Global Credit Supply Shocks and Exchange Rate Regimes*

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June 4, 2018

Abstract

The recent global financial crisis has re-emphasized the need for better understanding the relation between the type of exchange rate regime (ERR) in place and the effects of global credit supply shocks. Recent advances in the measurement of such shocks and their large realizations in the recent financial crisis produce a suitable quasi-natural experiment for studying this relation. Toward this end, I use ERR classification data for a panel of 40 emerging market economies (EMEs) to establish the following main findings: output responds significantly more adversely to contractionary global credit supply shocks in the fixed ERR than in the non-fixed ERR; deleveraging and the fall in imports are much more severe in the fixed ERR; and the lack of exchange rate depreciation in the fixed ERR is accompanied by a stronger fall in exports. These results are broadly consistent with predictions from models which include both the expenditure-switching channel and the balance sheet channel of exchange rate depreciation, where the latter channel effectively becomes expansionary, rather than contractionary as commonly thought, owing to favorable effects of the expenditure-switching channel on balance sheets' asset side.

JEL classification: F31,F41,F44

Key words: Exchange rate regime; Global credit supply shocks; Emerging market economies

*This is a substantially revised version of the paper previously circulated as "Sudden Stops and Exchange Rate Regimes." I am grateful to Josh Brault, Chris Gunn, Hashmat Khan, Minjoon Lee, Anderson Nzabandora, and seminar participants at Carleton University for helpful comments and suggestions.

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1 Introduction

Adverse global credit supply shocks tend to produce severe net capital outflows and economic contractions for the typical economy, as we have been vividly reminded of by the recent 2008-2009 global financial crisis. As these severe net capital outflows result in considerable downward pressure on the exchange rate, a natural policy regime to focus attention on in the context of such shocks is that of the exchange rate regime (ERR). The relevance of the type of ERR in place for the amplification or moderation of global credit supply shocks' real effects is of particular importance in emerging market economies (EMEs), whose net capital outflow during credit bust episodes and prevalence of foreign currency-denominated debt are both much stronger than their advanced economies' counterparts (see, e.g., Cesa-Bianchi et al. (2018)).

The two main transmission channels of exchange rate depreciation are the expansionary classical expenditure-switching channel and the (potentially) contractionary balance sheet channel, where the latter channel's ultimate direction of effect can in theory become even expansionary if the asset side of economic agents' balance sheets gains more from depreciation than their liabilities' side loses. Nevertheless, in theory, the total effect of these two channels can be either contractionary or expansionary, owing to the potentially contractionary effect of the balance sheet channel in the presence of foreign currency-denominated debt.

What This Paper Does. The empirical questions this paper tries to address are the following: *i*) are the contractionary effects of global credit supply shocks more adverse in EMEs that have fixed exchange rate regimes (ERRs)?; *ii*) which exchange rate channel dominates the other?; and *iii*) is the balance-sheet channel expansionary or contractionary? To address these questions, I employ a state-of-the-art, widely used *de-facto* ERR classification measure originally developed by Reinhart and Rogoff (2004) and updated by Ilzetzki et al. (2017) through 2016 (henceforth IRR). Its construction makes use of monthly data on market-determined parallel exchange rates to generate a fine classification of ERRs comprising of 15 categories. These categories appear in Table 1, where larger category integers represent more flexible ERRs. To divide the observations in my sample into fixed and non-fixed ERRs, I define categories 1-4 as corresponding to a fixed ERR and categories 5-13 as belonging to the non-fixed ERR, removing from the analysis categories 14-15 to ensure my results are not biased by severe inflationary periods and/or missing parallel market data. Categories 1-4 effectively correspond to pegged ERRs, while higher categories represent regimes in which there is more exchange rate flexibility. (The coarse classification of Ilzetzki et al. (2017) groups categories 1-4 into one category on the premise that they indeed represent fixed ERRs whereas higher categories (e.g., 5-8 and 9-12) begin to reflect cases of different degrees of limited flexibility.)

To measure the effects of global credit supply shocks, I make use of the Gilchrist and Zakrajsek (2012) credit supply shock series.[1] Their shock series serves as an exogenous and common global credit supply shock to EMEs; as such, the Gilchrist and Zakrajsek (2012) series can be employed to study whether fixed ERRs amplify global credit supply shocks' adverse effects.[2] I then integrate the ERR and credit supply shock data with quarterly frequency macroeconomic data of 40 EMEs and estimate nonlinear, dynamic fixed-effects panel regressions to study whether the effect of global credit supply shocks differs across peggers and non-peggers. Furthermore, I employ the Jorda (2005) local projections approach in the panel regression specification so as to be able to directly estimate the nonlinear, state-dependent impulse responses to global credit supply shocks.

My empirical findings can be summarized as follows. There is a statistically significant negative difference between the response of output in the fixed ERR state and the non-fixed one. This difference is also economically significant. Specifically, the peak output decline in the fixed ERR

[1] Gilchrist and Zakrajsek (2012) use micro-level data to construct a credit spread index which they decomposed into a component that captures firm-specific information on expected defaults and a residual component that they termed as the excess bond premium.Gilchrist and Zakrajsek (2012) show that their spread measure has better predicative power for macroeconomic variables than more standard credit spread measures such as the Baa-Aaa Moody's bond spread.

[2] From an econometric or identification standpoint, my focus on this shock is motivated by the global-financial-crisis-induced quasi-natural experiment it was such a central force in, which in turn greatly facilitates addressing the type of question I am asking in this paper. While the goal of this paper is not to ascertain the importance of global credit supply shocks in driving EMEs' business cycles, it is interesting to note that these shocks are not dominant drivers of business cycles in EMEs but also not negligible ones; applying the forecast error variance decomposition methodology from Gorodnichenko and Lee (2017), I have found that the share of output's business cycle variation explained by credit supply shocks is 18%.

state takes place after two years reaching -2.7%, compared to -1.5% in the non-fixed ERR state, reflecting a t-statistic of -3.9 associated with the response difference between the two states. Both investment and consumption also decline significantly more in the fixed ERR. And there is a significantly stronger rise in the trade balance in the fixed ERR state, with both exports and imports declining significantly more in this state.

To shed light on the mechanism behind these results, I turn my analysis to exchange rates, leverage, stock prices, capital flows, and country credit spreads data. I first demonstrate, using market-determined parallel exchange rate data from Ilzetzki et al. (2017), that exchange rates do not move significantly in the fixed ERR while significantly depreciating in the non-fixed ERR. Then, using data from the Bank for International Settlements (BIS) on cross-border credit, I demonstrate that the GDP share of debt owed to international banks falls by much more in the fixed ERR than in the non-fixed ERR. Moreover, stock prices also fall by much more in the fixed ERR, indicating that the asset side of firms' balance sheets declines by more in the fixed ERR. These results on leverage and stock prices, coupled with those on the stronger decline in imports in the fixed ERR state, are consistent with models with occasionally binding collateral constraints where imports are financed by debt and the asset side of economic agents' balance sheets is sufficiently positively affected by exchange rate depreciation so as to overturn the adverse depreciation effect on the liability side, thus ultimately resulting in an expansionary balance sheet channel of exchange rate depreciation (see, e.g., Devereux and Yu (2017)). In line with this interpretation, I also show that capital outflows in the fixed ERR are much more acute than in the non-fixed ERR and that country credit spreads rise by much more in the fixed ERR.

Related Literature. Milton Friedman, more than 60 years ago, was the first to put forward the notion that flexible exchange rates can serve as shock absorbers (Friedman (1953)). His focus was on the classical expenditure-switching effect of exchange rate depreciation, which is also at the core of traditional models such as the open economy Mundell-Fleming framework as well its micro-founded, dynamic successor, the New Keynesian (NK) Open Economy model.

More sophisticated recently developed models focus on the shock-amplifying nature of fixed

ERRs in the presence of downward nominal wage rigidly, where the lack of currency depreciation following an adverse shock enhances the increase in unemployment due to lack of downward adjustment in real wages (Schmitt-Grohé and Uribe (2013, 2014, 2016)). In models containing financial frictions, the shock-amplifying nature of fixed ERRs becomes less conclusive in theory due to the adverse balance sheet effect of currency depreciations in the presence of foreign currency-denominated debt.[3] Ottonello (2015) extends the framework developed by Schmitt-Grohé and Uribe (2013, 2014, 2016) by adding an occasionally binding collateral constraint that is based on current income, as in Mendoza (2002). His setting produces a contractionary balance sheet channel of currency depreciation because the latter leads to a reduction in the foreign currency value of income derived from the non-tradable sector, thus tightening the collateral constraint and exacerbating financial frictions. Nevertheless, currency depreciation is still superior to no depreciation as its favorable effect on labor markets turns out to be stronger than its adverse balance sheet effect. Fornaro (2015) also assumes nominal wage rigidities that assign a shock-absorbing role to flexible exchange rates through real wage adjustment as well as an occasionally binding collateral constraint but differs from Ottonello (2015) in using a different constraint that is based on the foreign currency value of the household's capital (land), similar to Mendoza (2010). In this setting currency depreciation actually relaxes the collateral constraint through its favorable effect on capital prices, thus resulting in an expansionary balance sheet channel of currency depreciation which enhances the amplification of financial crises in a fixed ERR.[4]

There have also been papers using models that incorporated both the classical expenditure-switching channel as well as the balance-sheet channel of exchange rate depreciation. Assuming financial frictions based on the costly state verification framework, Cspedes et al. (2004) and

[3]Focusing mainly on this channel by precluding nominal rigidities, Benigno et al. (2016) establish that fixed ERRs can greatly moderate the adverse effects of financial crises.

[4]In general, financial crises in models with occasionally binding collateral constraints are defined as periods in which these constraints bind. It is important to stress that my empirical analysis is not able to identify such episodes; rather, it identifies an arguably exogenous decline in global investors' risk appetite which may or may not ultimately lead to a binding of borrowers' collateral constraints. Nevertheless, such declines are likely to produce a tightening in collateral constraints, and this makes my empirical analysis potentially informative also for theoretical models that study the implications of binding collateral constraints.

Gertler et al. (2007) stress that currency depreciation can have an expansionary effect on firms' balance sheets owing to its favorable effect on their asset side; and Devereux and Yu (2017) show a similar result assuming financial frictions resulting from an occasionally binding collateral constraint that is based on the foreign currency value of the borrower's capital.

Notwithstanding the rather vast theoretical work cited above, there has been fairly limited empirical work on the relation between ERRs and adverse shocks' effects.[5] The papers that have looked at the general shock-amplifying nature of fixed ERRs relative to non-fixed ERRs can be divided into two strands: *i*) one which has studied the shock-amplifying nature of fixed ERRs indirectly, i.e., not by conditioning on a particular identified shock, and *ii*) one that has done so directly but by focusing on aspects of the regime's shock-amplifying nature that are not explicitly related to global credit supply shocks.

The first strand of the literature has been initiated by Edwards (2004), who shows that more fixed ERRs generate more adverse effects of current account reversals on output growth. While there is a positive relation between current account reversals and sudden stops (sharp capital flow reversals), this relation is quite imperfect; as reported by Edwards (2004), more than 50% of the sudden stops in his sample are not related to current account reversals. Moreover, his analysis is mostly static, focusing on the effect of current account reversals on impact while ignoring the potentially interesting dynamics of this effect. Hence, the results of Edwards (2004) have limited informativeness for the relation between ERRs and global credit supply shocks' effects.

Subsequent works belonging to this strand of literature have focused on the current account

[5]This issue is stressed by Cesa-Bianchi et al. (2018), who show results in an online supplement to their paper (Figure S.8) from estimating the effects of positive U.S. broker-dealer firms' leverage shocks separately for fixed and non-fixed ERR countries and emphasize at the end of their paper that a detailed exploration of the role of ERRs in the transmission of global credit supply shocks is warranted and left for future research. They find that fixed ERRs experience a stronger consumption increase but the real exchange rate actually seems to appreciate more on impact relative to its appreciation in the non-fixed ERR while at later horizons the appreciation is quite similar across the two ERRs. One reason for this could be their inclusion of developed economies in their sample or perhaps their choice to divide the countries in their sample on the basis of averaging the IRR ERR measure over the 2000-2010 period, rather than doing it in a dynamic, time-dependent manner. It is my hope that my paper is an important step toward accomplishing what Cesa-Bianchi et al. (2018) highlight as an important task to undertake in future research, while improving upon previous work along both the choice of global shock dimension (by using a more clearly structural shock) and methodology dimension (by using a dynamic, state-dependent identification approach).

as their main outcome variable. Chinn and Wei (2013) show that EMEs that move from a fixed regime to a less fixed regime do not necessarily benefit from a more rapid adjustment of the current account; rather than measuring the type of ERR with de facto regime measures, Ghosh et al. (2013) use a trade-weighted bilateral exchange rate volatility measure to characterize the level of exchange rate flexibility and find that flexible exchange rates imply less persistent current account dynamics. While these two papers have not explicitly controlled for the occurrences of sudden stops, Eguren-Martin (2016) compares the speed of current account adjustment across ERRs while explicitly accounting for the occurrence of sudden stops, finding that flexible exchange rates deliver a faster current account adjustment among EMEs. Although useful for our understanding of the mean-reverting behavior of the current account and thus its ability to adjust in response to its reduced form innovations, these papers (much like the paper of Edwards (2004)) do not directly shed light on the role of fixed ERRs in amplifying global credit supply shocks' adverse effects because the latter innovations are essentially combinations of various structural shocks, some of which are likely non-credit-supply type shocks.[6]

The second strand includes Broda (2004) and Edwards and Levy-Yeyati (2005), who examine the effects of terms of trade shocks as a function of the ERR; di Giovanni and Shambaugh (2008), who study the effects of foreign interest rate shocks as a function of the ERR; Born et al. (2013) and Ilzetzki et al. (2013), who look at the relation between ERRs and the effects of fiscal policy shocks on output; and Adler and Mora (2012), who run static regressions of output growth on VIX interacted with ERR. All papers generally find that a fixed ERR amplifies the effects of the

[6] Also susceptible to this limitation are the works by Doma and Peria (2003), Ghosh et al. (2015), and Magud and Vesperoni (2015). Using a comprehensive dataset for developing and developed economies for 1980-1997, Doma and Peria (2003) regress banking crises propensities and costs on both de jure and de facto ERR measures to investigate ERRs' implications for banking crises likelihood and costs; Ghosh et al. (2015) study the link between different ERRs and financial variables, crises propensities, and real variables for an annual 1980-2011 panel of 50 EMEs by regressing the latter on the IMF de facto ERR measures; and Magud and Vesperoni (2015) use a similar methodology but focus on the effect of ERRs on credit behavior during capital outflow crises preceded by capital inflow surges. This methodological approach, while suitable for studying the general relation between macroeconomic performance and ERRs, is unsuitable for uncovering the nexus between ERRS and global credit supply shocks' effects given that it does not condition on a credit supply type shock but rather captures the unconditional effect of ERRs on macroeconomic performance, which can be thought of as the average effect of various economic shocks in a particular ERR.

respective shocks they consider. However, the first three shocks are likely to be quite different from global credit supply shocks in terms of their structural interpretation and the types of effects they produce.

Even foreign interest rate shocks, which are more financial in nature than the other two shocks, are insufficient proxies for global credit supply shocks from a structural standpoint. To see this more clearly, it is useful to consider as a conceptual framework for fixing ideas the small open economy model from Christiano et al. (2011), whose working paper version shows the economy's response to both foreign monetary policy shocks and global credit supply shocks in a setting that incorporates Bernanke et al. (1999)-type financial frictions between domestic entrepreneurs and global banks.[7] While their model predicts that a foreign contractionary monetary policy shock should raise domestic entrepreneurs' net worth and reduce credit spreads, owing to the export-driven rise in output, a contractionary global credit supply reduces net worth and raises credit spreads which in turn produce enough of a drop in investment to bring about a drop in output (starting after about a year). Therefore, interpreted through the lens of the Christiano et al. (2011) framework, my empirical results accord well with theory along the important dimension of the behavior of net worth and credit spreads; this is particularly important given that this dimension seems to play a crucial role in differentiating between the structural implications of the two shocks at hand.[8]

As for the VIX shock, while it is true that movements in this variable capture in part financial shocks, one may also argue that they also capture other, non-financial shocks such as U.S. technology and policy shocks given the potential endogeneity of the VIX measure.[9] Hence, one

[7]The global credit supply shocks are modeled as shocks to idiosyncratic volatility of domestic entrepreneurs returns, also termed 'risk shocks' and later more extensively studied in a closed economy setting by Christiano et al. (2014) to investigate the role of credit supply shocks. These shocks can be thought of as increases in perceived risk on the part of global lenders.

[8]The differences between these two shocks seem to also be borne out by the data as Uribe and Yue (2006) show that foreign interest rate shocks, while producing point estimate responses of output and trade balance of the opposite sign, have statistically insignificant effects on both variables.

[9]The correlation between my global credit supply shock measure from Gilchrist and Zakrajsek (2012) and VIX is 0.73, a significant correlation though clearly one that manifests a noticeable wedge between the two series.

advantage of my analysis is the use of a more structural shock that more clearly represents global credit supply shocks. Two additional important advantages are as follows. First, I perform a dynamic analysis that allows for the estimation of ERR-dependent impulse responses. Second, my analysis looks at various additional variables beyond the output outcome variable so as to learn about the mechanism driving my results.

Outline. The remainder of the paper is organized as follows. In the next section, I begin with a description of the data, after which the methodology and main empirical evidence are presented. Section 3 examines the robustness of the results to alternative specifications. The final section concludes.

2 Empirical Analysis

2.1 Data

Data are quarterly, cover 40 EMEs with samples that span 1973-2016. The panel is an unbalanced panel with the included countries chosen on the basis of belonging to the universe of EMEs and having quarterly data on real macroeconomic aggregates with reasonable length. Appendix A contains a detailed description of the data and its sources. The main outcome variable I consider is output, defined as local currency current GDP divided by the GDP deflator. I seasonally adjusted the output variable using ARIMA X12.

The variable I use to measure global credit supply shocks is the excess bond premium (EBP) from Gilchrist and Zakrajsek (2012), who use micro-level data to construct a credit spread index which they decomposed into a component that captures firm-specific information on expected defaults and a residual component that they termed as the excess bond premium.

To measure the ERR in each EME, I utilize the Reinhart and Rogoff (2004) measure, as updated by Ilzetzki et al. (2017) through 2016 and taken from Carmen Reinhart's website. The IRR measure uses monthly data on market-determined parallel exchange rates to construct a fine classification of ERRs comprising of 15 categories. These categories appear in Table 1, where larger category integers represent more flexible ERRs. I convert monthly values to quarterly ones by averaging over the respective values in each quarter and define the fixed ERR state as a dummy that obtains 1 if the IRR measure obtains an integer that is not greater than 4. I only use categories 1-13 in my empirical analysis, omitting observations corresponding to the last two categories ('Freely falling' and 'Dual Market in which Parallel Market Data is Missing', which account for 9.2% of my sample) to ensure my results are not biased by severe inflationary periods and/or missing parallel market data.

Other outcome variables I consider to learn more about the mechanism behind the results are investment, consumption, exports, imports, trade balance, exchange rates, leverage, stock prices, international capital flows, country credit spreads, and central bank policy rates. The first two are defined as gross fixed capital formation and private consumption expenditure (both in local currency) divided by the GDP deflator; exports and imports are local currency exports and imports of goods and services divided by the GDP deflator; the trade balance is nominal exports minus nominal imports (both in local currency) divided by local currency current GDP. I use market-determined parallel exchange rates from Ilzetzki et al. (2017) to measure nominal exchange rates (with respect to countries' respective anchor currencies) and real effective, CPI-based exchange rate data to measure the real effective exchange rate.

Leverage is the ratio of total claims of Bank for International Settlements (BIS) reporting banks' claims on each EME to its GDP, where the former is taken from the consolidated banking statistics database of the BIS and is converted to local currency by multiplying the dollar value of claims by the corresponding dollar exchange rate. Stock prices are market price indices of equities based on major stock exchange indices available from the International Financial Statistics (IFS) database. I employ the following data on international capital flows: net outflows related to foreign direct investment, portfolio investment, and other investment; and capital flows related to the monetary authority's foreign exchange reserves. All of these items are in raw dollar values and are thus converted to local currency using the respective dollar exchange rates and then divided by local currency current GDP. I seasonally adjusted the raw variables using ARIMA X12.

The country credit spread is the stripped Emerging Markets Bond Index (EMBI) Global computed by JP Morgan, which is a composite of different U.S. dollar-denominated bonds. The stripped spread is computed as an arithmetic, market-capitalization-weighted average of bond spreads over U.S. Treasury bonds of comparable duration. The central bank policy rate represents the interest rate used by a central bank to implement its monetary policy stance; the underlying financial instrument of the policy rate varies across the EMEs in my sample, being the discount rate for some while in others it is a repurchase agreement rate.

Except for exchange rates, central bank policy rate, and country credit spreads, all variables were seasonally adjusted using ARIMA X12. Apart from the trade balance and capital flows, I take logs of all of the variables. To extract the cyclical components of the trending variables in my sample, I estimate a cubic-trend time polynomial for each trending variable and take the associated residuals as the corresponding variables' cyclical components (as in, e.g., Garcia-Cicco et al. (2010)). (I do this for all variables except the capital flows variables, for which there is no significant trend.) See Section 3.2.3 for more details on why I have opted to use this detrending technique; in that section I also present results from using alternative detrending filters.

2.2 Methodology

I follow the econometric framework employed in Auerbach and Gorodnichenko (2012), Owyang et al. (2013), Ramey and Zubairy (2017), and Tenreyro and Thwaites (2016), who use the local projection method developed in Jorda (2005) to estimate impulse responses. This method allows for state-dependent effects in a straightforward manner while involving estimation by simple regression techniques. Moreover, it is more robust to misspecification than a non-linear VAR. As in Auerbach and Gorodnichenko (2012), I make use of the Jorda (2005) local projections method within a fixed effects panel model, where inference is based on Driscoll and Kraay (1998) standard errors that allow arbitrary correlations of the error term across countries and time.

In particular, I estimate the impulse responses to the credit supply shock by projecting a variable of interest on its own lags and current and lagged values of Gilchrist and Zakrajsek (2012)'s EBP variable, while allowing the estimates to vary according to the level of ERR fixity in place in a particular country and time.

Econometric Specification. For example, when I use the detrended log of output (y_t) as the dependent variable, which is the main variable of interest in this paper, the response of output at horizon h is estimated from the following non-linear panel fixed effects regression:[10]

$$\begin{aligned} y_{i,t+h} - y_{i,t-1} = I_{i,t-1}[\alpha_{A,i,h} + \Xi_{A,h} EBP_t + \Omega_{A,h}(L) EBP_{t-1} + \Gamma_{A,h}(L)\Delta y_{i,t-1}] + \\ +(1 - I_{i,t-1})[\alpha_{B,i,h} + \Xi_{B,h} EBP_t + \Omega_{B,h}(L) EBP_{t-1} + \Gamma_{B,h}(L)\Delta y_{i,t-1}] + u_{i,t+h}, \end{aligned} \tag{1}$$

where i and t index countries and time; α_i is the country fixed effect; $\Omega(L)$ and $\Gamma(L)$ are lag polynomials; Ξ_h gives the response of the outcome variable at horizon h to a credit supply shock at time t; $u_{i,t+h}$ is the residual; and, importantly, coefficients vary according to whether we are in state "A", i.e., fixed ERRs are in place, or state "B", i.e., a state of non-fixed ERRs, where I is a dummy variable that takes the value of one when the ERR is fixed (i.e., belonging to categories 1-4 in the fine classification of Ilzetzki et al. (2017)).

As explained in Section 2.1, I only consider observations corresponding to categories 1-13, which implies that the non-fixed ERR dummy obtains 1 if an observation belongs to categories 5-13 while obtaining 0 if it belongs to either categories 1-4 or categories 14-15. Note that the fixed and non-fixed ERR dummies are perfect complements also in the presence of the omission of categories 14 and 15 owing to the fixed ERR dummy also obtaining 0 when an observation corresponds to either of these two categories. A total of 759 observations, or 22.5% of all available observations, are consistent with being in a state of fixed ERR; in terms of country coverage, the fixed ERR

[10] All outcome variables are entered in cumulative differences and first-differences in the left- and right-hand sides of Equation (1), respectively, except for the capital flows variables which are entered in levels in both sides as they are effectively already first-differences of their corresponding stock variables. Note that my pre-estimation log-cubic-trend removal applied to the trending variables does not remove stochastic trends; hence, the differencing procedure is important in removing any such potential stochastic trends and making the data stationary, which is necessary for making the local projections estimation and inference approach of Jorda (2005) applicable to my setting.

corresponds to a total of 18 countries (with only 3 countries having a fixed ERR continuously), or 40% of the total number of available countries in my analysis.

Identification. Lags of output and EBP are included in the regression to remove any predictable movements in EBP. This facilitates the identification of the unanticipated shock to EBP, which is what is sought after. I assign the value of the order of lag polynomials $\Omega(L)$ and $\Gamma(L)$ to 8, i.e., I allow for 8 lags of output growth and EBP in the regression. I assume a relatively large number of lags because of the classification method of Ilzetzki et al. (2017), which is based on the absolute value of percentage changes in a country's currency against its anchor currency over a two-year or five-year rolling window. Since past macroeconomic events from more than a year ago can potentially affect the Ilzetzki et al. (2017) classification, it is necessary to include in the regression more than four lags of EBP and output growth so as to avoid correlation of the error term with past shocks. While potentially such an argument can also apply to bias resulting from past shocks from more than two years ago, here I make a reasonable compromise between preservation of degrees of freedom and the desire to limit the bias from this potential correlation of ERR with past shocks. In Section 3 I examine the robustness of the results to using a different number of lag specifications.

The impulse responses to the credit supply shock for the two states at horizon h are simply $\Xi_{A,h}$ and $\Xi_{B,h}$, respectively. The EBP credit supply shock is normalized so that it has a zero mean and unit variance. I base inference on Driscoll and Kraay (1998) standard errors that account for the serial and spatial correlation of $u_{i,t+h}$. Note that a separate regression is estimated for each horizon. I will estimate a total of 16 regressions and collect the impulse responses from each estimated regression, allowing for an examination of the state-dependent effects of credit supply shocks for the 4 years following the shock.

For comparison purposes, I will also estimate a linear analogue of Specification (1):

$$y_{i,t+h} - y_{i,t-1} = \alpha_{i,h} + \Xi_h EBP_t + \Omega_h(L)EBP_{t-1} + \Gamma_h(L)\Delta y_{i,t-1} + u_{i,t+h}. \tag{2}$$

The coefficient of interest from this linear regression is Ξ_h, which gives the linear impulse response to the credit supply shock at horizon h. The linear specification effectively assumes equality of the model's coefficients across the two states.

2.3 Results

This section presents the main results of the paper. It is first established that being in a fixed ERR state increases the adverse output effects of global credit supply shocks. In what follows after that, I turn to inspecting the behavior of other macroeconomic variables as a function of the ERR state in order to uncover the underlying mechanisms that drive the output-based results.

Output. The first set of results, shown in Figure 1, depicts the output response to credit supply shocks in the non-linear model. For comparison purposes, the results from the linear model are also shown in this figure, as well as in all of the remaining figures. Specifically, in each Figure the first sub-figure jointly shows the point estimates of the impulse responses from the linear model (solid lines), fixed ERR (dotted lines), and non-fixed ERR (dashed lines); the next three sub-figures depict the impulse responses along with Driscoll and Kraay (1998) 90% confidence bands for the linear model, fixed ERR state, and non-fixed ERR state; and the last sub-figure shows the t-statistics of the difference between impulse responses in the fixed ERR state and the non-fixed ERR state.

The results from Figure 1 clearly indicate that being in a fixed ERR significantly amplifies the effects of credit supply shocks on output. The amplification is both economically and statistically significant. The peak output response in the fixed ERR occurs after two years reaching -2.7%, compared to -1.5% in the non-fixed ERR. The difference between the responses in the two states is statistically significant for 9 horizons with the t-statistic of this difference bottoming at -3.9 after two years.

These results clearly show that the data support the notion that a fixed ERR is a stability-reducing policy tool in the presence of global credit supply shocks. I now turn to inspecting the behavior of other macroeconomic variables so as to help in uncovering the mechanism behind the output-based results.

Investment, Consumption, and the Trade Balance. Figures 2a-3 depict the responses of investment, consumption, and the GDP share of the trade balance. The results from Figure 2a, which depict the investment responses, indicate that investment responds significantly more adversely in the fixed ERR state, with a trough t-statistic for the response difference of -2.8 taking place after two years. As in the case of output, the main takeaway from this figure is that a fixed ERR state appears to significantly enhance the adverse response of investment to credit supply shocks. Figure 2b presents the responses of consumption. Consumption declines significantly more in the fixed ERR than in the non-fixed ERR, with the t-statistic of the response difference bottoming at -3.5 after 11 quarters. Overall, similar to investment, the differential behavior of consumption is consistent with the more adverse response of output in the fixed ERR state. Figure 3 presents the responses of the GDP share of the trade balance. The trade balance significantly rises in both ERRs but more so in the fixed ERR, with t-statistics of the difference between the responses of the trade balance in the two states being significant for a total of 7 horizons.

To better understand what is driving the trade balance based results, it is important to turn to the responses of exports and imports, depicted by Figures 4a and 4b, respectively. The *relative* behavior of exports across the two ERR states is broadly in line with the predictions of basic theory based on the classical expenditure-switching channel (to be confirmed below when looking at exchange rate behavior), declining significantly more in the fixed ERR. Note that the absolute decline in exports in both ERRs is consistent with the fact that the EBP shock is a contractionary U.S. credit supply shock that induces a U.S. recession, and thus we should expect to see EMEs' exports decline; but, importantly, so long that peggers' trade exposure to the U.S. is not systematically higher than non-peggers, the stronger exports decline for the former need not be amplified by this foreign-demand-induced channel and hence should not affect the interpretation of the differential exports response as being driven mainly by the expenditure-switching channel. (Evidence for the U.S. trade exposure channel is shown below in Section 3.1, where I provide evidence that this channel is unlikely to be playing a meaningful role in driving this paper's results.)

In tandem with the significantly stronger exports decline in the fixed ERR, there is also a much stronger imports decline in this state that more than offsets the stronger exports decline, resulting in the significantly stronger rise in the trade balance response in the fixed ERR. That imports fall by much more in the fixed ERR can be potentially explained by models that integrate the classical expenditure-switching channel with occasionally binding collateral constraints in the spirit of Mendoza (2010) where imports are financed with debt (see, e.g., Devereux and Yu (2017)). (This interpretation is further explored below when I turn the analysis to financial variables.)

Nominal and Real Exchange Rate. Figures 5a and 5b present the responses of the nominal and real exchange rate. The nominal exchange rate data are the market-determined, parallel exchange rates from Ilzetzki et al. (2017), while the real exchange rate is measured by effective, CPI-based real exchange rates. The exchange rate, both in nominal and real terms, depreciates significantly more in the non-fixed ERR state (a positive response corresponds to a weakening, or depreciation, of the exchange rate). The significant difference between the responses for the nominal exchange rate begins on impact and lasts for 7 quarters, with the associated t-statistics bottoming at -4.8 in the second quarter after the shock. Importantly, these significant differences translate into a much more significant *real* exchange rate depreciation, where the associated t-statistics are significant from the impact horizon through the 7th horizon (reaching a bottom of -6.7 in the second quarter).

Importantly, the nominal exchange rate does not move significantly in the fixed ERR, enhancing confidence in the suitability of the choice of fixed ERR measure. Note that the Ilzetzki et al. (2017) classification of categories 1-4 does permit exchange rate fluctuations, albeit to a very limited extent. E.g., Category 3 is assigned to an observation if the corresponding exchange rate has not fluctuated by more than 2% in absolute terms on a monthly basis for at least 80% of the months within a five-year window. Hence, it could still be the case that some exchange rate fluctuation takes place in response to a global credit supply shock even in the fixed ERR. Nevertheless, it is apparent that exchange rate depreciation is both economically and statistically insignificant conditional on an adverse global credit supply shock, providing reassurance that the Ilzetzki et al. (2017) classification is an appropriate ERR measure for the purposes of this paper.

The significantly stronger depreciation of the exchange rate in the non-fixed ERR can explain the weaker fall in exports in this state observed in Figure 4a. And it serves as evidence consistent with the classical-expenditure switching channel. To better understand the stronger fall in imports in the fixed ERR coupled with that in exports, I now turn to inspect the behavior of leverage so as to examine the potential role of financial frictions in driving the results presented so far.

Leverage. Given the important theoretical role of leverage in models of EMEs based on collateral constraints (see, e.g., Durdu et al. (2009), Mendoza (2010), Fornaro (2015), and Devereux and Yu (2017)) as well as those based on the Bernanke et al. (1999) financial accelerator framework (see, e.g., Fernández and Gulan (2015)), it is important to uncover the behavior of leverage across the two states to better understand the mechanism underlying the results shown so far.

Toward this end, I measure leverage using BIS-reporting banks' claims on an EME divided by its GDP. This debt-to-GDP measure embodies debt of all economic agents in the economy to internationally active foreign banks that report to the BIS (currently consisting of banking groups from 31 countries).[11]

Importantly, my leverage series is based on the BIS *consolidated* banking statistics and therefore excludes inter-office claims held by parent banks on their EMEs subsidiaries, this in contrast to the locational banking statistics database which includes them. This exclusion is important given that inter-office lending, which need not be considered as a true form of economic debt, is expected to behave very differently from interbank lending. Consistent with this notion, there is rather ample evidence that parent bank funding of subsidiaries can be an important source of funding in quantitative terms and, importantly, is a much more stable funding source than interbank lending to unaffiliated banks during periods of financial stress (see, e.g., Takats et al. (2011), Reinhardt and Riddiough (2015), and the references in Kerl and Niepmann (2015)).

[11] This measure of debt is termed as '*international claims*' in the BIS dataset and excludes local currency claims of parent banks' subsidiaries in EMEs on domestic borrowers.

Figure 6 presents the response of the log of leverage to a credit supply shock. These results stress that leverage falls much more in the fixed ERR state. Leverage falls significantly in the fixed ERR from the 5th horizon onwards, with the difference between leverage responses across the two states being statistically significant for a total of 12 horizons. The t-statistics reach their trough of -4.9 after 11 quarters, where leverage falls by 6.5% in the fixed ERR compared to a small and insignificant decline of 0.6% in the non-fixed ERR. After 10 quarters through the 4-year mark leverage begins to fall significantly for some horizons (4 in total) also in the non-fixed ERR, but as noted this fall is much weaker than the corresponding fall in the fixed ERR. This significantly stronger deleveraging process experienced in the fixed ERR is consistent with the recent models developed in Fornaro (2015) and Devereux and Yu (2017), which combine exchange rate policies and occasionally binding collateral constraints within a small open economy framework. These models emphasize that a fixed ERR exacerbates financial frictions due to a lack of exchange rate adjustment, which in turn produces a more acute deleveraging process.

To better understand which sectors drive the responses from Figure 6, I now turn to study the responses of leverage of the private non-financial sector, financial sector, and the public sector, all measured as the BIS-reporting banks' claims on an EME's corresponding sector divided by its GDP. These results are shown in Figures 7a-7c, from which it is apparent that leverage in all sectors undergoes a stronger deleveraging process in the fixed ERR relative to the non-fixed ERR. Particulary notable is the much more acute fall in financial sector leverage which seems to be the strongest driver of the behavior of aggregate leverage, although clearly the other sectors also undergo a stronger deleveraging process in the fixed ERR state that contributes to the overall bigger fall in leverage in this state.[12]

[12] The underlying data used to construct my leverage series does not allow for a decomposition of debt into bonds and loans. This would make for a potentially informative distinction given the evidence recently documented and analyzed by Caballero et al. (2016) and Chang et al. (2017) that one of the most salient facts in the past decade in EMEs has been the large direct external borrowing by corporations via bond issuance. Aside from claims on the public sector, which are mostly comprised of bond debt (Caballero et al. (2016)), the claims underlying my leverage variable are largely consisting of loans. In results not shown here for space reasons, I make use of BIS data on corporate debt securities collected on a nationality basis so as to gain an understanding as to whether corporate bond debt issuance plays an important role in the transmission of the different output effects of global credit supply shocks across the two ERR states.

Stock Prices. That a more acute deleveraging process takes place in the fixed ERR is consistent with there being an exacerbation of financial frictions due to the lack of exchange rate adjustment in this state. But to more forcefully make this claim one needs to also examine the behavior of the asset side of firms' balance sheets. Toward this end, I make use of stock price data which represent countries' major stock market exchange indices. The rationale behind using stock prices to measure the asset side of firms' balance sheet is based on the notion that firms' market value serves as a reasonable proxy for Tobin's q, a central variable in models with financial frictions that represents the price of capital.

Figure 8 shows the results for stock prices.[13] Clearly, stock prices decline by much more in the fixed ERR, with t-statistics of the response difference far exceeding conventional rejection levels. E.g., after two years, stock prices decline by 19.3% in the fixed ERR compared to 10% in the non-fixed ERR, reflecting a corresponding t-statistic of -4.9. Interpreted through the lens of models with occasionally binding collateral constraints, the significantly stronger fall in stock prices in the fixed ERR implies a stronger tightening of collateral constraints which in turn exacerbates financial frictions and amplifies the decline in economic activity.

Capital Flows. I now turn my attention to studying the behavior of international capital flows, which can be seen as complementary to the previous analysis of leverage. Figures 9a-10b depict the responses of total net capital outflows and their components: net outflows of foreign direct investment, portfolio investment, and other investment,[14] respectively. All variables are in terms of shares of GDP.

Taken together, the results stress that capital flows out of fixed ERR EMEs in a more significant and persistent manner (a positive response of this variable implies that capital flows out of the

Interestingly, corporate bond debt response differences across the two states were insignificant, suggesting that corporate bond debt issuance does not play a role in driving this paper's results. One reason for this may be that debt covenants are more common and restrictive for bank loans than bond debt, thus rendering the theoretical implications of models with occasionally binding collateral constraints more relevant to bank loans than to bond debt.

[13] Results are similar when stock prices are deflated by the gdp deflator or consumer price index.

[14] 'Other investment' includes loans as well as other forms of cross-border finance such as trade credit, bank deposits, and cash.

economy). The difference between the net capital outflows' response across the fixed the and non-fixed ERRs is significantly positive for a total of 7 horizons. These results are broadly consistent with the previous ones on leverage as they emphasize that global credit supply shocks erode international investors' confidence in domestic assets much more strongly in the fixed ERR.

In terms of the sub-components of the net capital outflows variable, the subsequent figures seem to indicate that the overall stronger net capital outflow in the fixed ERR is driven mainly by a stronger net outflow for foreign direct investment and portfolio investment, where the former appears to be the dominant driver of total net outflows' response.

Foreign Exchange Reserves. How does the central bank respond, it terms of foreign exchange market intervention, to the above-mentioned capital outflows? Conventional wisdom and the mere essence of the definition of a fixed ERR imply that such intervention should be stronger in the fixed ERR.

Figure 11 presents the response of foreign exchange reserves' inflows as a share of GDP. (A negative response of this measure implies a drawing down of reserves.) It is apparent that in the fixed ERR state the monetary authority has a stronger tendency to intervene in the foreign exchange market. I.e., in response to the capital outflow that takes place after global credit supply shocks, the monetary authority in the fixed ERR sells foreign currency to defend the exchange rate to a significantly greater extent than its counterpart in the non-fixed ERR.[15] Accordingly, the t-statistics of the differences between the responses in the two states exceed conventional rejection levels for 4 horizons and are negative for most horizons.

While one may argue that the textbook differential response of foreign exchange reserves is more significant than the one observed from my analysis, it is important to stress that the behavior of the foreign exchange market also seems to be somewhat different from its textbook coun-

[15] Note that we should expect that non-peggers' central banks also intervene in foreign exchange markets, at least to some extent, given that the non-fixed ERR state corresponds to intermediate ERRs and floaters, both of which may also have a tendency to intervene in foreign exchange markets. The latter group in theory should not intervene but may very well be susceptible to the 'fear of floating' phenomena originally documented by Calvo and Reinhart (2002), where EMEs claiming to be floaters are de facto reluctant to let their exchange rates float freely.

terpart in the presence of a capital outflow shock. The most apparent discrepancy is related to the behavior of imports, which fall by much more in the fixed ERR and thus necessitate a weaker differential fall in reserves for stabilizing the exchange rate than otherwise. This stronger imports fall also leads to a more favorable trade balance improvement (see Figure 3 and associated discussion above) which in turn lessens the excess demand for foreign currency resulting from the credit-supply-shock-induced capital outflows. In other words, the global credit supply shock seems to be rather different from a standard capital outflow shock, and this difference also leads to a lesser need by the central bank to intervene in the FX market. But, importantly, it still does so to the extent needed for eliminating any excess-demand-driven exchange rate depreciation, supporting the intervention-based-mechanism emphasized by standard theory.

Country Credit Spreads. The previous results on leverage and stock prices indicate that financial frictions may have role in driving the differential output response across the two ERR states. To further study this financial frictions based channel, I now focus my attention on the role of EMEs' perceived riskiness in driving this paper's results.

Perhaps the most natural empirical proxy for the level of riskiness of EMEs as perceived by international credit market participants is the Emerging Markets Bond Index (EMBI) Global variable, which is computed by JP Morgan and proxies for country credit spreads.[16] I utilize the stripped spread version of the index, which is computed as an arithmetic, market-capitalization-weighted average of bond spreads over U.S. Treasury bonds of comparable duration. Understanding the behavior of this variable across the ERR states in response to global credit supply shocks can shed important light on whether financial frictions may play a role in driving this paper's results.[17]

[16] Data on EMBI is available for 21 countries, where the longest range of the unbalanced panel is 1994:Q1-2016:Q4. More details are provided in Appendix A. I have confirmed that the baseline output-based results are robust to using the smaller EMBI-based sample. These results are presented below in the robustness Section.

[17] As emphasized in Elekda and Tchakarov (2007) and Fernández and Gulan (2015), country credit spreads constitute a suitable proxy for the external finance premium in EMEs. As such, it encapsulates valuable information about the magnitude of financial frictions and their potential dependence on the state of ERR.

The results for logged EMBI appear in Figure 12, showing that spreads rise significantly more in the fixed ERR state. The significantly stronger increase in perceived riskiness is consistent with the stronger deleveraging process and stock price decline already established above. And it is a clear indication that an important interplay between the type of ERR and financial frictions takes place following credit supply shocks, where a fixed ERR exacerbates financial frictions and effectively produces a contractionary balance sheet channel by which global credit supply shocks get amplified. Importantly, interpreted though the lens of models of the likes of Fornaro (2015) and Devereux and Yu (2017), the results presented so far imply that the balance sheet channel of exchange rate depreciation is indeed expansionary rather than contractionary as commonly thought.

Disentanglement of the Expenditure-Switching and Balance Sheet Channels. An important question that rises in light of the results presented so far is the following: can the roles of the expenditure-switching and balance sheet channels in driving my results be disentangled? More specifically, do exports fall more in the fixed ERR because of worsening balance sheet conditions or, rather, the expenditure-switching channel causes this greater fall which in turn then produces also a contractionary balance sheet channel in the fixed ERR that further exacerbates the fall in economic activity.

To shed light on what the data has to say about this question, I turn attention to the timing of the responses of country credit spreads and exports. While the differential response of the former starts to become significant only after a year, that of exports begins one quarter prior to that and actually peaks in absolute terms already in that quarter; on top of that, the differential EMBI response peaks only after two years. These timing differences seem to indicate that an expenditure-switching channel is initially dominant, moderating the fall in exports in the non-fixed ERR and in turn setting the stage for a less acute financial-accelerator-induced fall in economic activity. Although it is quite hard in general to disentangle any pair of endogenous transmission channels with a reduced-form type of analysis such as the one pursued here, using the above-mentioned timing information for my specific set of results and setting proves to shed valuable structural light on what my results imply for the role of each channel. Overall, the evidence is consistent with two main channels operating following the shock, i.e., expenditure-switching and balance sheet channels, where the former seems to lead the latter.

An additional potential channel that can contribute to the absolute exports decline and therefore potentially also the relatively stronger decline in the fixed ERR is the mechanism emphasized in Alessandria et al. (2013), where an increase in the interest rate lower exports due to adversely altering how the future benefits of exporting are discounted.[18] In my setting, the higher EMBI observed in the fixed ERR may contribute to the greater fall in exports that takes place earlier on as potential exporters' may foresee this future relative EMBI rise and thus be further disincentivized to export. However, notably, this mechanism is likely to be somewhat limited owing to the somewhat temporary nature of the differential EMBI response (which dies out after 10 quarters), especially if potential exporters' decisions are based on long-term horizon planning (as is the case in the model in Alessandria et al. (2013), where they effectively solve an infinite-horizon optimization problem). Even so, this mechanism is definitely worth highlighting in the context of my analysis as a potential amplifier of the differential responses I find in the data.

The timing-based argument used above to better understand the mechanisms driving the exports differential response can also be applied to inform us about what is driving the differential leverage response. Specifically, one may argue that the leverage differential response can stem from both higher interest rates as well as exchange-rate-induced balanced sheet effects, in which case it would be hard to pin down the exact mechanism at hand driving this response. In the case of leverage, it is apparent that it falls by significantly more in the fixed ERR for 4 periods through the 6-quarter mark and then even more strongly so from the 9th period onwards. The dynamics of the EMBI response is informative for the mechanisms driving the dynamics of the deleveraging process, much like it is for exports behavior. Since credit spreads' differential response becomes significant only after a year and peaks only after two years, whereas the exchange rate differential

[18] In the model from Alessandria et al. (2013) this negative relation between exports and interest rates is amplified by the sunk aspect of export costs which implies that the costs of expanding the stock of exporters are front-loaded while future export profits are back-loaded.

response is significant from the impact horizon onwards, it seems fair to argue that the spike in spreads is likely due to the aforementioned leading exchange rate behavior which mainly drives deleveraging in the short-run whereas spreads' differential rise has a likely more important role in driving the subsequent enhanced deleveraging process.[19] In other words, it seems that much of what takes place early on in terms of the leverage response is likely to be driven by differential exchange rate fluctuations whereas in the periods after that the exacerbation of financial frictions plays a more dominant role.

Monetary Policy: An Additional Potential Mechanism? The results presented so far suggest that financial frictions seem to play a role in driving the different output responses across the two ERR states. E.g., interpreted through the lens of models with occasionally binding collateral constraints, this paper's results imply that global credit supply shocks make credit constraints tighter in the fixed ERR than in the non-fixed ERR owing to the favorable implications of the currency depreciation for economic activity in the latter state; this, in turn, produces a much more acute deleveraging process in the fixed ERR that exacerbates the fall in economic activity in this state. Notwithstanding the aforementioned, potentially important role of financial frictions, it is also important to look at another potential, theoretically sound mechanism which may also play a role in driving this paper's results: the monetary policy response to global credit supply shocks.

The way by which monetary policy responds to global credit supply shocks can affect the severity of their effects. E.g., one may argue that global credit supply shocks have more adverse effects on EMEs with fixed ERRs in part because they are forced to keep rates relatively higher in order to defend their peg (see, e.g., Lahiri and Vgh (2007)). To examine this reasoning, I estimate Specification (1) when using the log of the central bank policy rate as the outcome variable. These results are shown in Figure 13.

[19] If interest rates (as encapsulated in EMBI) hiked more so in the fixed ERR on impact or even during the first year, it would be more difficult to make this timing-based argument. But their lagging nature and the exchange rate's leading nature conditional on the credit supply shock support the view that the stronger hike in spreads likely reflects an endogenous response to the differential exchange rate response, which in turn further contributes to the strong differential fall in leverage in the fixed ERR.

There are no significant differences in the way that monetary policy responds to credit supply shocks across the two ERRs except for the last two horizons at which rates are significantly higher in the fixed ERR. Overall, rates seem to go down at business cycle frequencies in the non-fixed ERR while largely moving insignificantly in the fixed ERR. That rates are largely unchanged in the fixed ERR may be an indication that peggers' central banks ultimate interest rate decisions reflect two opposing forces: one the one hand, they aspire to defend their peg by raising the interest rate; on the other hand, they desire to reduce interest rates to alleviate the economic downturn. But the fact that there is no significant difference between the two states for all horizons but the last two in terms of the ultimate interest rate response is what should be the main takeaway from Figure 13, indicating that monetary policy does not seem to play an important role in driving the results of this paper.

Including Higher Categories in the Fixed ERR Measure. As already explained above, much of the merit of my choice of ERR as being based on categories 1-4 from the IRR classification is the stability of the exchange rate conditional on a global credit supply shock, which contrasts the significant depreciation that takes place for the JS and LYS ERR measures. However, one may still argue that including less fixed categories in the fixed ERR measure is advisable if the latter stability and the relatively greater depreciation in the accordingly adjusted non-fixed ERR state are maintained.

To test this argument and, more generally, to check the implications of increasing the fixed ERR sample by considering additional IRR classification categories, I have estimated the baseline model under three alternative assumptions regarding which categories from the Ilzetzki et al. (2017) classification the fixed ERR corresponds to: *i*) categories 1-6, which add pre-announced crawling pegs and pre-announced narrow bands to the baseline definition of a fixed ERR; *ii*) categories 1-7, where category 7 covers de facto crawling peg; and *iii*) categories 1-8, where category 8 covers de facto narrow crawling bands. The results from these 3 estimations appear in the first row of Figure 14, showing the t-statistics of the differential output response; the second row presents the exchange rate response for categories 5-6, category 7, and category 8.[20]

The results indicate that there are strongly significant differences between the output response for categories 1-6 relative to categories 7-13, with output falling by much more for the former. By contrast, differences for categories 1-7 and 1-8 with respect to their respective complementary categories, albeit mostly negative and even significant at 3 horizons for the 1-7 categories specification and for 2 horizons for the 1-8 categories specification, are far less strong than the baseline and categories 1-6 cases and do not appear powerful enough for drawing statistically conclusive inference (particularly the categories 1-8 specification).

The results on the exchange rate response shed important light on why one need be cautious when grouping together categories 7 and 8 with lower, more fixed categories: the exchange rate depreciates significantly for both these categories (for all horizons for the former and for 13 horizons for the latter), indicating that they fail a basic litmus test of qualifying as a fixed ERR for the purposes of my analysis, i.e., encompassing a stable exchange rate conditional on a global credit supply shock. The exchange rate for categories 5-6 exhibits a largely insignificant response to the global credit supply shock, except for horizons 12, 13, and 15 for which there is a marginally significant nominal appreciation; nevertheless, categories 5-6 still do much better on the aforementioned litmus test than categories 7 and 8, even if not as good as the baseline categories 1-4.

2.4 Comparison to Results from Using the Shambaugh (2004) and Levy-Yeyati and Sturzenegger (2001, 2003, 2005) ERR Measures

An important asset of my empirical approach is its use of the most recent, updated Reinhart and Rogoff (2004) ERR measure from Ilzetzki et al. (2017), which classifies ERRs according to the variability of market-determined parallel exchange rates over rolling two- or five-year horizons and is available at a monthly frequency.[21]

[20] I look at both categories 5 and 6 jointly because category 6 has an insufficient number of observations to be looked at separately. Categories 5-6 correspond to a total of 147 observations; category 7 corresponds to 471 observations; and category 8 corresponds to 708 observations.

[21] When a parallel exchange rate deviates substantially from the official rate, movements in the parallel rate, rather than the official rate, are used to gauge the flexibility of the regime as they are better proxies for

Two other prominent ERR measures are the annual Shambaugh (2004) (JS) measure (available through 2014),[22] and the annual Levy-Yeyati and Sturzenegger (2001, 2003, 2005) (LYS) measure, as updated by Levy-Yeyati and Sturzenegger (2016) through 2013 and taken From Eduardo Levy-Yeyati's website. The JS measure focuses exclusively on the volatility of the exchange rate and divides countries into pegs and non-pegs, where the former are classified as such if their official exchange rate remains within a 2% band with respect to its base country.[23] The LYS measure uses cluster analysis to group countries according to the relative volatility of exchange rates and reserves; I identify fixed ERR observations in line with the grouping of Levy-Yeyati and Sturzenegger (2001, 2003, 2005), who divide the observations into fixed, intermediate, and flexible regimes. I transform the JS and LYS measures to quarterly frequency by assuming within-year identical values.[24]

The disagreement between the IRR, JS, and LYS measures is well documented (see, e.g., Klein and Shambaugh (2012)). My sample is no exception in this regard. The proportions of pegged observations in agreement between the IRR measure and the JS and LYS measures for my sample are 36% and 33%, respectively.[25] These rather low agreement rates stress the empirical difficulty facing a researcher of ascertaining the actual exchange rate regime of a country, let alone the macroeconomic implications of different ERR types, as emphasized by Rose (2011). That said, I take a different approach to establishing the superiority of the IRR measure for the type of question I am

the true flexibility or lack thereof of the ERR. When there is no parallel market for exchange rates, the official exchange rate is used for determining ERR flexibility. For my sample of EMEs, the Ilzetzki et al. (2017) exchange rate data indicates that over 20% of the observations correspond to parallel market exchange rate premiums; specifically, except for Argentina, Bolivia, Egypt, Iran, and Lithuania for which premiums exist through 2015:M8, 2002:M12, 2002:M12, 2002:M2, and 2014:M12, respectively, and for Armenia, Croatia, Macedonia, Moldova, and Serbia for which there are no premiums at all, all countries' premiums go through 1998:M12.

[22]This updated dataset is available from the NBER data sources catalogue website, whose link is http://www.nber.org/data/international-finance/#err.

[23]In addition, to prevent breaks in the peg status due to one-time realignments, Shambaugh (2004) classifies as fixed any exchange rate that had a zero percentage change in eleven out of twelve months in a given year.

[24] Note that this frequency conversion makes it is necessary to include the dummy variables associated with these ERR measures in the regressions with four lags so as to avoid correlation of the error term with it.

[25]The agreement rate between the JS and LYS measures is 46%.

trying to answer in this paper based on the following reasoning. A natural litmus test of fixed ERRs is their fixity *conditional* on a shock that in theory (and in the data) conclusively and significantly moves exchange rates in non-fixed ERRs. Figure 5a has already established that the IRR measure passes this test and is therefore a suitable ERR measure for studying the relation between global credit supply shocks and ERRs. I now turn to looking at how the JS and LYS measures do on this test.

Figures 15a and 15b present the output and nominal exchange rate responses for the JS measure whereas 16a and 16b show the counterpart responses for the LYS measure. It is rather encouraging that the t-statistics for the output response differences across the two ERR states are significant for all horizons for the JS measure and for 6 horizons for the LYS measure, indicating that output falls significantly more in the fixed ERR for these two ERR measures as well. Notwithstanding these encouraging results, I now turn to looking at the exchange rate responses in the fixed ERR to establish the superiority of the IRR ERR measure for the purposes of this paper relative to the JS and LYS ERR measures.

Despite the fact that the exchange rate depreciates by significantly more in the non-fixed ERR for 6 quarters for both the JS and LYS measures, it is apparent that for both measures the nominal exchange rate exhibits a significant and rather persistent depreciation. Specifically, there is significant depreciation for the JS measure for 13 horizons and for 6 horizons there is even more depreciation (point estimate wise) in the fixed ERR than in the non-fixed ERR; for the LYS measure, significant depreciation in the fixed ERR takes place for 12 horizons. Since the global credit crunch of 2008-2009 is characterized by a series of adverse global credit supply shock whose sum exceeds 14 EBP shock standard deviations, the significant depreciation observed for these two fixed ERR measures implies that a global financial crisis of the kind observed in 2008-2009 produces a depreciation rate for a fixed ERR country's nominal exchange rate vis-à-vis its anchor currency that can exceed 30%.

Therefore, I view the exchange rate behavior in the fixed JS and LYS ERRs as evidence that these measures are inferior to the IRR measure for the purposes of what I try to do in this paper.

How can one have satisfactory trust in output results that are based on an ERR measure whose fixed ERR, conditional on a global credit supply shock, results in such large currency depreciation? Clearly, this type of conditional behavior indicates that such an ERR measure is an insufficiently adequate proxy for measuring a fixed ERR conditional on this shock. By contrast, the stable conditional behavior of the exchange rate for the IRR measure suggests that it is a sufficiently adequate ERR measure and one that is superior to the JS and LYS measures for my purposes.

3 Robustness Checks

This section examines the robustness of the baseline results along three main dimensions: controlling for various other states; considering alternative model specifications, including estimating a continuous specification and a random effects model as well as using alternative detrending techniques; and considering different lag specifications and sub-samples. In all checks I consider output as the outcome variable; to save space, I only present the relevant t-statistics.

3.1 Controlling for Other Potentially Important States

One may argue that the ERR is an endogenous state variable that is potentially related to other state variables. If this is the case, then a relevant concern is that my baseline results could be biased by omission of these other states and not controlling for the transmission channels induced by them, channels that are separate from the ERR-induced expenditure-switching and balance sheet channels. To alleviate this concern, I proceed by providing both unconditional and conditional evidence that other such states are unlikely to be driving this paper's results, where the states I focus on are the level of economic development, capital inflow and outflow controls, and trade exposure to U.S.

I base the unconditional evidence on simple correlations of the other considered states with the fixed ERR (presented in Table 2, and to be discussed below separately for each state),[26] while the

[26] I only show correlations with the fixed ERR and not also the non-fixed ERR state because the latter is a

conditional evidence is obtained from estimating 4 extended specifications, each corresponding to controlling for each other state, given by

$$
\begin{aligned}
y_{i,t+h} - y_{i,t-1} = I_{i,t-1}[\alpha_{A,i,h} + \Xi_{A,h}EBP_t + \Omega_{A,h}(L)EBP_{t-1} + \Gamma_{A,h}(L)\Delta y_{i,t-1}]+ \\
+(1 - I_{i,t-1})[\alpha_{B,i,h} + \Xi_{B,h}EBP_t + \Omega_{B,h}(L)EBP_{t-1} + \Gamma_{B,h}(L)\Delta y_{i,t-1}]+ \\
+I^C_{i,t-4}[\alpha_{C,i,h} + \Xi_{C,h}EBP_t + \Omega_{C,h}(L)EBP_{t-1} + \Gamma_{C,h}(L)\Delta y_{i,t-1}]+ \\
+I^D_{i,t-4}[\alpha_{D,i,h} + \Xi_{D,h}EBP_t + \Omega_{D,h}(L)EBP_{t-1} + \Gamma_{D,h}(L)\Delta y_{i,t-1}] + u_{i,t+h}.
\end{aligned}
\tag{3}
$$

Effectively, relative to the baseline specification, I add two additional state variables to the estimation: one state dummy (I^C) that obtains the value of 1 if an observation corresponds to an EME whose level of the considered state variable is at or above the upper quartile of the distribution for the EMEs in my sample and another (I^D) that obtains 1 if it corresponds to an EME whose level of the considered state variable is at or below the lower quartile of the distribution. By controlling for these two states I am effectively controlling for the effects of both relatively higher values of the considered states' distribution as well as relatively lower values of its distribution.[27]

Also noteworthy is the lagging of $I^C_{i,t-4}$ and $I^D_{i,t-4}$ by 4 lags rather than 1. This is due to the fact that three of the considered states are available only in annual frequency and are converted to quarterly frequency assuming within-year constancy of quarterly values, thus necessitating entering these three states with 4 lags in the regressions so as to avoid a correlation between them and the error term (also see Footnote 27 for a similar explanation in relation to the JS and LYS ERR measures). The fourth considered state, trade exposure to the U.S., is available in quarterly frequency and therefore enters the regressions with one lag. I now turn to providing details on each

perfect complement of the former by definition, thus resulting in merely a change in sign of the correlations of the other states with these two ERR measures.

[27]Note that controlling for the entire state distribution by including a particular dummy along with its perfect complement is impossible as it renders perfect colinearity in the regression. The reason for this lies in the fact that I already have perfectly complementary states from the inclusion of the pair of ERR dummies. For the purposes of this specific robustness check, it is arguably preferable to control for the more acute ends of each considered state's distribution so as to ensure that the baseline results are not driven by observations corresponding to *high* and *low* levels of these states. Notwithstanding this point, I have confirmed that results are robust to controlling for alternative percentile thresholds.

of the considered states, their correlations with the baseline ERR measure, and their associated specifications' results.

Economic Development. A-priori, it seems important to control for the level of economic development in the regressions because of at least two potential channels by which economic development can alter an economy's sensitivity to global credit supply shocks: First, more developed EMEs may have better monetary and fiscal policies, and better institutions in general, which in turn can act as potentially important shock absorbers; and, second, although less developed EMEs have less sound institutions which limits their shock-absorbing capacity, they are likely to have less financial depth which is likely to moderate their response to global credit supply shocks. As these two channels counteract one another, it is unclear which should dominate. Either way, it is potentially important to control for these effects so as to ensure that the identification strategy only picks up ERR driven effects. (This is especially relevant given that there is non-negligible variation along the economic development dimension in my sample, e.g., Latvia on the poor end and Korea on the relatively rich end.)

Toward this end, I measure economic development as the standardized values of PPP-adjusted per capita GDP for my sample of EMEs, where the standardization works as follows: each observation's value of PPP-adjusted per capita GDP is standardized with respect to its corresponding cross-sectional mean and standard deviation. This way a meaningful, stationary distribution of economic development is obtained. The high economic development state is accordingly measured as a dummy that obtains 1 if the corresponding observation is at or above the upper quartile of the distribution of standardized values of PPP-adjusted per capital GDP for the EMEs in my sample and the low economic development state is measured as a dummy that obtains 1 if it corresponds to an EME whose standardized value of economic development is at or below the lower quartile of the distribution. As seen from the first element of Table 2, whose first and second values in squared brackets represent the correlations between the fixed ERR dummy and the dummies corresponding to being in the high and low economic development states, respectively, there is a rather weak unconditional link between fixed ERR and economic development. The low correlations of -0.08 and 0.05 do not seem to imply a meaningful relation between these two states. I now turn to presenting conditional evidence that supports the aforementioned unconditional evidence.

The results from estimation of Specification (3) for the case of controlling for economic development are summarized in the first sub-figure of Figure 17, which shows the t-statistics associated with the difference between the output responses in the fixed ERR and non-fixed ERR. The results clearly illustrate that the baseline results of this paper are robust to controlling for economic development. The differences between the output responses across the two ERR states continue to be highly significant, with output falling much more strongly in the fixed ERR. Taken together, both the unconditional and the conditional evidence presented in this section support the assertion that economic development is unlikely to be driving this paper's results.

Capital Inflow and Outflow Controls. Controlling for the non-linear effects arising from the level of capital controls is also potentially important as it would ensure that the estimated differences between being in a fixed and non-fixed ERR state are not contaminated by being in a state of strict or light controls. From a theoretical standpoint, based on the well known '*trilemma*', we should expect a positive relation between capital controls and ERR fixity conditioned on having independent monetary policy. In the data, however, this does not seem to hold as correlations between the fixed ERR and strict and light inflow and outflow controls are quite negligible. (The strict inflow/outflow controls measure is defined as a dummy corresponding to a capital inflow/outflow controls level that is at or above the upper quartile of the Fernández et al. (2015) capital inflow/outflow controls measure and the light capital inflow/outflow controls measure is defined as a dummy corresponding to values lying within the lower quartile of the corresponding distributions.)[28,29]

To augment the unconditional evidence reported above with conditional evidence, I estimate Specification (3) separately for the case of controlling for capital inflow controls and for the one

[28] I have also confirmed that results are robust to using the outflow and total control measures as well to using alternative control percentiles to the 75%-25% percentiles choice.

[29] Details on the Fernández et al. (2015) capital inflow controls measure are included in Appendix A.

where capital outflow controls are controlled for. The results from these estimation exercises appear in the second and third sub-figures of Figure 17. It is apparent that the main results of this paper are robust to controlling for both capital inflow and outflow controls as the fixed ERR continues to be associated with much more adverse output declines.

Trade Exposure to U.S. Given that the EBP shock is ultimately a U.S.-originating shock, one may argue that a foreign aggregate demand channel could be partly driving my baseline results. The crux of this argument lies in the following assertion: there is a differential trade exposure of fixed ERR EMEs and non-fixed ones to the U.S. where the former are more exposed than the latter, and this in turn could potentially invalidate my structural interpretation of the results as this omitted foreign demand channel partly drives the observed differential output response.

To alleviate this concern, I now show both unconditional and conditional evidence negating any meaningful role of a foreign aggregate demand channel in driving this paper's results. To measure each EME's trade exposure to the U.S., I use the ratio of exports to U.S. to GDP and define a state of high exposure as a dummy variable corresponding to being at or above the upper quartile of the distribution of U.S. trade exposure and a state of low exposure as a dummy variable corresponding to being at or below the lower quartile of the distribution. As the fourth element of Table 2 demonstrates, being in a fixed ERR is completely disassociated with being in a state of high trade exposure to the U.S. and is actually positively associated with being in a state of low exposure to the U.S. I.e., if anything, the foreign demand channel is potentially causing a downward bias in my estimated output response differences, albeit a rather limited bias given that the correlation between the two states is quite modest at 0.18.

The fourth sub-figure of Figure 17 presents the results from estimating Specification (3) now including the U.S. trade exposure dummies as the other considered states. Notably, the associated t-statistics from this estimation continue to point to a much stronger fall in output in the fixed ERR, supporting the notion that the foreign aggregate demand channel is unlikely to be playing a meaningful role in driving this paper's results. Taken together, the evidence of this section goes a long way toward establishing the central role of the expenditure-switching and balance sheet channels as the two main channels driving this paper's results.

3.2 Continuous Specification, Random Coefficients Model, and Alternative Detrending Filters

This section presents results from various alternative model specifications and detrending filters that further reinforce the reliability of the baseline results.

3.2.1 Continuous Specification

The baseline specification I use in this paper is dummy-based, making a binary division between the fixed ERR and non-fixed ERR states. An alternative specification to consider is one that defines ERR continuously rather than binarily. It is my view that the main advantage of the binary ERR based specification over a continuous specification à la Iacoviello and Navarro (2018), where ERR and the other considered states there are treated in a continuous manner, is that the former is more consistent with the traditional binary view of the fixed vs non-fixed ERR dichotomy. This view is based on the notion that, while fixed ERRs are well defined monetary regimes, non-fixed ERRs are less well defined and can take various forms (see, e.g., Rose (2011)). It is therefore appealing to use a binary regime based specification, which exploits the clear definition of what a fixed ERR constitutes and delivers clearly interpretable results regarding the implications of being in that well defined regime relative to its complementary regime. Also noteworthy is that the alternative, which is to treat ERR as a continuous variable, seems to be less consistent with theory, which normally models ERRs in binary terms (as in, e.g., Gali and Monacelli (2005) and Schmitt-Grohé and Uribe (2016)).

That said, the main drawback of the binary regime based specification is its somewhat lack of flexibility owing to degrees of freedom related issues. E.g., interacting the ERR state with other states or jointly controlling for all other states in the same regression is effectively infeasible because of the smaller number of observations belonging to the fixed ERR.[30] To address this issue

[30] E.g., the number of observations common to both the fixed ERR and the 75th and 25th percentiles of

I therefore estimate a continuous, extended specification that allows for both accounting for all other states' effects as well as interactions between ERR and the other states, which is given by

$$
\begin{aligned}
y_{i,t+h} - y_{i,t-1} = \alpha_{i,h} + \Xi_h EBP_t + \Omega_h(L)EBP_{t-1} + \Gamma_h(L)\Delta y_{i,t-1} + \\
+ERR_{i,t-1}[\Xi_{ERR,h}EBP_t + \Omega_{ERR,h}(L)EBP_{t-1}] + \sum_{j=1}^{j=4} S^j_{i,t-p_j}[\Xi_{S^j,h}EBP_t + \Omega_{S^j,h}(L)EBP_{t-1}] + \\
+\sum_{j=1}^{j=4} ERR_{i,t-1}S^j_{i,t-p_i}[\Xi_{ERR^j,h}EBP_t + \Omega_{ERR^j,h}(L)EBP_{t-1}] + u_{i,t+h},
\end{aligned}
\tag{4}
$$

where ERR is the ERR variable itself and S^j is the variable corresponding to state j, where $j = 1, 2, 3, 4$ corresponds to the economic development, capital inflow controls, capital outflow controls, and U.S. trade exposure states, respectively; and p_j equal 4 for $j = 1, 2, 3$ and 1 for $j = 4$ to account for the annual frequency of the first three states (see also discussion above from Section 3.1). I use the scaling employed in Iacoviello and Navarro (2018), where I first standardize each state variable, then apply a logistic transformation to it, and finally subtract its median value from it and divide the result by the difference between the 95th percentile and median values. For the ERR variable, e.g., this scaling implies that a one unit change in the scaled ERR variable represents a shift from a median ERR (8 in the raw IRR ERR classification, which can be interpreted as an intermediate ERR) to the 95th percentile of the ERR distribution, which is represented by category 2 in the IRR ERR classification (i.e., a pegged regime). (Note that, for interpretation purposes, I multiply the ERR variable by -1 prior to the scaling described above so that increases in it correspond to the ERR being more fixed.) I have confirmed that my pooled OLS, fixed-effects panel estimation approach ensures orthogonality between all interaction terms, in equivalence with the regression by successive (Gram-Schmidt) orthogonalization approach taken by Iacoviello and Navarro (2018). Finally, the coefficient of interest is now $\Xi_{ERR,h}$ which measures the additional effect of global credit supply shocks that a higher level of ERR (where higher implies more fixed) induces

the capital inflows controls index are 74 and 52, respectively; the corresponding numbers for the outflow controls index are 107 and 63, respectively.

relative to the average, or main, effect.

The fifth sub-figure of Figure 17 presents the t-statistics of $\Xi_{ERR,h}$. Importantly, results from this specification indicate that moving to a more fixed ERR results in a significantly greater fall in output, stressing that my baseline results are unlikely to be driven by omitted states or by not accounting for possible varying effects of ERR on the output response to credit supply shocks as a function of other states' levels.

3.2.2 Random Coefficients Model

Another alternative specification wroth considering in my analysis is the random coefficients model from di Giovanni and Shambaugh (2008), which in its general form allows for full heterogeneity in countries' responses to a particular shock and then examines how these responses relate to countries' time-invariant structural characteristics (e.g., the share of time a country spends in a fixed ERR).

Prior to presenting results from estimating such a model for my setting, I elucidate why I view my baseline specification as advantageous relative to the random coefficients model. First, from a statistical standpoint, there does not seem to be support for rejecting the ERR-state-homogenous specification I have opted for in my baseline analysis. Specifically, I conducted a Chow-test to test the validity of the null hypothesis that coefficients within the ERRs are equal with the alternative being allowing all country-specific coefficients to vary. The results of this test indicated that the sum-of-squared-residuals from the constrained, ERR-state-homogeneous specification is only moderately higher than the one from the unconstrained, fully heterogenous specifications, resulting in negligible and insignificant F-statistics. (The average percentage decline in the sum-of-squared-residuals across the different horizon-based regressions ($h = 0, 1, \ldots, 16$) from moving to the unconstrained specification from the constrained one is 4.9%, peaking at 10.2% for the one-year-ahead rolling regression. This implies a fairly modest (and statistically insignificant) increase in fit resulting from relaxing the restriction that coefficients be equal within the ERR state.)

Second, one can make the case that my baseline specification is consistent with theory (more precisely, with the true data generating process which is the outcome of some true model) both in absolute terms and also in relative terms with respect to the random coefficients model. This advantage results from two aspects of my baseline specification: *i*) the theory-consistent binary regime based specification applied to my baseline setting (as already discussed above in the context of the continuous specification) and *ii*) my treatment of ERR in a dynamic, time-variant manner.

By contrast, while having much value for environments where the state-dependence is time-invariant, the random coefficients model does not cleanly fit the binary-regime-based data generating process because it effectively assumes that a country's ERR can be summarily and accurately measured from the share of time a country is in a fixed ERR. Only if countries in my sample did not change ERRs at all, would the random coefficients model be suitable for mimicking the binary ERR based true data generating process. But, since this is not the case, a bias may result from this attempt to measure ERR in a time-invariant way owing to the imprecision from avoiding to use the time-variant nature of ERRs. (Of the 18 countries which correspond to the fixed ERR, only 3 have had a fixed ERR for the entirety of the sample period. I.e., there is ample information relevant for precisely measuring the fixed ERR that is not utilized in the random coefficients framework.) My baseline specification circumvents this issue by separating observations in a dynamic, time-variant way that goes beyond the country-specific-based division inherent in the random coefficients model.

Notwithstanding the above discussion on the arguably superior nature of the binary-regime time-variant specification, there is still much merit in confirming that this paper's results are robust to estimating a random coefficients model. Toward this end, I apply the modeling framework used in di Giovanni and Shambaugh (2008) to my setting, resulting in the following random coefficient model:

$$y_{i,t+h} - y_{i,t-1} = \alpha_{i,h} + \Xi_{i,h} EBP_t + \Omega_{i,h}(L) EBP_{t-1} + \Gamma_{i,h}(L) \Delta y_{i,t-1} + u_{i,t+h}, \tag{5}$$

$$\Xi_{i,h} = \gamma_h Z_{i,h} + \epsilon_{i,h}, \tag{6}$$

where now the response of output to the credit supply shock, $\Xi_{i,h}$, is a linear function (governed by parameter γ) of the share of time a country has spent in a fixed ERR, $Z_{i,h}$, and an independently and homoscedastically distributed error term, $\epsilon_{i,h}$. Combined together, these two equation yield

$$y_{i,t+h} - y_{i,t-1} = \alpha_{i,h} + \gamma_h Z_{i,h} EBP_t + \Omega_{i,h}(L) EBP_{t-1} + \Gamma_{i,h}(L)\Delta y_{i,t-1} + u_{i,t+h}. \tag{7}$$

The coefficient of interest is γ_h. I follow di Giovanni and Shambaugh (2008) in estimating it via a two-step Feasible Generalized Least Squares (FGLS) estimation technique: in the first stage I estimate Equation (5), regress the resulting $\Xi_{i,h}$ on $Z_{i,h}$ and collect the sum of the error covariance-variance matrices from these two estimations; then, in the second stage, I use this summed error covariance matrix as the weighting matrix in a FGLS estimation of Equation (7). The results from this estimation exercise appear in the sixth sub-figure of Figure 17. It is apparent that the t-statistics are strongly significant, confirming that my baseline results are robust to using the random coefficients model specification.

3.2.3 Alternative Detrending Filters

As explained at the end of Section 2.1, I detrend the trending variables in my data by fitting to them a third-order polynomial time trend prior to estimation. The objective of this procedure is to extract the cyclical component of the series which is taken to be the residual of the latter cubic polynomial time trend regression. My choice of using a cubic time trend is consistent with standard wald tests which suggest that the trending data contain both second- and third-order time trend terms in addition to the first order term. E.g., Wald tests (adjusted for robust HAC standard errors) for the null that cumulative growth rates of output at business cycle frequencies (e.g., two-year growth rates) have no linear trend and no quadratic trend were strongly rejected for all but two output series in my sample (the exceptions being South Africa and Thailand); and for nearly 70% of these cumulative growth rate series the quadratic trend term was individually significant, rendering it advisable to assume a log-cubic trend representation for logged output which can be consistently estimated using OLS for extracting the cyclical component of logged output.[31]

Nevertheless, there are other alternatives for extracting the cyclical component of trending data whose deterministic trend is not a simple log-linear trend but rather a higher-order polynomial time trend. I consider three such alternative. First, the standard HP-filer. Second, the detrending procedure proposed by Hamilton (2018). And third, a log-quadratic time trend polynomial instead of the baseline log-cubic trend polynomial.[32]

HP-Filter. A recent paper by Hamilton (2018) advises against using the HP filter, arguably the most popular detrending tool used in macro, on the grounds that its cyclical component has a tendency to be characterized by spurious behavior. This point is also demonstrated by Phillips and Jin (2015), who develop a limit theory for the HP-filter for various classes of stochastic and deterministic trends. Nevertheless, Sakarya and de Jong (2017) show that the HP-filer can at least asymptotically extract the cyclical component of trend polynomials of less than order 4. Overall, while recent work does suggest taking caution in choosing the HP-filer as a detrending method, it still seems worthwhile to examine the robustness of my results to estimating a specification in which the log of output is detrended using the HP filter prior to taking its differences.

Results from this exercise appear in the seventh sub-figure of Figure 17. It is apparent that t-statistics continue to be highly significant with output falling by much more in the fixed ERR. This suggests that the main result regarding the shock-amplifying nature of fixed ERRs is robust to HP-filtering the output data instead of using a cubic trend polynomial.

Detrending Method from Hamilton (2018). Hamilton (2018) argues against using the HP-filer and proposes an alternative detrending method which regresses the variable at date $t+h$ on the four most recent values as of date t, where the residual from this regression is taken to be the

[31] This amounts to estimating the following equation for logged output (y_t), $y_t = a + bt + ct^2 + dt^3 + \varepsilon_t$, and taking ε_t to be the corresponding cyclical component of the series.

[32] While results remain significant also when a simple log-linear detrending filter is applied, the bias from doing this can be material given the significance of the higher order trend terms prevalent in the data. Specifically, not accounting for these higher order trend terms results in a misspecified model where part of the estimated effects are likely driven by higher order deterministic trends taking place in the sample's EMEs.

estimated cyclical component of the variable. Hamilton (2018) makes the case that, in contrast to the HP-filter, this detrending method does not suffer from the drawback of having spuriousness in its cyclical component. However, a recent paper by Schuler (2018) provides theoretical and empirical insights on the attributes of the Hamilton (2018) filter, arguing that although not subject to the exact same drawbacks as the HP filter, Hamilton's filter still modifies the original cyclical structure of economic time series and its performance naturally depends on the choice of h.

Nevertheless, I view as important checking that using Hamilton's regression filter in my estimations yields similar results given that it is an additional dimension along which to further enhance my results' reliability. Toward this end, I choose $h = 16$, which means that my cyclical component is obtained from regressing 4-year-ahead logged output on current and three lags of logged output. This cyclical component can be thought of as output variation caused by shock components that do not persist longer than h periods. One may argue that taking a longer h is sensible for my setting as credit supply shocks may have rather persistent effect on output but I make a compromise here between this issue and avoiding losing too many observations in the estimation done after detrending the data.

Results from this exercise appear in the eighth sub-figure of Figure 17. Importantly, output continues to fall by significantly more in the fixed ERR, further increasing confidence in the robustness of my results to filtering the data differently from the baseline procedure.

Log-Quadratic Detrending. While, as discussed above, my output data exhibits a rather clear and significant log-cubic trend component in addition to a significant log-quadratic trend component, it is still important to ensure that my results are insensitive to lowering the trend polynomial's order by one and consider a log-quadratic trend polynomial. This second-order trend polynomial detrending is quite common for extracting the cyclical component of macro data (see, e.g., Uribe and Schmitt-Grohé (2017)). Results from log-quadratic detrending are shown in the last sub-figure of Figure 17, indicating that output response differences from log-quadratic detrending are very similar to those from log-cubic detrending.

3.3 Number of Lags and Various Sub-Samples

As explained in Section 2.2, since the Ilzetzki et al. (2017) classification procedure looks at exchange rate variability at rolling two- or five-year windows, it is important to include a relatively large number of lags in my estimations so as to purge the ERR dummy variable of any potentially endogenous sources. In this section I confirm that specifying a different (both smaller and larger) number of lags has no significant bearing on the baseline results. Moreover, I also consider in this section the robustness of my results to various sub-samples: sample covered by the EMBI variable; sample that excludes the BRIC economies (Brazil, Russia, India, and China); 2000-2016 sample; only Dollar-anchoring countries sample; and a sample that only includes observations corresponding to a constant ERR.

The first sample is useful to consider to ensure that the baseline results hold also when using the sample that corresponds to that covered by the EMBI variable. The merit of examining the second sample lies in the fact that most of the theoretical literature on the role of fixed ERRs in amplifying adverse shocks employs a small open economy framework. The BRIC economies constitute the largest EMEs in my sample and, more generally, have the potential of violating the small open economy assumption. It is thus important to confirm that these relatively large economies are not driving the baseline results. The 2000-2016 sample is worthwhile considering because the leverage variable used in this paper only starts in 2000; hence, confirming that the baseline results for output carry over to this shorter sample is valuable. The only Dollar-anchoring sample is useful to consider for ensuring that my results are not driven by potential differences between Euro-anchoring and Dollar-anchoring economies (there are 11 Euro-anchoring countries in my sample). Lastly, one may argue that including observations where a shift in the ERR has taken place could bias the results if this shift were endogenous; it is theretofore advisable to confirm the robustness of the results to excluding such observations.[33]

[33] Note, however, that this last robustness check necessitates removing 15 countries from the sample, leaving me with only 3 fixed ERR countries and merely 233 fixed ERR observations. Nevertheless, it is still encouraging that results for this much reduced fixed ERR sample (shown in the last sub-figure of Figure 18) survive in terms of there still being a significantly stronger drop in output in the fixed ERR.

Figure 18 presents the t-statistics associated with the various lag and sub-sample specifications discussed above. First, lag specification results clearly demonstrate that altering the number of lags does not have any noticeable impact on the baseline results. Second, t-statistics continue to be highly significant in all sub-samples considered in Figure 18. Taken together, these results lend further credence to the baseline results of this paper.

4 Conclusion

The question of whether the type of ERR in place constitutes a relevant policy tool for affecting global credit supply shocks' adverse effects is an important question from both a policy standpoint as well as an intellectual curiosity standpoint. Theory stresses, in tandem, an expansionary exchange rate depreciation channel resulting from expenditure-switching effects and a potentially contractionary balance sheet channel resulting from the prevalence of foreign currency-denominated debt.

This paper presents empirical evidence that validates the expenditure-switching channel but at the same time stresses that it co-exists with an expansionary, rather than contractionary, balance sheet channel by which exchange rate depreciation actually improves economic agents' balance sheets owing to favorable asset side effects resulting from the expenditure-switching channel. This is an important result as it goes beyond the classical expenditure-switching exchange rate channel emphasized in more traditional models and beyond the liabilities-based contractionary balance sheet channel framework by providing evidence that financial frictions are an important element that facilitates the shock-amplifying nature of fixed ERRs. And this empirical result is consistent with recent theoretical models that study the role of exchange rate policies during financial stress (see, e.g., Fornaro (2015) and Devereux and Yu (2017)).

Finally, while it is beyond the scope of this paper to investigate the long-run implications of fixed ERRs for macroeconomic performance in general and trade in particular, the empirical evidence put forward in this paper lends credence to the view that ERR fixity as a policy tool should be taken with caution on the grounds of its negative effect on macroeconomic stability.

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Appendix A Data

A.1 Output, Investment, Consumption, and the Trade Balance.

Variables Definitions. Output is defined as local currency nominal GDP divided by the GDP deflator; investment is local currency gross private capital formation divided by the GDP deflator; consumption is defined as local currency nominal household consumption divided by the GDP deflator; and the trade balance is the difference between local currency exports and imports divided by local currency nominal GDP. All series were seasonally adjusted using ARIMA X12 and downloaded from the International Financial Statistics (IFS) database, which is published by the International Monetary Fund, except for China for which data from Chang et al. (2015) was collected from the Atlanta Fed website.

Sample. My panel for these variables consists of a total of 3367 observations. I use quarterly data for the following countries (40 in total) and periods: Argentina 1993:Q1-2016:Q4; Armenia 1999:Q4-2016:q4; Bolivia 1990:Q1-2015:Q4; Brazil 1995:Q1-2016:Q4; Bulgaria 1996:Q1-2016:Q4; Chile 1990:Q1-2016:Q4; China 1992:Q1-2016:Q4; Colombia 1994:Q1-2016:Q1; Costa Rica 1991:Q1-2016:Q4; Croatia 1997:Q1-2016:Q4; Czech Republic 1994:Q1-2016:Q4; Ecuador 1991:Q1-2016:Q3; Egypt 2002:Q1-2013:Q4; Estonia 1995:Q1-2016:Q4; Georgia 1996:Q1-2016:Q4; Guatemala 2001:Q1-2016:Q4; Hungary 1995:Q1-2016:Q4; India 2004:Q1-2016:Q4; Indonesia 1997:Q1-2016:Q4; Iran 1988:Q1-2007:Q4; Korea 1973:Q1-2016:Q4; Kyrgyz 2000:Q1-2016:Q3; Latvia 1990:Q1-2016:Q4; Lithuania 1995:Q1-2016:Q4; Macedonia 1995:Q1-2016:Q4; Malaysia 1991:Q1-2016:Q4; Mauritius 2000:Q1-2016:Q4; Mexico 1981:Q1-2016:Q4; Moldova 2000:Q1-2008:Q4; Paraguay 1994:Q1-2016:Q4; Peru 1990:Q3-2016:Q4; Philippines 1981:Q1-2016:Q4; Poland 1995:Q1-2016:Q4; Romania 1998:Q1-2016:Q4; Russia 1995:Q1-2016:Q4; Serbia 1995:Q1-2016:Q4; South Africa 1973:Q1-2016:Q4; Thailand 1993:Q1-2016:Q4; Turkey 1987:Q1-2016:Q4; Ukraine 2001:Q1-2016:Q4.

A.2 Exchange Rate Regime.

Variables Definitions. I use the Reinhart and Rogoff (2004) ERR Measure, as updated by Ilzetzki et al. (2017) through 2016, to divide the observations in my sample into fixed and non-fixed ERRs. The series I use are taken from Carmen Reinhart's website (http://http://www.carmenreinhart.com/data/browse-by-topic/topics/11/). Their construction makes use of monthly data on market-determined parallel exchange rates to generate a fine classification of ERRs comprising of 15 categories. These categories appear in Table 1, where larger category integers represent more flexible ERRs. I convert monthly values to quarterly ones by averaging over the respective values in each quarter and define the fixed ERR state as a dummy that obtains 1 if the IRR measure obtains an integer that is not greater than 4.

I also consider two other ERR measures in a comparison exercise:

Shambaugh (2004) ERR Measure. This annual measure focuses exclusively on the volatility of the exchange rate and divides countries into pegs and non-pegs, where the former are classified as such if their official exchange rate remains within a 2% band with respect to its base country. In addition, to prevent breaks in the peg status due to one-time realignments, Shambaugh (2004) classifies as fixed any exchange rate that had a zero percentage change in eleven out of twelve months in a given year. I directly employ the raw Shambaugh (2004) peg dummy variable (which obtains 1 if an observation corresponds to a peg) in my analysis, which is available through 2014 and downloaded from the NBER data sources catalogue website (http://www.nber.org/data/international-finance/#err). I convert annual values into quarterly ones by assuming within-year constancy of observations.

Levy-Yeyati and Sturzenegger (2001, 2003, 2005) ERR Measure. This annual measure is based on cluster analysis to group countries according to the relative volatility of exchange rates and reserves; I identify fixed ERR observations in line with the grouping of Levy-Yeyati and Sturzenegger (2001, 2003, 2005), who divide the observations into fixed, intermediate, and flexible regimes. They define fixed ERRs as those corresponding to low volatility of exchange rates and high volatility of foreign exchange reserves. My fixed ERR dummy is defined such that it obtains 1 if it corresponds to the fixed grouping of Levy-Yeyati and Sturzenegger (2001, 2003, 2005). I make use in my analysis of the updated series from Levy-Yeyati and Sturzenegger (2016), which runs through 2013 and is available from Eduardo Levy-Yeyati's website (http://eduardolevyyeyati.com.ar/publicaciones/).

A.3 Economic Development.

Variable Definition. To control for the level of economic development in my robustness exercise from Section 3.1, I use annual PPP-adjusted per capita GDP for the EMEs in my sample taken from the World Bank Database and transform the annual data into quarterly frequency by assuming identical within-year quarterly values equal to the corresponding annual values. To obtain stationarity and a meaningful stationary distribution of economic development, each observation's value of PPP-adjusted per capita GDP is standardized with respect to its corresponding cross-sectional mean and standard deviation. I then construct two dummy variables corresponding to high and low economic development: the first obtains 1 if an observation exceeds or is equal to the upper quartile of the standardized PPP-adjusted per capita GDP distribution and the second obtains 1 if an observation is at or below the lower quartile of the standardized distribution.

A.4 Capital Controls.

Variable Definition. The capital controls data I use in the robustness exercise from Section 3.1 is taken from Fernández et al. (2015), who revise, extend, and widen the dataset originally developed by Schindler (2009) and later expanded by Klein (2012) and Fernández et al. (2015). This dataset reports the presence or absence of capital controls, on an annual basis, for 100 countries over the period 1995 to 2015 and provides information on restrictions on capital inflows and outflows separately while distinguishing between six categories of assets and the residency of the transacting agent. In terms of country coverage relative to my baseline sample, the capital controls data is not available for 6 countries and thus only covers 34 out of the 40 countries covered by my baseline sample.

Given the robust finding by Fernández et al. (2015) that capital controls are strongly acyclical and have a very small standard deviation at annual frequencies, I make the thus innocuous assumption that capital controls do not exhibit variation within the year; accordingly, I transform the capital control annual data into quarterly frequency by assuming identical within-year quarterly values equal to the corresponding annual values.

Below are the specific definitions of the capital inflow and outflow control measure I use in the paper:

Total Capital Inflow Controls Index. This index is an average of the following 10 inflow restrictions binary sub-indices: Equity inflow restrictions; Bond inflow restrictions; Money Market inflow restriction; Collective Investments inflow restrictions; Derivatives inflow restrictions; Commercial Credits inflow restrictions; Financial Credits inflow restrictions; Guarantees, sureties and financial backup facilities inflow restrictions; Direct Investment inflow restrictions; and Real Estate inflow restrictions.

Total Capital Outflow Controls Index. This index is defined in accordance with the definition of the inflow index, only that all 10 sub-categories pertain to capital outflow resrictions.

A.5 Global Credit Supply Shock.

Variable Definition. To measure global credit supply shocks, I make use of the Gilchrist and Zakrajsek (2012) credit supply shock series. Gilchrist and Zakrajsek (2012) use micro-level data to construct a credit spread index which they decomposed into a component that captures firm-specific information on expected defaults and a residual component that they termed as the excess bond premium. The most updated series of the excess bond premium variable, available from Favara et al. (2016),[34] is my measure of credit supply shocks in this paper. It is in quarterly

[34] The permanent link for this updated excess bond premium series is https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv.

frequency and covers the sample period 1973:Q1 to 2016:Q4. Quarterly values are averages of corresponding raw monthly values.

A.6 Exchange Rates.

Variables Definitions. The exchange rate data consist of the nominal market-determined parallel exchange rate vis-à-vis each country's anchor currency from Ilzetzki et al. (2017), taken from Carmen Reinhart's website (http://http://www.carmenreinhart.com/data/browse-by-topic/topics/11/); and real effective exchange rate (CPI based) data, downloaded from the IFS database.

Sample. My panel for the nominal exchange rate corresponds to the countries and periods covered by the output, investment, consumption, and trade balance variables; that for the real effective exchange rate lacks the following countries: Egypt, Guatemala, Kyrgyz, Mauritius, and Serbia.

A.7 Leverage.

Variable Definition. The leverage data is defined as the ratio of total BIS-reporting banks' international claims on each country to its GDP. I also make use of the three sub-compoenents of the total claims series: claims on private non-financial sector, claims on financial sector, and claims on public sector; the sectoral leverage variables are divided by GDP. All claims series are taken from the BIS consolidated banking statistics database. Raw claims are in dollar terms and are therefore converted to local currency terms using the average quarter dollar exchange rate from each country taken from the IFS database. The BIS claims data exclude intragroup positions and are currently reported to the BIS by banking groups from 31 countries.

Sample. The panel for leverage consists of a total of 2464 observations. The data is quarterly and covers the 40 countries that correspond to the output-based sample of countries for the sample period 2000:Q1-2016:Q4.

A.8 Stock Prices.

Variable Definition. The stock price data is based on countries' major stock market exchange indices, downloaded from the IFS.

Sample. The panel for stock prices consists of a total of 2229 observations. This panel covers 28 countries, with the following omitted countries relative to those covered by the output variable: Armenia, Bolivia, Colombia, Costa Rica, Ecuador, Georgia, Guatemala, Kyrgyz, Macedonia, Moldova, Paraguay, and Romania.

A.9 Balance of Payments.

Variables Definitions. The balance of payments data consists of the sum of GDP shares of local currency net capital outflows of foreign direct investment, portfolio investment, and other investment;[35] and changes of the monetary authority's local currency foreign exchange reserves as a share of GDP. All variables were available in dollar values in raw form and were thus converted to local currency values by using the dollar exchange rate. All raw series were seasonally adjusted using ARIMA X12 and downloaded from the IFS.

Sample. My panel for these variables consists of a total of 2660, 2726, 2676, and 2766 observations for foreign direct investment, portfolio flows, other investment, and foreign exchange reserves, respectively. This panel corresponds to the countries covered by the output variable except for Ecuador, Egypt, Iran, Paraguay, and Serbia. The total capital flows variable (whose results appear in Figure 9a) is defined as the sum of the GDP shares of the three capital flow types.

[35]'Other investment' includes loans as well as other forms of cross-border finance such as trade credit, bank deposits, and cash.

A.10 EMBI Spread.

Variable Definition. I use the Emerging Markets Bond Index (EMBI) Global computed by JP Morgan as a measure of country spread. This index is a composite of different U.S. dollar-denominated bonds. The Stripped Spread is computed as an arithmetic, market-capitalization-weighted average of bond spreads over U.S. Treasury bonds of comparable duration and downloaded from Datastream. Quarterly values are average of corresponding raw spread daily values.

Sample. My panel for EMBI consists of a total of 1608 observations. I use quarterly data for the following countries (21 in total) and periods: Argentina 1994:Q1-2016:Q4; Brazil 1994:Q3-2016:Q4; Bulgaria 1994:Q3-2014:Q1; Chile 1999:Q2-2016:Q4; China 1994:Q1-2016:Q4; Colombia 1997:Q1-2014:Q4; Ecuador 1995:Q1-2016:Q4; Egypt 2001:Q3-2016:Q4; Hungary 1999:Q1-2016:Q4; Indonesia 2004:Q2-2016:Q4; Korea 1994:Q1-2004:Q2; Kyrgyz 1999:Q1-2016:Q4; Malaysia 1996:Q4-2016:Q4; Mexico 1994:Q1-2016:Q4; Peru 1997:Q1-2016:Q4; Philippines 1994:Q1-2016:Q4; Poland 1994:Q1-2016:Q4; Russia 1997:Q4-2016:Q4; South Africa 1994:Q4-2016:Q4; Thailand 1997:Q2-2006:Q1; Turkey 1996:Q3-2016:Q4.

A.11 Central Bank Policy Rate.

Variable Definition. The central bank policy rate represents the interest rate used by a central bank to implement its monetary policy stance; the underlying financial instrument of the policy rate varies across the EMEs in my sample, being the discount rate for some while in others it is a repurchase agreement rate. Data for this variable was downloaded from the IFS database.

Sample. My panel for policy rates consists of a total of 2219 observations. Data for this variable is covered by 32 countries (Argentina, Armenia, Estonia, Iran, Lithuania, Macedonia, Moldova, and Ukraine are excluded).

Table 1: **Reinhart and Rogoff (2004) Exchange Rate Regime Classification**.

Category	Description
1	No Separate Legal Tender
2	Pre-Announced Peg or Currency Board Arrangement
3	Pre-Announced Horizontal Band that is Narrower than or Equal to $+/-2\%$
4	De Dacto Peg
5	Pre-Announced Crawling Peg
6	Pre-Announced Crawling Band that is Narrower than or Equal to $+/-2\%$
7	De Facto Crawling Peg
8	De Facto Crawling Band that is Narrower than or Equal to $+/-2\%$
9	Pre-Announced Crawling Band that is Wider than or Equal to $+/-2\%$
10	De Facto Crawling Band that is Narrower than or Equal to $+/-5\%$
11	Moving Band that is Narrower than or Equal to $+/-2\%$
12	Managed Floating
13	Freely Floating
14	Freely falling
15	Dual Market in which Parallel Market Data is Missing

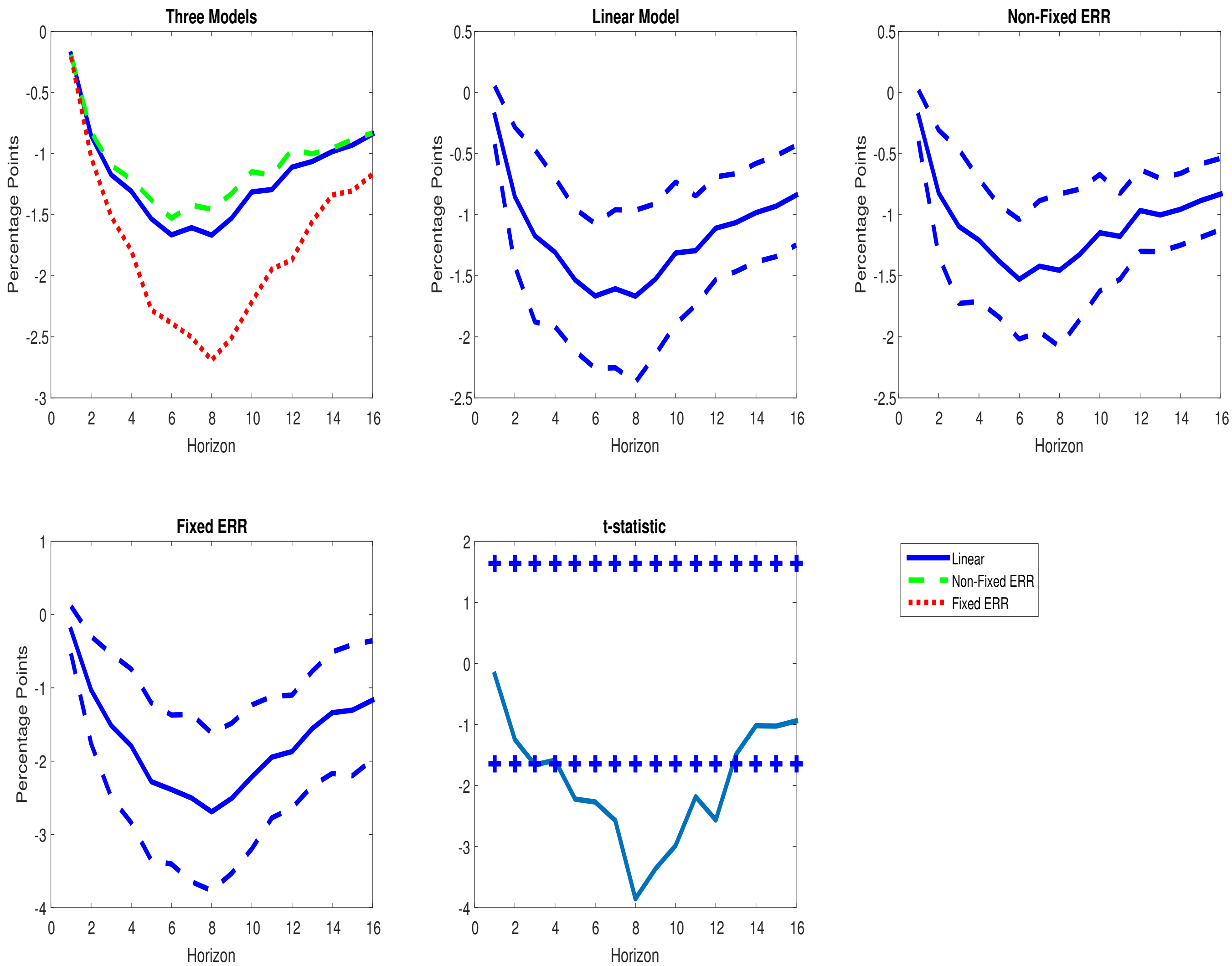
Notes: This table consists of the ERR classification codes from Ilzetzki et al. (2017), which are the basis for the ERR measure used in this paper.

Table 2: **Correlations Between Fixed ERR and Other State Variables**.

	Economic Development [High,Low]	Capital Inflow Controls [Strict,Light]	Capital Outflow Controls [Strict,Light]	U.S. Trade Exposure [High,Low]
Fixed ERR	[-0.08,0.05]	[0,-0.01]	[0.06,0.05]	[0,0.18]

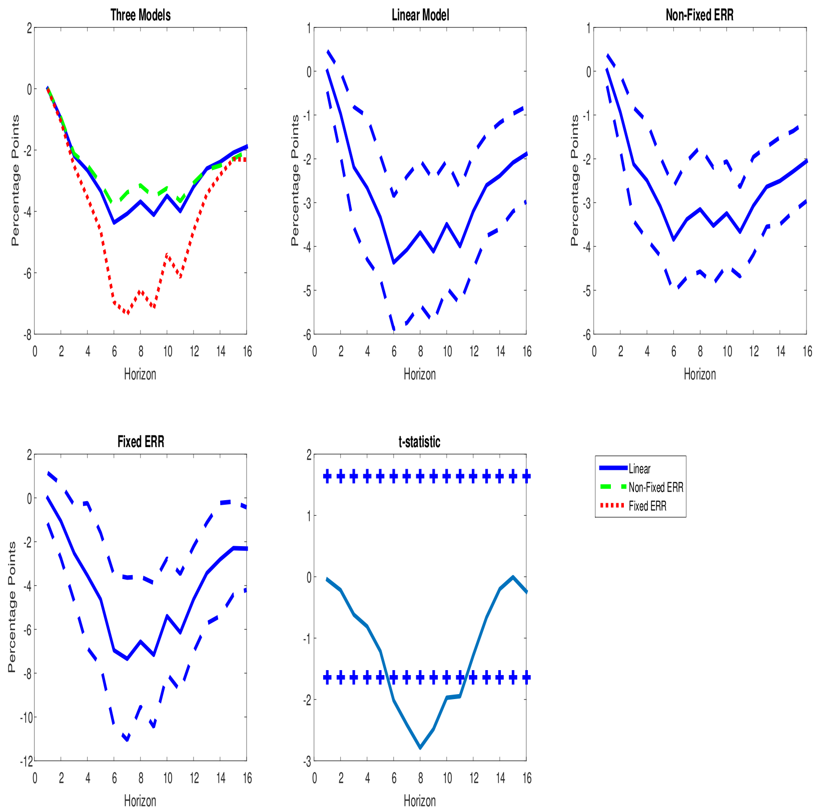
Notes: This table presents the correlations between the fixed ERR dummy and the dummies corresponding to the upper and lower quartiles of the following variables' distributions: economic development, as measured by the standardized values of PPP-adjusted per capita GDP; capital inflow and outflow controls, as measured by the Fernández et al. (2015) indices; and trade exposure to the U.S. (measured as the ratio of exports to U.S. to GDP). The numbers in squared brackets correspond to the correlation of the fixed ERR dummy with the dummies corresponding to the upper ('high' for economic development and U.S. trade exposure, 'strict' for the capital controls measures) and lower ('low' for economic development and U.S. trade exposure, 'light' for the capital controls measures) quartiles of the corresponding state's distribution.

Figure 1: **ERR's Effect on Output's Sensitivity to Credit Supply Shocks**.

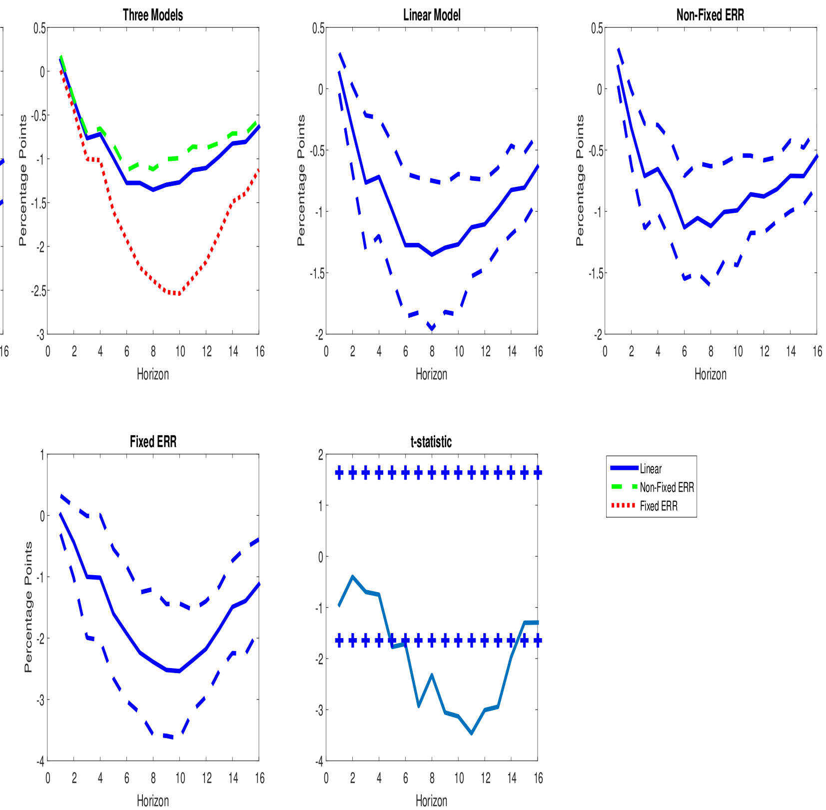


Notes: This figure presents the impulse responses of output to a one standard deviation credit supply shock from the linear model and non-linear model. In the first sub-figure the solid lines show the responses from the linear model, the dashed lines depict the responses in the non-fixed ERR state, and the dotted lines are the responses in the fixed ERR state. The next three sub-figures present the impulse responses from the linear model and the two states along with Driscoll and Kraay (1998) 90% confidence bands. The last sub-figure shows the t-statistic of the difference between the responses in the fixed ERR state and the non-fixed ERR state, where for convenience the 5% significance levels (± 1.645) are added. The responses are shown in terms of percentage deviations from pre-shock values. Horizon is in quarters.

Figure 2: **ERR's Effect on Investment's and Consumption's Sensitivity to Credit Supply Shocks: (a) Investment; (b) Consumption**.



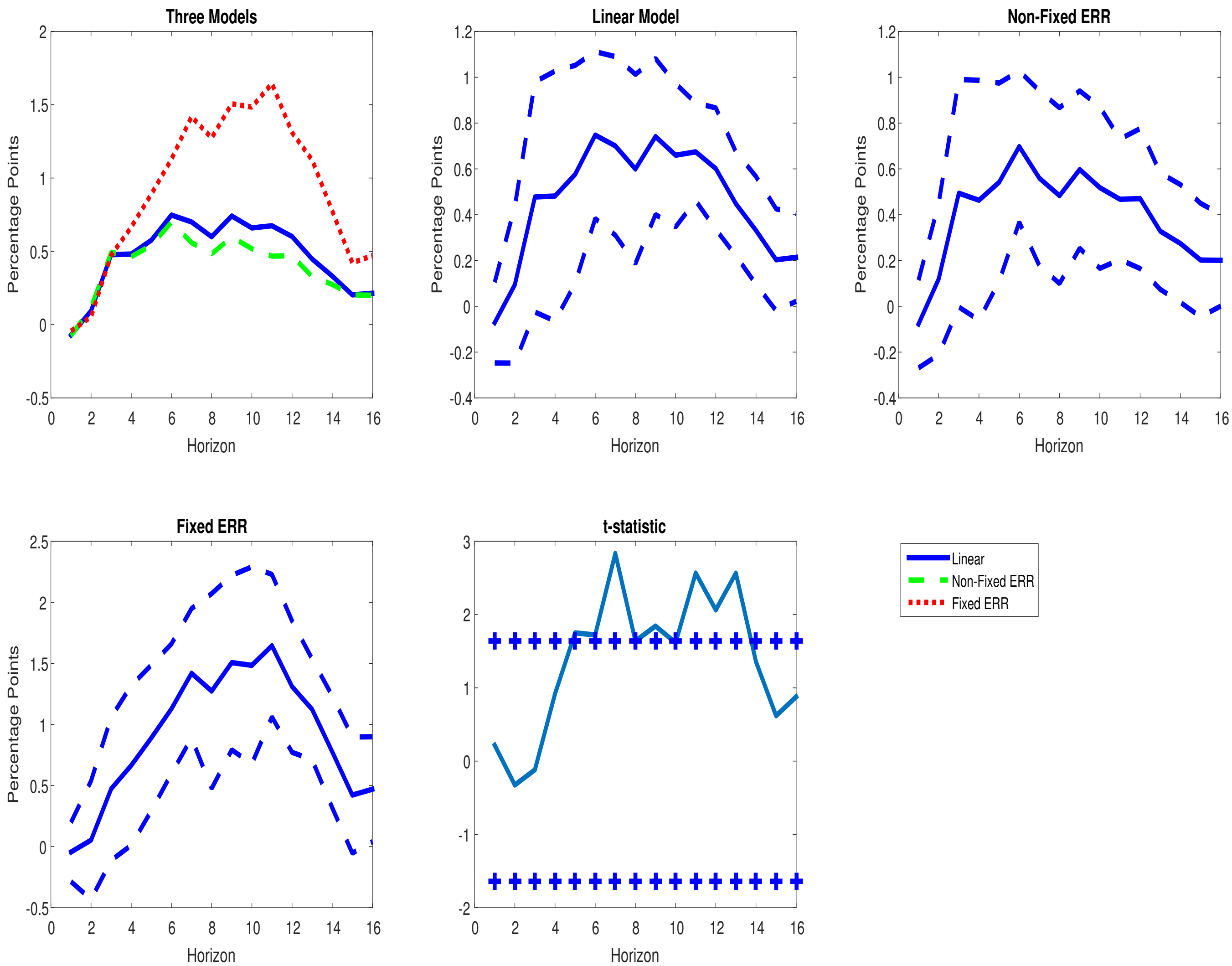
(a) Impulse Responses to a One Standard Deviation Credit Supply Shock (Investment).



(b) Impulse Responses to a One Standard Deviation Credit Supply Shock (Consumption).

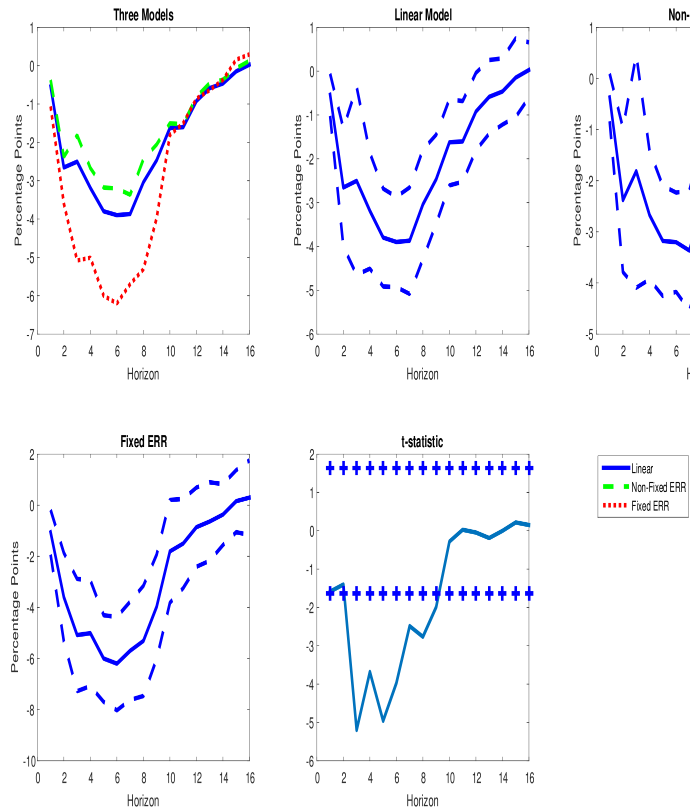
Notes: Panel (a): This figure presents the impulse responses of investment to a one standard deviation credit supply shock from the linear model and non-linear model. Panel (b): This figure presents the impulse responses of consumption to a one standard deviation credit supply shock from the linear model and non-linear model.
See notes from Figure 1 for details on these sub-figures' components.

Figure 3: **ERR's Effect on the Trade Balance's Sensitivity to Credit Supply Shocks**.

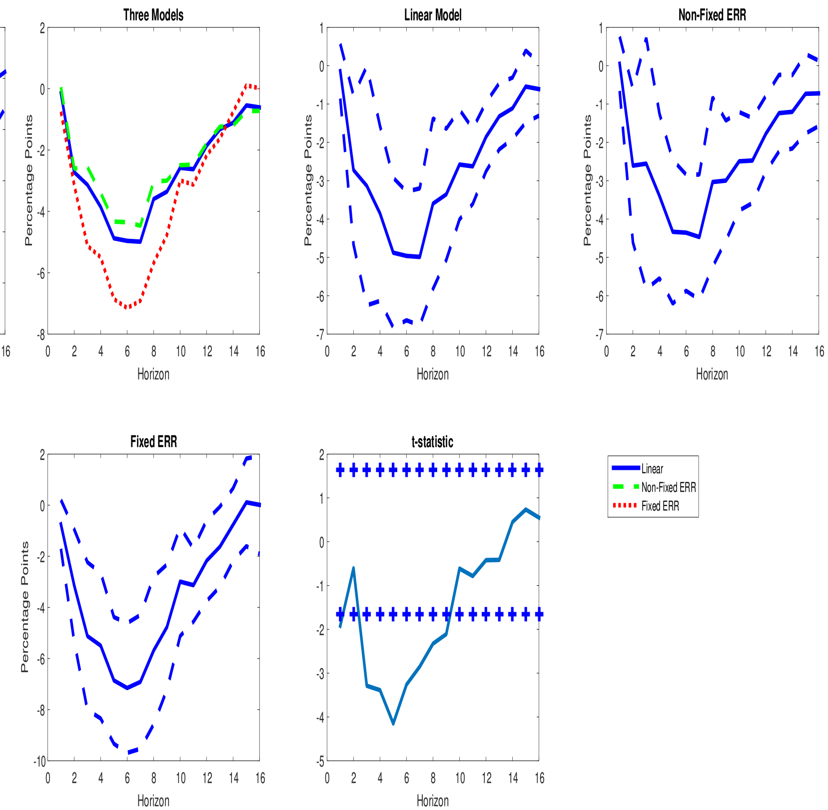


Notes: This figure presents the impulse responses of the GDP share of the trade balance to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figure 1 for details on this figure's components.

Figure 4: **ERR's Effect on Exports' and Imports' Sensitivity to Credit Supply Shocks: (a) Exports; (b) Imports**.



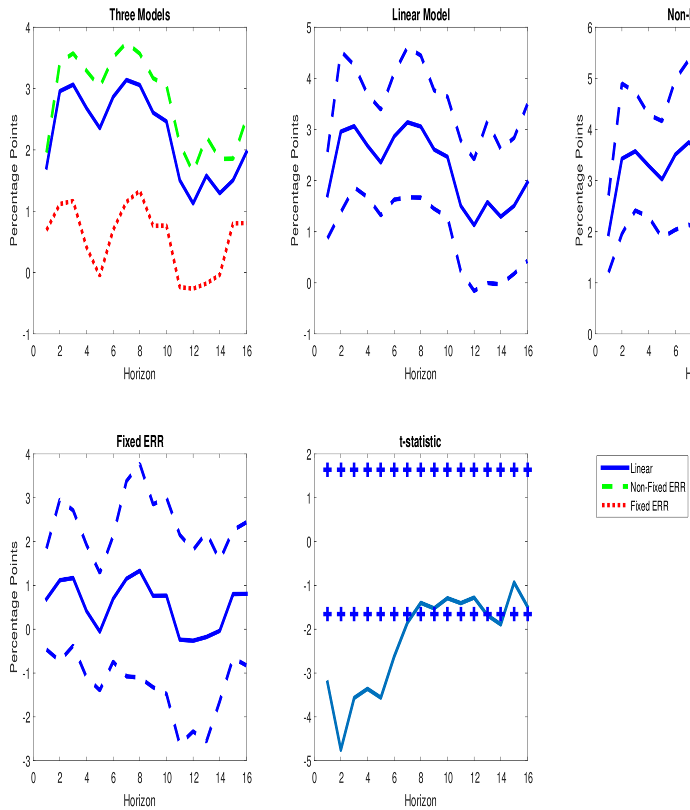
(a) Impulse Responses to a One Standard Deviation Credit Supply Shock (Exports).



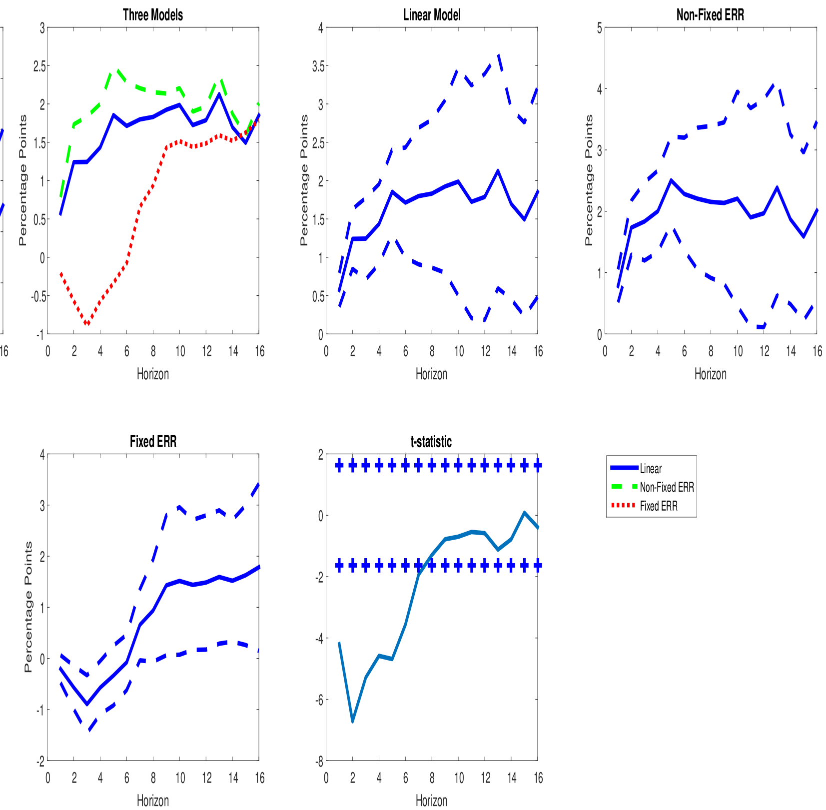
(b) Impulse Responses to a One Standard Deviation Credit Supply Shock (Imports).

Notes: Panel (a): This figure presents the impulse responses of exports' (measured as local currency exports divided by GDP deflator) to a one standard deviation credit supply shock from the linear model and non-linear model. Panel (b): This figure presents the impulse responses of imports' (measured as local currency imports divided by GDP deflator) to a one standard deviation credit supply shock from the linear model and non-linear model.
See notes from Figure 1 for details on these sub-figures' components.

Figure 5: **ERR's Effect on Nominal and Real Exchange Rate's Sensitivity to Credit Supply Shocks: (a) Nominal Exchange Rate; (b) Real Effective Exchange Rate**.



(a) Impulse Responses to a One Standard Deviation Credit Supply Shock (Nominal Exchange Rate).

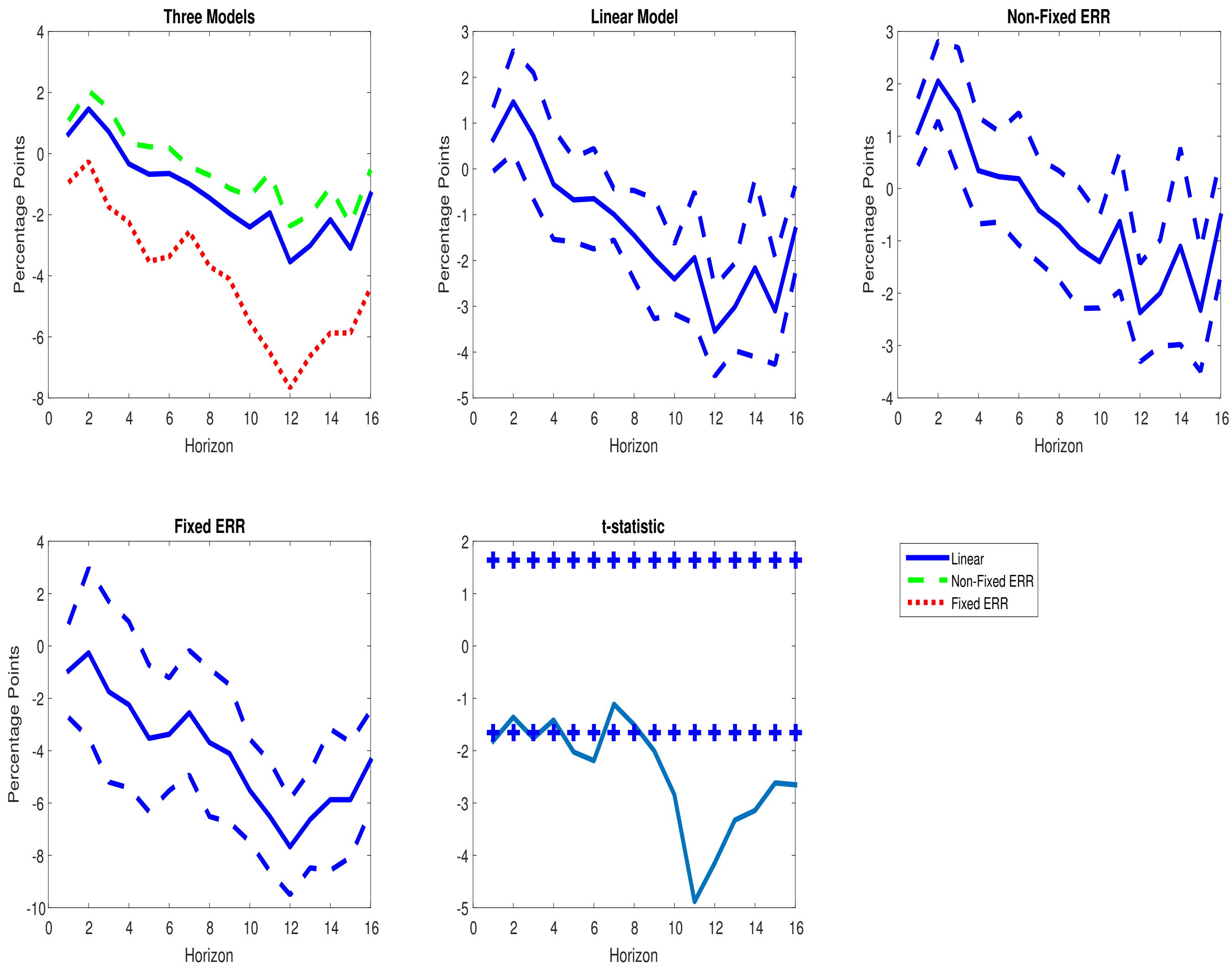


(b) Impulse Responses to a One Standard Deviation Credit Supply Shock (Real Effective Exchange Rate).

Notes: Panel (a): This figure presents the impulse responses of the nominal market-determined parallel exchange rate vis-a-vis each country's anchor currency (taken from Ilzetzki et al. (2017)) to a one standard deviation credit supply shock from the linear model and non-linear model. Panel (b): This figure presents the impulse responses of the real effective (CPI-based) exchange rate to a one standard deviation credit supply shock from the linear model and non-linear model.

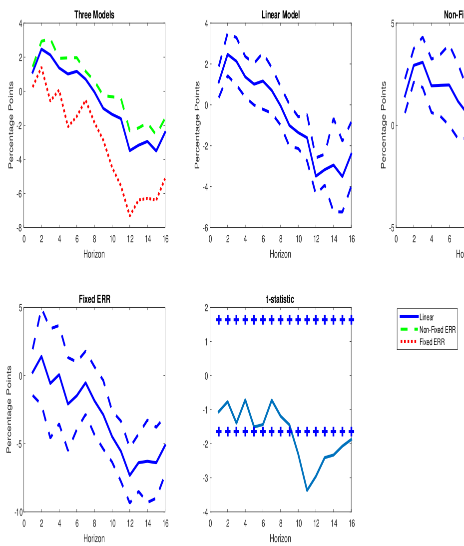
See notes from Figure 1 for details on these sub-figures' components.

Figure 6: **ERR's Effect on Leverage's Sensitivity to Credit Supply Shocks**.

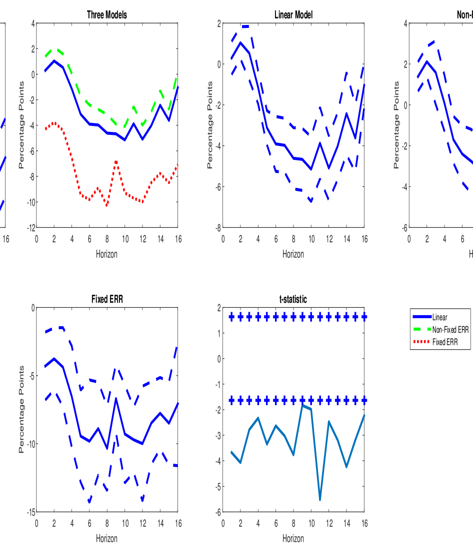


Notes: This figure presents the impulse responses of leverage to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figure 1 for details on this figure's components.

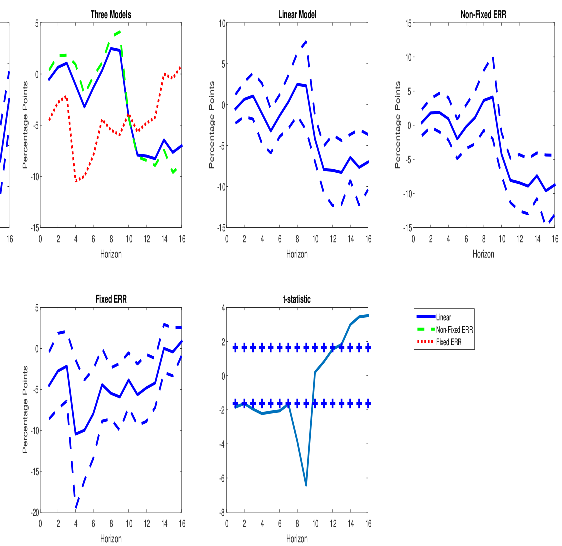
Figure 7: **ERR's Effect on Sectoral Leverage's Sensitivity to Credit Supply Shocks: (a) Private Non-Financial Sector's Leverage; (b) Financial Sector's Leverage; (c) Public Sector's Leverage**.



(a) Impulse Responses to a One Standard Deviation Credit Supply Shock (Private Non-Financial Sector's Leverage).



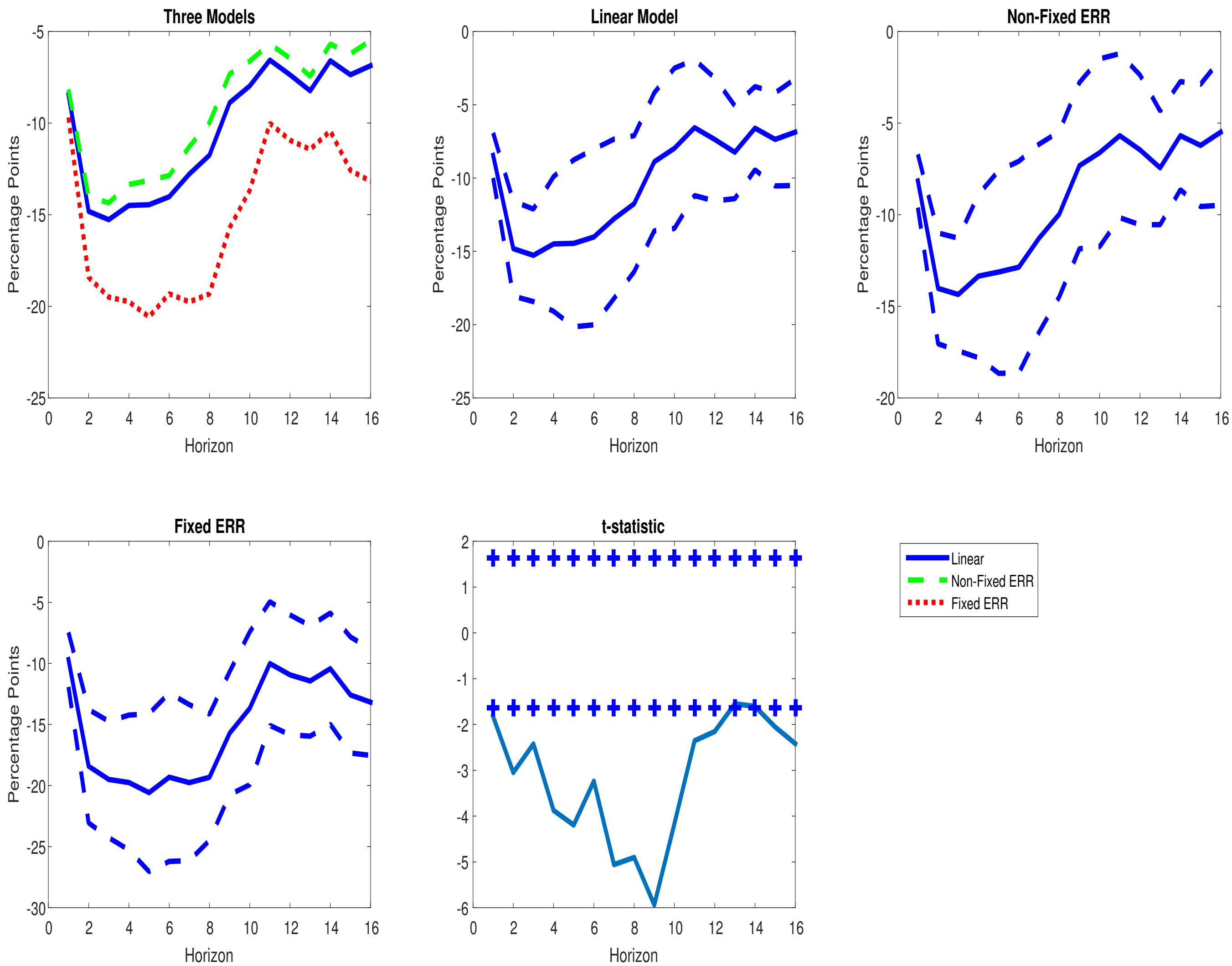
(b) Impulse Responses to a One Standard Deviation Credit Supply Shock (Financial Sector's Leverage).



(c) Impulse Responses to a One Standard Deviation Credit Supply Shock (Public Sector's Leverage).

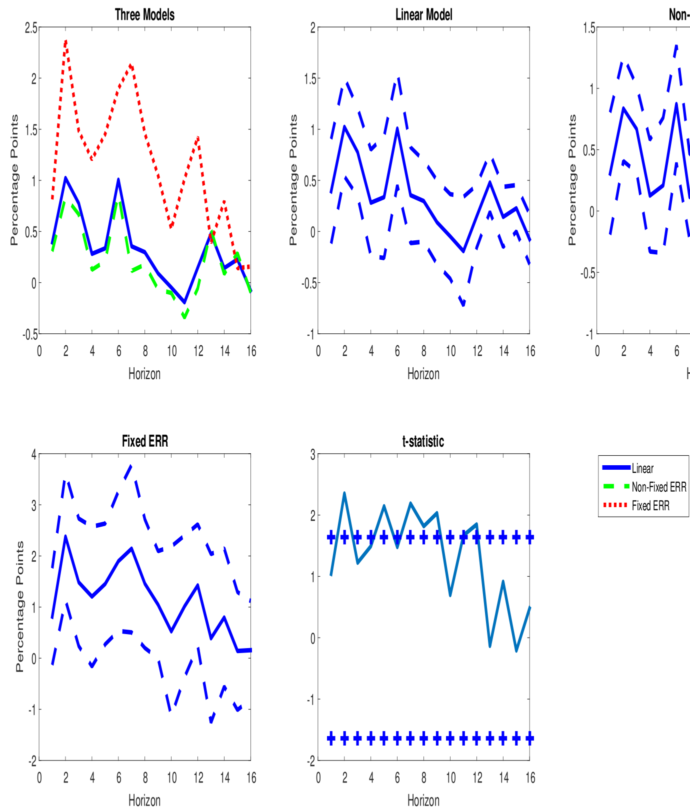
Notes: Panel (a): This figure presents the impulse responses of private non-financial sector's leverage to a one standard deviation credit supply shock from the linear model and non-linear model. Panel (b): This figure presents the impulse responses of financial sector's leverage to a one standard deviation credit supply shock from the linear model and non-linear model. Panel (c): This figure presents the impulse responses of public's sector's leverage to a one standard deviation credit supply shock from the linear model and non-linear model.
See notes from Figure 1 for details on these sub-figures' components.

Figure 8: **ERR's Effect on Stock Prices' Sensitivity to Credit Supply Shocks**.

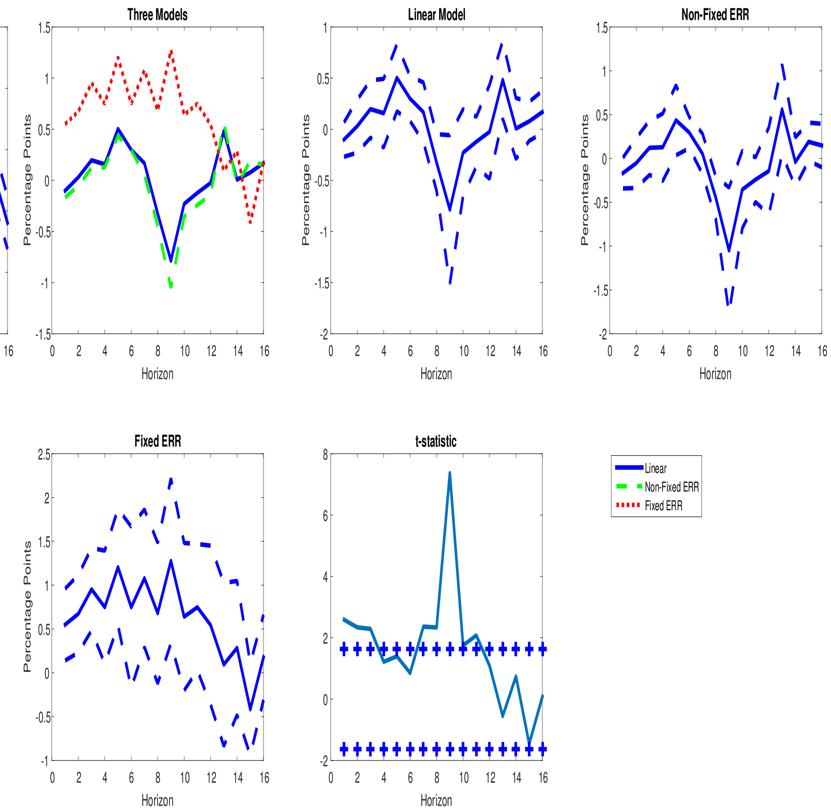


Notes: This figure presents the impulse responses of stock prices to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figure 1 for details on this figure's components.

Figure 9: **ERR's Effect on Total Capital Flows' and Foreign Direct Investment Flows' Sensitivity to Credit Supply Shocks: (a) Total Capital Flows; (b) Foreign Direct Investment**.



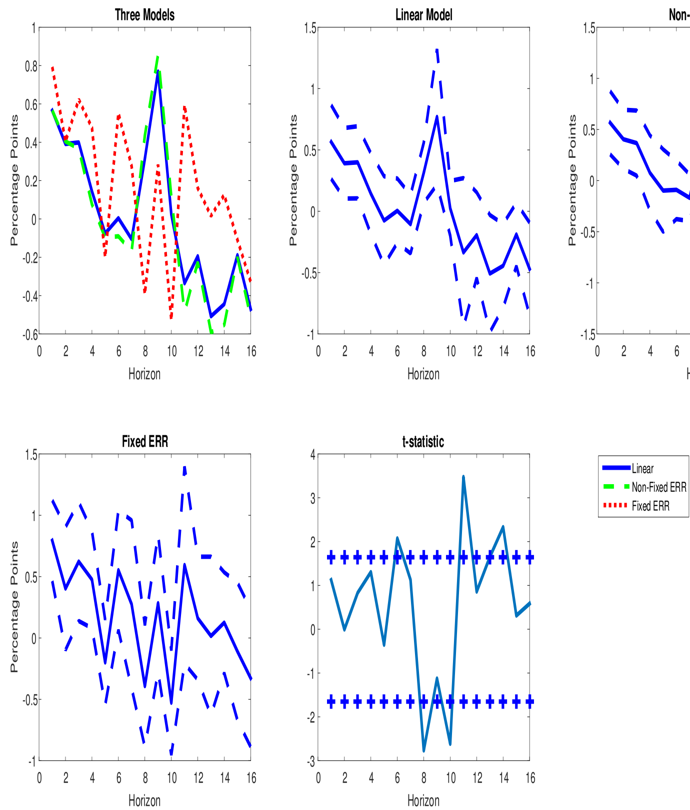
(a) Impulse Responses of Total Capital Flows to a One Standard Deviation Credit Supply Shock.



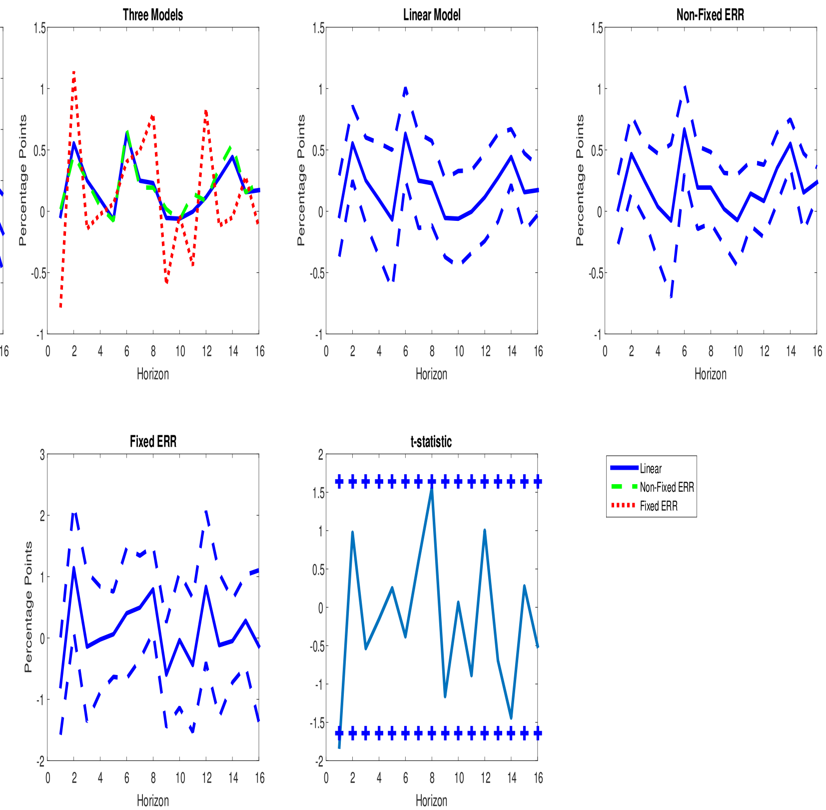
(b) Impulse Responses of Foreign Direct Investment Flows to a One Standard Deviation Credit Supply Shock.

Notes: Panel (a): This figure presents the impulse responses of total net capital outflows to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figure 1 for details on this figure's components. Panel (b): This figure presents the impulse responses of net foreign direct investment outflows to a one standard deviation credit supply shock from the linear model and non-linear model.
See notes from Figure 1 for details on these sub-figures' components.

Figure 10: **ERR's Effect on Portfolio Flows' and Other Investment Flows' Sensitivity to Credit Supply Shocks: (a) Portfolio Flows; (b) Other Investment Flows**.



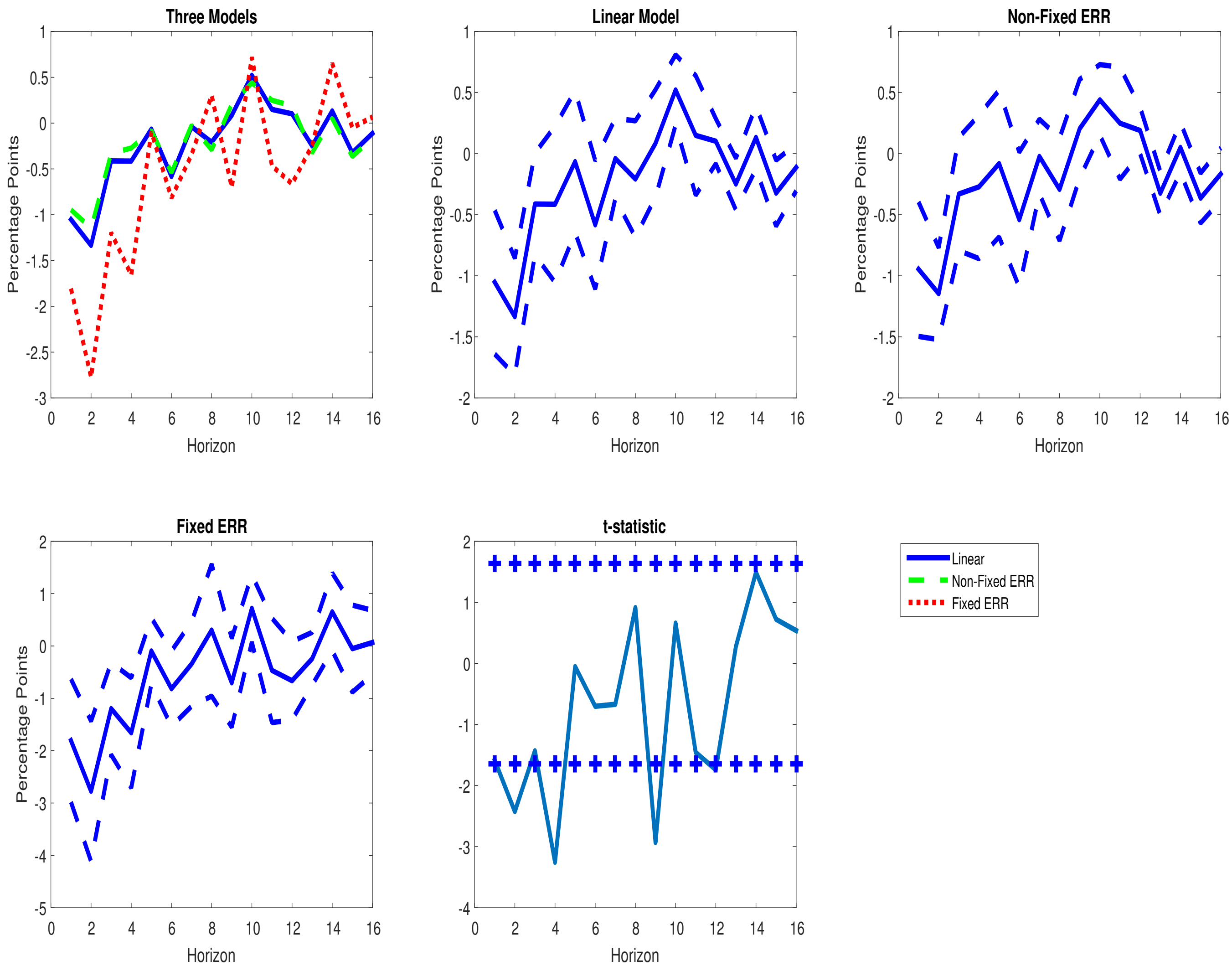
(a) Impulse Responses of Portfolio Flows to a One Standard Deviation Credit Supply Shock.



(b) Impulse Responses of Other Investment Flows to a One Standard Deviation Credit Supply Shock.

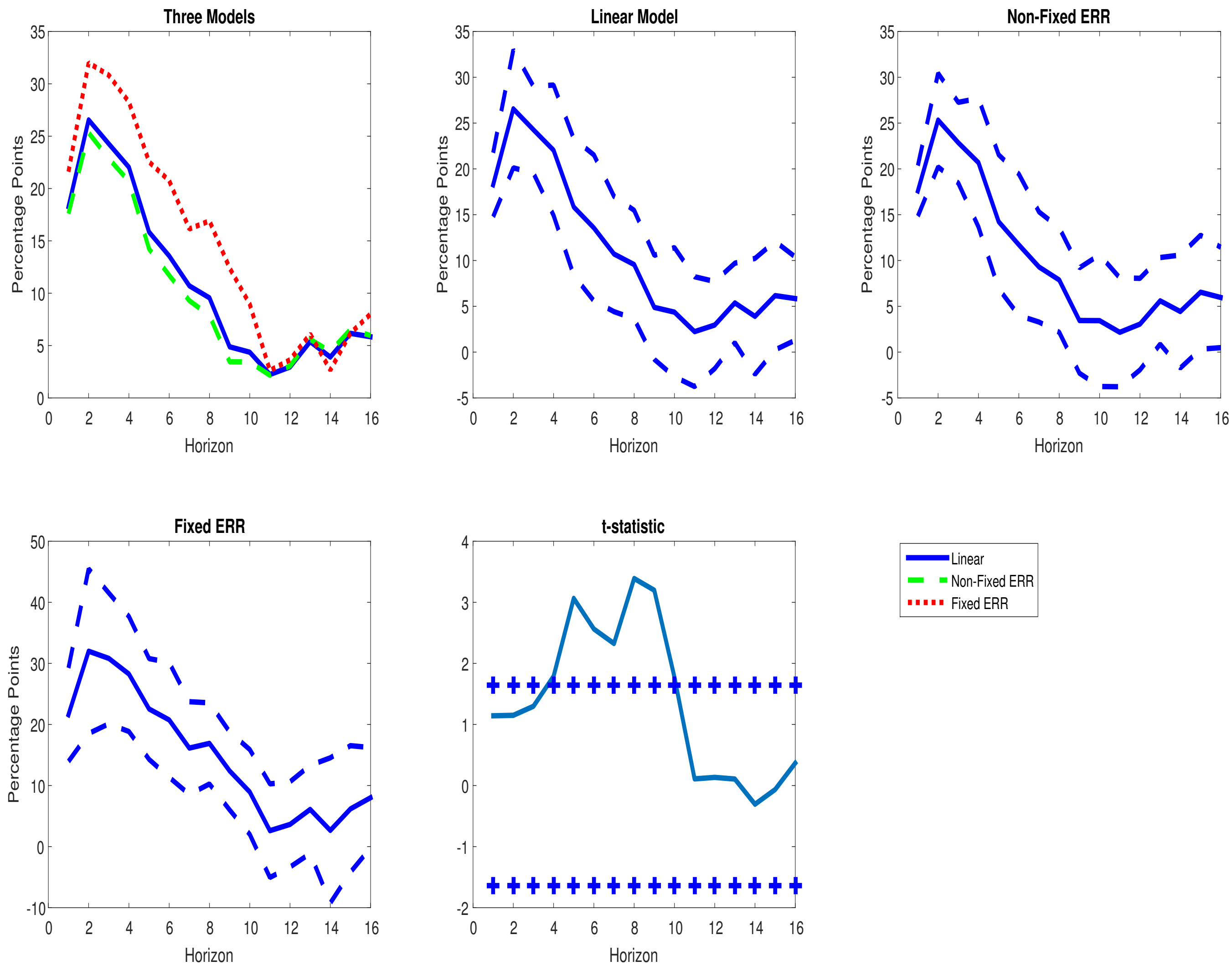
Notes: Panel (a): This figure presents the impulse responses of net portfolio outflows to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figure 1 for details on this figure's components. Panel (b): This figure presents the impulse responses of net other investment outflows (these include loans as well as other forms of cross-border finance such as trade credit, bank deposits, and cash) to a one standard deviation credit supply shock from the linear model and non-linear model.
See notes from Figure 1 for details on these sub-figures' components.

Figure 11: **ERR's Effect on Foreign Exchange Reserves' Sensitivity to Credit Supply Shocks**.



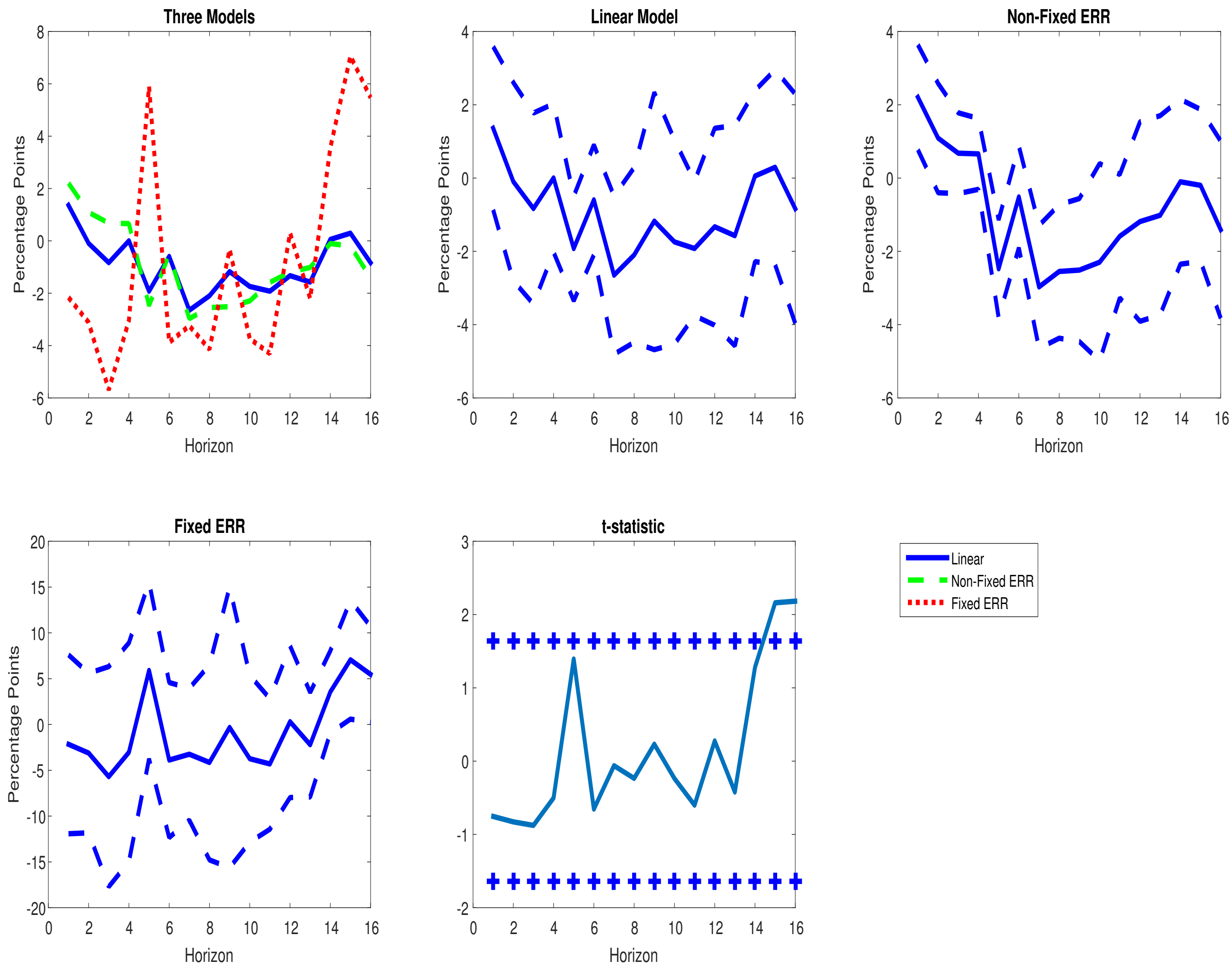
Notes: This figure presents the impulse responses of the GDP share of foreign exchange reserves' inflows to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figure 1 for details on this figure's components.

Figure 12: **ERR's Effect on EMBI's Sensitivity to Credit Supply Shocks**.



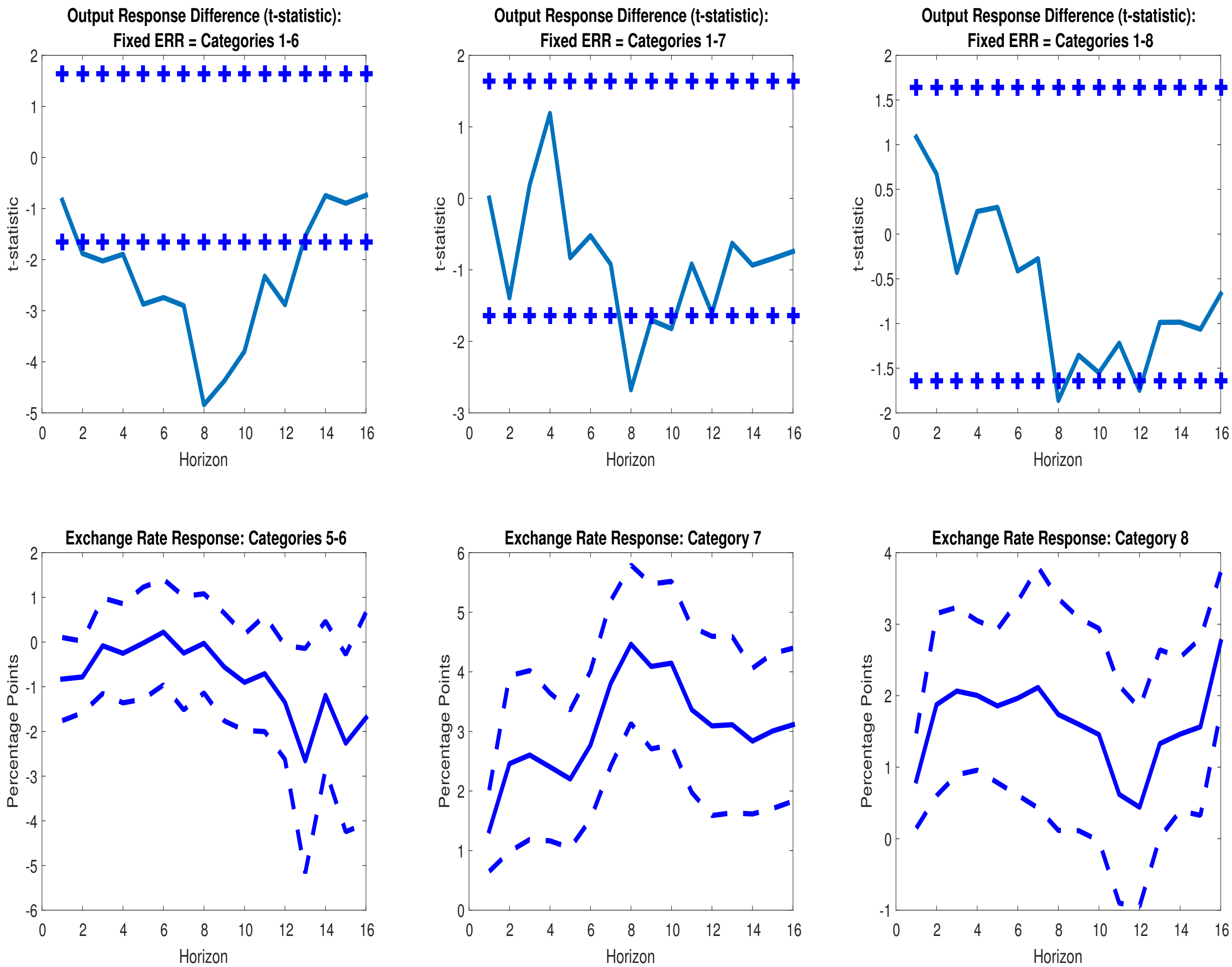
Notes: This figure presents the impulse responses of the log of EMBI (country credit spreads) to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figure 1 for details on this figure's components.

Figure 13: **ERR's Effect on Central Bank Rate's Sensitivity to Credit Supply Shocks**.



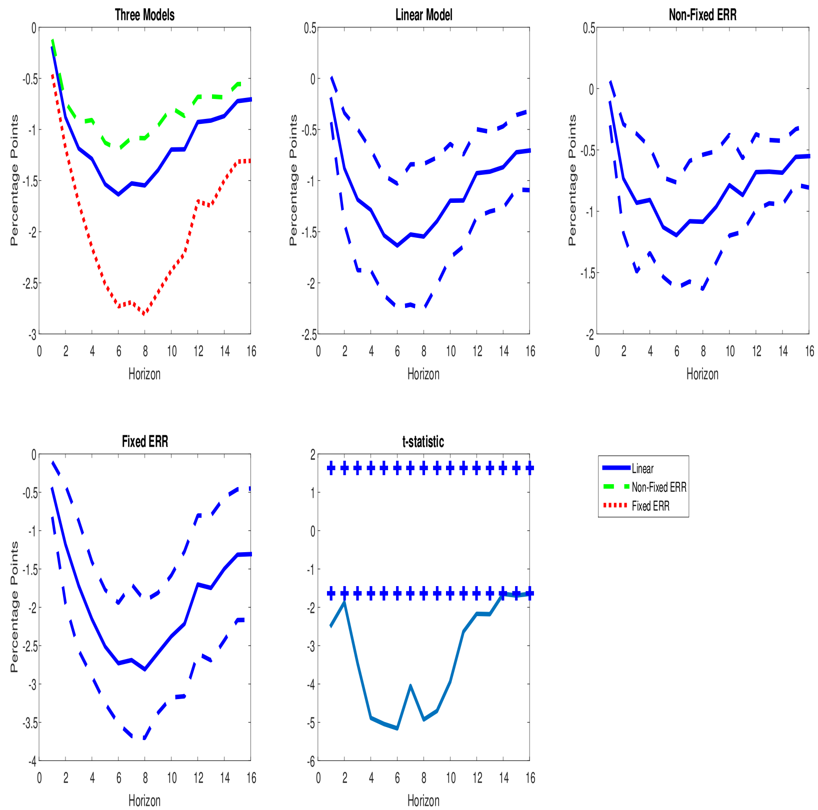
Notes: This figure presents the impulse responses of the log of the central bank rate to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figure 1 for details on this figure's components.

Figure 14: **Increasing the Number of Categories Included in the Fixed ERR Measure**.

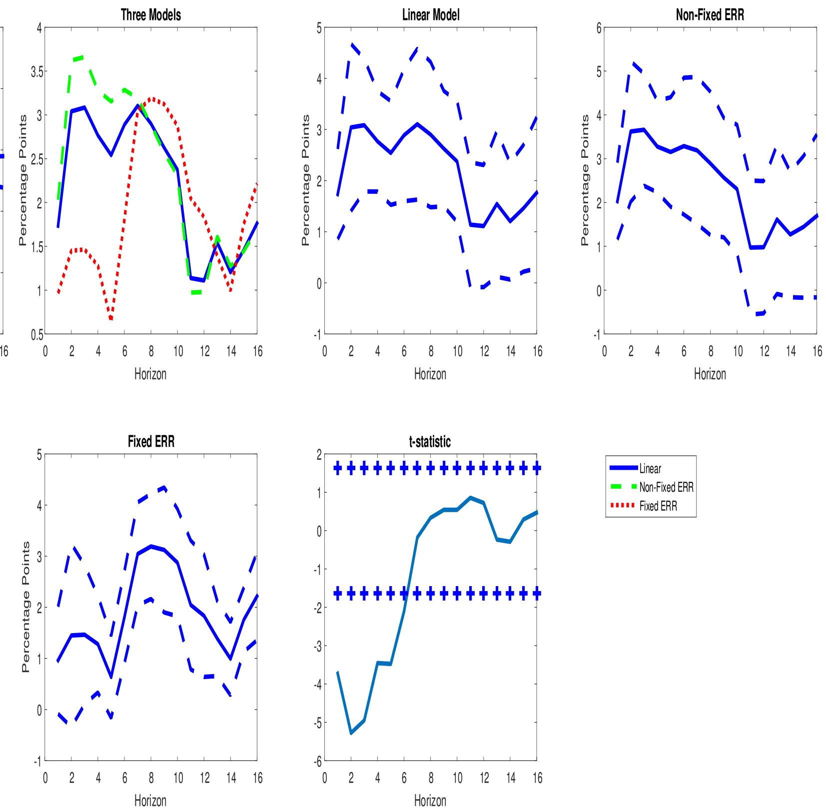


Notes: This figure presents results from estimating the baseline model under three alternative assumptions regarding which categories from the Ilzetzki et al. (2017) classification the fixed ERR corresponds to: *i*) categories 1-6, which add pre-announced crawling pegs and pre-announced narrow bands to the baseline definition of a fixed ERR; *ii*) categories 1-7, where category 7 covers de facto crawling peg; and *iii*) categories 1-8, where category 8 covers de facto narrow crawling bands. The t-statistics from these 3 estimations of the difference between the responses in the fixed ERR state and the non-fixed ERR state appear in the first row of the figure, where for convenience the 5% significance levels (± 1.645) are added; the second row presents the nominal exchange rate response for categories 5-6, category 7, and category 8. (I look at both categories 5 and 6 jointly because category 6 has an insufficient number of observations to be looked at separately.) The responses are shown in terms of percentage deviations from pre-shock values. Horizon is in quarters.

Figure 15: **ERR's Effect on Output's and Nominal Exchange Rate's Sensitivity to Credit Supply Shocks for the JS ERR Measure: (a) Output; (b) Nominal Exchange Rate**.



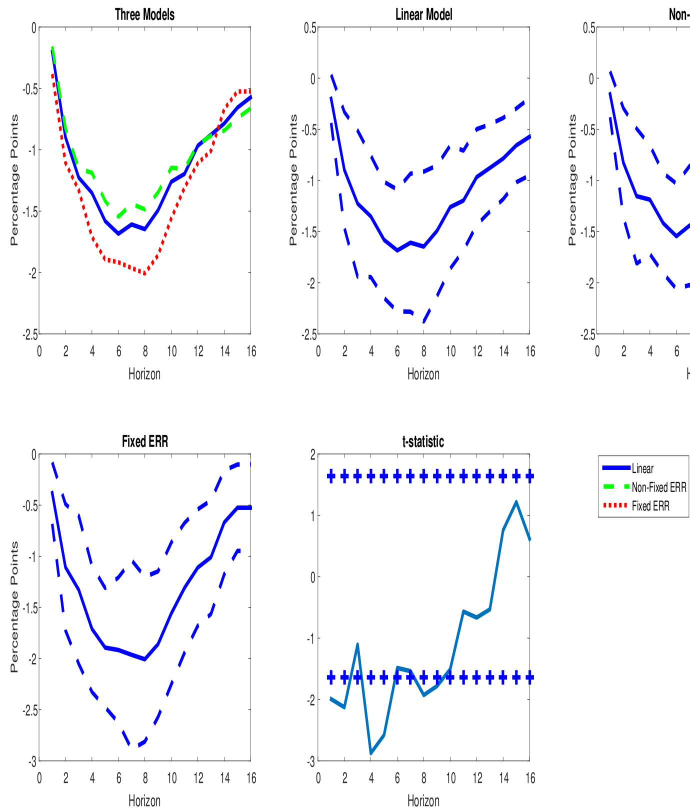
(a) Impulse Responses to a One Standard Deviation Credit Supply Shock (Output).



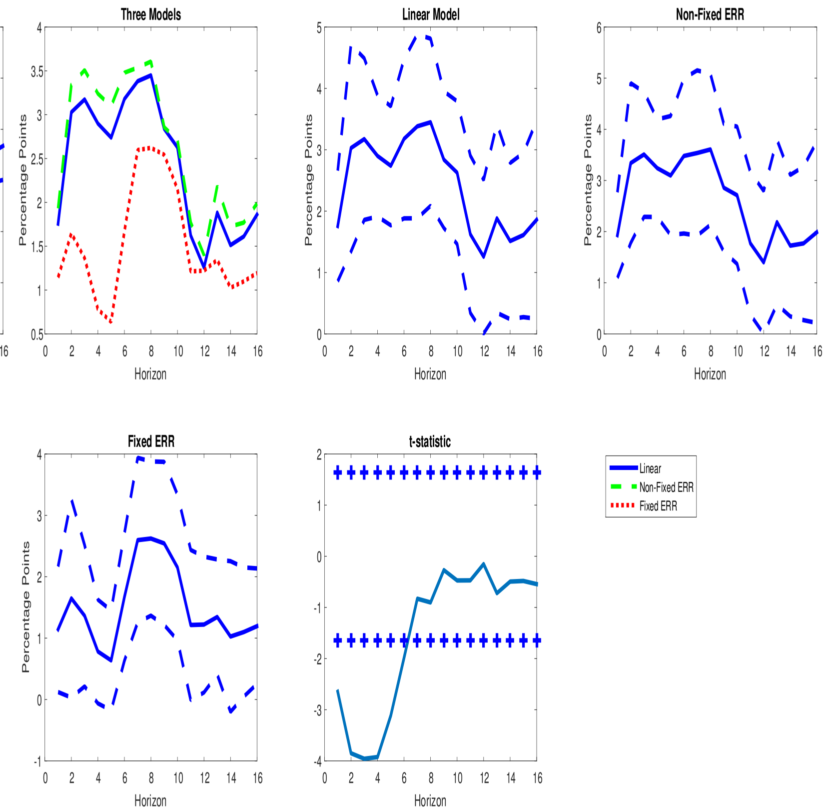
(b) Impulse Responses to a One Standard Deviation Credit Supply Shock (Nominal Exchange Rate).

Notes: Panel (a): This figure presents the impulse responses of output to a one standard deviation credit supply shock from the linear model and non-linear model when using the Shambaugh (2004) ERR measure. Panel (b): This figure presents the impulse responses of the nominal market-determined exchange rate vis-a-vis each country's anchor currency (taken from Ilzetzki et al. (2017)) to a one standard deviation credit supply shock from the linear model and non-linear model when using the Shambaugh (2004) ERR measure.
See notes from Figure 1 for details on these sub-figures' components.

Figure 16: **ERR's Effect on Output's and Exchange Rate's Sensitivity to Credit Supply Shocks for the LYS ERR Measure: (a) Output; (b) Nominal Exchange Rate**.



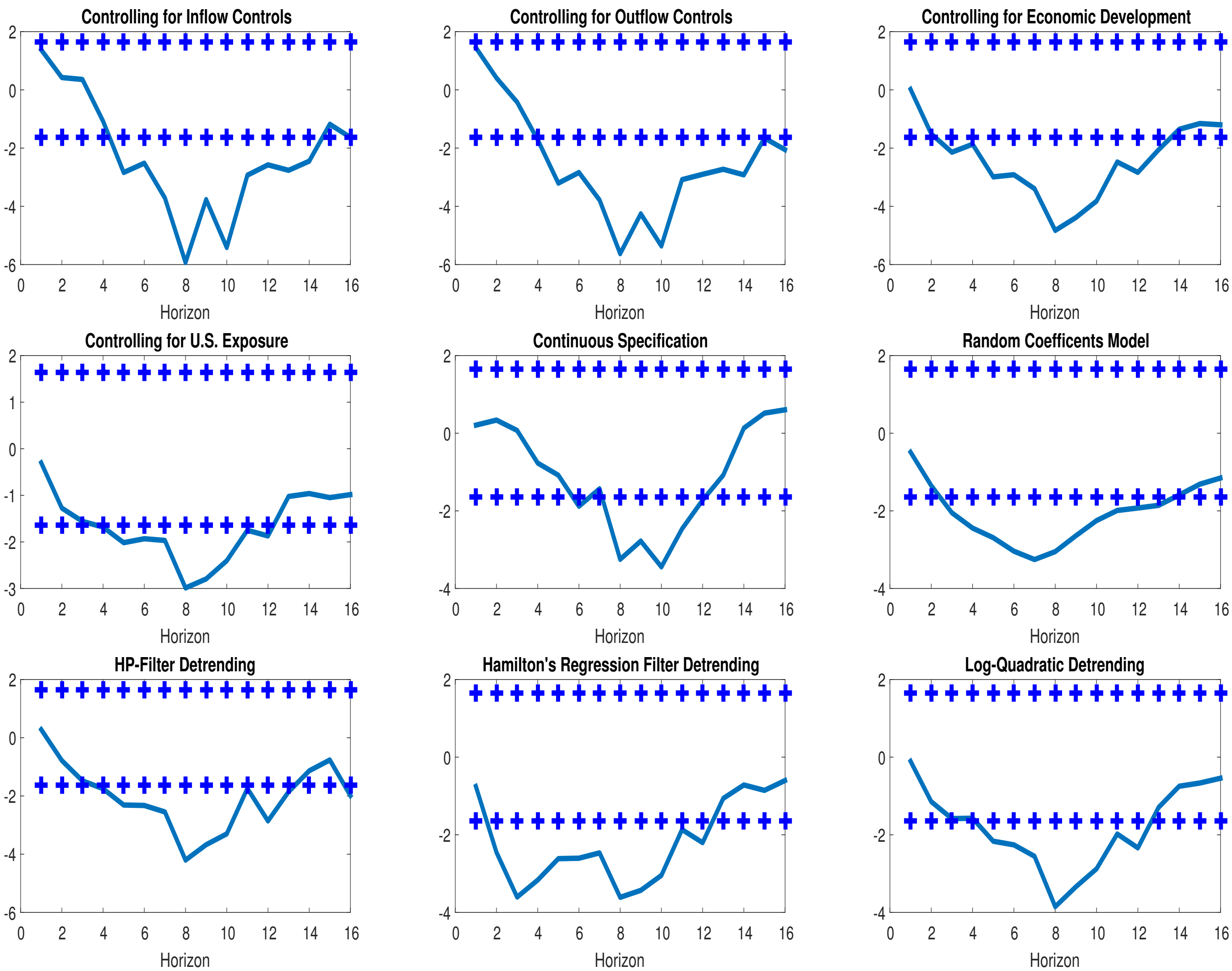
(a) Impulse Responses to a One Standard Deviation Credit Supply Shock (Output).



(b) Impulse Responses to a One Standard Deviation Credit Supply Shock (Nominal Exchange Rate).

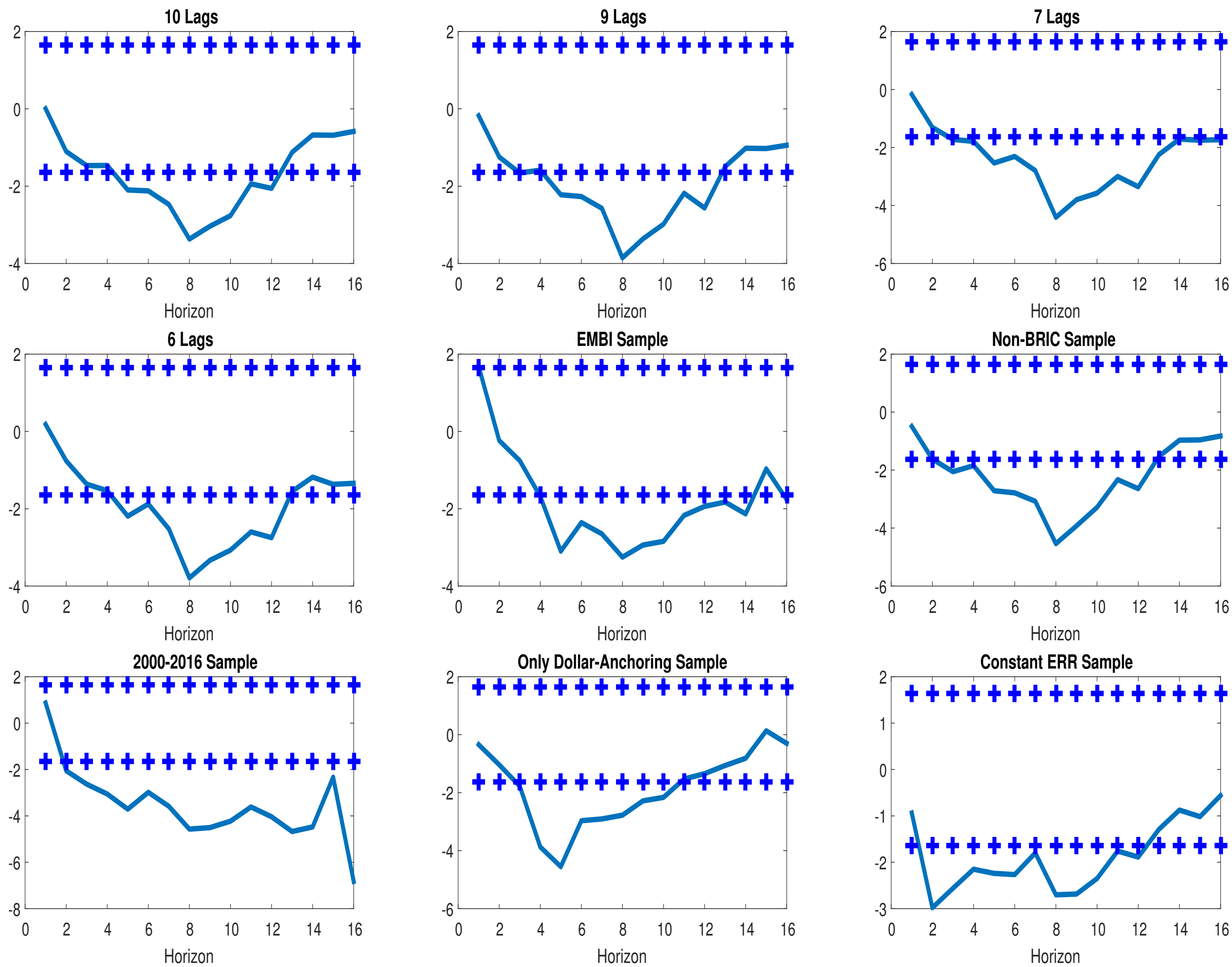
Notes: Panel (a): This figure presents the impulse responses of output to a one standard deviation credit supply shock from the linear model and non-linear model when using the Levy-Yeyati and Sturzenegger (2001, 2003, 2005) ERR measure. Panel (b): This figure presents the impulse responses of the nominal market-determined exchange rate vis-a-vis each country's anchor currency (taken from Ilzetzki et al. (2017)) to a one standard deviation credit supply shock from the linear model and non-linear model when using the Levy-Yeyati and Sturzenegger (2001, 2003, 2005) ERR measure.
See notes from Figure 1 for details on these sub-figures' components.

Figure 17: **ERR's Effect on Output's Sensitivity to Credit Supply Shocks: Controlling for Other States and Alternative Model Specifications**.



Notes: This figure shows the t-statistics of the difference between output responses in the fixed ERR and the non-fixed ERR for controlling for various other states and various alternative model specifications, including: using the continuous specification from Equation (4); the random coefficients model presented in Equations (5)-(7); and three alternative detrending filters for extracting the cyclical component of output (described in Section 3.2.3). For convenience, the 5% significance levels (± 1.645) are added. Horizon is in quarters.

Figure 18: **ERR's Effect on Output's Sensitivity to Credit Supply Shocks: Alternative Lag and Sub-Sample Specifications**.



Notes: This figure shows the t-statistics of the difference between output responses in the fixed ERR and the non-fixed ERR for various alternative lag and sub-sample specifications described in Section 3.3. For convenience, the 5% significance levels (±1.645) are added. Horizon is in quarters.