-series properties, we note the problem of non-stationarity for some of our variables. Stationarity means that the probability distributions of the variables are stable over time and have no unit roots. To verify stationarity, we conduct the Augmented Dickey-Fuller (ADF) test, the Fischer-type test and the Im-Pesaran-Shin test (Choi 2001; Im et al. 2003).[4] Indeed, three of our macroeconomic variables display some non-stationarity: Money supply, debt-to-GDP and net foreign assets. In order to correct for non-stationarity, we compute the log-difference.[5] The process of de-trending yields stationary variables in the end.

Multicollinearity arises when predictor variables are correlated. We use the rule of thumb that correlation should not have a variance inflation factor (VIF) above a value of 8 (Chatterjee and Hadi 1986). We observe a mild multicollinearity between the two variables net foreign assets and money supply. This problem is tackled by excluding the variable NFA, which has the highest VIF, being of approximately 8. After this adjustment the models are free of multicollinearity (Appendix A Table A2).

In order to test for heteroscedasticity, we apply the Breusch-Pagan test (Breusch and Pagan 1979 1980; Cook and Weisberg 1983) as well as the modified Wald test. None of the tests can reject heteroscedasticity in our panel (Appendix A Tables A3 and A4; Appendix B). Similarly, we use the Wooldridge test in order to check for autocorrelation (Drukker 2003). We cannot reject autocorrelation either (Appendix A Table A5). For both issues we apply the standard techniques including robust estimation with panel-corrected standard errors and autoregressive terms.[6] Finally, the Ramsey REST test does reject omitted variables in our models (Appendix A Table A6).

Last but not least, when deciding between the different panel regression techniques, we utilize the Breusch-Pagan test and the Hausman-Test. The Hausman test specifies whether a fixed effects (FE) or random effects (RE) model is appropriate. The FE model allows for variances in the intercept parameter, while the RE model is a special case where the heterogeneity across countries is treated as random. The Breusch-Pagan test compares the pooled OLS regression with a random effects model. In virtually all cases the fixed effects model is selected, except in one case in which it is rejected (Appendix A Tables A7 and A8). Consequently, the appropriate choice for our panel data is the fixed effects model. As in the exchange rate literature, we presume that the variables reject endogeneity. A lack of instrumental variables hinders the formal process of controlling for endogeneity.

4. Results

In a first step, we estimate the OM-model and AM-model with different panel estimation techniques.[7] It follows from the Hausman test that the fixed-effects model delivers consistent estimates for the OM-model. For the AM-model we utilize the random-effects.

While the sign of the coefficients follow our expectations, their p-values and respectively significance denote the impact of the variables on the exchange rate (Table 2). At first glance, we can observe that the interest rate, $IR_{i,t}$, is robustly positive and significant across all models. This highlights the robust importance of the interest rate channel to the exchange rate dynamics. Similarly, the consumer price index (CPI) is negative, however, not robust in all models. Likewise, we find highly robust and significant coefficients across all models for the relative price of non-tradable goods and terms-of-trade. In general, this confirms the importance of the macroeconomic variables in determining the exchange rate as proposed by Dornbush (1976).

Table 2. Panel Regression Table Random-Effects AM Models.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
MM	0.071 ***	0.190 ***	0.172 ***	0.156 ***	0.153 ***	0.174 ***	0.195 ***
	(0.0176)	(0.0379)	(0.0373)	(0.0338)	(0.0340)	(0.0326)	(0.0380)
GDP	0.201	0.127	−0.041	0.031	−0.063	−0.073	0.107
	(0.370)	(0.352)	(0.376)	(0.386)	(0.389)	(0.368)	(0.352)
IR	2.732 ***	2.702 ***	2.464 ***	2.497 ***	2.590 ***	2.474 ***	2.679 ***
	(0.318)	(0.316)	(0.328)	(0.340)	(0.355)	(0.324)	(0.316)
CPI	−106.400 *	−74.090	−82.890	−92.770	−112.600 *	−82.920	−74.210
	(52.830)	(49.560)	(52.920)	(54.810)	(56.520)	(52.160)	(49.510)
PNT	77.780 ***	98.240 ***	35.870	27.950	32.380	45.490 *	93.23 ***
	(12.380)	(21.540)	(20.700)	(20.150)	(20.390)	(19.180)	(21.800)
DBT	4.539	15.16 ***	8.593 **	8.578 **	9.033 **	9.370 **	15.94 ***
	(2.750)	(2.996)	(2.991)	(3.111)	(3.218)	(2.971)	(3.043)
ToT	40.020 ***	34.820 ***	43.84 ***	43.290 ***	44.250 ***	43.21 ***	35.140 ***
	(4.038)	(4.070)	(4.176)	(4.536)	(4.666)	(4.123)	(4.071)
NFA		−0.243	−0.441 **	−0.381 **	−0.368 **	−0.445 ***	−0.267
		(0.135)	(0.133)	(0.136)	(0.139)	(0.129)	(0.136)
SI-INF		0.00243					
		(0.0359)					
SI-GDP		0.0605					
		(0.0355)					
SI-CPI		−0.167 ***					
		(0.0352)					
SI-IR		−0.00556					
		(0.0356)					
SI-LOAN		0.0286					
		(0.0341)					
SI-ATM		−0.0266					
		(0.0339)					
SI-JO		−0.0669 **					
		(0.0230)					
SI-SHOP		0.0427					
		(0.0330)					
SI-ExR		−0.238 ***					
		(0.0310)					
$SI^{\overline{INF}}$			−0.0503				
			(0.0423)				
$SI^{\overline{IR}}$			−0.0896				
			(0.0493)				
$SI^{\overline{CON}}$			−0.0172				
			(0.0526)				
ACSI-INF				−0.111			
				(0.116)			
ACSI-GDP				−0.0773			
				(0.202)			
ACSI-CPI				0.109			
				(0.209)			
ACSI-IR				−0.0987			
				(0.176)			
ACSI-LOAN				−0.158			
				(0.170)			
ACSI-ATM				0.0259			
				(0.156)			
acgjo				−0.0147			
				(0.141)			
ACSI-VC				0.143			
				(0.113)			

Table 2. *Cont.*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ACSI-SHOP				0.0734 (0.124)			
ACSI-ExR				−0.0731 (0.128)			
LASI-INF					2.131 (3.886)		
LASI-GDP					−8.505 (4.978)		
LASI-CPI					3.865 (4.112)		
LASI-IR					−5.502 (4.293)		
LASI-LOAN					−1.986 (3.447)		
LASI-ATM					0.790 (3.347)		
LASI-JO					0.806 (3.504)		
LASI-VC					3.210 (3.622)		
LASI-SHOP					0.721 (4.693)		
LASI-ExR					−0.755 (2.429)		
SII						−0.229 *** (0.0645)	
ASSI-INF							0.0291 (0.680)
ASSI-GDP							0.859 (0.513)
ASSI-CPI							−3.194 *** (0.668)
ASSI-IR							−0.106 (0.541)
ASSI-LOAN							0.639 (0.761)
ASSI-ATM							−0.696 (0.823)
ASSI-JO							−1.262 ** (0.466)
ASSI-VC							0.580 (0.410)
ASSI-SHOP							0.714 (0.549)
ASSI-ExR							−5.479 *** (0.706)
Constant	70.810 (55.900)	38.640 (56.860)	124.0 * (58.110)	130.500 * (59.200)	143.400 * (60.910)	117.700 * (56.780)	43.020 (56.870)
Observations	447	447	447	441	433	447	447
Adjusted R^2	0.341	0.465	0.357	0.331	0.335	0.369	0.466
F	35.060	24.250	24.230	13.560	13.530	30.910	23.070

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Moreover, the augmented model confirms the famous Balassa-Samuelson effect. Indeed, the relative price of non-tradable goods impacts the real exchange rate through changes in real costs (Balassa 1964; Samuelson 1964).[8] Finally, GDP growth is not significant but the debt-to-GDP ratio is significant at 1 percent similarly to Cheung et al. (2005). A potential reason for the insignificance of GDP growth is its aggregate nature.

Having selected the consistent panel estimator, we estimate all model variants, including the search intensity indices. For all models, the regression output reveals that search intensity model 1 and model 6 deliver the best results (Tables 3 and Appendix C Table A14).[9] Note, search intensity model 1 includes all search intensity data for each keyword. Under search intensity model 6, we include our metric of the average standardized search intensity index, $ASSI_{i,t}$. Both models outperform the benchmark macroeconomic OM- or AM-model respectively. Noteworthy, both search intensity models 1 and 6 have the highest R-square[10] and highly significant F-statistics.

Table 3. Panel Regression Table Fixed-Effects OM Models.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
dmm	0.465	0.722 *	0.416	0.533	0.662	0.459	0.724 *
	(0.331)	(0.331)	(0.349)	(0.333)	(0.347)	(0.331)	(0.331)
GDP	0.317	0.0300	0.340	0.0521	0.0662	0.258	0.0250
	(0.463)	(0.447)	(0.474)	(0.476)	(0.482)	(0.466)	(0.448)
IR	1.303 ***	1.302 ***	1.341 ***	1.223 ***	1.186 ***	1.231 ***	1.288 ***
	(0.245)	(0.318)	(0.276)	(0.253)	(0.266)	(0.253)	(0.321)
CPI	−221.400 ***	−160.900 **	−220.300 ***	−230.600 ***	−233.700 ***	−221.800 ***	−161.500 **
	(62.230)	(59.490)	(62.630)	(62.920)	(64.440)	(62.210)	(59.560)
SI-INF		−0.0756					
		(0.0432)					
SI-GDP		0.184 ***					
		(0.0391)					
SI-CPI		−0.214 ***					
		(0.0423)					
SI-IR		−0.0444					
		(0.0398)					
SI-LOAN		−0.0259					
		(0.0318)					
SI-ATM		0.0887 *					
		(0.0379)					
SI-JO		−0.0768 **					
		(0.0269)					
SI-SHOP		0.0739 *					
		(0.0317)					
SI-ExR		−0.135 ***					
		(0.0280)					
$SI^{\overline{INF}}$			−0.00631				
			(0.0483)				
$SI^{\overline{IR}}$			0.0131				
			(0.0494)				
$SI^{\overline{CON}}$			−0.0290				
			(0.0551)				
ACSI-INF				−0.0464			
				(0.148)			
ACSI-GDP				−0.0992			
				(0.264)			
ACSI-CPI				0.123			
				(0.246)			
ACSI-IR				−0.231			
				(0.204)			
ACSI-LOAN				−0.384 *			
				(0.152)			
ACSI-ATM				0.0895			
				(0.190)			

Table 3. *Cont.*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ACSI-JO				0.310 (0.189)			
ACSI-VC				0.124 (0.142)			
ACSI-SHOP				0.177 (0.241)			
ACSI-ExR				−0.212 (0.155)			
LASI-INF					−2.160 (4.344)		
LASI-GDP					0.458 (5.785)		
LASI-CPI					2.923 (4.735)		
LASI-IR					−5.854 (5.167)		
LASI-LOAN					−5.952 (4.303)		
LASI-ATM					−0.488 (3.671)		
LASI-JO					9.589 * (4.196)		
LASI-VC					−0.283 (4.308)		
LASI-SHOP					−4.695 (4.801)		
LASI-ExR					−3.349 (2.760)		
SII						−0.0842 (0.0705)	
ASSI-INF							−1.414 (0.823)
ASSI-GDP							2.644 *** (0.567)
ASSI-CPI							−4.106 *** (0.810)
ASSI-IR							−0.681 (0.605)
ASSI-LOAN							−0.609 (0.715)
ASSI-ATM							2.099 * (0.933)
ASSI-JO							−1.510 ** (0.551)
ASSI-VC							0.198 (0.504)
ASSI-SHOP							1.225 * (0.528)
ASSI-ExR							−3.072 *** (0.639)
Constant	319.100 *** (62.410)	265.000 *** (59.710)	319.300 *** (62.870)	329.200 *** (63.110)	331.800 *** (64.640)	323.700 *** (62.500)	265.300 *** (59.770)
Observations	506	506	506	501	494	506	506
Adjusted R^2	0.045	0.176	0.039	0.055	0.042	0.045	0.175
F	9.147	10.010	5.244	3.718	3.181	7.609	9.291

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The regression results of the pure exchange rate models with the macroeconomics variables only are reported in Tables 4 and 5. Both Tables illustrate the well-known results from the exchange rate literature. All coefficients and effects of the pure macroeconomics exchange rate variables are as expected. Consequently, the exchange rate models are sufficiently well-specified.

Table 4. Panel Regression Table AM Model.

	Model OLS	Model PA	Model FE	Model RE	Model ML
MoM	0.0316	0.0715 ***	0.0711 ***	0.0484 **	0.0715 ***
	(0.0183)	(0.0171)	(0.0176)	(0.0172)	(0.0170)
GDP	−0.438	0.192	0.201	−0.146	0.192
	(0.496)	(0.369)	(0.370)	(0.445)	(0.367)
IR	1.433 ***	2.691 ***	2.732 ***	1.907 ***	2.692 ***
	(0.274)	(0.310)	(0.318)	(0.280)	(0.309)
CPI	5.647	−104.3 *	−106.4 *	−51.38	−104.3 *
	(70.42)	(52.68)	(52.83)	(63.37)	(52.39)
PNT	110.1 ***	79.27 ***	77.78 ***	99.67 ***	79.22 ***
	(13.56)	(12.25)	(12.38)	(13.14)	(12.20)
DBT	−0.368	3.948	4.539	0.716	3.965
	(1.101)	(2.419)	(2.750)	(1.250)	(2.425)
ToT	20.55 ***	38.90 ***	40.02 ***	25.72 ***	38.94 ***
	(3.500)	(3.906)	(4.038)	(3.545)	(3.916)
Constant	−43.27	68.49	70.81	15.36	68.56
	(73.43)	(55.75)	(55.90)	(66.40)	(55.44)
sigma(u)					
Constant					6.569 ***
					(1.595)
sigma(e)					
Constant					6.375 ***
					(0.215)
Observations	447	447	447	447	447
Adjusted R^2	0.241		0.341		
F	21.18		35.06		

Standard errors in parentheses, FE = Fixed-Effects, RE = Random-Effects, PA = Pooled, ML = Maximum-Likelihood. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

In a second step, we compare the estimates of the OM- and AM-model with search intensity model 6, meaning the search metric $ASSI_{i,t}$ (Tables A13–A15).[11] This confirms that search intensity enhances the estimation performance such as robustness and significance of our models. Interestingly some of the $ASSI_{i,t}$ indices are highly significant, particularly the keyword 'exchange rate'. Therefore, a higher search intensity for the respective currency, which represents the online attention about the currency, significantly affects the market exchange rate. This finding is highly robust across all models.

Indeed, the predictive power of search intensity SI_t^{Σ} and $ASSI_{i,t}$ is impressive. Interestingly, our aggregate search intensity indices, such as $SI_t^{\overline{CAT}}$, are mostly insignificant. This could be due to the information loss during the aggregation process. The remaining three online search indices $ACSI_{i,t}$, $LASI_{i,t}$ and SII_t are rather insignificant too. This underscores that the specific choice of keywords and the design of the search intensity index have a major impact on the final outcome.

Table 5. Panel Regression Table OM Model.

	Model OLS	Model PA	Model FE	Model RE	Model ML
dmm	1.472 ***	0.565	0.465	0.631	0.537
	(0.327)	(0.337)	(0.331)	(0.326)	(0.327)
GDP	1.269 *	0.397	0.317	0.451	0.375
	(0.574)	(0.479)	(0.463)	(0.468)	(0.461)
IR	0.110	1.231 ***	1.303 ***	1.181 ***	1.252 ***
	(0.224)	(0.250)	(0.245)	(0.242)	(0.243)
CPI	−105.3	−217.2 ***	−221.4 ***	−214.2 ***	−218.4 ***
	(79.00)	(64.44)	(62.23)	(63.05)	(61.96)
Constant	202.6 *	315.7 ***	319.1 ***	312.6 ***	316.9 ***
	(79.12)	(64.66)	(62.41)	(63.24)	(62.19)
sigma(u)					
Constant					8.027 ***
					(1.863)
sigma(e)					
Constant					8.197 ***
					(0.260)
Observations	506	506	506	506	506
Adjusted R^2	0.054		0.045		
F	8.196		9.147		

Standard errors in parentheses, FE = Fixed-Effects, RE = Random-Effects, PA = Pooled, ML = Maximum-Likelihood. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

In this paper, we follow the online search literature by defining the most appropriate keywords in order to have comparable results (Bank et al. 2011; Takeda and Wakao 2013; Vlastakis and Markellos 2012). Nonetheless, a more systematic method or theory of selecting relevant keywords is an open research question. Vaughan and Chen (2015) finds that search indices have different predictive power in different countries.

Therefore, we estimate country specific regressions of the overshooting model and augmented-overshooting model for each country. Results are in the Appendix C in Table A19, which summarize the estimation results for the benchmark model. Similarly, Tables A20 and A23 illustrate search intensity model 1 with all disaggregated search intensity variables. In Tables A21 and A24 we report search intensity model 6 with our $ASSI_{i,t}$ search variables. The results show that the interest rate is at least significant at 1 percent in eight of ten countries, the relative price and terms of trade in six of ten countries, the debt-to-GDP ratio in five of ten countries, and the money supply, GDP and net foreign assets in three of ten countries. Noteworthy, the direction of those significant macroeconomic fundamentals vary from currency to currency (Tables A19 and A22). The results confirm the previous findings of the macroeconomic variables. In the OM-model search intensity variables are significant particularly for the keyword 'exchange rate' (Table A20). In the AM-model, however, search intensity is significant only for the keyword exchange rate in three out of nine countries (Table A23). Even though the search intensity model 6 has a similar pattern, our search intensity variables have a higher significance across most countries.

Indeed, the overshooting model delivers mixed results, however, the augmented-overshooting model has significant results for all countries with an R-square in the range of $[0.53; 0.89]$. Notably, search intensity variables are particularly significant in the US (Tables A20 and A21). The results for the other countries are rather mixed, yet having Germany, Japan, Mexico and the UK with high significance. This can be explained by Vaughan and Chen (2015) because online search data is better in countries where the market share of Google's search engine is high, particularly in Western democracies and English speaking countries.

The AM-model including search intensity variables stand out in regard of the adjusted R-square in a range of [0.77; 0.91] and highly significant F-statistics (Appendix C Tables A23 and A24). All findings corroborate that online search intensity covers market expectations in a similar way than news does as explored by Andersen et al. (2003), however, the results vary significantly across countries.

At a first stage, we conclude that search intensity improves the estimation results and the overall fit of the models. Yet, we have findings indicating that some search variables offer minor explanatory value. In our view, further research could address this issue through a more systematic method to gather the relevant keywords.

4.1. Performance of Model Prediction and Forecasting

In a next step, we evaluate the prediction performance of search intensity model 1 and model 6 in comparison to the benchmark macroeconomic OM- and AM-models. Juxtaposing the prediction of the exchange rates, we find evidence that the predictive power is raised significantly in models including search intensity. The exchange rate prediction for each country is almost always inside the 95% confidence intervals. On the contrary, the benchmark OM- and AM-models devoid of search intensity perform significantly inferior. A detailed evaluation of the prediction error is represented in Table 6. The smaller prediction errors in models 1 and 6 with the search intensity variables confirm the usefulness of search data under a prediction exercise.

Table 6. Prediction Performance Test.

	Basic	SI Model	ASSI Model
Australia	15.44 *	20.21	15.22
	(4.530)	(11.38)	(7.984)
China	3.214	2.124	0.994
	(1.672)	(1.931)	(0.453)
Germany	0.618	5.058	5.296
	(0.598)	(0.961)	(1.503)
Mexico	303.9 **	16.31	16.74
	(40.64)	(5.456)	(5.496)
Swiss	7.447	5.287	7.840
	(5.900)	(5.193)	(6.309)
UK	28.74	1.051	1.488
	(12.87)	(0.624)	(0.808)
Observations	4	4	4

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Surprising, however, is the forecasting performance. Table 7 and particularly Table 8 corroborate that models with search intensity outperform those lacking it. The hypothesis that the forecasting error is of zero cannot be rejected for most of the models with search intensity data. On the contrary, the forecasting error of the macroeconomic benchmark model or ARIMA model is significantly different to zero (Table 8). Nonetheless, the naive forecast is tantamount to that of our two top models 1 and 6. Not surprisingly, the confidence intervals under forecasting are rather wide in contrast to the naive forecast. However, looking to the forecasting direction, we interestingly find that our models do predict the direction better than the naive forecast (Table 8).

Table 7. Forecast Performance Test.

	Basic	ARIMA	Model ASSI Prediction	Naive Forecast
Australia	15.44 *	9.045	15.22	1.653
	(4.530)	(3.006)	(7.984)	(0.679)
China	3.214	10.74	0.994	1.218
	(1.672)	(5.054)	(0.453)	(0.769)
Germany	0.618	3.489	5.296	8.192
	(0.598)	(1.968)	(1.503)	(4.582)
Mexico	303.9 **	23.61	16.74	48.86
	(40.64)	(14.75)	(5.496)	(22.59)
Swiss	7.447	5.973	7.840	12.81
	(5.900)	(3.515)	(6.309)	(9.440)
UK	28.74	1.787 *	1.488	2.946
	(12.87)	(0.468)	(0.808)	(1.479)
Observations	4	4	4	4

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8. Square-Mean Error of Forecasting after 1 year.

	Basic	ARIMA	Model ASSI Forecast	Naive Forecast
Australia	41.84 *	25.61 *	23.21	4.683 *
	(10.80)	(5.425)	(13.45)	(0.939)
Canada	116.8	24.33	13.74	9.497
	(.)	(7.666)	(.)	(4.573)
China	8.387 *	18.34	2.446	3.448 *
	(2.371)	(8.670)	(0.851)	(1.014)
Germany	0.932	12.25 **	8.893 *	12.47
	(0.304)	(1.638)	(1.700)	(7.706)
Mexico	796.8 *	70.38 **	50.82 *	103.1
	(173.1)	(8.030)	(10.00)	(45.59)
Sweden	0.0808	27.62	1.841	17.59
	(.)	(11.92)	(.)	(7.193)
Swiss	14.51 ***	10.18	15.30 ***	15.92
	(0.387)	(4.638)	(0.383)	(12.02)
UK	62.74 *	4.574 *	4.045 **	7.058
	(13.58)	(1.359)	(0.413)	(2.227)
US	319.3	69.42 **	0.0780	33.53
	(.)	(8.401)	(.)	(18.23)
Observations	4	4	4	4

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate. In case of unreported std. errors. in the table, the regression algorithm either cannot compute or report errors well below zero. Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Finally, we apply a forecasting exercise by using a vector error correction (VEC) model (Figures 1 and 2). The VEC models broadly corroborate the prediction and forecasting performance from the previous exercises. The models including search intensity are almost always significant, while the pure macroeconomic models pale into insignificance. Note, we only illustrate the forecasting- and VEC-model for the US due to high Google search intensity and longer timeseries data in the US (Figures 1 and 2).[12] All in all, we find first evidence that search intensity might enhances the prediction and forecasting of exchange rate models.

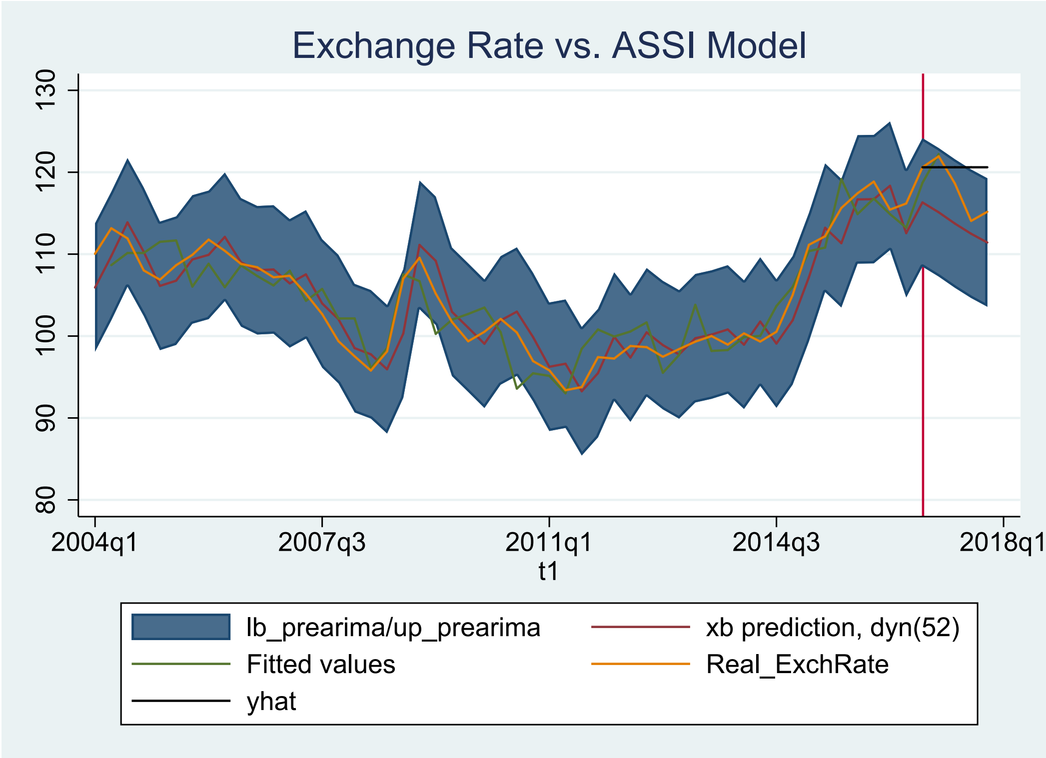

Figure 1. US—Forecasting Errors.

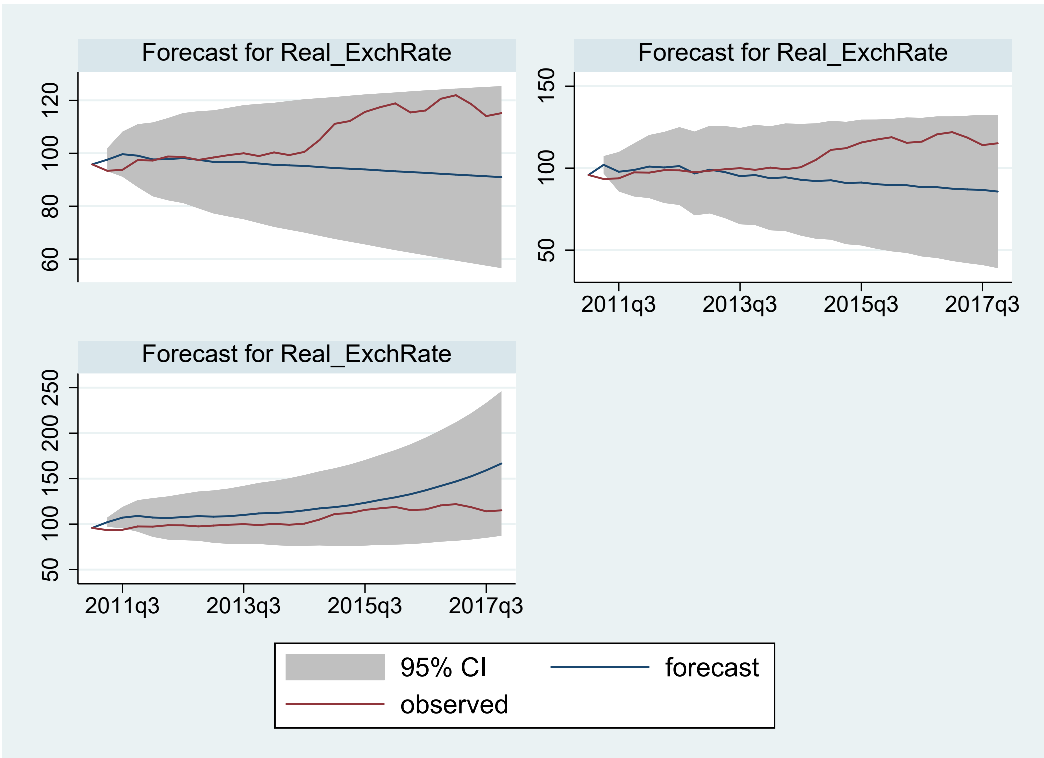

Figure 2. US—VEC-Model Forecasting.

4.2. Limitations

Panel data are a prefect tool for studying exchange rate dynamics across countries and time. Nevertheless, one obstacle is missing data points in large panel sets. However, we minimize this issue by using quarterly data over fourteen years and 10 countries.

In this study, we have further limitations due to the availability of the search intensity data. Google provides data from the year of 2004 onwards. Thus, our sample starts in 2004 and runs until 2018. Moreover, there is an unsolved limitation of possible structural breaks during the time period of 14 years and across various countries. This issue is up to future research. In the near future, as the time range of online data enlarges and as the timing of structural breaks is feasible, we plan to enhance the research by practical applications.

Last but not least, when working with online search data, the choice of keywords is critical (Naccarato et al. 2018). Different search terms deliver partly different outputs. So far, there is no universal method of selecting keywords. Yet, even search data has internal flaws. Google Trends is using sampling methods, which might affect the data by a few percentage points from day to day according to Choi and Varian (2012). This creates replication problems if data is downloaded at different times.

5. Conclusions

In today's post-coronavirus economy, the challenges of the globalized supply chains and the respective exchange rate dynamics has come to the foreground. Much like the sunlight to flowers to grow, the exchange rates is key to international trade, economic and political stability in an interconnected and globalized world. Modeling exchange rates, however, is a rather tedious and sophisticated task due to complex non-linear dynamics. Most of the time, the literature argues that the naive forecast is the best prediction of exchange rates in the short-run. Yet, we show that exchange rate models augmented by online search intensity metrics enhance the estimation as well as the prediction and forecasting performance of standard macroeconomic models. In some instances, our generalized exchange rate models even beat the gold-standard of the naive forecast.

Our paper reveals the following results: Some single-word online search queries appear to be of high relevance. Particularly the keywords 'interest rate' and 'exchange rate' are robust and significant across almost all models. Indeed, we find that four out of ten search variables are robustly significant at one percent and enhance the macroeconomic exchange rate models. Furthermore, one of our newly created search metrics are beneficial, particularly our $ASSI$-metric. Moreover, we demonstrate that the country regressions corroborate the panel results, yet the predictive power of search intensity in regard to exchange rates vary by country. Finally, we find higher prediction performance for our exchange rate models with search intensity, particularly in regard to the direction of the exchange rate forecast.

Overall, our approach reveals a value-added of search intensity in exchange rate models. The practicality and benefits of online search cannot be understated. As the field develops and some of its limitations are overcome, big data analytics will enhance present exchange rate models. A more thorough keyword selection process might pave the way for a more systematic evaluation in future. In the end, we might obtain a better understanding of the complex non-linear currency dynamics in the global economy.

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Abbreviations

Abbreviations and Variables used in this manuscript:

RRT	Real exchange rate
NRT	Nominal exchange rate
MM	Money Supply
dmm	Log-difference of MM
GDP	Gross Domestic Product
IR	Interest rate
CPI	Consumer Price Index
PNT	Relative price of non-tradable goods
DBT	Debt-to-GDP ratio
ddbt	Log-difference of DBT
TOT	Terms of Trade
NFA	Net foreign assets
dnfa	Log-difference of NFA
SI	Search Intensity
SI-INF	Search Intensity of Inflation
SI-GDP	Search Intensity of GDP
SI-CPI	Search Intensity of CPI
SI-IR	Search Intensity of Interest Rate
SI-LOAN	Search Intensity of Loan
SI-ATM	Search Intensity of ATM
SI-JO	Search Intensity of Job Opening
SI-VC	Search Intensity of Vacation
SI-SHOP	Search Intensity of Shopping
SI-ExR	Search Intensity of Exchange Rate
$SS_{i,t}$	Standardized search defined by $SI_{i,t}$ divided by σ_i
$\overline{SS}_{i,t}$	Quarterly means of $SS_{i,t}$
SI_t^{Σ}	Aggregate sum of all search intensities
$SI_t^{\overline{CAT}}$	Mean of each search category
$ACSI_{i,t}$	Abnormal average change in search intensity
$LASI_{i,t}$	Logarithmic difference of $SI_{i,t}$
$SII_{i,t}$	Aggregate normalized mean value of search intenstiy
$ASSI_{i,t}$	Difference of $SI_{i,t}$ and $\overline{SS}_{i,t}$

Appendix A

Table A1. Summary statistics.

Variable	Mean	(Std. Dev.)	Min.	Max.	N
NRT	100.195	(11.807)	66.326	130.573	560
RRT	99.743	(11.146)	69.283	132.054	560
MM	107.72	(35.901)	33.641	249.786	560
dmm	1.84	(1.53)	−1.501	8.519	550
GDP	0.537	(0.845)	−5.22	2.704	532
IR	1.935	(2.312)	−2	10.05	543
CPI	1.005	(0.007)	0.972	1.036	560
PNT	1.012	(0.037)	0.908	1.177	560
DBT	0.852	(0.511)	0.185	2.388	460
ddbt	0.001	(0.018)	−0.284	0.033	451
ToT	1.009	(0.131)	0.616	1.498	474
NFA	99.856	(8.793)	71.986	134.897	560
dnfa	0.456	(1.368)	−12.237	6.618	550
SI-INF	47.754	(18.979)	6	92.333	560
SI-GDP	50.965	(14.454)	17	93.667	560
SI-CPI	45.892	(18.973)	6	96.333	560
SI-IR	48.085	(15.188)	5	89	560
SI-LOAN	48.132	(22.33)	5	97	560
SI-ATM	44.246	(24.275)	1	99.333	560
SI-JO	44.92	(20.134)	0	96.333	560
SI-SHOP	58.042	(16.645)	2	96.667	560
SI-ExR	29.958	(22.78)	0	97.333	560

Table A2. Test of Multi-collinearity (VIF Values).

Variable	Pooled OLS OM Model 1	Pooled OLS AM Model 1	Pooled OLS OM Model 2	Pooled OLS AM Model 2
IR	1.34	2.34	1.21	1.36
CPI	1.21	1.21	1.20	1.70
MM	1.16	0.79		
Log(Money)			1.12	1.15
GDP	1.04	1.04	1.08	1.09
DBT			1.87	
Log(Debt)				1.11
ToT		1.27		1.05
RNT			1.10	1.13
Mean VIF	1.18	1.44	1.15	1.29

Table A3. Breusch-Pagan (LM) test for heteroscedasticity.

Variable	chi2-Value	*p*-Value
Pooled OLS OM Model 1	28.13	0.00
Fixed-Effect OM Model 1	553.27	0.00
Pooled OLS OM Model 2	7.96	0.00
Pooled OLS AM Model 1	3.41	0.06
Fixed-Effect AM Model 1	219.81	0.00
Pooled OLS AM Model 2	8.03	0.00

Table A4. Modified Wald Test for group (panel) heteroscedasticity.

Variable	chi2-Value	*p*-Value
Fixed-Effect OM Model 1	230.58	0.00
Fixed-Effect AM Model 1	214.66	0.00

Table A5. Wooldridge test for autocorrelation in panel data.

Variable	F-Statistic	*p*-Value
Fixed-Effect OM Model 1	239.08	0.00
Fixed-Effect AM Model 1	186.57	0.00

Table A6. Ramsey REST test for omitted variables in panel data

Variable	F-Statistic	*p*-Value
Pooled OLS OM Model 1	1.43	0.23
Pooled OLS OM Model 2	5.13	0.00
Pooled OLS AM Model 1	2.38	0.07
Pooled OLS AM Model 2	3.76	0.01

Table A7. Breusch-Pagan LM test for random effects.

Variable	chi2-Statistic	*p*-Value
OM Model 1	1451.87	0.00
OM Model 2	1371.34	0.00
AM Model 1	1707.50	0.00
AM Model 2	0.00	1.00

Table A8. Hausman test for panel data.

Variable	chi2-Statistic	*p*-Value
OM Model 1	29.09	0.00
OM Model 2	289.52	0.00
AM Model 1	−596.81	1.00
AM Model 2	51.39	0.00

Appendix B. Figures about Country- and Time-Effects

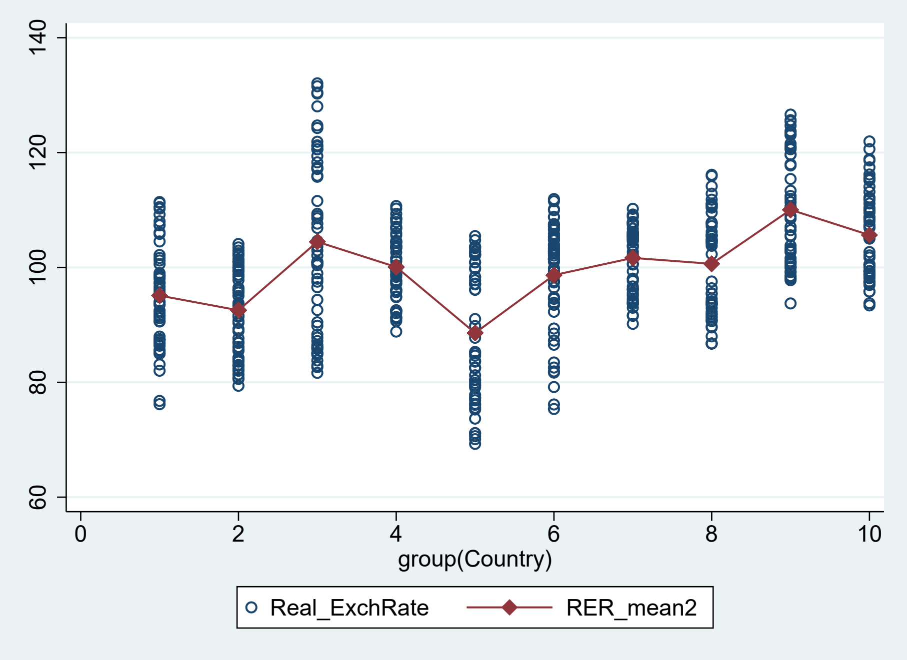

Figure A1. Scatter Plot for Country Effects.

Figure A2. Scatter Plot for Time Effects.

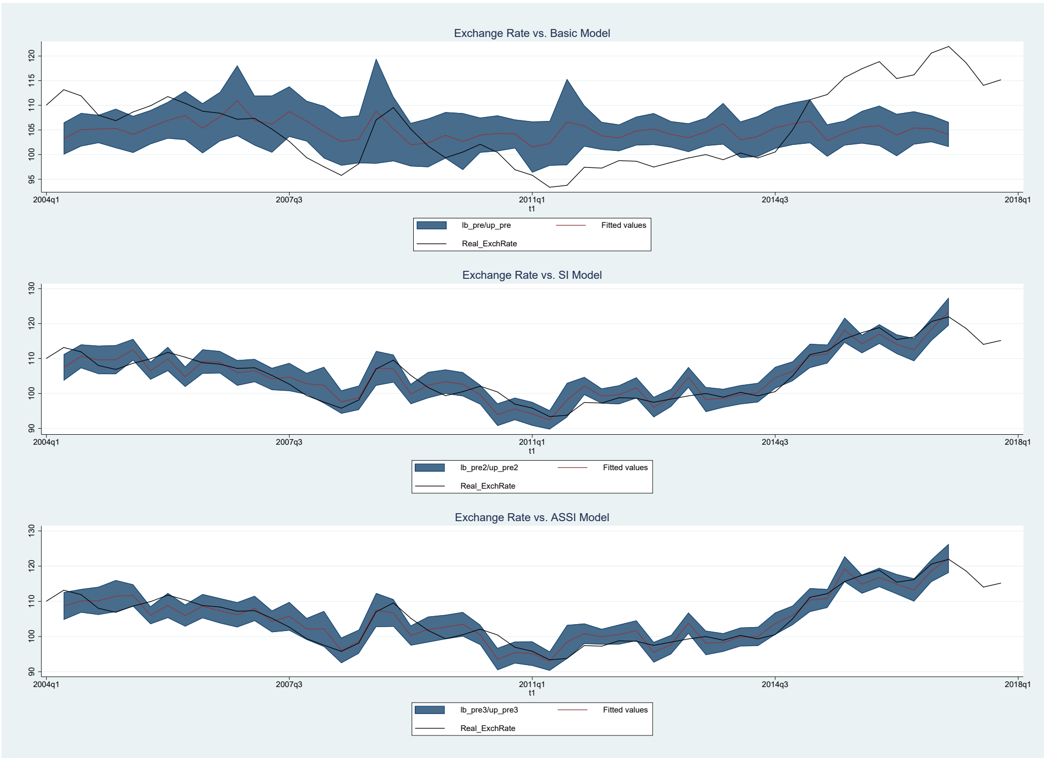

Figure A3. US—Exchange Rate Prediction.

Appendix C

Table A9. Panel Regression OM-Fixed-Effects and AM-Random-Effects Models 1.

	OM-Model	OM-FE Model	AM-Model	AM-RE Model
MM	0.0241	0.162 ***	0.0484 **	0.175 ***
	(0.0152)	(0.0233)	(0.0172)	(0.0280)
GDP	0.545	1.161 *	−0.146	0.173
	(0.467)	(0.522)	(0.445)	(0.462)
IR	1.478 ***	0.320	1.907 ***	1.445 ***
	(0.299)	(0.254)	(0.280)	(0.296)
CPI	−214.1 ***	−169.0 *	−51.38	−90.08
	(62.70)	(70.25)	(63.37)	(64.92)
SI-INF		2.603 ***		2.618 ***
		(0.658)		(0.659)
SI-GDP		2.704 ***		1.874 **
		(0.597)		(0.618)
SI-CPI		−1.161		−0.397
		(0.685)		(0.618)
SI-IR		−2.058 ***		−0.743
		(0.575)		(0.521)
SI-LOAN		−3.525 ***		0.750
		(0.661)		(0.716)
SI-ATM		−0.178		1.108
		(0.538)		(0.657)
SI-JO		−1.231 *		−1.990 ***
		(0.554)		(0.579)
SI-VC		−0.967 *		−0.210
		(0.487)		(0.476)
SI-SHOP		2.071 **		0.212
		(0.656)		(0.701)
SI-ExR		−3.985 ***		−6.330 ***
		(0.734)		(0.835)
PNT			99.67 ***	158.2 ***
			(13.14)	(16.03)
DBT			0.716	3.632 *
			(1.250)	(1.513)
ToT			25.72 ***	10.93 **
			(3.545)	(3.711)
Constant	310.4 ***	256.3 ***	15.36	−5.667
	(62.91)	(70.32)	(66.40)	(67.82)
Observations	515	515	447	447

Standard errors in parentheses, FE = Fixed-Effects, RE = Random-Effects. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A10. Panel Regression OM-Fixed-Effects and AM-Fixed-Effects Models 2.

	OM-Model	OM-FE Model	AM-Model	AM-FE Model
Log(MM)	0.465	0.724 *	0.722 *	0.766 **
	(0.331)	(0.331)	(0.291)	(0.296)
GDP	0.317	0.0250	0.0291	−0.247
	(0.463)	(0.448)	(0.387)	(0.373)
IR	1.303 ***	1.288 ***	1.573 ***	1.560 ***
	(0.245)	(0.321)	(0.214)	(0.281)
CPI	−221.4 ***	−161.5 **	−114.9	−92.27
	(62.23)	(59.56)	(64.56)	(61.05)

Table A10. *Cont.*

	OM-Model	OM-FE Model	AM-Model	AM-FE Model
SI-INF		−1.414		−0.659
		(0.823)		(0.737)
SI-GDP		2.644 ***		1.364 *
		(0.567)		(0.541)
SI-CPI		−4.106 ***		−4.661 ***
		(0.810)		(0.690)
SI-IR		−0.681		−0.0611
		(0.605)		(0.551)
SI-LOAN		−0.609		0.821
		(0.715)		(0.826)
SI-ATM		2.099 *		0.0191
		(0.933)		(0.903)
SI-JO		−1.510 **		−1.158 *
		(0.551)		(0.503)
asgvc		0.198		−0.143
		(0.504)		(0.455)
SI-SHOP		1.225 *		0.289
		(0.528)		(0.569)
SI-ExR		−3.072 ***		−3.102 ***
		(0.639)		(0.649)
PNT			83.83 ***	115.6 ***
			(13.61)	(16.01)
Log(Debt)			51.53 **	62.29 ***
			(18.96)	(18.19)
ToT			36.93 ***	30.16 ***
			(3.989)	(4.069)
Log(NFA)			0.212	0.479
			(0.299)	(0.290)
Constant	319.1 ***	265.3 ***	88.73	54.30
	(62.41)	(59.77)	(66.21)	(62.60)
Observations	506	506	438	438
Adjusted R^2	0.045	0.175	0.314	0.406

Standard errors in parentheses, FE = Fixed-Effects. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A11. Panel Regression Table OM Model 1.

	Model OLS	Model PA	Model FE	Model RE	Model ML
MM	0.0374 *	0.0234	0.0219	0.0241	0.0230
	(0.0149)	(0.0158)	(0.0155)	(0.0152)	(0.0152)
GDP	1.700 **	0.507	0.424	0.545	0.483
	(0.569)	(0.481)	(0.465)	(0.467)	(0.463)
IR	0.479 *	1.504 ***	1.562 ***	1.478 ***	1.521 ***
	(0.237)	(0.311)	(0.308)	(0.299)	(0.301)
CPI	−101.3	−215.8 ***	−219.3 ***	−214.1 ***	−216.8 ***
	(79.89)	(64.44)	(62.08)	(62.70)	(61.81)
Constant	196.2 *	312.2 ***	315.0 ***	310.4 ***	313.3 ***
	(79.89)	(64.68)	(62.29)	(62.91)	(62.06)
sigma(u)					
Constant					8.224 ***
					(1.899)
sigma(e)					
Constant					8.220 ***
					(0.259)
Observations	515	515	515	515	515
Adjusted R^2	0.028		0.044		
F	4.640		9.163		

Standard errors in parentheses, FE = Fixed-Effects, RE = Random-Effects, PA = Pooled, ML = Maximum-Likelihood. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A12. Panel Regression Table AM Model 2.

	Model OLS	Model PA	Model FE	Model RE	Model ML
dmm	0.323	0.716 *	0.722 *	0.323	0.716 *
	(0.336)	(0.290)	(0.291)	(0.336)	(0.286)
GDP	−0.439	0.0167	0.0291	−0.439	0.0178
	(0.499)	(0.388)	(0.387)	(0.499)	(0.383)
IR	1.142 ***	1.568 ***	1.573 ***	1.142 ***	1.568 ***
	(0.207)	(0.211)	(0.214)	(0.207)	(0.208)
CPI	−15.66	−112.8	−114.9	−15.66	−112.9
	(82.58)	(64.73)	(64.56)	(82.58)	(63.90)
PNT	127.9 ***	86.04 ***	83.83 ***	127.9 ***	85.85 ***
	(14.04)	(13.53)	(13.61)	(14.04)	(13.40)
ddbt	98.26 ***	53.44 **	51.53 **	98.26 ***	53.28 **
	(24.07)	(19.01)	(18.96)	(24.07)	(18.78)
ToT	19.80 ***	35.55 ***	36.93 ***	19.80 ***	35.67 ***
	(3.191)	(3.900)	(3.989)	(3.191)	(3.901)
dnfa	0.396	0.218	0.212	0.396	0.218
	(0.387)	(0.300)	(0.299)	(0.387)	(0.296)
Constant	−36.34	85.40	88.73	−36.34	85.66
	(83.78)	(66.38)	(66.21)	(83.78)	(65.54)
sigma(u)					
Constant					6.217 ***
					(1.520)
sigma(e)					
Constant					6.478 ***
					(0.221)
Observations	438	438	438	438	438
Adjusted R^2	0.261		0.314		
F	20.31		27.01		

Standard errors in parentheses, FE = Fixed-Effects, RE = Random-Effects, PA = Pooled, ML = Maximum-Likelihood. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A13. Panel Regression Table Fixed-Effects OM Models 1.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
MM	0.0219	0.0913 ***	0.0285	0.0218	0.0300	0.0232	0.0906 ***
	(0.0155)	(0.0240)	(0.0204)	(0.0161)	(0.0169)	(0.0156)	(0.0241)
GDP	0.424	0.329	0.437	0.229	0.192	0.382	0.320
	(0.465)	(0.448)	(0.475)	(0.477)	(0.481)	(0.467)	(0.449)
IR	1.562 ***	1.669 ***	1.565 ***	1.522 ***	1.529 ***	1.519 ***	1.655 ***
	(0.308)	(0.327)	(0.313)	(0.313)	(0.316)	(0.311)	(0.329)
CPI	−219.3 ***	−170.1 **	−222.5 ***	−225.6 ***	−228.2 ***	−219.3 ***	−170.3 **
	(62.08)	(59.15)	(62.53)	(62.64)	(64.15)	(62.08)	(59.21)
SI-INF		−0.0533					
		(0.0427)					
SI-GDP		0.174 ***					
		(0.0384)					
SI-CPI		−0.166 ***					
		(0.0412)					
SI-IR		−0.0392					
		(0.0391)					
SI-LOAN		−0.0729 *					
		(0.0351)					
SI-ATM		0.0624					
		(0.0366)					
SI-JO		−0.0584 *					
		(0.0259)					
SI-SHOP		0.128 ***					
		(0.0342)					
SI-ExR		−0.162 ***					
		(0.0292)					
$SI^{\overline{INF}}$			0.0226				
			(0.0500)				
$SI^{\overline{IR}}$			−0.0186				
			(0.0565)				
$SI^{\overline{CON}}$			0.0128				
			(0.0568)				

Table A13. *Cont.*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ACSI-INF				−0.108 (0.142)			
ACSI-GDP				0.0385 (0.238)			
ACSI-CPI				0.0571 (0.236)			
ACSI-IR				−0.182 (0.200)			
ACSI-LOAN				−0.230 (0.142)			
acgat				0.0588 (0.177)			
ACSI-JO				0.222 (0.158)			
ACSI-VC				0.0814 (0.139)			
ACSI-SHOP				−0.0387 (0.144)			
ACSI-ExR				−0.183 (0.141)			
LASI-INF					−1.627 (4.321)		
LASI-GDP					−0.522 (5.630)		
LASI-CPI					1.040 (4.544)		
lagir					−3.059 (4.996)		
LASI-LOAN					−3.668 (4.022)		
LASI-ATM					−2.021 (3.298)		
LASI-JO					10.27 * (4.094)		
LASI-VC					−1.640 (4.056)		
LASI-SHOP					−4.963 (4.594)		
LASI-ExR					−3.809 (2.653)		
SII						−0.0688 (0.0695)	
ASSI-INF							−1.005 (0.812)
ASSI-GDP							2.494 *** (0.557)
ASSI-CPI							−3.182 *** (0.789)
ASSI-IR							−0.598 (0.594)
ASSI-LOAN							−1.649 * (0.788)
ASSI-ATM							1.481 (0.895)
ASSI-JO							−1.150 * (0.526)
ASSI-VC							0.174 (0.486)
ASSI-SHOP							2.119 *** (0.571)
ASSI-ExR							−3.698 *** (0.665)
Constant	315.0 *** (62.29)	262.0 *** (59.25)	316.6 *** (62.67)	321.9 *** (62.86)	323.5 *** (64.45)	318.2 *** (62.37)	262.0 *** (59.31)
Observations	515	515	515	509	501	515	515
Adjusted R^2	0.044	0.179	0.039	0.047	0.044	0.044	0.178
F	9.163	10.31	5.250	3.448	3.271	7.526	9.567

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A14. Panel Regression Table Fixed-Effects AM Models 2.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
dmm	0.722 *	0.762 *	0.476	0.803 **	0.815 **	0.752 **	0.766 **
	(0.291)	(0.295)	(0.302)	(0.297)	(0.313)	(0.289)	(0.296)
GDP	0.0291	−0.245	−0.0960	−0.113	−0.162	−0.131	−0.247
	(0.387)	(0.373)	(0.392)	(0.404)	(0.409)	(0.391)	(0.373)
IR	1.573 ***	1.554 ***	1.836 ***	1.494 ***	1.533 ***	1.515 ***	1.560 ***
	(0.214)	(0.280)	(0.233)	(0.229)	(0.243)	(0.214)	(0.281)
CPI	−114.9	−90.67	−119.0	−152.1 *	−141.9 *	−120.1	−92.27
	(64.56)	(60.77)	(64.24)	(66.06)	(68.06)	(64.25)	(61.05)
PNT	83.83 ***	114.9 ***	98.81 ***	79.73 ***	82.46 ***	96.13 ***	115.6 ***
	(13.61)	(15.84)	(15.19)	(14.38)	(15.00)	(14.51)	(16.01)
ddbt	51.53 **	61.48 ***	55.12 **	52.77 **	52.27 **	50.25 **	62.29 ***
	(18.96)	(17.99)	(18.94)	(19.16)	(19.57)	(18.86)	(18.19)
ToT	36.93 ***	30.13 ***	37.15 ***	35.02 ***	36.05 ***	35.99 ***	30.16 ***
	(3.989)	(4.063)	(3.959)	(4.179)	(4.327)	(3.988)	(4.069)
dnfa	0.212	0.462	0.347	0.318	0.182	0.241	0.479
	(0.299)	(0.285)	(0.302)	(0.317)	(0.320)	(0.298)	(0.290)
SI-INF		−0.0347					
		(0.0388)					
SI-GDP		0.0947 *					
		(0.0374)					
SI-CPI		−0.246 ***					
		(0.0363)					
SI-IR		−0.00445					
		(0.0362)					
SI-LOAN		0.0371					
		(0.0370)					
SI-ATM		−0.000647					
		(0.0369)					
SI-JO		−0.0562 *					
		(0.0246)					
SI-SHOP		0.0177					
		(0.0341)					
SI-ExR		−0.136 ***					
		(0.0285)					
$SI^{\overline{INF}}$			−0.0974 *				
			(0.0410)				
$SI^{\overline{IR}}$			0.0359				
			(0.0446)				
$SI^{\overline{CON}}$			−0.114 *				
			(0.0562)				
ACSI-INF				0.000416			
				(0.122)			
ACSI-GDP				−0.213			
				(0.232)			
ACSI-CPI				0.213			
				(0.223)			
ACSI-IR				−0.110			
				(0.185)			
ACSI-LOAN				−0.316			
				(0.207)			
ACSI-ATM				0.0392			
				(0.172)			
ACSI-JO				0.293			
				(0.180)			
ACSI-VC				0.127			
				(0.117)			
ACSI-SHOP				0.442 *			
				(0.224)			
ACSI-ExR				−0.0865			
				(0.144)			
LASI-INF					3.364		
					(4.018)		
LASI-GDP					−10.61 *		
					(5.296)		
LASI-CPI					5.982		
					(4.447)		

Table A14. *Cont.*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
LASI-IR					−6.452		
					(4.638)		
LASI-LOAN					−3.693		
					(3.866)		
LASI-ATM					2.447		
					(3.705)		
lagjo					2.730		
					(3.710)		
LASI-VC					1.369		
					(3.972)		
LASI-SHOP					−0.695		
					(5.218)		
LASI-ExR					0.487		
					(2.492)		
SII						−0.158 *	
						(0.0670)	
ASSI-INF							−0.659
							(0.737)
ASSI-GDP							1.364 *
							(0.541)
ASSI-CPI							−4.661 ***
							(0.690)
ASSI-IR							−0.0611
							(0.551)
ASSI-LOAN							0.821
							(0.826)
ASSI-ATM							0.0191
							(0.903)
ASSI-JO							−1.158 *
							(0.503)
ASSI-VC							−0.143
							(0.455)
ASSI-SHOP							0.289
							(0.569)
ASSI-ExR							−3.102 ***
							(0.649)
Constant	88.73	53.00	86.54	132.6	118.3	90.22	54.30
	(66.21)	(62.39)	(65.70)	(68.08)	(69.65)	(65.86)	(62.60)
Observations	438	438	438	433	426	438	438
Adjusted R^2	0.314	0.408	0.325	0.307	0.299	0.321	0.406
F	27.01	19.15	20.88	12.10	11.51	24.89	18.05

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A15. Panel Regression Table Fixed-Effects OM Models (HAR).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
MM	−0.00411	0.00959	0.0109	0.000941	0.00408	−0.00347	0.0102
	(0.0338)	(0.0355)	(0.0343)	(0.0341)	(0.0347)	(0.0338)	(0.0356)
GDP	−0.0498	−0.130	−0.0763	−0.109	−0.121	−0.0659	−0.132
	(0.158)	(0.160)	(0.159)	(0.159)	(0.163)	(0.159)	(0.160)
IR	1.324 ***	1.231 ***	1.274 ***	1.438 ***	1.378 ***	1.301 ***	1.225 ***
	(0.341)	(0.344)	(0.340)	(0.342)	(0.355)	(0.342)	(0.344)
CPI	−21.27	−28.94	−25.17	−29.71	−30.34	−21.19	−28.74
	(16.54)	(16.84)	(16.82)	(16.84)	(17.29)	(16.55)	(16.87)
SI_INF		−0.00245					
		(0.0161)					
SI_GDP		0.0203					
		(0.0175)					
SI_CPI		0.0124					
		(0.0183)					
SI_IR		−0.0595 ***					

Table A15. *Cont.*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
		(0.0179)					
SI_LOAN		−0.00457					
		(0.0176)					
SI_ATM		0.0117					
		(0.0188)					
SI_JO		0.0217					
		(0.0175)					
SI_SHOP		0.0199					
		(0.0167)					
SI_ExR		−0.0233					
		(0.0210)					
$SI^{\overline{INF}}$			0.00480				
			(0.0168)				
$SI^{\overline{IR}}$			−0.0740 **				
			(0.0286)				
$SI^{\overline{CON}}$			0.0319				
			(0.0265)				
ACSI-INF				−0.0206			
				(0.0399)			
ACSI-GDP				0.132			
				(0.0715)			
ACSI-CPI				0.0310			
				(0.0682)			
ACSI-IR				−0.165 **			
				(0.0579)			
ACSI-LOAN				−0.0118			
				(0.0417)			
ACSI-ATM				0.0261			
				(0.0544)			
ACSI-JO				0.0424			
				(0.0466)			
ACSI-VC				0.0264			
				(0.0393)			
ACSI-SHOP				0.0413			
				(0.0445)			
ACSI-ExR				−0.0304			
				(0.0464)			
LASI-INF					−0.242		
					(1.425)		
LASI-GDP					1.343		
					(1.804)		
LASI-CPI					0.957		
					(1.463)		
LASI-IR					−5.140 **		
					(1.619)		
LASI-LOAN					−0.753		
					(1.357)		
LASI-ATM					0.252		
					(1.330)		
LASI-JO					2.132		
					(1.215)		
LASI-VC					0.413		
					(1.226)		
LASI-SHOP					1.250		
					(1.589)		
LASI-ExR					−0.400		
					(1.141)		
SII						−0.0345	
						(0.0352)	
ASSI-INF							−0.0493
							(0.306)
ASSI-GDP							0.297
							(0.254)
ASSI-CPI							0.235
							(0.348)

Table A15. *Cont.*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
ASSI-IR							−0.909 ***
							(0.273)
ASSI-LOAN							−0.108
							(0.395)
ASSI-ATM							0.257
							(0.469)
ASSI-JO							0.414
							(0.363)
ASSI-VC							0.0527
							(0.196)
ASSI-SHOP							0.347
							(0.285)
ASSI-ExR							−0.550
							(0.484)
Constant	120.0 ***	125.9 ***	124.0 ***	127.5 ***	128.0 ***	121.5 ***	125.6 ***
	(17.23)	(17.79)	(17.65)	(17.47)	(17.89)	(17.31)	(17.85)
Observations	515	515	515	509	501	515	515
Adjusted R^2							
F							

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A16. Panel Regression Table AM Model 2 (Robust and HAR).

	Model OLS	Model FE	Model RE	Model FE-HAR	Model RE-HAR	Model GLS(h)	Model GLS(p)
GDP	−0.431	0.137	−0.431	0.0273	0.0212	0.106	−0.0173
	(0.558)	(0.636)	(0.532)	(0.153)	(0.153)	(0.376)	(0.148)
IR	1.516 ***	2.413 *	1.516 *	2.211 ***	2.099 ***	1.439 ***	2.041 ***
	(0.236)	(0.777)	(0.604)	(0.369)	(0.354)	(0.225)	(0.323)
CPI	−0.111	−114.9	−0.111	−36.31	−39.36 *	6.738	−41.17 *
	(70.83)	(83.95)	(76.25)	(20.05)	(18.62)	(58.05)	(17.57)
PNT	122.2 ***	87.28	122.2 ***	81.84 ***	86.78 ***	108.2 ***	90.49 ***
	(14.34)	(43.65)	(35.76)	(23.67)	(19.52)	(12.33)	(17.12)
DBT	−0.372	4.985	−0.372	6.239	0.0403	1.965	4.727
	(1.322)	(7.994)	(4.188)	(6.983)	(3.674)	(1.133)	(4.738)
ToT	20.76 ***	40.55 ***	20.76	18.90 ***	20.58 ***	25.34 ***	20.81 ***
	(3.577)	(6.494)	(13.36)	(4.258)	(3.951)	(3.354)	(3.792)
NFA	0.119	0.128	0.119	0.0764	0.120	0.114 *	0.120
	(0.0654)	(0.150)	(0.113)	(0.189)	(0.128)	(0.0535)	(0.0988)
Constant	−58.76	64.09	−58.76	16.25 ***	13.99	−58.02	6.294
	(75.75)	(115.1)	(116.2)	(3.304)	(29.23)	(60.28)	(26.29)
Observations	447	447	447	438	447	447	447
Adjusted R^2	0.241	0.333		0.131			
F	31.50	99.01		11.57			

Standard errors in parentheses, FE/RE-HAR = Fixed/Random-Effects heteroskedasticity and autocorrelation robust, GLS(h or p) = Generalized. Least Square Regression with heteroscedastic but uncorrelated error structure or panel-specific AR1 autocorrelation structure. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A17. Panel Regression Table Random-Effects OM Model 2 (HAR).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
GDP	0.0212	−0.0888	−0.0341	−0.0494	−0.0747	−0.0238	−0.0935
	(0.153)	(0.155)	(0.155)	(0.156)	(0.160)	(0.156)	(0.155)
IR	2.099 ***	1.799 ***	1.909 ***	2.047 ***	2.108 ***	1.978 ***	1.795 ***
	(0.354)	(0.347)	(0.343)	(0.340)	(0.357)	(0.342)	(0.347)
CPI	−39.36 *	−51.57 *	−44.72 *	−64.41 **	−47.80 *	−43.97 *	−50.04 *
	(18.62)	(21.45)	(21.64)	(21.93)	(22.51)	(21.32)	(21.59)
PNT	86.78 ***	74.17 ***	74.26 ***	79.59 ***	75.29 ***	77.02 ***	74.07 ***
	(19.52)	(15.59)	(15.58)	(16.05)	(16.15)	(15.59)	(15.60)
DBT	0.0403						
	(3.674)						
ToT	20.58 ***	20.37 ***	21.23 ***	20.51 ***	21.57 ***	21.13 ***	20.52 ***
	(3.951)	(4.006)	(4.019)	(4.000)	(4.083)	(4.018)	(4.014)

Table A17. *Cont.*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
NFA	0.120 (0.128)						
dmm		−0.110 (0.140)	−0.148 (0.140)	−0.119 (0.141)	−0.0723 (0.146)	−0.178 (0.141)	−0.103 (0.140)
ddbt		11.07 (15.59)	8.267 (15.64)	8.819 (15.51)	7.278 (15.75)	8.556 (15.68)	10.35 (15.64)
dnfa		0.00239 (0.135)	0.0684 (0.133)	0.134 (0.137)	0.0204 (0.140)	0.0911 (0.133)	−0.00846 (0.136)
SI_INF		0.00558 (0.0171)					
SI_GDP		0.00445 (0.0188)					
SI_CPI		0.0112 (0.0184)					
SI_IR		−0.0666 *** (0.0182)					
SI_LOAN		−0.00624 (0.0199)					
SI_ATM		0.00728 (0.0210)					
SI_JO		0.0359 * (0.0183)					
SI_SHOP		−0.000263 (0.0188)					
SI_ExR		−0.0509 * (0.0229)					
$SI^{\overline{INF}}$			−0.00489 (0.0170)				
$SI^{\overline{IR}}$			−0.0860 ** (0.0301)				
$SI^{\overline{CON}}$			0.0368 (0.0290)				
ACSI-INF				0.00422 (0.0402)			
ACSI-GDP				0.0773 (0.0791)			
ACSI-CPI				0.0702 (0.0755)			
ACSI-IR				−0.206 ** (0.0632)			
ACSI-LOAN				−0.0723 (0.0727)			
ACSI-ATM				−0.0285 (0.0629)			
ACSI-JO				0.171 ** (0.0612)			
ACSI-VC				0.0411 (0.0385)			
ACSI-SHOP				0.101 (0.0799)			
ACSI-ExR				−0.0236 (0.0532)			
LASI-INF					−0.0405 (1.642)		
LASI-GDP					−0.337 (1.988)		
LASI-CPI					1.374 (1.622)		
LASI-IR					−5.998 *** (1.740)		
LASI-LOAN					−0.777 (1.500)		
LASI-ATM					−0.619 (1.628)		

Table A17. *Cont.*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
LASI-JO					2.807 *		
					(1.259)		
LASI-VC					1.597		
					(1.346)		
LASI-SHOP					−0.760		
					(2.087)		
LASI-ExR					−0.594		
					(1.166)		
SII						−0.0585	
						(0.0379)	
ASSI-INF							0.0908
							(0.325)
ASSI-GDP							0.0818
							(0.273)
ASSI-CPI							0.214
							(0.349)
ASSI-IR							−1.031 ***
							(0.278)
ASSI-LOAN							−0.136
							(0.445)
ASSI-ATM							0.114
							(0.519)
ASSI-JO							0.681
							(0.373)
ASSI-VC							0.137
							(0.206)
ASSI-SHOP							0.0378
							(0.319)
ASSI-ExR							−1.211 *
							(0.528)
Constant	13.99	53.84 *	46.25 *	58.79 **	45.08 *	43.04 *	51.98 *
	(29.23)	(21.74)	(22.07)	(22.50)	(22.85)	(21.58)	(21.93)
Observations	447	438	438	433	426	438	438
Adjusted R^2							
F							

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A18. Panel Regression OM- And AM-Model 2 with Random-Effects (Robust).

	OM-Model	OM-FE Model	AM-Model	AM-RE Model	ModelAM_FEH2	ModelAM_FEH7
dmm	−0.183	−0.141	−0.140		−0.110	−0.103
	(0.131)	(0.133)	(0.133)		(0.140)	(0.140)
GDP	−0.0508	−0.139	−0.141	0.0212	−0.0888	−0.0935
	(0.159)	(0.160)	(0.160)	(0.153)	(0.155)	(0.155)
IR	1.361 ***	1.259 ***	1.255 ***	2.099 ***	1.799 ***	1.795 ***
	(0.341)	(0.345)	(0.346)	(0.354)	(0.347)	(0.347)
CPI	−23.38	−34.08 *	−33.99 *	−39.36 *	−51.57 *	−50.04 *
	(16.69)	(17.06)	(17.09)	(18.62)	(21.45)	(21.59)
SI_INF		0.000549			0.00558	
		(0.0165)			(0.0171)	
SI_GDP		0.0269			0.00445	
		(0.0178)			(0.0188)	
SI_CPI		0.00479			0.0112	
		(0.0187)			(0.0184)	
SI_IR		−0.0659 ***			−0.0666 ***	
		(0.0182)			(0.0182)	
SI_LOAN		−0.0140			−0.00624	
		(0.0181)			(0.0199)	
SI_ATM		0.0212			0.00728	
		(0.0195)			(0.0210)	
SI_JO		0.0193			0.0359 *	
		(0.0184)			(0.0183)	

Table A18. *Cont.*

	OM-Model	OM-FE Model	AM-Model	AM-RE Model	ModelAM_FEH2	ModelAM_FEH7
SI_SHOP		0.0201			−0.000263	
		(0.0166)			(0.0188)	
SI_ExR		−0.0161			−0.0509 *	
		(0.0209)			(0.0229)	
ASSI-INF			0.00877			0.0908
			(0.314)			(0.325)
ASSI-GDP			0.391			0.0818
			(0.257)			(0.273)
ASSI-CPI			0.0908			0.214
			(0.355)			(0.349)
ASSI-IR			−1.004 ***			−1.031 ***
			(0.278)			(0.278)
ASSI-LOAN			−0.314			−0.136
			(0.404)			(0.445)
ASSI-ATM			0.499			0.114
			(0.488)			(0.519)
ASSI-JO			0.380			0.681
			(0.378)			(0.373)
ASSI-VC			0.0243			0.137
			(0.198)			(0.206)
ASSI-SHOP			0.342			0.0378
			(0.284)			(0.319)
ASSI-ExE			−0.377			−1.211 *
			(0.481)			(0.528)
PNT				86.78 ***	74.17 ***	74.07 ***
				(19.52)	(15.59)	(15.60)
DBT				0.0403		
				(3.674)		
ToT				20.58 ***	20.37 ***	20.52 ***
				(3.951)	(4.006)	(4.014)
NFA				0.120		
				(0.128)		
ddbt					11.07	10.35
					(15.59)	(15.64)
dnfa					0.00239	−0.00846
					(0.135)	(0.136)
Constant	121.7 ***	132.3 ***	132.2 ***	13.99	53.84 *	51.98 *
	(16.99)	(17.68)	(17.72)	(29.23)	(21.74)	(21.93)
Observations	506	506	506	447	438	438

Standard errors in parentheses, FE/RE = Fixed/Radome Effects, FEH = Fixed-Effects Robust Std. Errors. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A19. Panel Regression OM Model for Countries.

	Australia	China	Canada	Germany	Japan	Mexico	Sweden	Switzerland	UK	US
dmm	1.732	−1.024	0.548	−3.791 ***	−15.03 ***	0.133	−0.813 *	0.728	2.047 *	0.890
	(1.299)	(1.073)	(1.298)	(0.600)	(3.935)	(0.731)	(0.390)	(0.641)	(0.932)	(1.476)
GDP	4.660	1.933	−20.59 **	−0.912	−1.135	1.767	1.942 **	0.707	4.991 ***	0.923
	(3.117)	(1.620)	(6.787)	(0.515)	(1.185)	(1.158)	(0.605)	(1.320)	(1.026)	(1.851)
IR	−2.248 **	0.826	−0.390	4.133 ***	−25.93 **	2.077 **	2.892 ***	−6.669 ***	3.101 ***	0.908
	(0.730)	(0.748)	(6.502)	(0.384)	(9.354)	(0.700)	(0.448)	(0.716)	(0.373)	(0.625)
CPI	600.6 *	64.63	−246.2	−142.3	−645.1 *	−248.0	−10.03	−104.4	−395.9 **	−173.5
	(293.5)	(178.4)	(187.4)	(155.7)	(244.9)	(166.4)	(111.4)	(108.8)	(129.2)	(142.3)
Constant	−506.9	28.06	399.3 *	242.5	745.2 **	335.3 *	107.9	205.3	498.0 ***	276.3
	(295.1)	(179.1)	(189.3)	(156.1)	(245.0)	(166.8)	(111.3)	(108.9)	(130.0)	(143.2)
Observations	55	52	28	53	52	55	52	53	54	52
Adjusted R^2	0.114	−0.000	0.347	0.712	0.298	0.135	0.486	0.680	0.759	0.015
F	2.735	1.000	4.595	33.18	6.410	3.108	13.05	28.64	42.63	0.810

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A20. Panel Regression OM Model with SI for Countries.

	Australia	China	Canada	Germany	Japan	Mexico	Sweden	Switzerland	UK	US
dmm	2.448	0.340	1.368	−3.035 **	2.860	0.669	−0.108	0.409	0.597	−1.246
	(1.468)	(1.033)	(0.836)	(1.008)	(3.806)	(0.534)	(0.395)	(0.541)	(1.297)	(0.813)
GDP	4.035	0.955	−5.698	−1.176 *	−1.265 *	0.971	1.825 **	0.424	3.415 **	−0.534
	(2.660)	(1.472)	(4.591)	(0.532)	(0.610)	(0.814)	(0.588)	(1.269)	(1.223)	(1.083)
IR	−0.198	−1.435	−1.951	2.155 *	−31.15 ***	1.290	3.079 ***	−2.036 *	4.607 ***	1.620 **
	(1.936)	(1.041)	(3.522)	(0.859)	(4.752)	(1.087)	(0.712)	(0.992)	(0.967)	(0.531)
CPI	888.0 **	93.61	−165.3	52.50	−228.4	−146.8	−80.15	−91.92	−328.4 *	−121.9
	(279.3)	(154.6)	(115.1)	(156.1)	(135.2)	(124.2)	(93.32)	(108.3)	(139.5)	(96.63)
SI-INF	−0.322	0.0349	0.104	0.158	−0.134	−0.258	0.103	0.0462	−0.0243	−0.0745
	(0.190)	(0.150)	(0.0798)	(0.0787)	(0.0686)	(0.225)	(0.0589)	(0.0690)	(0.125)	(0.117)
SI-GDP	−0.0808	−0.0869	0.0917	−0.0940	0.101	0.0488	−0.0483	0.0434	0.0657	0.222 *
	(0.203)	(0.111)	(0.111)	(0.0824)	(0.0856)	(0.273)	(0.0701)	(0.104)	(0.129)	(0.107)
SI-CPI	−0.121	−0.362 **	0.109	−0.0414	−0.194	−0.156	−0.0552	−0.181	−0.148	0.510 **
	(0.184)	(0.113)	(0.130)	(0.0784)	(0.110)	(0.173)	(0.0551)	(0.114)	(0.106)	(0.160)
SI-IR	0.114	−0.165	0.240	−0.129	−0.128	−0.0514	−0.0299	0.0237	−0.0791	−0.0968
	(0.133)	(0.204)	(0.234)	(0.0719)	(0.107)	(0.216)	(0.0844)	(0.0657)	(0.116)	(0.121)
SI-LOAN	−0.385	−0.178	0.0559	0.131	0.0332	−0.346 ***	−0.126	0.0521	0.207	0.324 ***
	(0.265)	(0.131)	(0.105)	(0.0678)	(0.104)	(0.0915)	(0.0735)	(0.0711)	(0.133)	(0.0902)
SI-ATM	0.134	−0.281 *	−0.309	−0.159 *	−0.0645	0.307	−0.0530	0.145	−0.313 *	0.674 ***
	(0.175)	(0.135)	(0.229)	(0.0757)	(0.0976)	(0.162)	(0.0808)	(0.117)	(0.126)	(0.160)
SI-JO	0.255 *	−0.167	−0.667	0.0278	−0.143	−0.141	0.158	−0.0633	0.0479	−0.248
	(0.102)	(0.0972)	(0.315)	(0.0676)	(0.139)	(0.150)	(0.0822)	(0.0643)	(0.0651)	(0.181)
SI-SHOP	0.265	−0.0918	0.140	−0.0824	0.310 *	0.343	0.419 ***	0.211 **	−0.176	0.362 ***
	(0.164)	(0.123)	(0.136)	(0.0625)	(0.127)	(0.200)	(0.106)	(0.0710)	(0.116)	(0.0884)
SI-ExR	−0.0913	−0.224	0.266 *	−0.0316	−0.406 ***	0.00885	−0.0550	0.00953	0.222	0.166 **
	(0.115)	(0.119)	(0.0970)	(0.0472)	(0.0581)	(0.0982)	(0.0492)	(0.0981)	(0.126)	(0.0607)
Constant	−785.6 **	78.85	270.8 *	58.03	334.9 *	225.6	154.8	174.5	457.8 **	118.6
	(281.5)	(159.7)	(118.8)	(156.2)	(140.9)	(125.6)	(94.05)	(105.2)	(142.4)	(95.06)
Obs.	55	52	28	53	52	55	52	53	54	52
Adj. R^2	0.452	0.577	0.865	0.775	0.854	0.658	0.700	0.843	0.797	0.802
F	4.429	6.346	14.29	14.79	23.87	9.002	10.15	22.42	16.97	16.94

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A21. Panel Regression OM Model with ASSI for Countries.

	Australia	**China**	**Canada**	**Germany**	**Japan**	**Mexico**	**Sweden**	**Swiss**	**UK**	**US**
dmm	2.411	−0.0523	1.561	−3.090 **	2.500	0.671	−0.0313	0.357	1.699	−1.176
	(1.455)	(1.068)	(0.786)	(1.037)	(3.719)	(0.541)	(0.386)	(0.535)	(1.232)	(0.791)
GDP	3.929	0.953	−3.980	−1.143 *	−1.564 *	0.992	1.803 **	0.806	3.148 **	−1.163
	(2.638)	(1.459)	(4.384)	(0.550)	(0.621)	(0.836)	(0.572)	(1.282)	(1.115)	(1.110)
IR	0.564	−1.061	−0.135	2.117 *	−32.83 ***	1.254	3.601 ***	−2.095 *	3.782 ***	1.343 *
	(2.003)	(1.072)	(3.435)	(0.879)	(4.738)	(1.127)	(0.752)	(0.980)	(0.919)	(0.539)
CPI	883.0 **	177.8	−133.3	71.37	−262.1	−150.6	−145.8	−93.54	−278.3 *	−156.6
	(276.8)	(166.6)	(108.7)	(170.4)	(133.3)	(128.4)	(97.98)	(107.0)	(127.8)	(95.95)
ASSI-INF	−7.237	0.141	2.455	2.975	−2.250	−4.818	2.544 *	1.397	−0.952	−0.0424
	(3.670)	(2.859)	(1.437)	(1.515)	(1.281)	(4.346)	(1.138)	(1.343)	(2.163)	(2.292)
ASSI-GDP	−1.347	−2.019	2.227	−1.449	1.192	0.806	−0.550	1.211	0.817	2.171
	(2.909)	(1.699)	(1.576)	(1.243)	(1.218)	(4.059)	(0.989)	(1.546)	(1.694)	(1.616)
ASSI-CPI	−0.0891	−6.420 **	1.527	−0.869	−2.890	−2.936	−1.889	−2.726	−2.989	6.331
	(3.841)	(2.148)	(2.314)	(1.531)	(2.079)	(3.331)	(1.121)	(2.198)	(1.828)	(3.500)
ASSI-IR	1.871	−2.338	4.002	−1.810	−2.647	−0.862	−1.138	0.620	−1.710	−1.505
	(2.004)	(3.072)	(3.317)	(1.207)	(1.642)	(3.359)	(1.304)	(1.003)	(1.609)	(1.787)
ASSI-LOAN	−10.27	−5.412	2.112	3.078	0.422	−7.573 **	−3.887 *	1.565	1.543	6.844 **
	(6.001)	(3.112)	(2.232)	(1.626)	(2.275)	(2.304)	(1.705)	(1.593)	(2.881)	(1.972)
ASSI-ATM	4.895	−5.734	−6.500	−3.718	−3.106	7.558	−1.685	0.655	−7.319 *	13.83 **
	(4.395)	(3.353)	(5.204)	(1.920)	(2.480)	(4.046)	(1.920)	(3.466)	(2.774)	(4.044)
ASSI-JO	5.147 *	−3.448	−11.87	0.681	−3.155	−2.751	3.270 *	−1.155	1.851	−7.540
	(2.044)	(1.942)	(5.964)	(1.437)	(2.732)	(3.123)	(1.611)	(1.282)	(1.226)	(3.816)
ASSI-VC	−3.535	2.348	−2.308	−0.256	2.695	−0.410	−1.336	1.856	3.826 **	3.085
	(2.668)	(1.819)	(1.301)	(0.866)	(1.575)	(2.815)	(0.751)	(1.312)	(1.247)	(1.727)

Table A21. *Cont.*

	Australia	China	Canada	Germany	Japan	Mexico	Sweden	Swiss	UK	US
ASSI-SHOP	4.955	−0.592	2.217	−1.350	7.872 **	5.628	6.287 **	3.888 **	−2.817	7.380 ***
	(2.728)	(2.159)	(2.108)	(1.055)	(2.592)	(3.419)	(1.762)	(1.197)	(1.758)	(1.618)
ASSI-ExR	0.115	−3.597	6.898 **	−0.655	−8.503 ***	0.303	−0.322	−0.608	2.418	3.933 **
	(3.080)	(2.938)	(2.109)	(1.111)	(1.364)	(2.367)	(1.209)	(2.283)	(2.739)	(1.348)
Constant	−780.4 **	−15.50	231.7	39.20	349.5 *	230.0	227.6 *	168.8	403.6 **	163.4
	(278.9)	(174.4)	(112.8)	(170.4)	(137.7)	(130.7)	(100.2)	(103.9)	(130.6)	(95.78)
Obs.	55	52	28	53	52	55	52	53	54	52
Adj. R^2	0.462	0.584	0.883	0.770	0.861	0.650	0.716	0.847	0.832	0.813
F	4.314	6.115	15.52	13.42	23.50	8.161	10.19	21.50	19.74	16.86

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A22. Panel Regression AM Model for Countries.

	Australia	China	Canada	Germany	Japan	Mexico	Sweden	Switzerland	UK
dmm	0.277	0.750	−2.618 ***	−6.784	0.124	−0.783 *	0.140	−0.661	−0.447
	(0.866)	(0.519)	(0.674)	(5.287)	(0.323)	(0.300)	(0.417)	(0.997)	(1.032)
GDP	2.052	−2.638 **	0.0985	0.483	−0.439	1.726 ***	−1.297	3.298 **	−1.414
	(1.794)	(0.947)	(0.522)	(1.117)	(0.542)	(0.472)	(0.961)	(0.990)	(1.460)
IR	1.782 *	−3.958 ***	3.290 ***	−42.86 ***	0.243	3.103 ***	−3.072 **	4.811 ***	1.608 ***
	(0.809)	(0.522)	(0.586)	(10.73)	(0.377)	(0.456)	(0.936)	(0.458)	(0.416)
CPI	305.8	56.57	−16.35	−657.8	−74.39	−39.73	−253.3 **	162.2	3.320
	(189.4)	(110.2)	(173.9)	(332.3)	(65.18)	(85.79)	(71.37)	(136.1)	(143.7)
PNT	191.3 ***	6.358	−9.541	−146.3	189.4 ***	83.24 ***	260.5 ***	188.3 ***	−95.05 *
	(37.43)	(33.72)	(50.53)	(154.6)	(33.42)	(12.61)	(53.16)	(41.77)	(41.86)
ddbt	−100.6	−823.0 ***	346.2 ***	1455.1 **	−18.85	−1.093	491.7 ***	−100.2	−378.4 **
	(74.34)	(130.2)	(76.74)	(484.0)	(74.25)	(13.57)	(99.65)	(68.78)	(116.2)
ToT	61.39 ***	203.2 ***	28.53	34.78	78.89 ***	−80.14 ***	22.48 ***	−96.36	241.7 ***
	(7.108)	(15.79)	(48.31)	(18.37)	(10.30)	(21.17)	(5.610)	(51.27)	(38.33)
dnfa	1.610 **	−1.149 *	−0.255	1.204	−0.914	−0.491	1.418	−2.721 *	0.245
	(0.525)	(0.464)	(0.661)	(1.461)	(0.878)	(0.547)	(1.013)	(1.040)	(0.578)
Constant	−469.0 *	−160.7	96.23	865.3 *	−93.22	130.7	64.38	−155.4	−42.88
	(195.4)	(113.5)	(177.9)	(363.4)	(71.01)	(92.48)	(79.07)	(151.9)	(143.2)
Observations	52	52	48	48	45	51	38	52	52
Adjusted R^2	0.742	0.792	0.782	0.534	0.745	0.746	0.896	0.875	0.612
F	19.32	25.22	22.12	7.738	17.11	19.40	40.63	45.55	11.07

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A23. Panel Regression AM Model with SI for Countries.

	Australia	China	Canada	Germany	Japan	Mexico	Sweden	Switzerland	UK
dmm	−0.590	−0.295	−0.643	3.074	−0.366	−0.0776	0.147	−1.251	−1.298 *
	(1.163)	(0.640)	(1.044)	(3.708)	(0.363)	(0.342)	(0.436)	(1.291)	(0.637)
GDP	0.848	−2.061 *	−0.161	−0.234	−0.499	1.302 *	−1.572	2.988 *	−0.518
	(1.943)	(0.967)	(0.493)	(0.593)	(0.513)	(0.537)	(1.083)	(1.175)	(0.963)
IR	2.185	−2.236 *	0.251	−25.25 ***	1.895 *	2.334 **	−0.845	5.781 ***	1.194 **
	(1.520)	(0.824)	(1.010)	(6.205)	(0.770)	(0.679)	(1.421)	(0.920)	(0.433)
CPI	334.6	50.81	−130.8	22.74	−88.84	−50.87	−260.7 **	296.1	5.838
	(219.0)	(103.9)	(173.2)	(207.4)	(72.28)	(89.84)	(90.99)	(167.7)	(116.9)
PNT	187.8 **	38.84	63.03	236.3	183.5 **	79.40 **	371.6 ***	198.9 **	−80.23
	(53.80)	(31.81)	(52.24)	(117.5)	(58.35)	(24.03)	(71.89)	(66.22)	(39.82)
ddbt	−65.80	−504.5 **	474.0 ***	913.9 **	88.89	15.87	315.4 *	−10.08	−257.2 *
	(82.97)	(148.6)	(104.1)	(286.6)	(73.12)	(16.91)	(130.4)	(100.7)	(98.08)
ToT	54.18 ***	163.2 ***	−120.8 *	−14.35	77.59 ***	−66.51 *	−3.128	−71.28	130.9 ***
	(8.782)	(17.49)	(54.49)	(15.48)	(9.742)	(25.23)	(11.68)	(62.00)	(32.32)
dnfa	1.186	−0.884 *	−1.504 *	−0.444	0.000573	−0.0723	2.468 *	−4.263 **	−0.151
	(0.651)	(0.427)	(0.705)	(0.844)	(0.919)	(0.557)	(1.145)	(1.531)	(0.366)
SI-INF	0.0518	0.00218	−0.00659	−0.0851	−0.164	0.0449	0.116 *	0.0451	−0.00463
	(0.140)	(0.0978)	(0.0793)	(0.0617)	(0.110)	(0.0505)	(0.0515)	(0.0981)	(0.0980)
SI-GDP	−0.274	−0.0195	−0.0152	0.0387	0.00161	0.00729	−0.103	−0.0189	0.0958
	(0.143)	(0.0736)	(0.0725)	(0.0980)	(0.145)	(0.0635)	(0.0846)	(0.107)	(0.0891)

Table A23. *Cont.*

	Australia	China	Canada	Germany	Japan	Mexico	Sweden	Switzerland	UK
SI-CPI	0.108	−0.164 *	0.0260	−0.0987	−0.00406	−0.0585	−0.168	0.0286	0.215
	(0.136)	(0.0687)	(0.0642)	(0.112)	(0.0811)	(0.0482)	(0.0995)	(0.0877)	(0.142)
SI-IR	−0.0614	−0.157	−0.142	0.0894	0.0224	−0.0166	0.0832	−0.0676	0.0502
	(0.103)	(0.117)	(0.0842)	(0.140)	(0.117)	(0.0758)	(0.0582)	(0.113)	(0.107)
SI-LOAN	0.109	−0.0442	0.0889	0.104	0.182	−0.0442	0.0969	0.268 *	0.149
	(0.202)	(0.0781)	(0.0562)	(0.104)	(0.232)	(0.0696)	(0.0786)	(0.103)	(0.0931)
SI-ATM	0.0309	0.0318	−0.196 **	−0.00328	0.115	−0.0618	−0.128	−0.189	0.528 ***
	(0.139)	(0.0866)	(0.0641)	(0.108)	(0.101)	(0.0688)	(0.116)	(0.153)	(0.141)
SI-JO	0.0989	−0.105	0.112	−0.231	−0.133	0.116	−0.0889	0.00254	−0.235
	(0.0759)	(0.0535)	(0.0694)	(0.160)	(0.0707)	(0.115)	(0.0642)	(0.0665)	(0.142)
SI-SHOP	0.186	−0.109	−0.0940	0.324 *	0.0795	0.199	0.0310	−0.233 *	0.367 ***
	(0.112)	(0.0791)	(0.0549)	(0.126)	(0.122)	(0.105)	(0.0775)	(0.105)	(0.0812)
SI-ExR	−0.0449	−0.0566	−0.0143	−0.455 ***	0.0703	−0.121 *	0.0229	0.113	0.118 *
	(0.0901)	(0.0768)	(0.0418)	(0.0683)	(0.0834)	(0.0530)	(0.157)	(0.121)	(0.0505)
Constant	−501.3 *	−116.9	299.6	−158.5	−88.08	124.5	−1.169	−312.9	−24.61
	(215.2)	(103.7)	(188.1)	(275.0)	(69.16)	(98.71)	(101.3)	(174.5)	(111.8)
Observations	52	52	48	48	45	51	38	52	52
Adjusted R^2	0.772	0.874	0.858	0.900	0.816	0.791	0.916	0.890	0.884
F	11.15	21.90	17.72	25.86	12.49	12.12	24.85	25.29	23.78

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A24. Panel Regression AM Model with ASSI for Countries.

	Australia	China	Canada	Germany	Japan	Mexico	Sweden	Switzerland	UK
dmm	−0.550	−0.312	−0.662	3.114	−0.359	−0.0662	0.186	−0.354	−1.292
	(1.171)	(0.646)	(1.053)	(3.642)	(0.369)	(0.345)	(0.435)	(1.245)	(0.649)
GDP	0.790	−2.022 *	−0.0927	−0.544	−0.469	1.292 *	−1.012	3.396 **	−0.557
	(1.956)	(0.978)	(0.506)	(0.620)	(0.526)	(0.542)	(1.191)	(1.100)	(1.047)
IR	2.538	−2.274 *	−0.000386	−27.38 ***	1.846 *	2.513 **	−1.009	5.386 ***	1.178 *
	(1.596)	(0.833)	(1.081)	(6.267)	(0.792)	(0.735)	(1.421)	(0.865)	(0.467)
CPI	346.4	97.69	−91.10	−37.03	−98.97	−74.40	−247.3 *	326.4 *	1.423
	(220.9)	(127.4)	(183.9)	(207.8)	(77.75)	(97.16)	(91.32)	(155.7)	(126.1)
PNT	188.7 **	35.39	50.77	227.0	183.5 **	76.20 **	363.7 ***	137.5 *	−80.10
	(54.13)	(32.53)	(55.58)	(115.6)	(59.29)	(24.70)	(71.87)	(65.76)	(40.43)
ddbt	−55.00	−526.8 **	491.3 ***	864.6 **	86.81	16.20	332.7 *	−19.01	−258.5 *
	(84.62)	(153.8)	(107.9)	(283.5)	(74.48)	(17.06)	(130.7)	(93.30)	(100.4)
ToT	52.83 ***	161.2 ***	−112.9	−17.05	77.62 ***	−63.22 *	0.620	−72.48	129.9 ***
	(9.007)	(17.89)	(56.14)	(15.31)	(9.897)	(25.92)	(12.10)	(57.40)	(34.24)
dnfa	1.094	−0.997 *	−1.342	−0.393	0.0160	0.00496	1.824	−4.535 **	−0.143
	(0.665)	(0.465)	(0.748)	(0.830)	(0.934)	(0.574)	(1.280)	(1.422)	(0.379)
ASSI-INF	0.462	0.148	−0.406	−1.453	−3.079	1.127	2.438 *	0.0850	−0.0230
	(2.765)	(1.880)	(1.571)	(1.156)	(2.115)	(1.050)	(0.996)	(1.749)	(1.989)
ASSI-GDP	−3.997	−0.700	−0.377	0.497	0.280	0.129	−0.934	0.192	1.348
	(2.080)	(1.252)	(1.081)	(1.392)	(2.224)	(0.927)	(1.318)	(1.446)	(1.357)
ASSI-CPI	3.022	−3.086 *	0.389	−1.015	−0.0229	−1.472	−2.189	0.282	3.912
	(2.890)	(1.315)	(1.238)	(2.163)	(1.569)	(1.069)	(2.084)	(1.543)	(3.157)
ASSI-IR	−0.921	−2.167	−1.805	0.229	0.177	−0.507	1.136	−1.289	0.758
	(1.568)	(1.822)	(1.386)	(2.233)	(1.845)	(1.221)	(0.888)	(1.591)	(1.643)
ASSI-LOAN	1.771	−1.444	2.289	2.261	4.710	−1.485	2.639	3.639	3.286
	(4.619)	(1.895)	(1.339)	(2.273)	(5.512)	(1.734)	(1.798)	(2.310)	(2.137)
ASSI-ATM	1.677	0.925	−4.544 **	−1.708	2.934	−1.534	−4.643	−5.050	12.77 ***
	(3.597)	(2.133)	(1.603)	(2.813)	(2.515)	(1.685)	(3.131)	(3.441)	(3.535)
ASSI-JO	2.055	−2.181	2.552	−4.374	−2.590	2.169	−1.453	0.895	−4.896
	(1.540)	(1.091)	(1.473)	(3.169)	(1.466)	(2.355)	(1.322)	(1.281)	(3.305)
ASSI-VC	−1.495	0.757	−0.561	2.116	−0.761	−0.492	1.261	2.669 *	0.169
	(1.935)	(1.171)	(0.807)	(1.457)	(1.918)	(0.734)	(1.145)	(1.034)	(1.627)

Table A24. *Cont.*

	Australia	China	Canada	Germany	Japan	Mexico	Sweden	Switzerland	UK
ASSI-SHOP	3.347	−1.534	−1.461	7.476 **	1.221	3.190	0.248	−4.054 *	6.198 ***
	(1.899)	(1.395)	(0.933)	(2.503)	(2.085)	(1.779)	(1.306)	(1.619)	(1.616)
ASSI-ExR	−0.251	−1.114	−0.0863	−9.938 ***	1.585	−2.293	−0.0998	2.190	2.700 *
	(2.294)	(1.786)	(1.021)	(1.556)	(1.931)	(1.395)	(3.613)	(2.558)	(1.180)
Constant	−513.6 *	−161.0	264.1	−101.3	−76.95	150.5	−16.79	−282.8	−19.01
	(217.1)	(125.0)	(196.5)	(272.9)	(75.66)	(106.9)	(101.8)	(162.0)	(125.6)
Observations	52	52	48	48	45	51	38	52	52
Adjusted R^2	0.769	0.872	0.856	0.903	0.810	0.787	0.917	0.906	0.880
F	10.44	20.35	16.47	25.45	11.44	11.28	23.79	28.23	21.81

Standard errors in parentheses. Note: Independent variable is the Real Exchange Rate; Source: Authors' estimations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Notes

1. Appendix A contains the summary statistics of all variables in detail.
2. First we include NFA_t in our regression models. However, NFA_t creates a multi-collinearity problem with the highest VIF-factor of 8.81. Thus, we drop NFA_t from our main regression models. Upon request, we provide the estimates including NFA_t.
3. In order to check the robustness of our regression, we estimate the fourteen variants based on our row data as well ($ModelRowDat$). The results are largely robust. The Tables are in the online Appendix.
4. Alternatively we conduct Kao's cointegration test (Kao 1999).
5. All non-stationary variables must be transformed into stationary. This is done through a process called differencing: $y_t := \ln(x_{t+1}) - \ln(x_t)$.
6. We also check the standard Prais-Winsten test-statistics.
7. Tables 5 and A12 represent the output of the basic regression model.
8. The variable NFA and its significance was discussed by Branson and Henderson (1985), who argue that changes in net holdings of foreign asset directly affect a country's currency.
9. Results for the estimates with non-transformed data are reported in the Appendix C (Table A13).
10. Note, however, R-square can be rather meaningless (Blackwell 2005).
11. In addition, Tables A9 and A10 summarize the results of our first regression exercise.
12. All other country related impulse response functions are available upon request.

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