Capital Controls as Shock Absorbers*

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Abstract

The recent global financial crisis has resuscitated the debate on the relevance of capital controls as effective policy instruments. This paper contributes to this debate by studying the shock-absorbing capacity of capital controls. Using a recently developed capital control dataset for a panel of 33 emerging market economies, I show that output in economies with stricter capital *inflows* controls responds significantly less to global credit supply shocks, whereas capital *outflow* controls have no significant shock-absorbing capacity. Leverage is significantly lower in economies enacting stricter capital inflow controls, suggesting that financial frictions play a role in driving the shock-absorbing capacity of inflow controls.

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1 Introduction

The Great Recession has revived the debate on the merit of international capital mobility restrictions. In the early 1990s, as large amounts of capital flowed into emerging market economies (EMEs), capital inflow controls were largely viewed as an anachronism that leads to distortions that slow economic growth; in accordance with this view, policymakers did not consider them as appropriate policy tools for macroeconomic stabilization. However, the subsequent economic crises in Southeast Asia and Russia in the late 1990s and South America in the early 2000s, and especially the recent financial crisis that produced abrupt and large capital outflows from peripheral Europe and many EMEs, have altered the view on capital inflow controls into a more favorable one that supports their inclusion as a viable macroprudential policy tool. The recent shift of opinion on the efficacy of capital inflow controls on the part of researchers is apparent both on the theoretical side (see, e.g., Bianchi (2011), Farhi and Werning (2012, 2014), Bianchi and Mendoza (2017), Brunnermeier and Sannikov (2015), Ottonello (2015), Schmitt-Grohé and Uribe (2017), Benigno et al. (2016), Korinek and Sandri (2016), and Davis and Presno (2017))[1] as well as on the policy side (see, e.g., Ostry et al. (2010) and Ostry et al. (2011)).

The objective of this paper is to conduct an empirical examination of the hypothesis that capital inflow controls constitute absorbers of global shocks. While this hypothesis has received strong support from the above cited theoretical work, empirical work on this topic has been quite limited; to the best of my knowledge, there has been no empirical work that provided direct empirical evidence on this hypothesis. The few papers that have looked at the shock-absorbing capacity of capital controls have either done so indirectly, i.e., not by conditioning on a particular identified shock but rather by regressing output on capital flows alone or their interaction with episodes of economic crises, or have done so directly but by only focusing on limited aspects of the controls' shock-absorbing capacity. In particular, Gupta et al. (2007) shows that EMEs that had in place capital inflow controls prior to currency crises recovered from them much faster; and Ostry et al.

[1] Jeanne and Korinek (2010) develop a closed economy model in which taxes on borrowing are welfare increasing and thus, notwithstanding the absence of an exchange rate and international trade from their model, can also be viewed as work that lends support to using capital controls as a stabilizing policy tool.

(2010) and Ostry et al. (2011) provide evidence that in the recent financial crisis EMEs that had capital inflow controls prior to the crisis suffered less from it. Lastly, Edwards and Rigobon (2009) did directly examine the shock-absorbing capability of capital inflow controls, but did so only in the context of the sensitivity of the exchange rate to external shocks and only in the context of Chile; the evidence in Edwards and Rigobon (2009) is also favorable in the sense that it indicates that capital inflow controls moderated the sensitivity of the Chilean exchange rate to external shocks.

To properly fill in the empirical gap in the literature, I improve upon the previous empirical work along two important dimensions. First, I make use of the Gilchrist and Zakrajek (2012) credit supply shock series to measure global credit supply shocks. Gilchrist and Zakrajek (2012) use micro-level data to construct a credit spread index which they decompose into a component that captures firm-specific information on expected defaults and a residual component that they term as the excess bond premium.[2] The latter component can be interpreted as capturing exogenous variation in the pricing of default risk and is the measure of global credit supply shocks used in this paper. Importantly, their shock series serves as an exogenous and common shock to EMEs; as such, it can be employed to study whether capital inflow controls constitute shock absorbers in EMEs.

Second, I utilize a newly developed capital control dataset from Fernández et al. (2016) that revises, extends, and widens 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 2013 and provides information on restrictions on capital inflows and outflows separately while distinguishing between 10 categories of assets and the residency of the transacting agent. The aggregate capital control index is an average of the various sub-indices. Details of the aggregation procedure are given in Appendix A. I integrate this capital control data with quarterly frequency output data of 33 EMEs and estimate nonlinear, state-dependent dynamic fixed-effect panel regressions to study whether

[2] Gilchrist and Zakrajek (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.

the effect of global credit supply shocks differs across states of strict and light capital controls.[3] I employ the Jorda (2005) local projections approach in the panel regression specification so as to be able to directly estimate the state-dependent impulse responses to global credit supply shocks.

My empirical findings can be summarized as follows. There is a statistically significant difference between the response of output in the strict controls state, defined as being equal or greater to the 75th percentile of the capital inflow control index, relative to the light controls state (i.e., being in the lower three quartiles). This difference is also economically significant, peaking at about 1.5 percentage points after 1.5 years; in relative terms, this difference implies that the response of output in the strict capital controls state is 6 times higher than that in the light capital controls state. The behavior of both real consumption and investment, which depict significant differences in their response (declining more in strict capital controls economies), is consistent with that of output; the trade balance does not move significantly in the strict controls state while rising in the light controls state, broadly consistent with the much stronger output decline in the latter state.

To shed light on the mechanism behind these results, I turn my analysis to financial variables. Using the Emerging Markets Bond Index (EMBI) Global computed by JP Morgan as a measure of country credit spread, I show that country risk-premiums respond much more aggressively in the light capital controls state. Then, using a measure of leverage that is based on the ratio of total claims of foreign banks on the corresponding EME to its GDP, I show that leverage does not fall in the strict controls state in response to a global credit supply shock, while significantly falling in the light controls state. This deleveraging process experienced in the light controls state, which is avoided by being in the strict controls state, is consistent with the significant rise (fall) in the trade balance in the light (strict) controls state. (Using Balance of Payments data, I also demonstrate that credit supply shocks lead to net capital outflows that are more significant in the light controls state, which also accords well with the behavior of the trade balance.) Finally, and importantly, I demonstrate that this measure of leverage is significantly lower in the strict capital controls state

[3] I transform the capital control annual measures into quarterly ones by assuming identical quarterly values equal to the corresponding annual values. This is an innocuous assumption given the strongly acyclical nature of these controls and their very small standard deviation at annual frequencies, as documented in Fernández et al. (2016).

relative to the light controls state.

How should these results be interpreted from a structural standpoint? Since capital controls on capital inflows effectively act as a credit-limiting tool, and since global credit supply shocks produce much stronger economic downturns accompanied by acute deleveraging in the light controls state, a suitable framework that can be used to interpret this paper's findings is the one put forward by the Sudden Stop literature. Specifically, as emphasized in Durdu et al. (2009), the effects of macroeconomic shocks are significantly amplified for reasonably higher initial levels of debt-to-GDP ratios. The reason for this amplification is that there is a credit constraint that limits the EME's ability to borrow from abroad and its presence causes nonlinear effects of shocks that lead the economy sufficiently close to making this constraint bind. Hence, interpreted through the lens of the Sudden Stops framework, this paper's results seem to suggest that EMEs with strict controls in place are able to better absorb shocks owing to having lower debt-to-GDP ratios which make credit constraints less likely to bind in the presence of contractionary global shocks.

Importantly, the results of this paper do not contradict those of Fernández et al. (2015), who provide empirical evidence that capital controls are largely exogenous to the business cycle. Their finding can prevail alongside this paper's results quite naturally as the former implies that capital controls can effectively be considered as exogenous state variables, while the latter suggest that being in a state of stricter inflow controls reduces the sensitivity of economic activity to global shocks. In fact, the results found in Fernández et al. (2015) facilitate the empirical analysis undertaken in this paper as they alleviate potential endogeneity concerns relating to the capital controls state.

The remainder of the paper is organized as follows. Section 2 begins with a brief description of the data, after which it presents the methodology and main empirical evidence. Section 3 examines the robustness of the baseline results. Section 5 examines the role of individual inflow controls categories. The final section concludes.

2 Empirical Analysis

2.1 Data

Data is quarterly and covers 33 EMEs with samples that span 1995-2014.[4] Strictly speaking, the panel is an unbalanced panel but the samples are mostly balanced aside from some discrepancies. The chosen countries were those belonging to the universe of EMEs for which quarterly data with reasonable length was available. 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 and enter it in the regressions in logs.

The variable I use to measure credit supply shocks is the excess bond premium (EBP) from Gilchrist and Zakrajek (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.

The capital control measures I employ are based on the newly developed and updated *de jure* annual measures of capital controls from Fernández et al. (2016), who revise, extend, and widen the dataset originally developed by Schindler (2009), and later expanded by Klein (2012) and Fernández et al. (2015). This capital controls dataset provides a quantitative measure of the existence of capital controls in both inflows and outflows separately, across 10 asset categories, for 100 economies between 1995 and 2013. The index is defined between zero (absence of controls in all asset categories) and one (controls in all categories). The total index is an average of the inflows and outflows control indices, which are in turn averages of their respective 10 asset category indices.

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 as-

[4] Even though the capital controls data run through 2013 only, I am still able to let the other data series run through 2014 owing to the fact the capital controls measures enter my regressions with 4 lags (see discussion on why this number of lags is warranted in Section 2.2).

sumption that capital controls do not exhibit variation within the year; accordingly, I transform the capital control annual measures into quarterly ones by assuming identical quarterly values equal to the corresponding annual values.

Other outcome variables I consider to learn more about the mechanism behind the results are investment, consumption, trade balance, country credit spreads, leverage, and capital flows. The first two are defined as gross fixed capital formation and private consumption expenditure (both in local currency) divided by the GDP deflator; the trade balance is export minus imports (both in local currency) divided by local currency current GDP. 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.

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 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.[5] I employ the following data on international capital flows: financial flows related to foreign direct investment, portfolio investment, and other investment, where 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. Except for EMBI, all variables were seasonally adjusted using ARIMA X12.

Apart from the trade balance, capital flows, and EMBI, I take logs of all of the variables. Data on investment, consumption, trade balance, and leverage span the 33 countries covered by the output variable; EMBI is covered by only 21 countries; and portfolio flows are covered by 29 countries while foreign direct investment and other investment are covered by 30 countries (see Appendix A for sample details).

[5] I also study the behavior of EMEs' bond debt using the BIS international debt securities database. Details on the bond debt data are provided in Appendix A.

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 state-dependent 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 Zakrajek (2012)'s EBP variable, while allowing the estimates to vary according to the level of capital controls in place in a particular country and time. For example, when I use the 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:

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

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, all the coefficients vary according to whether we are in state "A", i.e., strict capital controls are in place, or state "B", i.e., there are light capital controls. I is a dummy variable that takes the value of one when the capital controls level is above a threshold. Since I am looking for a threshold that divides capital controls into strict versus light levels of controls, I define $I_{i,t-4} = 1$ when the level of controls is at or above the upper quartile level of controls across all observations. Accounting for the loss of observations resulting from the number of lags included in the regressions well as from unavailability of data for some countries in some of the periods, this threshold dictates that a total of 511 observations, or 24% of all available observations, are consistent with being in a state of strict capital controls.

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 construction of the controls variable. Since the latter was converted from annual to quarterly frequency by assuming identical values within the year, it is necessary to include it in the regression with four lags so as to avoid correlation of the error term with it; this in turn requires that more than 4 lags of output and EBP be included in the regression so as to purge $I_{i,t-4}$ of any potentially endogenous sources.

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 capital *inflow* controls, rather than *outflow* controls, are relevant for reducing the output effects of credit supply shocks. In what follows after that, I turn to inspecting the behavior of other macroeconomic variables as a function of the capital inflows controls state in order to uncover the underlying mechanisms that drive the output-based results.

Capital Inflow Controls Versus Capital Outflow Controls. The first set of results, shown in Figures 1a and 1b, depicts the output response to credit supply shocks in the non-linear model considering two measures of capital controls: the capital inflow controls index (Figure 1a) and the capital outflows controls index (Figure 1b). Notwithstanding the theory-driven focus of the literature on capital inflow controls, it is still useful for comparison purposes to examine the empirical role of both control types and to substantiate the centrality of inflow controls.

For comparison purposes, the results from the linear model are also shown in all of the figures. Specifically, in each Figure the first sub-figure jointly shows the point estimates of the linear model (solid lines), strict capital controls state (dotted lines), and the light capital controls state (dashed lines); the next three sub-figures depict the impulse responses along with Driscoll and Kraay (1998) 95% confidence bands for the linear model, the strict capital controls state, and the light capital controls state; and the last sub-figure shows the t-statistics of the difference between impulse responses in the strict capital controls state and the light capital controls state.

The results from Figure 1a clearly indicate that controls on total capital inflows reduce the effects of credit supply shocks on output. The reduction is both economically and statistically significant. The peak output response in the light capital controls state takes place after 1.5 years reaching -1.8%, compared to only -0.3% in the strict capital controls state. Beginning with one quarter following the shock, the difference between the responses in the two states becomes very statistically significant with t-statistics of this difference far exceeding conventional rejection levels, peaking at 4.3 after 1.5 years.

By contrast, the results from Figure 1b demonstrate that outflow controls are unable to significantly moderate the sensitivity of output to credit supply shocks. The difference between the responses in the strict and light capital outflow states is statistically insignificant for all horizons, and is actually negative for half of the horizons.

Taken together, the results of the two figures clearly show that the theory-driven emphasis on inflow controls as policy tools for increasing macroeconomic stability is well-warranted. Having established the shock-absorbing capacity of capital *inflow* controls, I now turn to inspecting the mechanism behind this result by studying the response of various other macroeconomic variables.

Investment, Consumption, and the Trade Balance. Figures 2, 3a, and 3b depict the responses of investment, consumption, and the GDP share of the trade balance from the model with the capital inflows control index.

The results from Figure 2 indicate that investment responds much more strongly in the light capital controls state, with a peak decline of 5.1% after 1.5 years compared to effectively a zero response at this time in the strict capital controls state. The t-statistics for the difference between the responses in the two states start exceeding conventional rejection levels in the third horizon and peak at 4.9 after 2.5 years. As in the case of output, the main takeaway from 2 is that imposing controls on capital inflows appears to significantly reduce the sensitivity of investment to credit supply shocks.

Figures 3a and 3b present the responses of consumption and the trade balance share of GDP, respectively. Consumption responds significantly more strongly in the light capital controls state than in the strict controls state. The response difference is highly significant for most horizons. Notably, the response of consumption in the strict capital controls state is insignificant for all horizons, this in contrast to the significant negative response observed for most horizons in the light capital controls state.

The trade balance response is positive in the light capital controls state and mostly negative in the light controls state; the former is statistically significant from the fifth period through the three year mark while the latter is insignificant for all horizons. Accordingly, the difference between the responses is significant for second and third year following the shock. This is broadly consistent with an interpretation that is based on the Sudden Stops literature where a contractionary global shock induces a sharper fall in capital inflows in the light controls state and consequently a more acute economic downturn. This interpretation will be further explored and formalized in the next sections that deal with responses of country credit spreads, leverage, and international capital flows.

Country Credit Spreads. 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.[6] 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 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.[7]

Figure 4 presents the response of EMBI to a credit supply shock. The results can be summarized as follows. First, the response in the linear model and in the light controls state is significantly positive for two years; by contrast, the response in the strict controls state is only significant for the first year and much lower than in the light controls state (e.g., its response in the second period is 0.6 percentage points compared to 1.3 percentage points in the light controls state). Second, the difference between the responses is statistically significant throughout the two year period following the shock. In sum, the results from Figure 4 stress that credit supply shocks' effects are transmitted through the increase of riskiness in the economy as measured by EMBI, and that this transmission is more powerful in the light controls state.

[6] Data on EMBI is available for 21 countries, where the longest range of the unbalanced panel is 1995:Q1-2014:Q4. More details are provided in Appendix A.

[7] As emphasized in Elekda and Tchakarov (2007) and Fernández and Gulan (2015), EMBI constitutes 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 capital inflow controls.

Leverage. Given the important theoretical role of leverage in models of EMEs based on credit constraints (e.g., Durdu et al. (2009) and Mendoza (2010)) as well as those based on the Bernanke et al. (1999) financial accelerator framework (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. Towards 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).[8]

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)).[9]

Figure 5 presents the response of the log of leverage to a credit supply shock. The results indicate that leverage significantly drops in the light controls state after about 1.5 years and onwards, stressing that a sharp process of deleveraging takes place following the credit supply shock in this state. Note that, since output also drops in this state, we can deduce that debt also declines in absolute terms in the light controls state. By contrast, in the strict controls state, leverage also begins to significantly drop roughly at the same time that is observed for the light controls state,

[8] 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.

[9] Data from the BIS on inter-office claims is rather limited and is only available from the location banking statistics database, which does not exclude inter-office bank lending from its claims data, from 2012 onwards. Using this data for my sample of countries and the 2012-2016 period, I have found that intrabank lending accounts on average for 34% of total cross-border bank lending. This further emphasizes the need to rely on consolidated banking data when constructing my leverage variable.

but this drop is much more short-lived remaining significant for only two quarters. The difference between the responses is significantly positive from the 10th horizon onwards, emphasising that a much more acute deleveraging process is taking place in the light controls state.

To better understand which sectors drive the responses from Figure 5, 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 sectors divided by its GDP. These results are shown in Figures 6a-6c, from which it is apparent that leverage in all sectors undergoes a stronger and more persistent deleveraging process in the light controls state relative to the strict one. Note the these results portray a deleveraging based narrative that is not limited to the private sector; it is apparent that the government also undergoes a significantly stronger deleveraging process in the light controls state in response to global credit supply shocks.

Corporate Debt via Bond Issuance. 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.[10]

To gain an understanding as to whether bond debt issuance plays an important role in the transmission of the different output effects of global credit supply shocks across the two states, I make use of BIS data on debt securities collected on a nationality basis. Figures 7a-8b present responses of the log of total bond debt to GDP, government bond debt to GDP, financial sector bond debt to GDP, and private non-financial sector bond debt to GDP, respectively. Overall, neither total bond debt nor any of its components seem to fall significantly more in the light controls state than

[10]I base this statement on the locational banking statistics database which distinguishes bond debt from loans and indicates that bond debt makes up on average less than 14% of total claims. This number includes sovereign bond debt and also inter-office related claims. Nevertheless, it points to the fact that most of international bank funding activity takes place via loans.

in the strict state. Somewhat puzzling is the behavior of government bond debt, which is rather different from the response in Figure 6c pertaining to the BIS-reporting banks' claims on the public sector. This can be mechanically explained, however, by the fact that the latter constitutes on average 8.6% of GDP compared to 18.1% for the former. I.e., international banks are significant holders of sovereign bond debt, holding nearly half of it on average, but there appear to be other significant holders of this debt which respond quite differently from them.

The results from Figures 8a and 8b imply an unimportant role for corporate bond debt issuance as a transmission mechanism for the different output effects of global credit supply shocks across the two capital control states. This may be driven by the fact that corporate bond debt has only become a significant source of funding for EMEs in the last decade; this means that for the most of my sample period this form of financing is not a major source of funding for EMEs.

Capital Flows. International capital flows are an additional type of data worth looking at to further pin down the mechanism driving the main results of this paper. Analyzing their response across the two states can be seen as a complementary analysis to that of the leverage variable as they allow me to study the behavior of financial flows while distinguishing equity flows from debt flows. Figures 9a-10b depict the responses of total net financial flows and their components, net flows of foreign direct investment, portfolio investment, and other investment, respectively. All variables are in terms of shares of GDP.

The results from Figure 9a stress that the Sudden Stop element encapsulated in global credit supply shocks is significantly stronger in the light controls state than in the strict state, as capital flows out of the average EME in a more significant and persistent manner in the light controls state.[11] The difference between the capital flows' response across the strict the light controls states begins to be significantly negative after one year, with this significance lasting through the 12th horizon continuously except for two intermediate horizons. In terms of the sub-components of the capital flows variable, the subsequent figures seem to indicate that the differential response of total

[11] A positive response of this variable implies that capital flows out of the economy.

flows is mainly driven by that of 'other investment', which mainly consists of debt related flows;[12] foreign direct investment and portfolio flows, albeit to a lesser extent, also seem to contribute somewhat to the differential response of total flows.

Portfolio flows (Figure 10a), which include both bond and short-term equity flows, do not exhibit a conclusive pattern in terms of the response difference across states. To make the analysis finer, I present the responses of the equity and debt related flows underlying the total portfolio flows variable (Figures 11a and 11b). These results indicate that there is a stronger decline in debt portfolio net inflows in the strict state whereas portfolio equity net inflows are more favorable in the light controls state, albeit only at relatively later horizons.

Overall, the results on capital flows are consistent with the notion that debt related flows play an important role in explaining the mechanism behind this paper's results. To further pin down the latter mechanism, I now to turn to inspecting the long-run relation between leverage and the level of capital inflow controls.

2.4 Do Capital Inflow Controls Reduce Leverage?

Interpreted through the lens of the models advanced in the Sudden Stops literature, the empirical results presented so far imply that steady state leverage should be lower in economies which have strict capital inflow controls in place. This lower steady state leverage, in turn, should moderate the effects of contractionary shocks relative to a state of higher initial leverage as in the former case the likelihood of a binding credit constraint is lower (see, e.g., Durdu et al. (2009)).

From an unconditional standpoint, a simple computation of the correlation between leverage and the capital inflows controls variable already tells an informative tale: the two variables have a significantly negative correlation of -0.19, implying that being in a stricter controls state is associated on average with also having lower leverage. This constitutes suggestive evidence supporting the notion that financial frictions play an important part in driving this paper's results. However,

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

it is important to complement this unconditional evidence with conditional evidence that controls for the effects of global credit supply shocks. Towards this end, I estimate a similar specification to the baseline one, given by

$$\begin{aligned} Lev_{i,t+h} - Lev_{i,t-1} = I_{i,t-4}[\Upsilon_{A,h} + \Xi_{A,h} EBP_t + \Omega_{A,h}(L) EBP_{t-1} + \Gamma_{A,h}(L)\Delta Lev_{i,t-1}] + \\ + (1 - I_{i,t-4})[\Upsilon_{B,h} + \Xi_{B,h} EBP_t + \Omega_{B,h}(L) EBP_{t-1} + \Gamma_{B,h}(L)\Delta Lev_{i,t-1}] + u_{i,t+h}, \end{aligned} \tag{3}$$

where *Lev* is log of leverage, as defined above with the ratio of BIS-reporting banks' claims on an EME to its GDP; and coefficients $\Upsilon_{A,h}$ and $\Upsilon_{B,h}$, which are now the center of my attention, represent the average effects of being in a state of strict controls and light controls, respectively.[13] My interest lies in estimating these coefficients and ascertain whether they are statistically different from one another.

Figure 12 shows the impulse responses of leverage to being in the two states. The results clearly demonstrate that the strict controls state moves the economy into a new steady state with lower leverage (3.7% lower after 4 years) whereas the light controls state moves it to a steady state with higher leverage (6.3% higher after 4 years), where the former response is statistically significant while the latter is not. After about two years and onwards, leverage becomes significantly lower in the strict controls state relative to the light controls state, with the point estimates' difference being negative already from the impact period. This result can be viewed as supporting evidence for the notion that strict inflow controls shift an economy into a steady state characterized by lower leverage. And, in line with economic theory, this result can help explain why real activity is more sensitive to credit supply shocks in the light controls state.

To better understand which sectors drive the responses from Figure 12, 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 sectors divided by its GDP. These results are shown in Figures 13a-13c, from which it is apparent that the responses

[13] Note that, since perfect collinearity results from putting together state-specific fixed effects ($\alpha_{A,i,h}$ and $\alpha_{B,i,h}$) and state-specific dummies, I omit the former from the regression.

of leverage in the private non-financial sector and public sector are the main drivers behind the results for total leverage. Private non-financial sector leverage exhibits dynamics that are particularly similar to those observed for total leverage, moving to a lower (higher) steady state in response to being in the strict (light) controls state. And as the associated t-statistics demonstrate, the difference in responses is highly significant. While public sector leverage seems to fall in both states, the decline in the light controls state becomes significant only in the last horizon with the fall in the strict controls state being strongly significant in all horizons; accordingly, the fall in leverage in the strict controls state is significantly stronger than that in the light state from the impact horizon onwards, with t-statistics far exceeding conventional levels.

Overall, the results of this section lend credence to the view that financial frictions are likely to play a role in driving this paper's results. Importantly, it appears that both private non-financial sector leverage as well as public sector leverage are especially important for these financial frictions.

3 Robustness Checks

This section examines the robustness of the baseline results along various dimensions, including: controlling for economic development; using different measures of credit supply shocks; detrending output via the popular HP filter; removing the assumption on the within-year constancy of the capital inflow controls index; examining various alternatives to the 75th percentile threshold used to construct the strict and light controls state dummies; and considering different lag specifications and sub-samples. In all checks I consider output as the outcome variable and employ the capital inflow controls index to distinguish between strict and light control states.

3.1 Controlling for Economic Development

Fernández et al. (2016) document a significantly negative correlation between economic development and capital controls for their sample, which is much larger than the one considered in this paper and includes both developed and developing economies. An important endogeneity bias concern that may arise in the context of this reported negative correlation pertains to my not controlling for the possible effect that different levels of economic development may have on the propagation mechanism underlying the effects of credit supply shocks on output across the two states. I.e., one may argue that the baseline results are partly driven by this negative relation through certain stability-increasing characteristics which are associated with low economic development, such as lack of financial depth, producing in turn an upward bias in the t-statistics presented in this paper.

Before formally addressing the above endogeneity bias concern, I would like to state two facts that can be considered as alleviators, in the a-priori sense, of this concern. The first fact, which is more general and can be utilized to alleviate the more general and common omitted variables bias concern, speaks to the difference in results for the outflow and inflow controls based regressions. If my results were really driven by omitted variable bias, one would expect that this would translate into positively significant t-statistics for the outflow controls state regressions, not only the inflow state ones. But this is certainly not the case, as stressed by the difference between Figures 1a and 1b. The second fact, which is specific to the economic development related issue, concerns the unconditional correlation between economic development and capital inflow controls in my sample of EMEs, which is negligible (-1.4%). This contrasts with the aforementioned fact documented by Fernández et al. (2016) on the significantly negative correlation between these measures for their sample. This dissimilarity implies that it is possible that the negative correlation found by Fernández et al. (2016) is driven, at least to some extent,[14] by the difference between developed and developing economies rather than the difference within developing ones.

Notwithstanding these two facts, it is worthwhile to formally confirm that my baseline results are not driven by the level of economic development, especially given that there is non-negligible variation along this dimension in my sample (e.g., Latvia on the poor end and Korea on the rela-

[14] It need be kept in mind that my sample of EMEs does not correspond to the universe of EMEs and thus the difference between my sample and that of Fernández et al. (2016) is not only due to their inclusion of developing economies.

tively rich end). Moreover, an additionally reasonable channel by which not controlling for economic development may bias the results is through more developed EMEs having better monetary and fiscal policy, or better institutions in general, which should be expected to increase macroeconomic stability. This potential channel suggests that it is advisable to control in my regressions not only for low economic development, but also for high levels of economic development. Towards this end, I estimate an extended specification given by

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

Effectively, relative to the baseline specification, I add two additional state variables to the estimation that facilitate controlling for the level of economic development: one state dummy (I^R) obtains the value of 1 if an observation corresponds to an EME that belongs to the upper quartile of the distribution of 1995 PPP-adjusted per capita GDP (initial value of economic development) for the EMEs in my sample and another (I^P) that obtains 1 if it corresponds to an EME that belongs to the lower quartile of the economic development distribution. By controlling for these two states I am effectively controlling for both the low-income state and the high-income state.[15]

The results from this exercise, which are shown in Figure 14, clearly illustrate that the main results of this paper are robust to controlling for economic development. The differences between the output responses across the two states continue to be strongly significant, with output falling

[15] Note that controlling for the entire income distribution by including a particular income 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 perfect complementarity states from the inclusion of the pair of capital controls state dummies. For the purposes of this specific robustness check, along the lines of the above discussion on the potential channels by which economic development can affect the baseline results, it is arguably preferable to control for the more acute ends of the income distribution so as to ensure that the baseline results are not driven by observations corresponding to *high* and *low* economic development. Notwithstanding this point, I have confirmed that results are robust to controlling for alternative income percentile thresholds.

much more strongly in the light controls state.

3.2 Alternative Global Credit Supply Shock Measures

My choosing the Gilchrist and Zakrajek (2012) EBP shock series as the baseline measure of global credit supply shocks in this paper mainly stems from its structural underpinning, which allows for a clear and appealing structural interpretation of this shock series and, therefore, also facilitates the structural interpretation of this paper's empirical results.[16] This virtue, coupled with the vast micro-data used to construct EBP, makes this series the state-of-the-art measure of credit supply shocks and, in turn, a suitable exogenous global shock for addressing this paper's research question.

One can argue that the EBP series ultimately represents a measure of global riskiness. As such, it has some natural competitors whose use as global risk measures can also be considered as appealing and are thus worthwhile using as robustness checks. Two such popular measures used by researchers as proxies for global risk factors are the VIX (see, e.g., Forbes and Warnock (2012)), the stock market (S&P 500) option-based implied volatility, and the Baa spread measured as the difference U.S. BAA corporate spread as the difference between the U.S. between Moodys Baa corporate bond yield and the 10-year U.S. Treasury bond yield (see, e.g., Akinci (2013)). rate. While these two risk measures clearly lack the structural base underlying the EBP series, their common use as global risk measures still warrants confirming that the baseline results are insensitive to employing them as the global risk shocks instead of the EBP series.

Results for using these two global risk measures instead of the EBP series are shown in Figures 15a and 15b, respectively. It is apparent from both figures that using alternative global risk measures do not have a noticeable effect on the baseline results, as the results are both qualitatively and quantitatively similar to the EBP based results. As stressed earlier, however, the clearer structural base underlying the EBP series facilitates more easily and naturally the structural interpretation

[16] As described in detail in Gilchrist and Zakrajek (2012), the base for this series is the distance-to-default model from the seminal work of Merton (1974).

of the EBP based results.

3.3 Using HP-Filtered Output

Two recent papers by Phillips and Jin (2015) and Hamilton (2016) strongly advise against using the HP filter, the most popular detrending tool used in macro, on the grounds that its cyclical component is characterized by spurious behavior (this is documented in both papers) and that it is an unsuitable tool for removing stochastic trends (this is formalized in the first paper for typical sample sizes in empirical macro work). Hence, one should proceed with caution when deciding upon whether to detrend the data.

In my analysis, where estimation and inference are reliable only when the data are stationary, simply using the detrended *level* of logged output in the regressions is inappropriate if the purpose of detrending is solely to remove the stochastic trend from the data. However, if the trend is not log-linear for some reason then the results could be affected by not detrending. Hence, notwithstanding the caution raised by Phillips and Jin (2015) and Hamilton (2016) regarding popular detrending methods, it seems worthwhile to examine the robustness of my results to estimating a specification in which the log of output is detended using the HP filter prior to taking its differences.

Results from this exercise appear in Figure 16.[17] It is apparent that responses are broadly similar to the baseline ones and, importantly, the differences between the responses across the states are still very significant. This suggests that the main result regarding the shock-absorbing capacity of capital inflow controls is robust to HP filtering the output data.

[17]When computing the cyclical component, I made use of all available observations for each country so as to estimate it as precisely as possible. This did not make for a noticeable difference with respect to using only the 1995-2014 sample when computing the HP-filered series because most output series do not go back much further than 1995. (The only major exceptions are: Iran (1988:Q1); Mexico (1981:Q1); South Africa (1960:Q1); and South Korea (1960:Q1).)

3.4 Interpolating the Capital Controls' Data

As explained in Section 2.1, I assume that capital controls do not exhibit variation within the year, in accordance with the robust finding by Fernández et al. (2015) that capital controls are strongly acyclical and have a very small standard deviation at annual frequencies. Accordingly, I transform the capital control annual measures into quarterly ones by assuming identical quarterly values equal to the corresponding annual values.

Nevertheless, it is still worthwhile confirming that this assumption, albeit appearing innocuous, does not drive the results of this paper. Towards this end, I use a cubic splined quarterly controls series interpolated from the annual series instead of the within-year constant baseline series. This rather popular interpolation procedure produces quarterly series that have varying levels of controls within the year, therefore relaxing the within-year constancy assumption. The results from this exercise are shown in Figure 17. They confirm that the baseline results are robust to allowing the controls series to vary within the year where the variation is produced using a popular interpolation procedure.

3.5 Alternatives to the 75th Percentile Threshold

In my baseline specification, I define the strict controls state as a dummy variable that obtains one if the corresponding observation is at or above the upper quartile level of controls across all observations. My choice of a dummy-based specification and its associated 75th percentile threshold aims at facilitating an empirical analysis that is capable of properly distinguishing between sufficiently strict and insufficiently strict controls, where sufficiency here is in terms of being strong enough to produce notable differences in output responses in the true data generating process (assuming, of course, that these differences do exist). These notable differences should in turn enhance the ability of the estimation method used in this paper to uncover true output responses differences across the two associated states of inflow controls.

The 75th percentile threshold for my sample is 0.70. Given that my controls measure is ultimately an average of various binary variables that obtain 1 if restrictions on the corresponding asset categories are in place, this threshold implies that observations consistent with having restrictions on at least 70% of the considered asset categories are defined as those belonging to the strict controls state.[18] To the extent that my qualitative controls measure reasonably proxies for controls' intensity,[19] differences in its distribution based on a sufficiently large cutoff value should provide a rough measure of intensity differences, thus warranting the use of a sufficiently high percentile threshold such as the 75th percentile. The 75th percentile can naturally only be implemented within a dummy-based interaction. Importantly, note that the fact that my controls measure is an imperfect proxy for controls intensity adds to the a-priori need for using a relatively high threshold so as to increase chances of detecting the true effect of controls' policy on the macroeconomic stability.

Notwithstanding the above discussion on the reason for my specification of choice, I view as important a robustness check that considers other thresholds within the baseline specification as well a continuous interaction based specification. Doing the latter amounts to estimating the regression

$$\begin{aligned} y_{i,t+h} - y_{i,t-1} = \alpha_{i,h} + \Xi_h EBP_t + \Omega_h(L) EBP_{t-1} + \Gamma_h(L)\Delta y_{i,t-1} + \\ + cc_{i,t-4}[\alpha_{cc,i,h} + \Xi_{cc,h} EBP_t + \Omega_{cc,h}(L) EBP_{t-1} + \Gamma_{cc,h}(L)\Delta y_{i,t-1}] + u_{i,t+h}, \end{aligned} \tag{5}$$

where cc is the capital controls variable itself, and the coefficient of interest is now $\Xi_{cc,h}$ which measures the additional effect of credit supply shocks that a higher level of controls induces (relative to the average, or main, effect).

[18] Note that my capital inflow controls measure consists of 10 asset categories, 5 of which are constructed themselves as averages of two sub-category binary variables relating to restrictions on the types of transactions associated with the corresponding asset category. I.e., my controls measure is effectively a weighted average of a total of 15 binary variables, 10 of which (those divided into two further transaction-based sub-categories) receive a 5% weight whereas the remaining 5 variables receive a 10% weight.

[19] Since my controls measure is computed from binary measures of having or not having controls on specific asset categories it is, at its core, more of a qualitative measure of controls along their extensive margin than a quantitative intensity measure along their intensive margin. That said, I view as a reasonable conjecture the notion that having controls on more asset categories should, at least to some extent, capture also controls' intensity. Accordingly, the controls measure I use is strongly correlated with that of Quinn (1997) (updated through 2007), which does not distinguish between inflow and outflow controls but is arguably a better measure of controls intensity; I thank Dennis Quinn for kindly sharing with me this updated controls series.

Figure 18 shows the results from using 0.90, 0.80, 0.70, 0.60, and 0.50 percentile thresholds (corresponding to cutoff values of 0.90, 0.75, 0.65, 0.50, and 0.33, respectively) within the baseline specification as well as from estimating the continuous interaction based specification. To save on space and to ease the exposition, Figure 18 concisely summarizes the results from these estimations by only presenting the corresponding t-statistics, where those for the continuous interaction based specification correspond to those of $\Xi_{cc,h}$ (the effect of the interaction term). While the 90th through the 60th percentile thresholds produce t-statistics that are quantitatively similar to the baseline ones, the 0.50 percentile threshold produces less significant t-statistics, albeit ones that still exceed conventional significance levels for several of the considered business cycle frequency horizons.[20] This is arguably due to the rather low value of the controls index of 0.33 (i.e., only 33% of asset categories are subject to restrictions) associated with the 0.50 percentile threshold. This cutoff value is likely insufficiently large, compared to the other larger considered thresholds, for picking up output response differences across the two states in the data. Nevertheless, the overall takeaway from the percentile threshold results is that the main results of this paper are robust to using alternative thresholds.

As apparent from the last sub-figure of Figure 18, the continuous interaction based estimation reinforces the notion that this paper's results are not driven by the particular cutoff value assumed for being in a strict controls state. It is clear that higher capital inflow controls produce highly significant positive effects of credit supply shocks, with the associated t-statistics far exceeding conventional significance levels. Overall, taken together, the results of this section should increase one's confidence in the reliability of the baseline results. It seems that true differences in output responses across the two states are sufficiently strong in the true data generating process for being picked up by identification procedures that opt for less distinctive thresholds or dropping the dummy-based specifications altogether.

[20]Since economic theory supports focusing on the alternative hypothesis that inflow controls increase macroeconomic stability, it is arguably more correct to look at the one-tailed p-values associated with these t-statistics rather than the two-tailed ones. Hence, since the t-statistics from 0.50 percentile threshold sub-figure are larger than 1.645 from the 6th horizon through the 10th horizon (and exceed 1.96 for the 8th horizon), it is implied by them that we can reject the null for these horizons with a 95% confidence level in favor of the theory-consistent alternative hypothesis.

3.6 Number of Lags and Various Sub-Samples

As explained in Section 2.2, the state dummy variable appears in its fourth lag in the regression due to the fact that it is converted from annual to quarterly frequency by assuming identical values within the year. It is therefore important to include a relatively large number of lags in my estimations so as to purge the state dummy variable of any potentially endogenous sources. In this section I confirm that specifying a smaller number of lags, while still ensuring that some amount of the potentially endogenous variation in the state dummy is removed by past output growth realizations, 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); 2000-2014 sample; and 1995-2007 sample. The first sample is useful to consider to ensure that the baseline results hold also when using the sample of countries 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 capital controls employs a small open economy framework. The BRIC economies, which 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 driving the baseline results.

The 2000-2014 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. Lastly, although the recent global financial crisis generated large adverse global credit supply shocks that provide a suitable quasi-natural experiment for addressing the research question of this paper, It is still interesting to examine whether the results still hold when the 2008-2009 financial crisis period is excluded from the analysis.

As in the previous section, for ease of exposition and to save space I present in Figure 19 only 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 19. Taken together, these results lend further credence to the baseline results of this paper.

4 Individual Inflow Controls Categories

As documented in Fernández et al. (2015), policymakers tend to place inflow controls on the various inflow categories quite in tandem, in accordance with the strong correlation between the various restrictions sub-indices that comprise the capital inflow controls index. It is therefore sensible, from an empirical standpoint, to follow the strategy pursued in this paper and consider the average inflow controls index in my analysis rather than looking at its individual sub-indices. Nevertheless, despite the fact that policymakers have rarely opted for imposing restrictions on a specific type of asset category independently of other categories, it still seems potentially appealing to study which components of the inflow controls index are responsible for driving the baseline results.

Figure 20 presents the t-statistics for the hypothesis that the difference between the output responses across the two states are zero, where the states are defined on the basis of the 10 sub-indices comprising the aggregate inflow controls index. The findings from Figure 20 suggest that 7 category restrictions act as significant shock absorbers: Equity inflow restrictions; Bond inflow restrictions; Collective investment inflow restrictions; Commercial Credits inflow restrictions; Guarantees, sureties and financial backup facilities inflow restrictions; Direct Investment inflow restrictions; and Real Estate inflow restrictions. While it is beyond the scope of this paper to provide an explanation for the results on each individual asset category restrictions, the finding that restrictions on commercial credit succeed in moderating the response of output is worth highlighting. In particular, one potential reason for this result may lie in the fact that the most obvious way to overcome capital controls, frequently cited by the literature albeit not quantified, is for firms to register short-term credit as commercial credit (see, e.g., Neely (1999), Cowan and Gregorio (2007), and Forbes (2007)). Hence, commercial credit controls may be important for enforcing controls and reducing their evasion, thus increasing in turn the overall effectiveness of capital inflows controls for increasing macroeconomic stability.

This line of reasoning applied to the case of commercial credit restrictions implies that their contribution to macroeconomic stability should be enhanced once they are combined with other asset category controls. It is possible that this reasoning also applies to other asset category restrictions. But this is a conjecture that may or may not be borne out by the data and it is therefore important to test its validity. To be more precise, the specific question arising from the findings of Figure 20 that I view as worth addressing is whether conditioning on the effects of the individual asset category restrictions eliminates the shock-absorbing capacity of the total inflow controls index. In other words, is there significant added value from the joint interaction of the various asset category restrictions?

To answer this question, I estimate the following extended nonlinear model:

$$\begin{aligned} y_{i,t+h} - y_{i,t-1} = I_{i,t-4}[\alpha_{A,i,h} + \Xi_{A,h}EBP_t + \Omega_{A,h}(L)EBP_{t-1} + \Gamma_{A,h}(L)\Delta y_{i,t-1}] + \\ +(1 - I_{i,t-4})[\alpha_{B,i,h} + \Xi_{B,h}EBP_t + \Omega_{B,h}(L)EBP_{t-1} + \Gamma_{B,h}(L)\Delta y_{i,t-1}] + \\ +I^{Ind}_{i,t-4}[\alpha_{Ind,i,h} + \Xi_{Ind,h}EBP_t + \Omega_{Ind,h}(L)EBP_{t-1} + \Gamma_{Ind,h}(L)\Delta y_{i,t-1}] + u_{i,t+h}, \end{aligned} \tag{6}$$

where the only extension relative to Specification (1) is the addition of the state $I^{Ind}_{i,t-4}$ and its associated coefficients; $I^{Ind}_{i,t-4}$ takes on the value of one if the considered individual asset category restriction sub-index takes on a value that is at or above the upper quartile of its distribution.[21,22]

[21] For the 5 sub-components which are binary (collective investment, commercial credit, financial credit, guarantees, and direct investment), the upper quartile threshold criteria could be equivalently replaced with letting the defined state simply receive these binary variables' raw values.

[22] Importantly, as noted in Footnote 16, including two pairs of perfectly complementary state dummies results in perfect colinearity; while for a non-binary variable it is possible to control for an approximately complementary state dummy the accounts for the bulk of the values not belonging to the non-binary based state dummy, this is not possible for a binary variable as any approximately complementary state will simply equal its perfect complement given that there are only two values taken by the underlying variable. This fact lays the grounds for only including $I^{Ind}_{i,t-4}$ without its complementary state. Although this could be done for the other non-binary sub-components by taking approximately complementary states, I have opted for excluding them so as to be consistent across all sub-components' specifications. I have nevertheless confirmed that results for the non-binary individual asset category controls are robust to including their approximately complementary states.

I estimate Specification (4) for all ten asset category restriction sub-indices that comprise the total inflow controls index and focus, as usual, on coefficients $\Xi_{A,h}$ and $\Xi_{B,h}$ which now measure the output response in the strict and light inflow controls state conditioned on the considered individual asset restrictions state.

Figure 21 presents the results from this exercise. It is apparent that none of the individual asset category restrictions eliminate the shock-absorbing capacity of the average inflow controls index. For all individual categories, the t-statistics continue to exceed conventional rejection levels. This indicates that the interaction between the different asset category restrictions is important in that it seems to significantly contribute to the shock-absorbing capacity of the total inflows controls index.

5 Conclusion

The question of whether capital inflow controls constitute a viable policy tool used for bolstering macroeconomic stability has become increasingly important in the last few years following the global financial crisis. Since capital controls on inflows effectively act as a credit-limiting tool, conventional economic intuition seems to suggest that economies with light controls should be more sensitive to credit supply shocks relative to those with strict controls. This paper empirically formalizes this intuitive notion.

The empirical evidence put forward in this paper, which shows that strict capital inflow controls moderate the effects of global credit supply shocks, lends credence to the potential viability of inflow controls as a stabilizing policy tool. Therefore, the policy implications of this paper are that policymakers should seriously consider inflow controls as an effective tool for increasing macroeconomic stability.

The finding that leverage in the stricter capital inflow controls state is significantly lower than that in the light controls state advances a structural interpretation of this paper's results in the spirit of the Sudden Stops literature. This is also an intuitive explanation of the driving mechanism behind this paper's results: EMEs that are hit by contractionary global shocks and have higher leverage to begin with are more likely to face binding credit constraints, thus resulting in an amplified output response.

I leave for future research the interesting task of better understanding the specific role of each asset category restrictions in producing the shock-absorbing capacity of capital inflow controls. This paper has demonstrated that there is added value in terms of achieving macroeconomic stability from allowing the different asset category restrictions to take place in tandem. And, indeed, policymakers have often opted for placing capital restrictions in an across-the-board manner, rather than focusing on specific categories in isolation.

I end this paper with an acknowledgement of an important caveat to this paper's policy implications. While it is beyond the scope of this paper to conduct a full-blown analysis of both the macroeconomic stability implications and long-run growth implications of capital controls, it is important to recognize that the 'no free lunch' concept in economics likely holds also for this paper. The empirical results in this paper imply that EMEs that have opted for strict inflow controls have gained in terms of reduced macroeconomic volatility. However, a simple look at the average growth rate experienced by observations that complied with being in the strict inflow controls state compared to those complying with the light state reminds us that, as usual, there is no free lunch in economics and policy-making in particular: while the former have obtained an average quarterly output growth rate of 0.32%, the latter have grown at more than double that rate with a 0.7% growth rate. This suggestive evidence is consistent with the view that capital controls are no free lunch and, as such, induce a trade-off between output volatility and output growth (see, e.g., Tornell et al. (2003), Forbes (2007a), and Agnor and da Silva (2017)).

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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 2439 observations. I use quarterly data for the following countries (33 in total) and periods: Argentina 1995:Q1-2014:Q4; Bolivia 1995:Q1-2014:Q4; Brazil 1995:Q1-2014:Q4; Bulgaria 1995:Q4-2014:Q4; Chile 1996:Q1-2014:Q4; China 1995:Q1-2014:Q4; Colombia 1995:Q1-2014:Q4; Costa Rica 2000:Q1-2014:Q4; Czech Republic 1995:Q1-2014:Q4; Ecuador 1995:Q1-2014:Q4; Egypt 2002:Q1-2014:Q4; Georgia 1996:Q1-2014:Q4; Guatemala 2001:Q1-2014:Q4; Hungary 1995:Q1-2014:Q4; India 2004:Q1-2014:Q4; Indonesia 1997:Q1-2014:Q4; Iran 1997:Q1-2007:Q4; Korea 1995:Q1-2014:Q4; Kyrgyz 1999:Q1-2014:Q4; Latvia 1995:Q1-2014:Q4; Malaysia 1995:Q1-2014:Q4; Mauritius 2000:Q1-2014:Q4; Mexico 1995:Q1-2014:Q4; Paraguay 1995:Q1-2014:Q4; Peru 1995:Q1-2014:Q4; Philippines 1995:Q1-2014:Q4; Poland 1995:Q1-2014:Q4; Romania 1998:Q1-2014:Q4; Russia 1995:Q1-2014:Q4; South Africa 1995:Q1-2014:Q4; Thailand 1995:Q1-2014:Q4; Turkey 1995:Q1-2014:Q4; Ukraine 2001:Q1-2014:Q4.

A.2 Capital Controls.

Variables Definitions. The capital controls data 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 2013 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.

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 measures into quarterly ones by assuming identical quarterly values equal to the corresponding annual values.

Below are the specific definitions of the capital control measures 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 an average of the same asset restrictions categories that underlie the total inflow index, only that the restrictions for the outflow index pertain to outflows of these assets.

A.3 Global Credit Supply Shock.

Variables Definition. To measure global credit supply shocks, I make use of the Gilchrist and Zakrajek (2012) credit supply shock series. Gilchrist and Zakrajek (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),[23] is my measure of credit supply shocks in this paper. It is in quarterly frequency and covers the sample period 1995:Q1 to 2014:Q4. Quarterly values are averages of corresponding raw monthly values.

A.4 EMBI Spread.

Variable Definition. My panel for the EMBI spread consists of a total of 1435 observations. 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 1142 observation. I use quarterly data for the following countries (21 in total) and periods: Argentina 1995:Q1-2014:Q4; Brazil 1995:Q1-2014:Q4; Bulgaria 1995:Q4-2014:Q4; Chile 1999:Q2-2014:Q4; China 1995:Q1-2014:Q4; Colombia 1997:Q1-2014:Q4; Ecuador 1995:Q1-2014:Q4; Egypt 2001:Q3-2014:Q4; Hungary 1999:Q1-2014:Q4; Indonesia 2004:Q2-2014:Q4; Korea 1995:Q1-2004:Q2; Kyrgyz 1999:Q1-2014:Q4; Malaysia 1996:Q4-2014:Q4; Mexico 1995:Q1-2014:Q4; Peru 1997:Q1-2014:Q4; Philippines 1995:Q1-2014:Q4; Poland 1995:Q1-2014:Q4; Russia 1997:Q4-2014:Q4; South Africa 1995:Q1-2014:Q4; Thailand 1997:Q2-2006:Q1; Turkey 1996:Q3-2014:Q4.

A.5 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

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

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 1916 observations. The data is quarterly and covers the 33 countries that correspond to the output-based sample of countries (33 countries in total) for the sample period 2000:Q1-2014:Q4.

A.6 Bond Debt.

Variables Definitions. Bond debt stocks come from international bond issuance statistics collected by the BIS on a nationality basis and include also a sectoral breakdown into debt securities issued by the public sector, financial sector, and the non-financial sector. All variables were available in dollar values in raw form and were thus converted to local currency values by using the dollar exchange rate, and then divided by local currency GDP. All raw series were seasonally adjusted using ARIMA X12.

Sample. My panel for total bond debt consists of a total of 2132 observations from 29 countries (Bolivia, Iran, Kyrgyz, and Poland are excluded) while the public sector, financial sector, and non-financial sector bond debt variables include 1975, 1547, and 1628 observations from 27 (India and Mauritius are further excluded relative to total bond debt), 22 (Costa Rica, Ecuador, Georgia, Guatemala, Latvia, Poland, and Romania are further excluded relative to total bond debt), and 24 (Ecuador, Latvia, Mauritius, Poland, and Romania are further excluded relative to total bond debt) countries, respectively. The periods covered by these variables (for those countries which they cover) are the same as those covered by output variable except for Bulgaria (2003:Q2-2014:Q4) and Mauritius (2005:Q4-2014:Q4).

A.7 International Capital Flows.

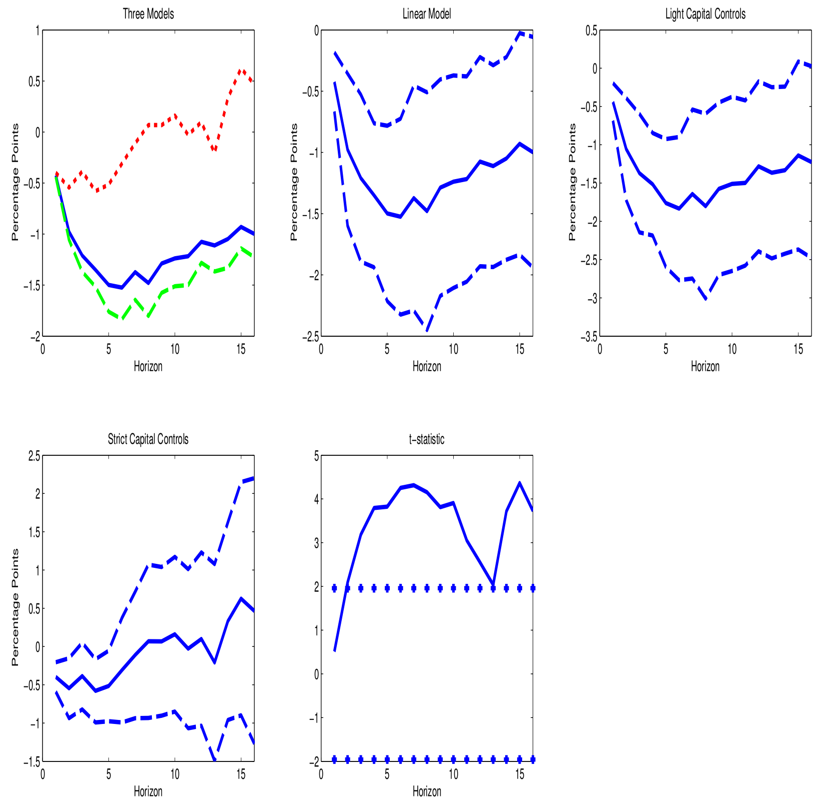
Variables Definitions. The capital flows data consists of the sum of GDP shares of local currency net capital flows from foreign direct investment, portfolio investment, and other investment.[24] I also use the GDP shares of equity and debt portfolio flows. All variables were available in dollar values in raw form and were thus converted to local currency values by using the average quarterly dollar exchange rate. All raw series were seasonally adjusted using ARIMA X12 and downloaded from the International Financial Statistics (IFS) database, which is published by the International Monetary Fund.

Sample. My panel for these variables consists of a total of 2196, 2097, and 2196 observations for foreign direct investment, portfolio flows, and other investment, respectively. This panel corresponds to the countries covered by the output variable except for Egypt, Iran, and Mauritius for foreign direct investment and other investment and Egypt, Iran, Mauritius, and Paraguay for portfolio flows. In terms of the periods covered by these variables, there are the following discrepancies with respect to the output variable: China (2005:Q1-2014:Q4), Costa Rica (1999:Q1-2014:Q4), and Poland (2000:Q1-2014:Q4). 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.

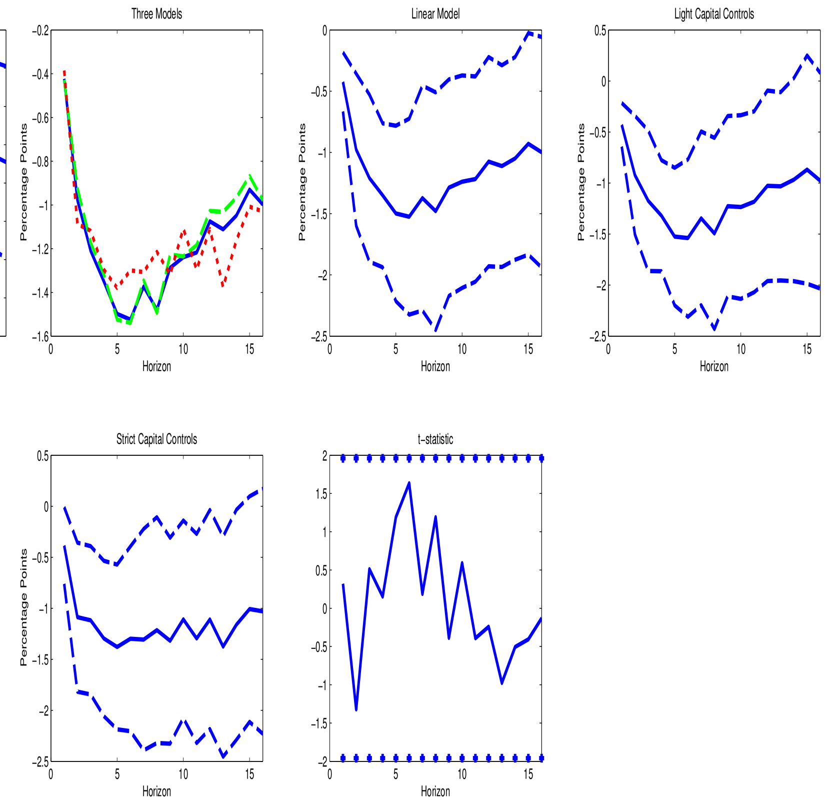
Within portfolio flows, the equity flows variable excludes Bolivia, Guatemala, Iran, Kyrgyz, Mauritius, and Paraguay and consists of 1845 observations; the debt portfolio flows variable excludes Egypt, Iran, Kyrgyz, Mauritius, and Paraguay and consists of 1877 observations.

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

Figure 1: **Capital Controls' Effect on Output's Sensitivity to Credit Supply Shocks: (a) Inflow Controls Index; (b) Outflow Controls Index**.



(a) Impulse Responses to a One Standard Deviation Credit Supply Shock (Inflow Controls Index).

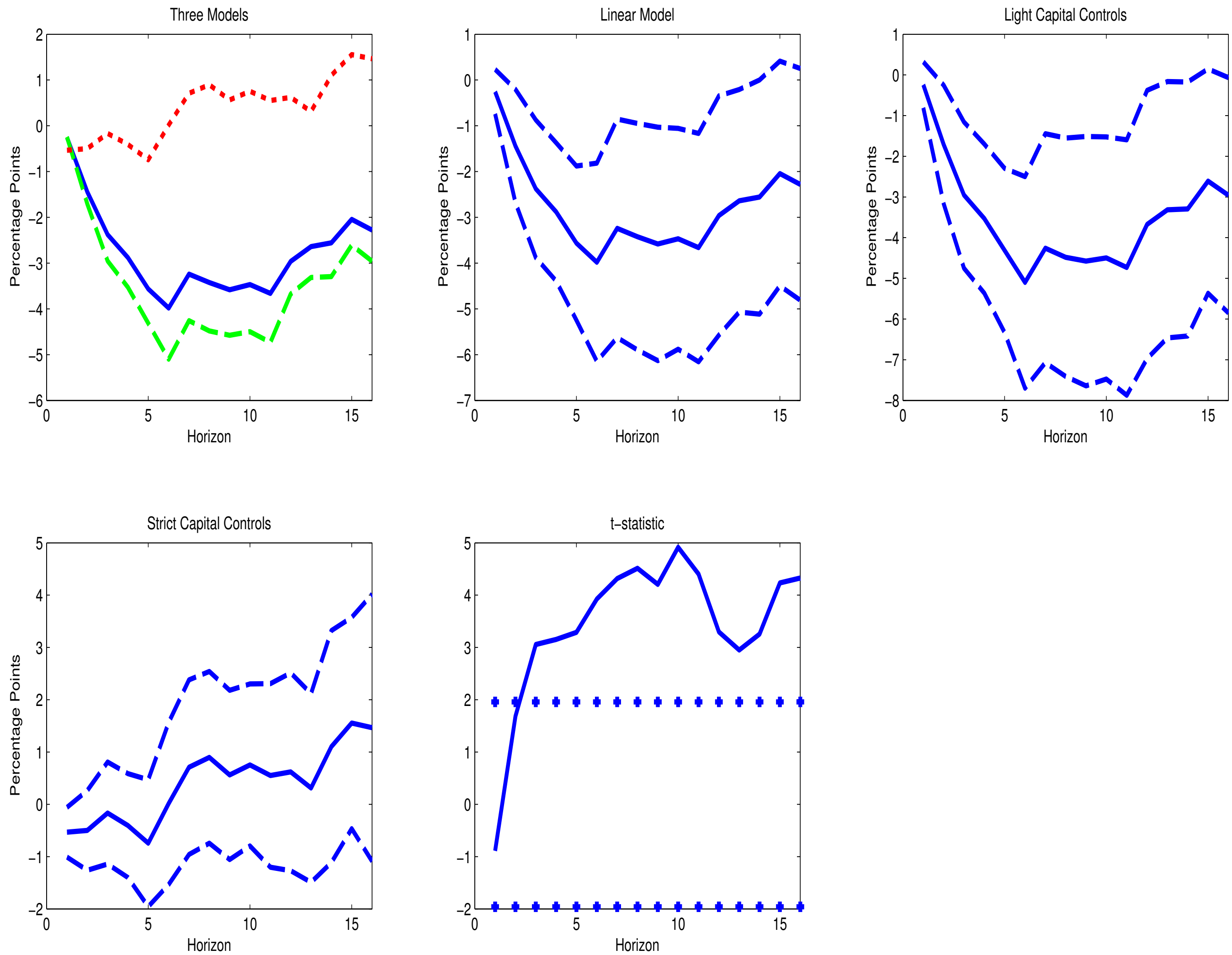


(b) Impulse Responses to a One Standard Deviation Credit Supply Shock (Outflow Controls Index).

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, where in the latter the capital inflow controls index is used. Panel (b): This figure presents the impulse responses of output to a one standard deviation credit supply shock from the linear model and non-linear model, where in the latter the capital outflow controls index is used.

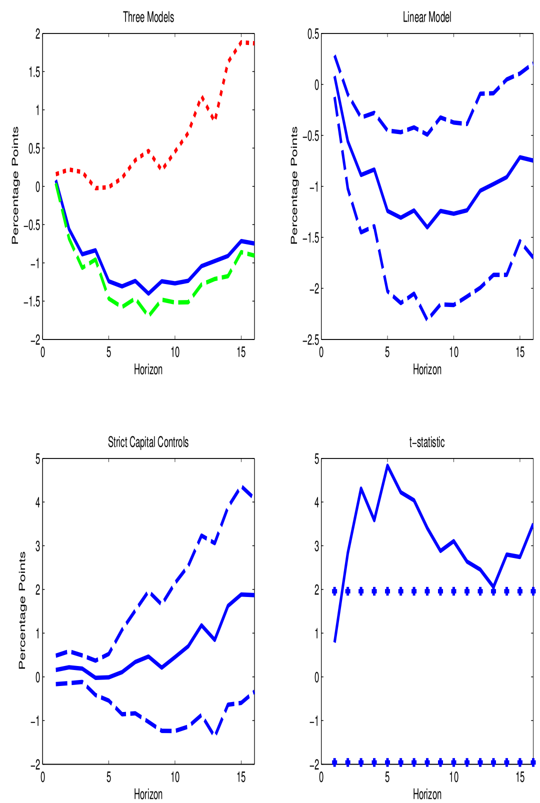
For both panels, in the first sub-figure the solid lines show the responses from the linear model, the dashed lines depict the responses in the light capital controls state, and the dotted lines are the responses in the strict capital controls state. The next three sub-figures present the impulse responses from the linear model and the two states along with Driscoll and Kraay (1998) 95% confidence bands. The last sub-figure shows the t-statistic of the difference between the responses in the strict capital controls state and the light controls state, where for convenience the 2.5% significance levels (± 1.96) are added. The responses are shown in terms of percentage deviations from pre-shock values. Horizon is in quarters.

Figure 2: **Capital Inflow Controls' Effect on Investment's Sensitivity to Credit Supply Shocks**.

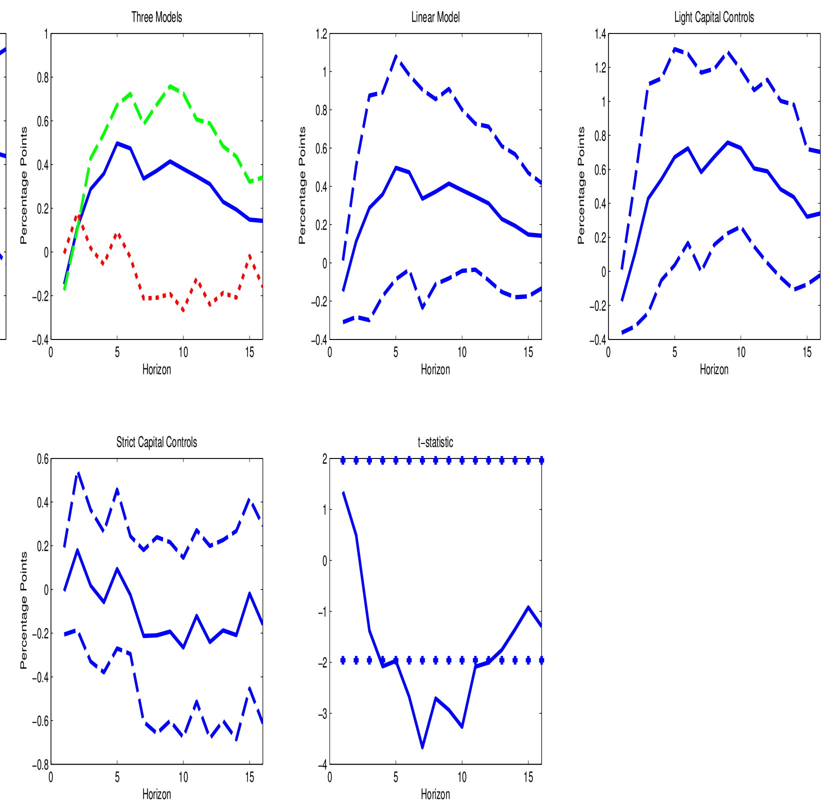


Notes: This figure presents the impulse responses of investment to a one standard deviation credit supply shock from the linear model and non-linear model. In the first sub-figure the solid lines show the responses from the linear model, the dashed lines depict the responses in the light capital controls state, and the dotted lines are the responses in the strict capital controls state. The next three sub-figures present the impulse responses from the linear model and the two states along with Driscoll and Kraay (1998) 95% confidence bands. The last sub-figure shows the t-statistic of the difference between the responses in the strict capital controls state and the light controls state, where for convenience the 2.5% significance levels (± 1.96) are added. The responses are shown in terms of percentage deviations from pre-shock values. Horizon is in quarters.

Figure 3: **Capital Inflow Controls' Effect on Consumption's and Trade Balance's Sensitivity to Credit Supply Shocks: (a) Consumption; (b) Trade Balance**.



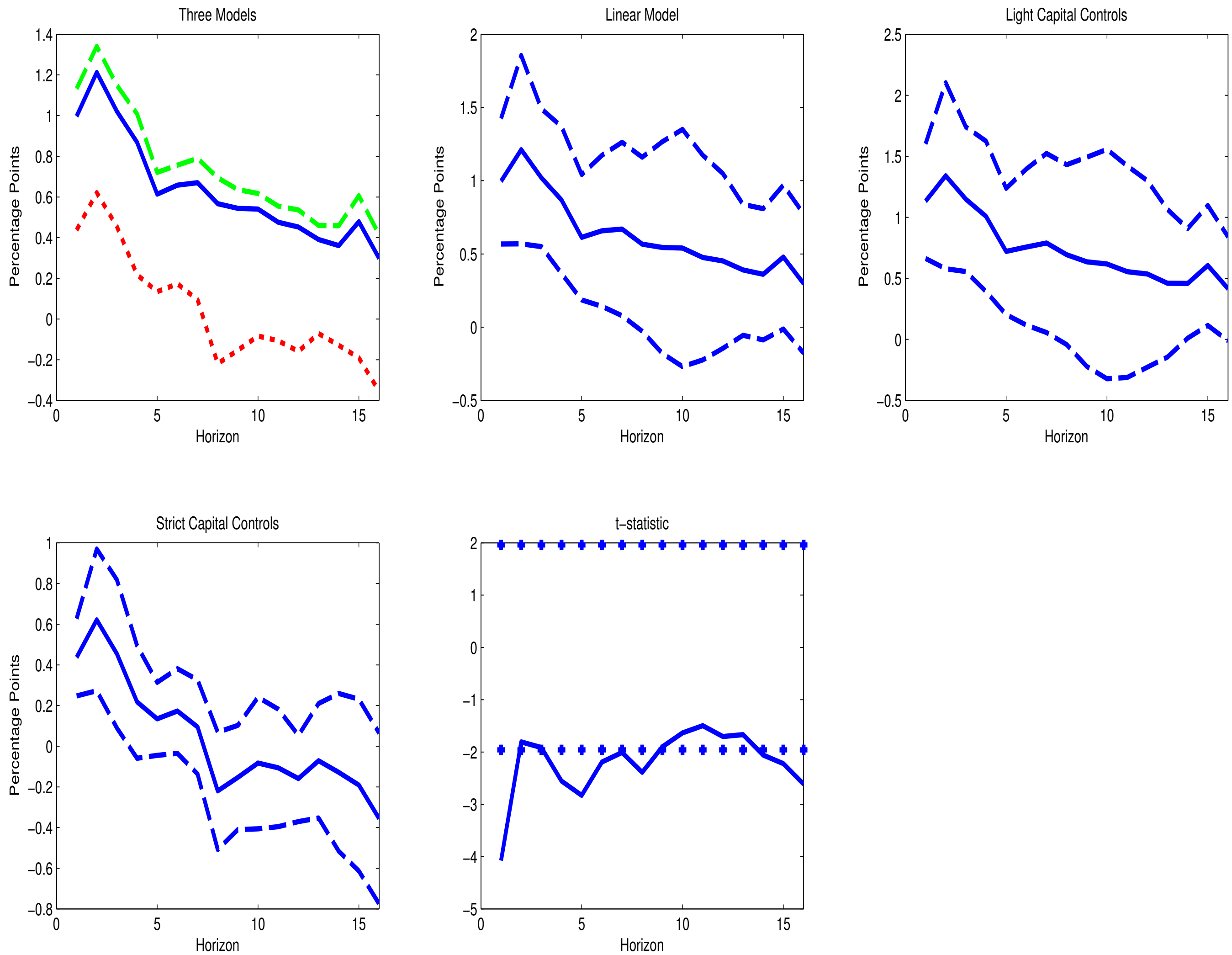
(a) Impulse Responses of Consumption to a One Standard Deviation Credit Supply Shock.



(b) Impulse Responses of the Trade Balance to a One Standard Deviation Credit Supply Shock.

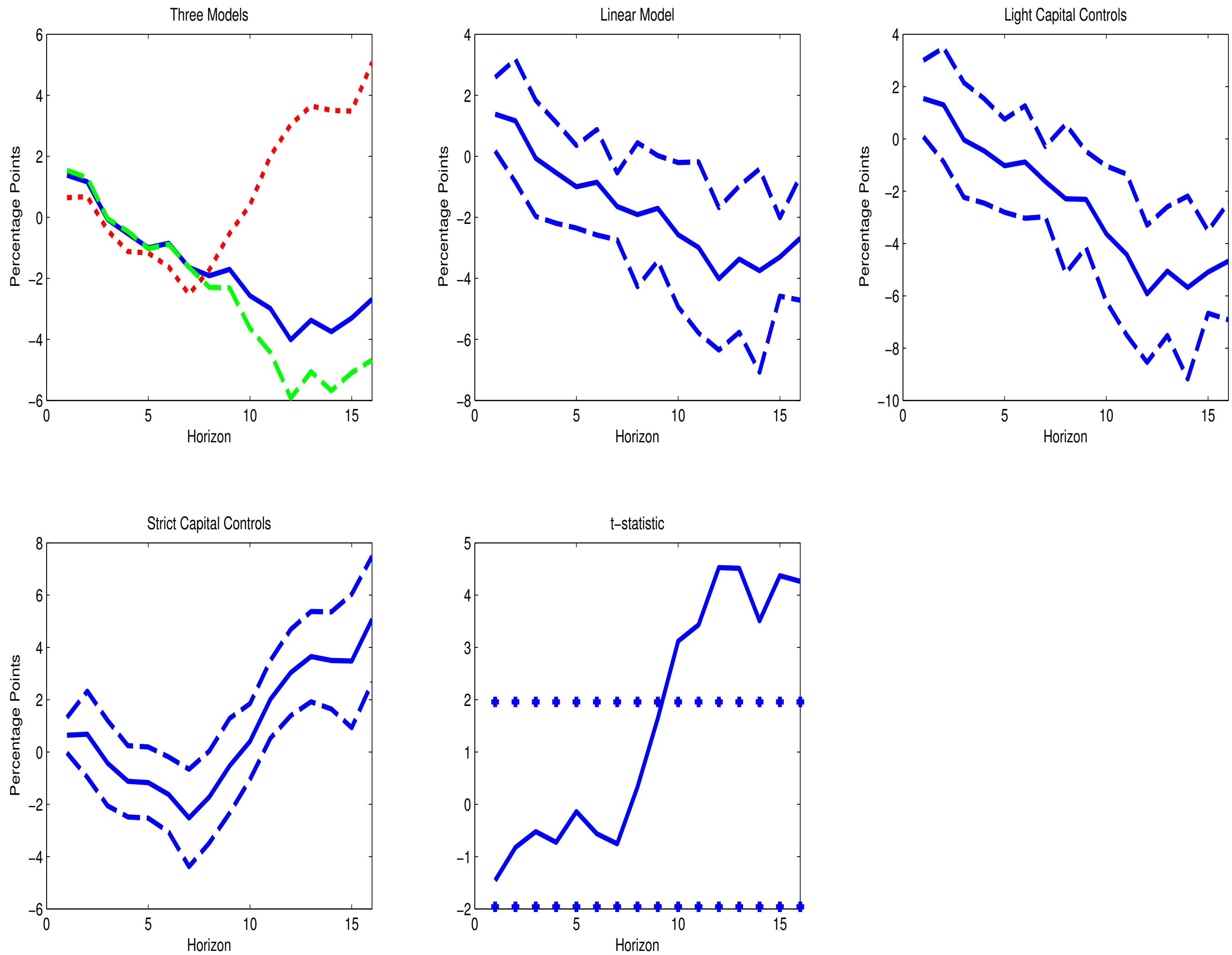
Notes: Panel (a): This figure presents the impulse responses of consumption to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figures 1a and 1b for details on this figure's components. Panel (b): This figure presents the impulse responses of the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

Figure 4: **Capital Inflow Controls' Effect on EMBI's Sensitivity to Credit Supply Shocks**.



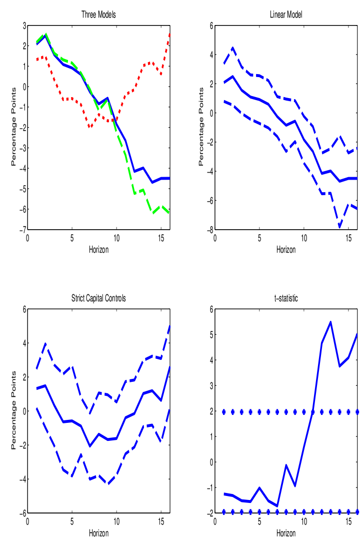
Notes: This figure presents the impulse responses of EMBI (country credit spread) to a one standard deviation credit supply shock from the linear model and non-linear model. In the first sub-figure the solid lines show the responses from the linear model, the dashed lines depict the responses in the light capital controls state, and the dotted lines are the responses in the strict capital controls state. The next three sub-figures present the impulse responses from the linear model and the two states along with Driscoll and Kraay (1998) 95% confidence bands. The last sub-figure shows the t-statistic of the difference between the responses in the strict capital controls state and the light controls state, where for convenience the 2.5% significance levels (±1.96) are added. The responses are shown in terms of percentage points deviations from pre-shock values. Horizon is in quarters.

Figure 5: **Capital Inflow Controls' Effect on Leverage's Sensitivity to Credit Supply Shocks**.

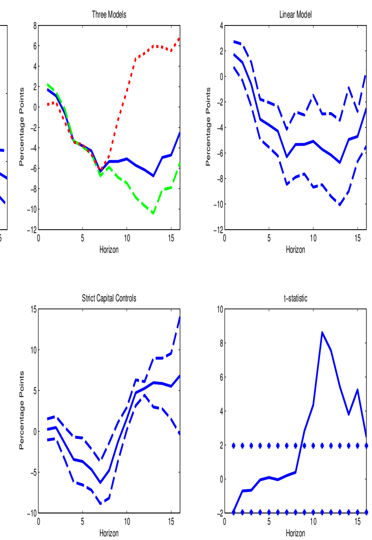


Notes: This figure presents the impulse responses of leverage to a one standard deviation credit supply shock from the linear model and non-linear model. In the first sub-figure the solid lines show the responses from the linear model, the dashed lines depict the responses in the light capital controls state, and the dotted lines are the responses in the strict capital controls state. The next three sub-figures present the impulse responses from the linear model and the two states along with Driscoll and Kraay (1998) 95% confidence bands. The last sub-figure shows the t-statistic of the difference between the responses in the strict capital controls state and the light controls state, where for convenience the 2.5% significance levels (±1.96) are added. The responses are shown in terms of percentage deviations from pre-shock values. Horizon is in quarters.

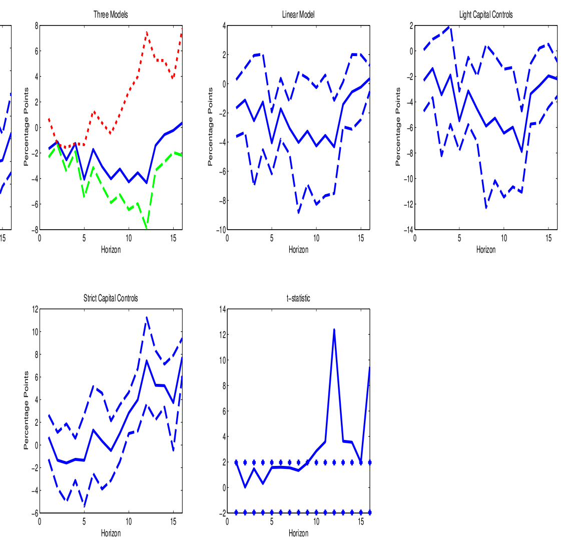
Figure 6: **Capital Inflow Controls' Effect on Sectoral Leverage's Sensitivity to Credit Supply Shocks: (a) Private Non-Financial Sector's Leverage; (b) Financial Sector's Leverage; (c) Public Sector's Leverage**.



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



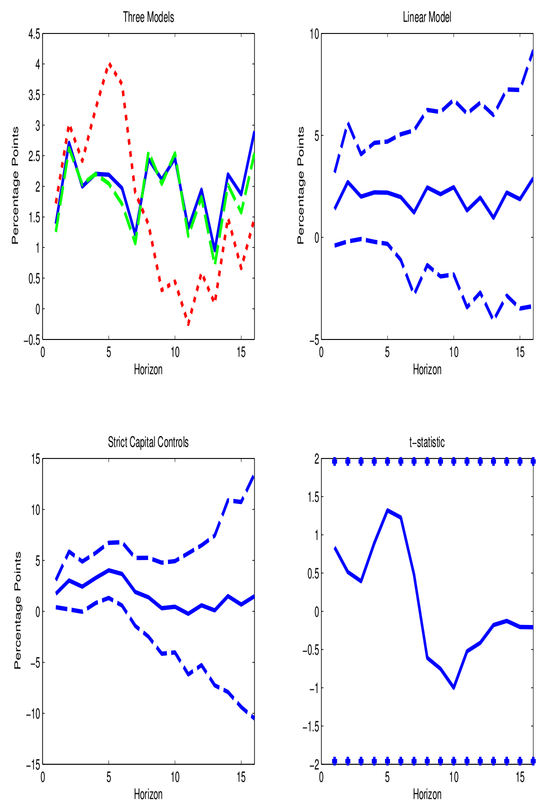
(b) Impulse Responses to a One Standard Deviation Credit Supply Shock (Financial Sector's Leverage).



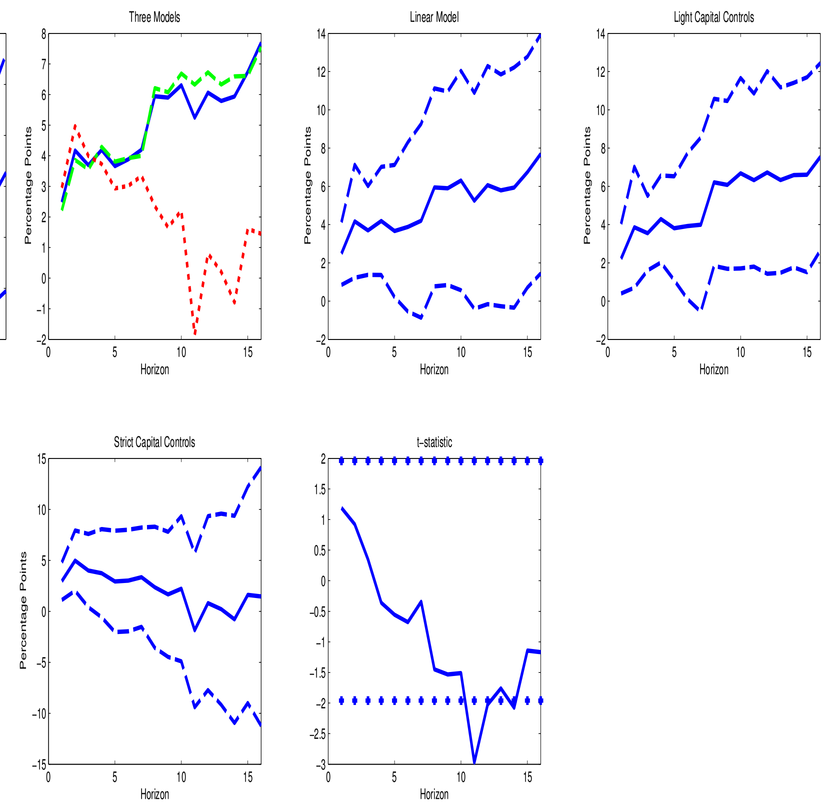
(c) Impulse Responses to a One Standard Deviation Credit Supply Shock (Public Sector's Leverage).

Notes: Panel (a): This figure presents the impulse responses of output to a one standard deviation credit supply shock from the linear model and non-linear model, where the outcome variable is private non-financial sector's leverage. Panel (b): This figure presents the impulse responses of output to a one standard deviation credit supply shock from the linear model and non-linear model, where the outcome variable is financial sector's leverage. Panel (c): This figure presents the impulse responses of output to a one standard deviation credit supply shock from the linear model and non-linear model, where the outcome variable is public's sector's leverage.

Figure 7: **Capital Inflow Controls' Effect on Total Bond Debt's and Government Bond Debt's Sensitivity to Credit Supply Shocks: (a) Total Debt; (b) Government Debt**.



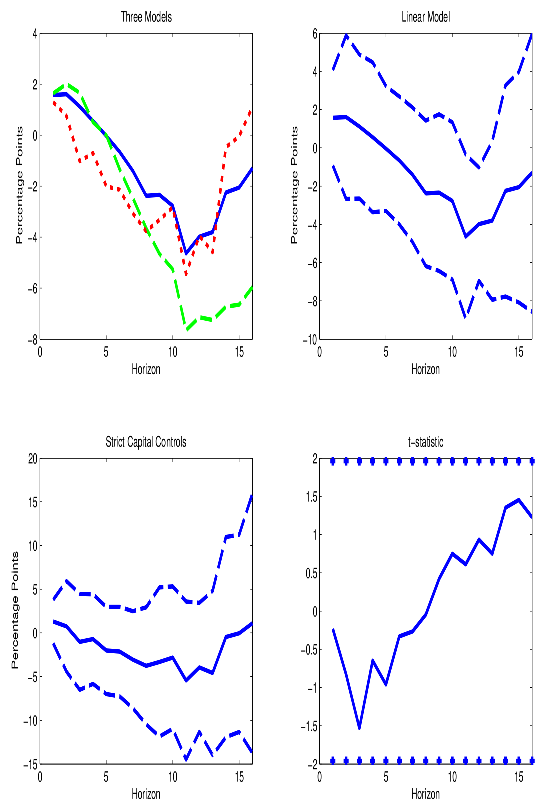
(a) Impulse Responses of Total Bond Debt to a One Standard Deviation Credit Supply Shock.



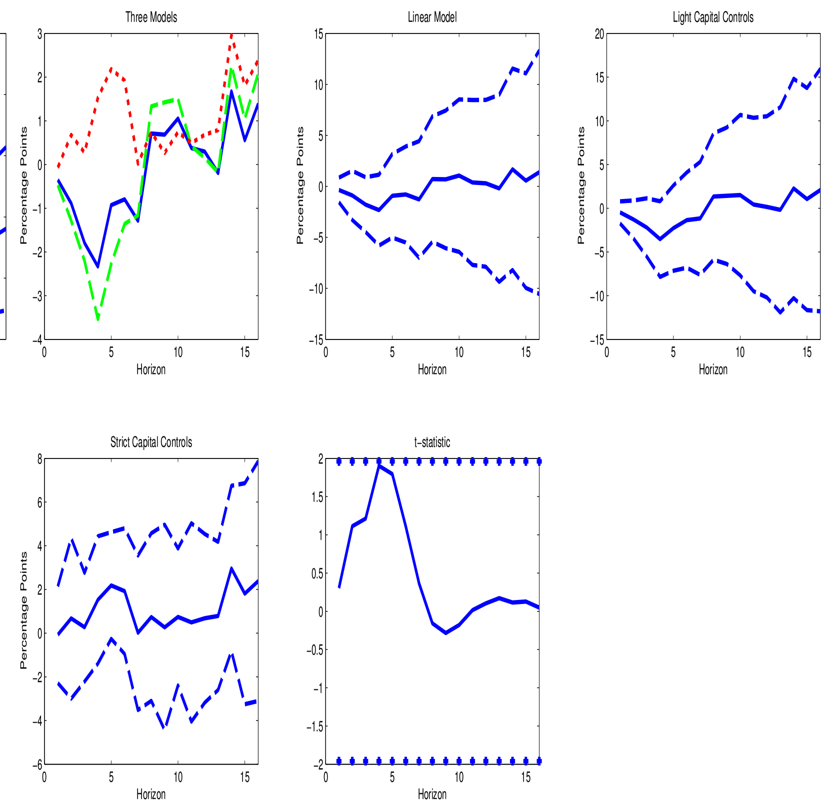
(b) Impulse Responses of Government Bond Debt to a One Standard Deviation Credit Supply Shock.

Notes: Panel (a): This figure presents the impulse responses of total bond debt to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figures 1a and 1b for details on this figure's components. Panel (b): This figure presents the impulse responses of government bond debt to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figures 1a and 1b for details on this figure's components.

Figure 8: **Capital Inflow Controls' Effect on Financial Sector Bond Debt's and Private Non-Financial Bond Debt's Sensitivity to Credit Supply Shocks: (a) Financial Sector Debt; (b) Private Non-Financial Sector Debt**.



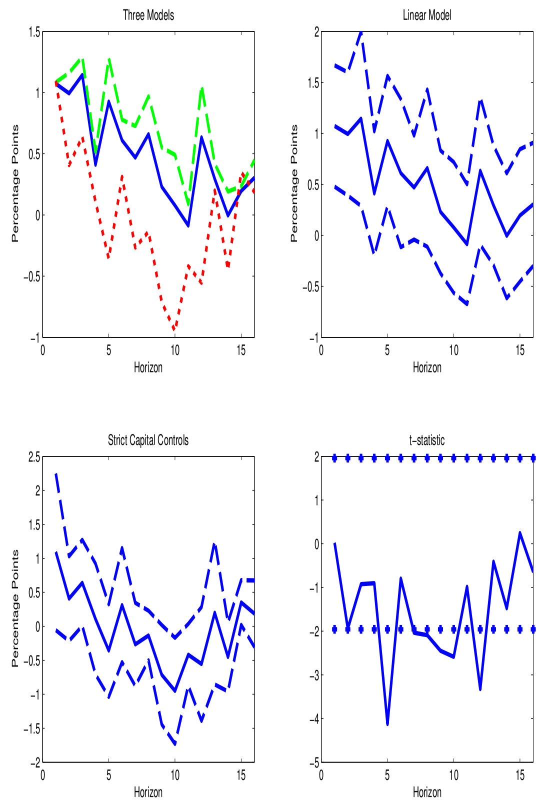
(a) Impulse Responses of Financial Sector Bond Debt to a One Standard Deviation Credit Supply Shock.



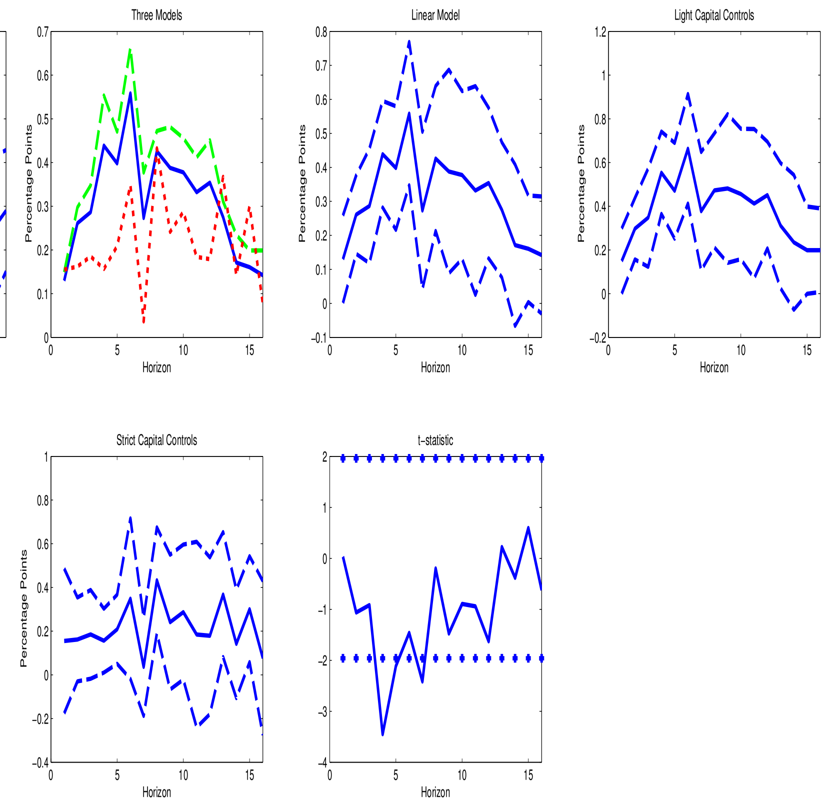
(b) Impulse Responses of Private Non-Financial Sector Bond Debt to a One Standard Deviation Credit Supply Shock.

Notes: Panel (a): This figure presents the impulse responses of financial sector bond debt to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figures 1a and 1b for details on this figure's components. Panel (b): This figure presents the impulse responses of private non-financial sector bond debt to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figures 1a and 1b for details on this figure's components.

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



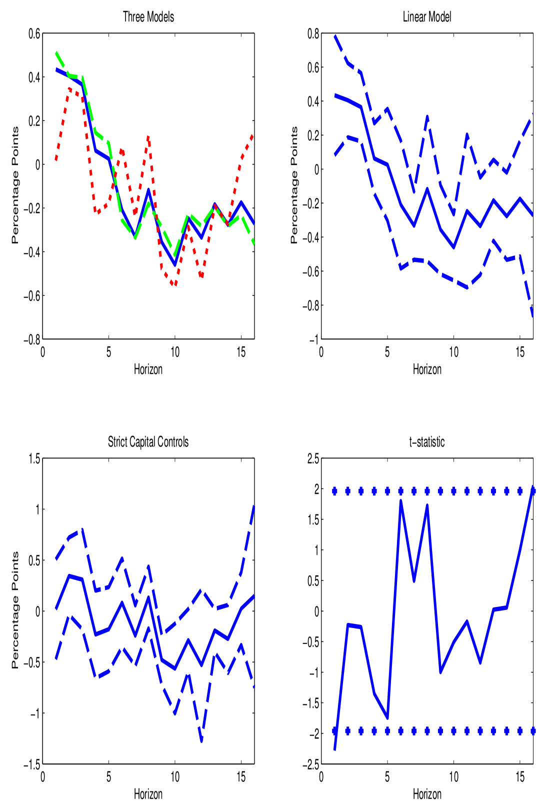
(a) Impulse Responses of Total Financial Flows to a One Standard Deviation Credit Supply Shock.



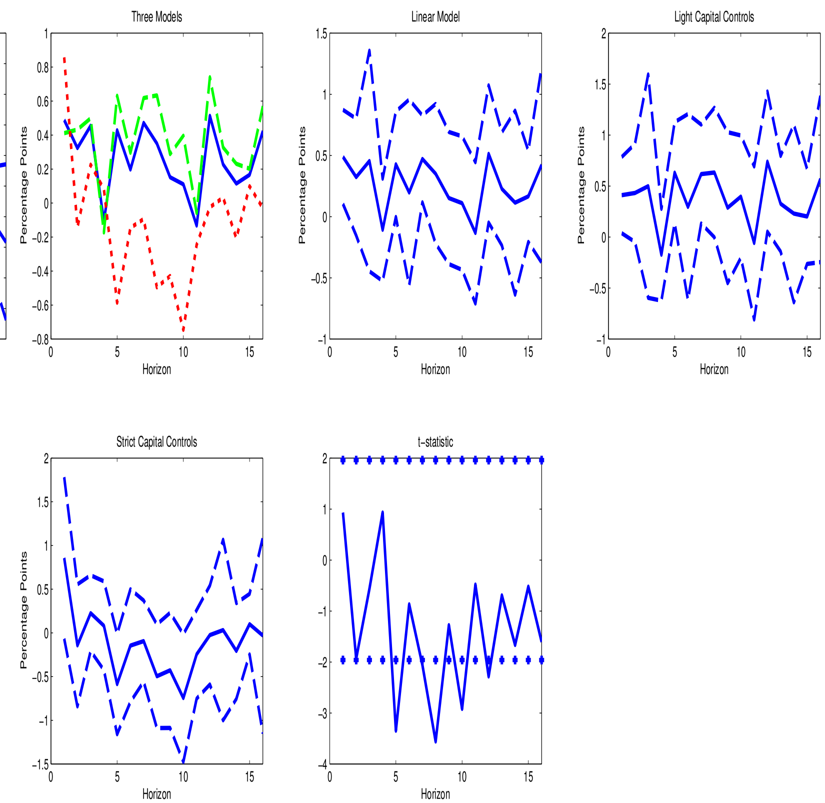
(b) Impulse Responses of Foreign Direct Investment Flows to a One Standard Deviation Credit Supply Shock.

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

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



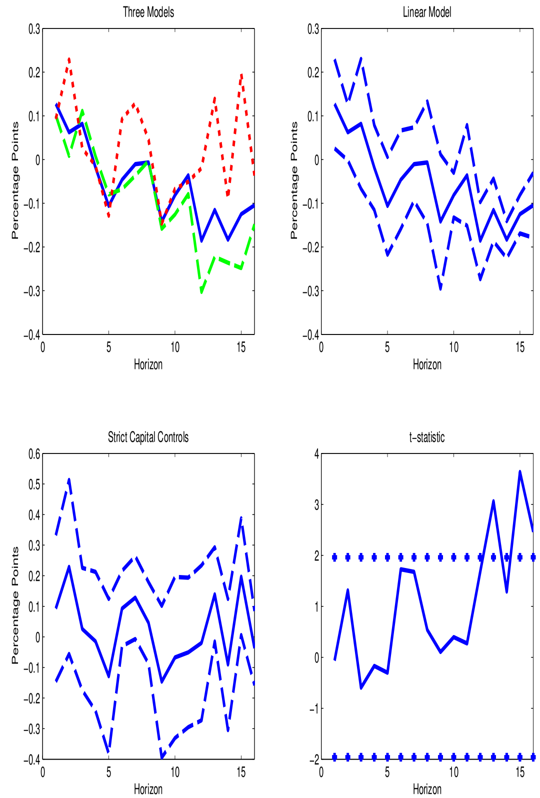
(a) Impulse Responses of Portfolio Flows to a One Standard Deviation Credit Supply Shock.



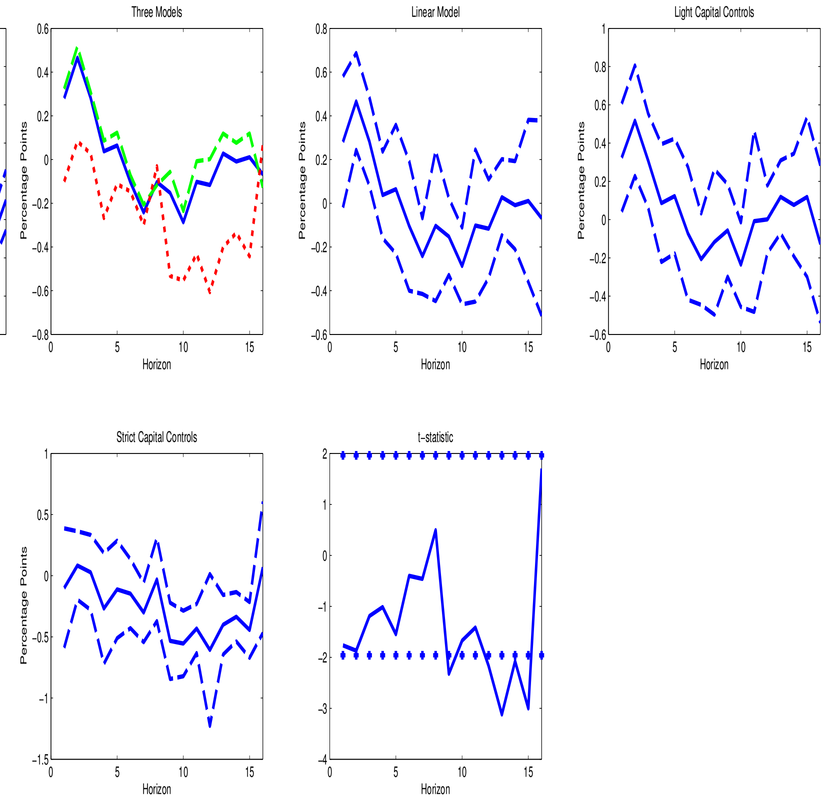
(b) Impulse Responses of Other Investment Flows to a One Standard Deviation Credit Supply Shock.

Notes: Panel (a): This figure presents the impulse responses of portfolio flows debt to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figures 1a and 1b for details on this figure's components. Panel (b): This figure presents the impulse responses of other investment flows (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 Figures 1a and 1b for details on this figure's components.

Figure 11: **Capital Inflow Controls' Effect on Portfolio Equity Flows' and Portfolio Debt Flows' Sensitivity to Credit Supply Shocks: (a) Portfolio Equity Flows; (b) Portfolio Debt Flows**.



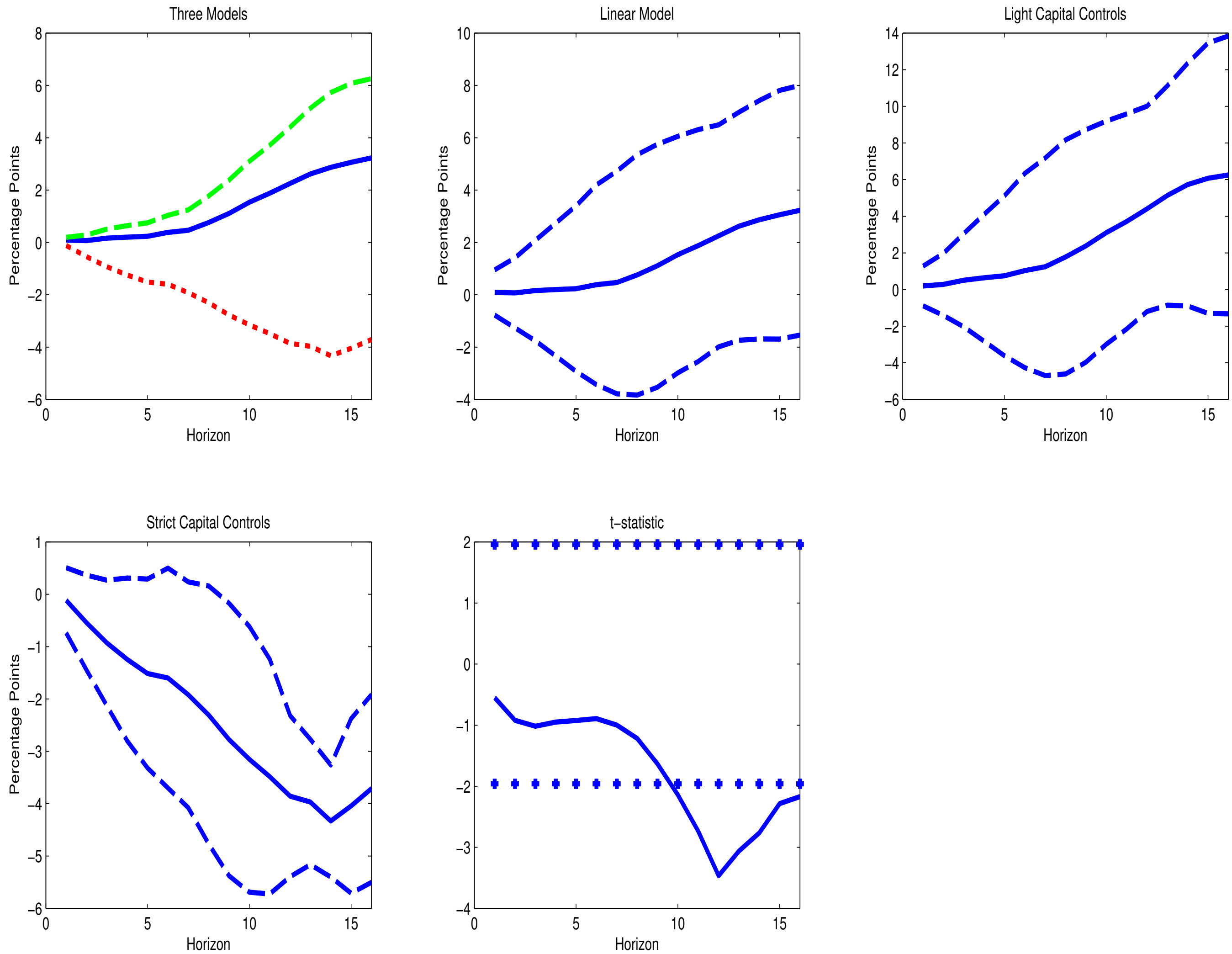
(a) Impulse Responses of Portfolio Equity Flows to a One Standard Deviation Credit Supply Shock.



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

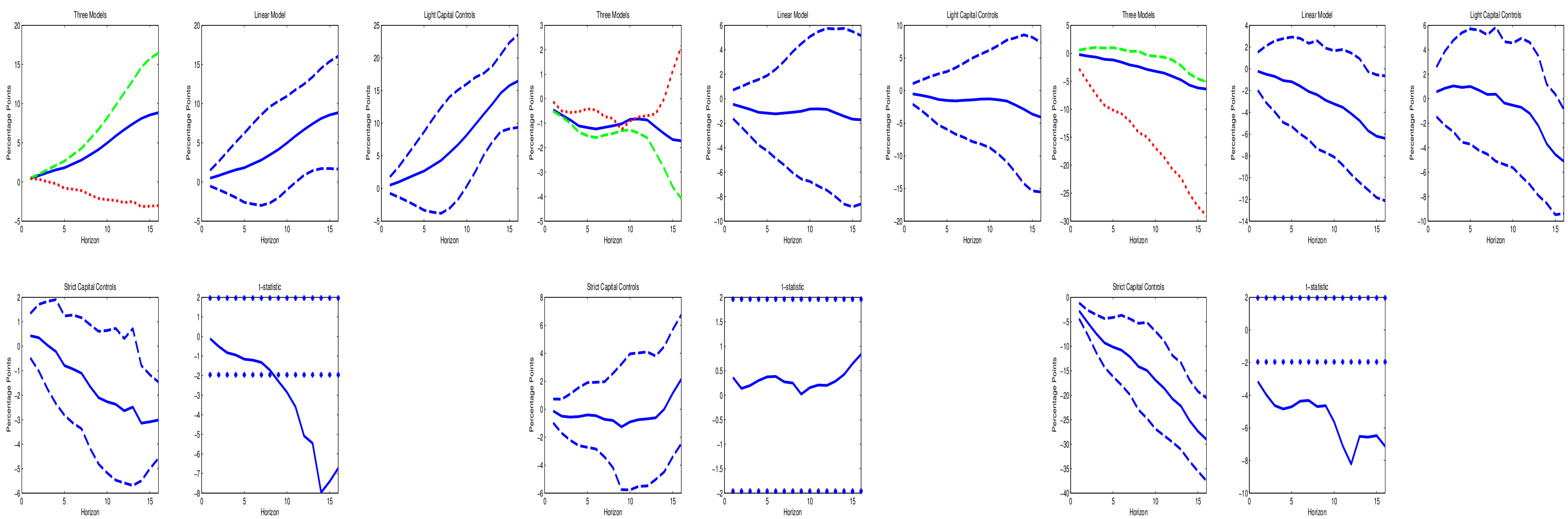
Notes: Panel (a): This figure presents the impulse responses of portfolio equity flows to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figures 1a and 1b for details on this figure's components. Panel (b): This figure presents the impulse responses of portfolio debt flows to a one standard deviation credit supply shock from the linear model and non-linear model. See notes from Figures 1a and 1b for details on this figure's components.

Figure 12: **Capital Inflow Controls' Effect on Leverage**.



Notes: This figure presents the impulse responses of leverage to the two inflow state dummies from the non-linear model described in Specification (3). In the first sub-figure the solid lines show the responses in the light capital controls state and the dashed lines are the responses in the strict capital controls state. The next two sub-figures present the impulse responses to the two state dummies along with Driscoll and Kraay (1998) 95% confidence bands. The last sub-figure shows the t-statistic of the difference between the responses in the strict capital controls state and the light controls state, where for convenience the 2.5% significance levels (± 1.96) are added. The responses are shown in terms of percentage deviations from pre-shock values. Horizon is in quarters.

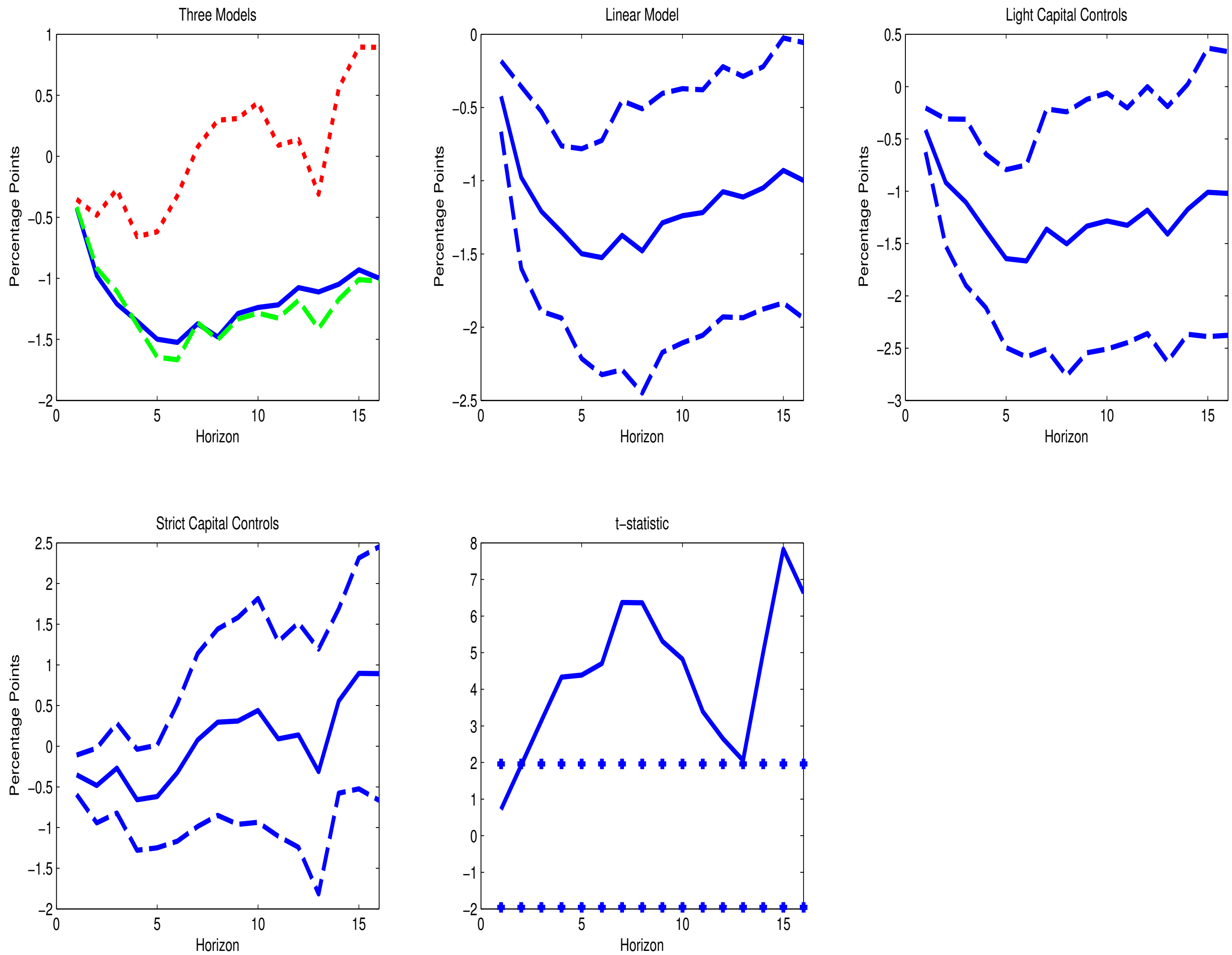
Figure 13: **Capital Inflow Controls' Effect on Sectoral Leverage Levels: (a) Private Non-Financial Sector's Leverage; (b) Financial Sector's Leverage; (c) Public Sector's Leverage**.



(a) Capital Inflow Controls' Effect on Private Non-Financial Sector's Leverage. **(b) Capital Inflow Controls' Effect on Financial Sector's Leverage.** **(c) Capital Inflow Controls' Effect on Public Sector's Leverage.**

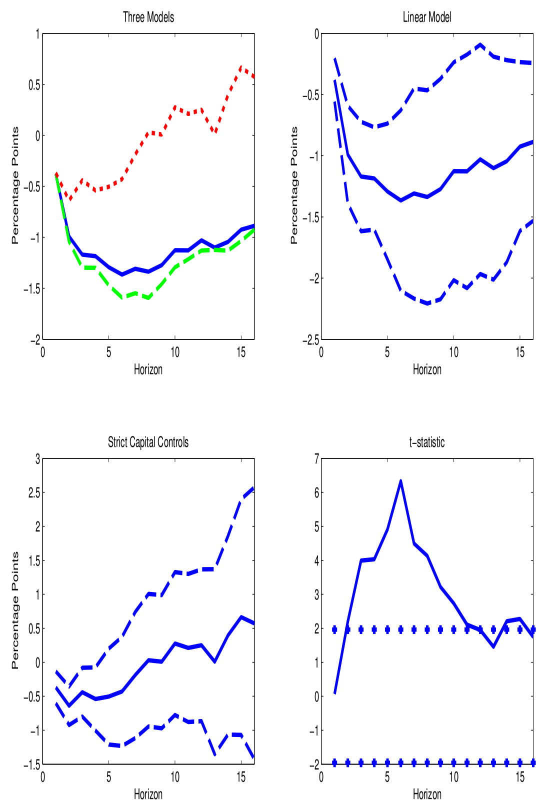
Notes: Panel (a): This figure presents the impulse responses of private non-financial sector's leverage to the two inflow state dummies from the non-linear model described in the Specification (3). Panel (b): This figure presents the impulse responses of private financial sector's leverage to the two inflow state dummies from the non-linear model described in the Specification (3). Panel (c): This figure presents the impulse responses of public sector's leverage to the two inflow state dummies from the non-linear model described in the Specification (3).

Figure 14: **Capital Inflow Controls' Effect on Output's Sensitivity to Credit Supply Shocks: Controlling for Economic Development**.

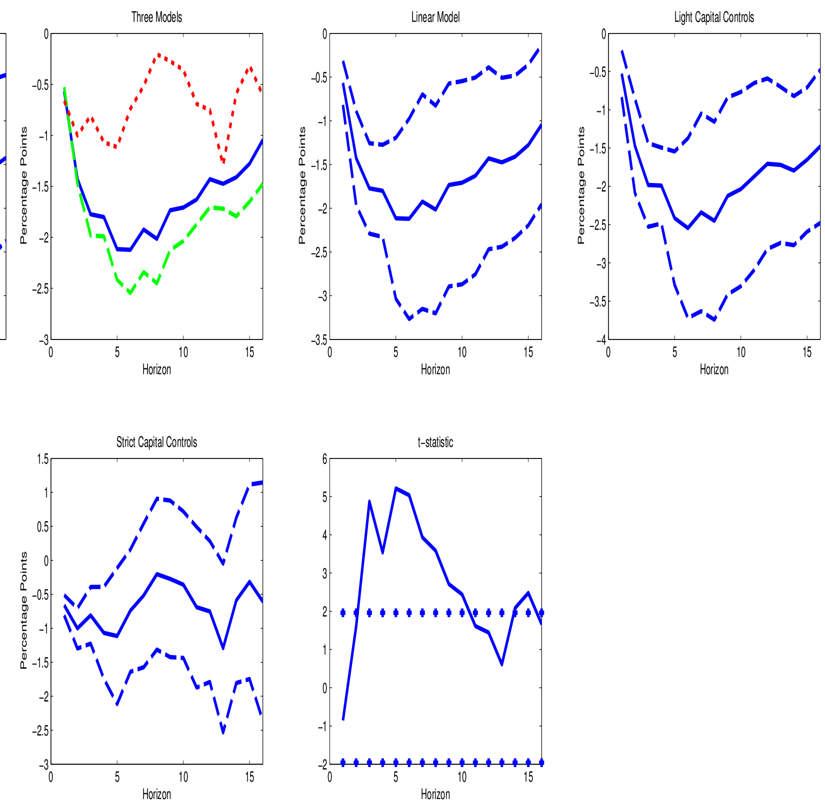


Notes: This figure presents the impulse responses of output to a one standard deviation credit supply shock from the linear model and non-linear model, where the extended specification (4) is estimated. In the first sub-figure the solid lines show the responses in the light capital controls state and the dashed lines are the responses in the strict capital controls state. The next two sub-figures present the impulse responses to the two state dummies along with Driscoll and Kraay (1998) 95% confidence bands. The last sub-figure shows the t-statistic of the difference between the responses in the strict capital controls state and the light controls state, where for convenience the 2.5% significance levels (± 1.96) are added. The responses are shown in terms of percentage deviations from pre-shock values. Horizon is in quarters.

Figure 15: **Capital Inflow Controls' Effect on Output's Sensitivity to Credit Supply Shocks: (a) VIX; (b) Baa Spread**.



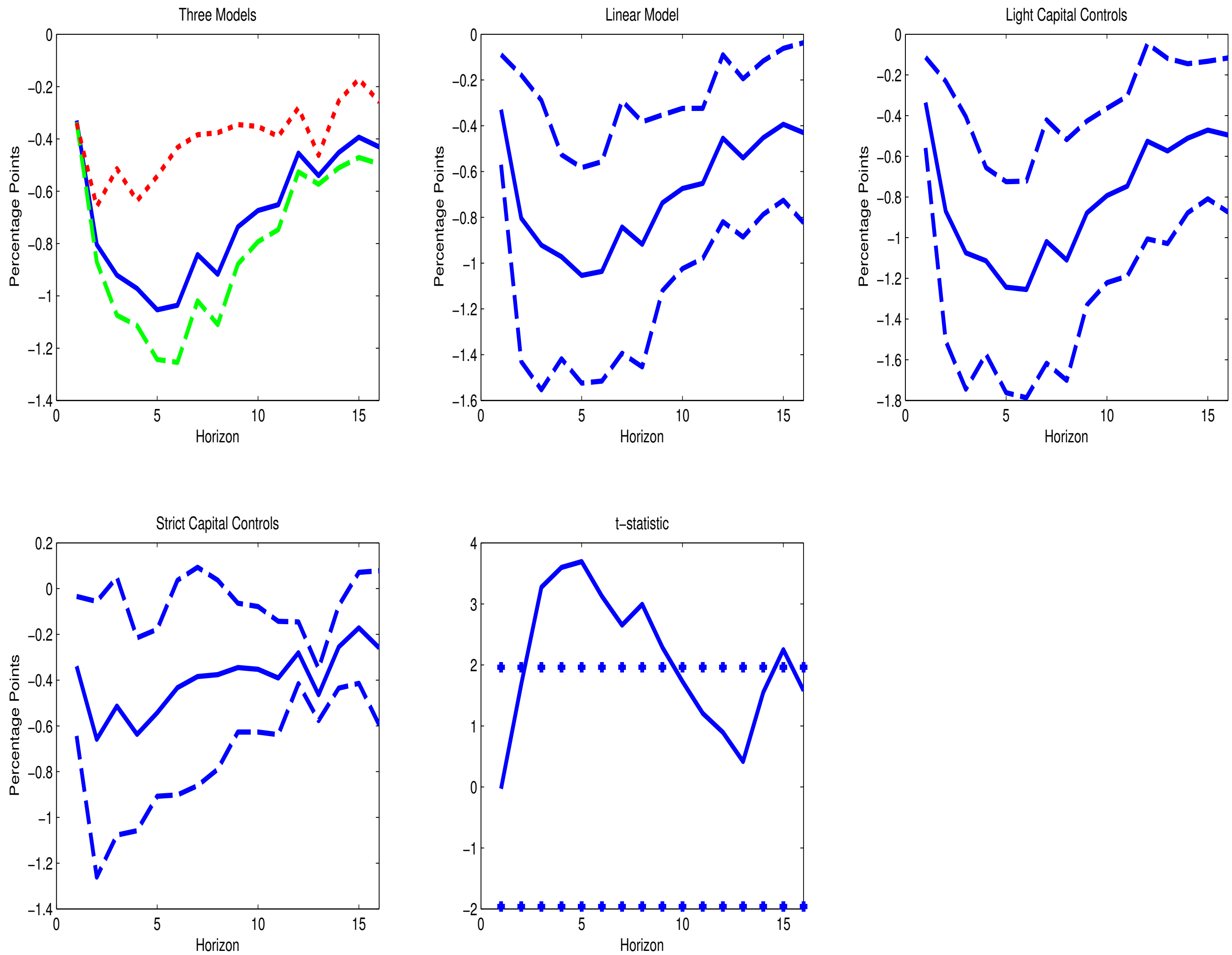
(a) Impulse Responses of Output to a One Standard Deviation Credit Supply Shock (VIX).



(b) Impulse Responses of Output to a One Standard Deviation Credit Supply Shock (Baa Spread).

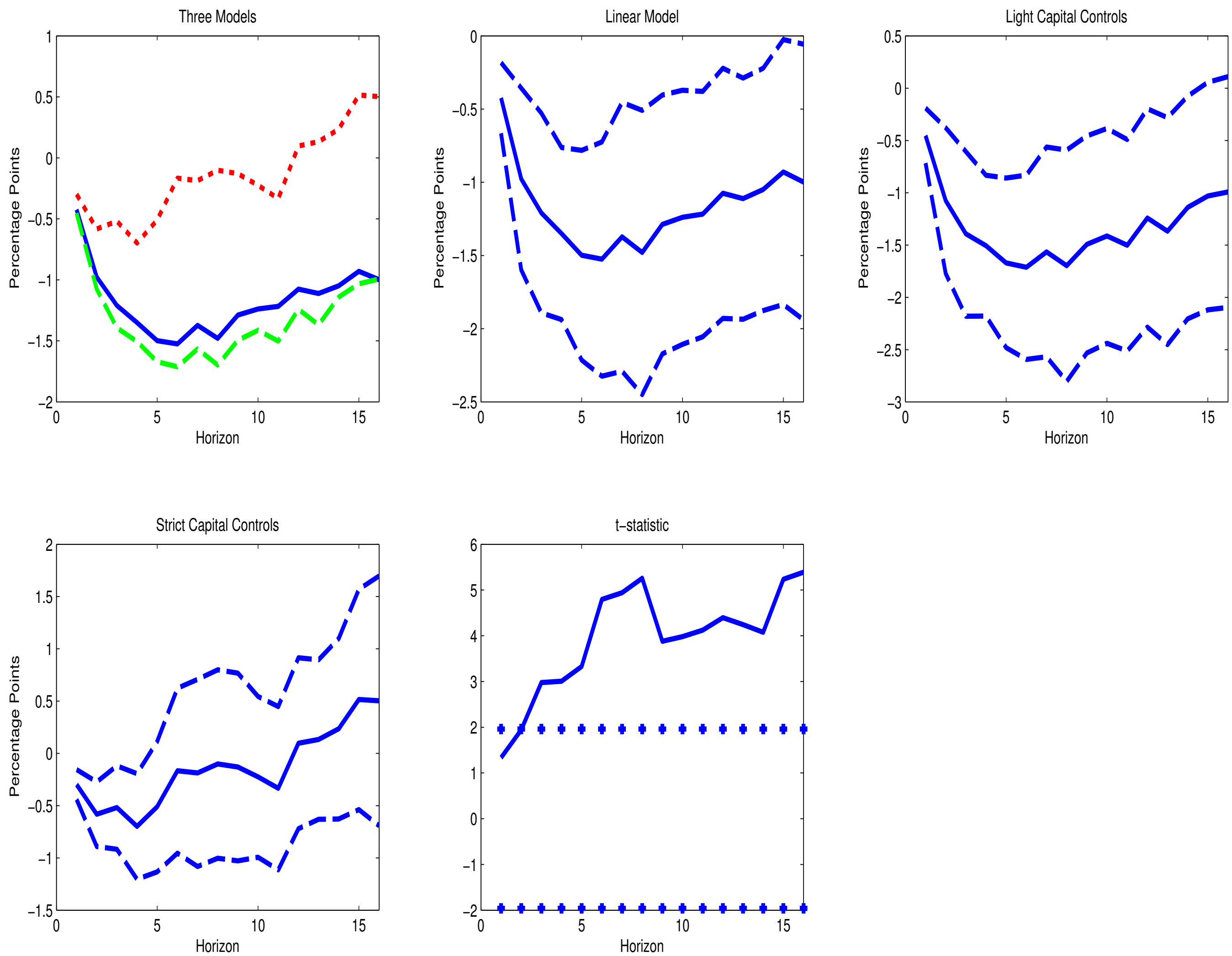
Notes: Panel (a): This figure presents the impulse responses of output to a one standard deviation credit supply shock from the linear model and non-linear model when using the VIX as the global shock measure instead of the EBP series. See notes from Figures 1a and 1b for details on this figure's components. Panel (b): 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 Baa spread as the global shock measure instead of the EBP series. See notes from Figures 1a and 1b for details on this figure's components.

Figure 16: **Capital Inflow Controls' Effect on Output's Sensitivity to Credit Supply Shocks: HP-Filtered Output**.



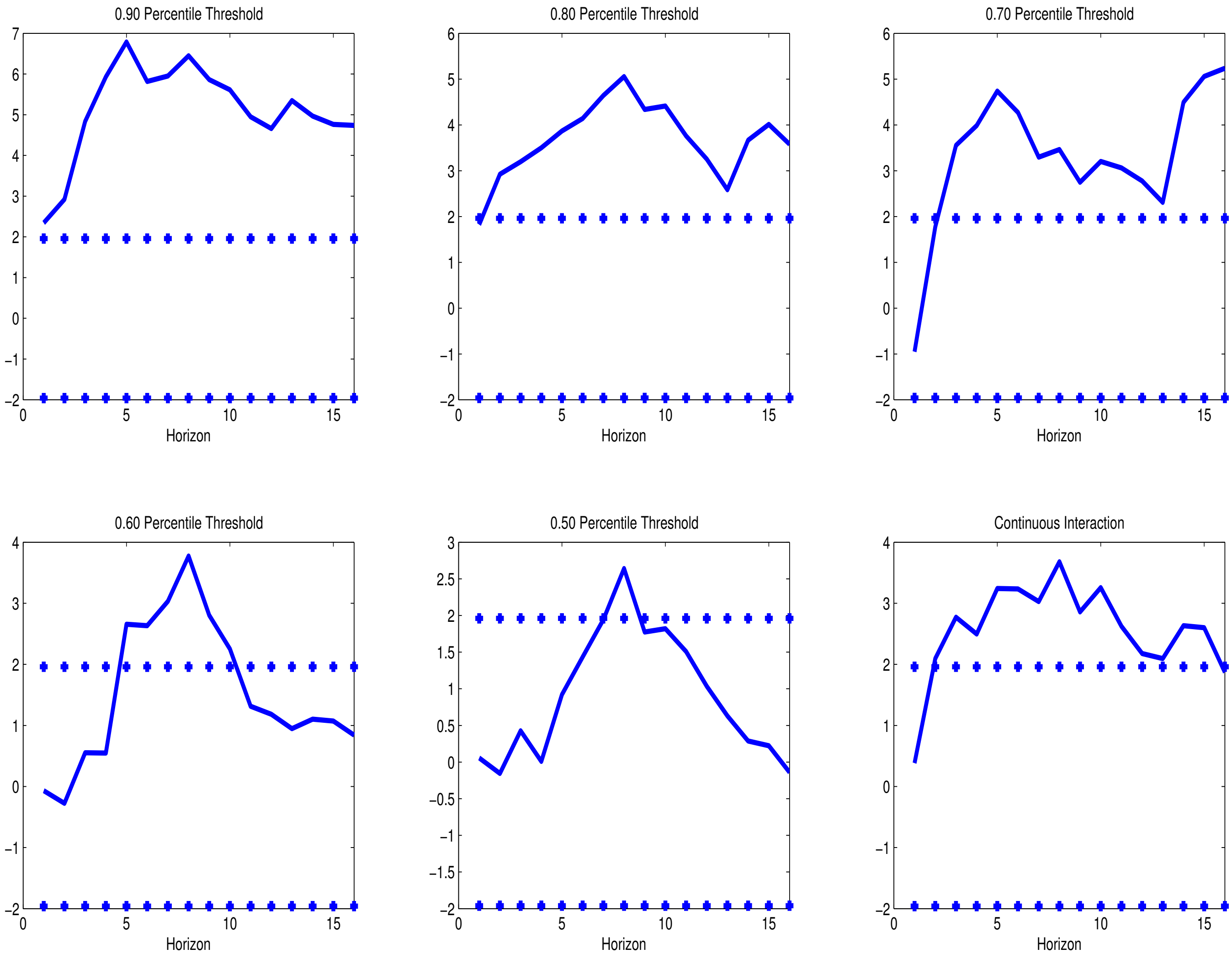
Notes: This figure presents the impulse responses of output to a one standard deviation credit supply shock from the linear model and non-linear model, where the log of output in the baseline specification (Equation (1)) is replaced by the log of HP-filtered output. In the first sub-figure the solid lines show the responses in the light capital controls state and the dashed lines are the responses in the strict capital controls state. The next two sub-figures present the impulse responses to the two state dummies along with Driscoll and Kraay (1998) 95% confidence bands. The last sub-figure shows the t-statistic of the difference between the responses in the strict capital controls state and the light controls state, where for convenience the 2.5% significance levels (± 1.96) are added. The responses are shown in terms of percentage deviations from pre-shock values. Horizon is in quarters.

Figure 17: **Capital Inflow Controls' Effect on Output's Sensitivity to Credit Supply Shocks: Interpolated Capital Controls Data**.



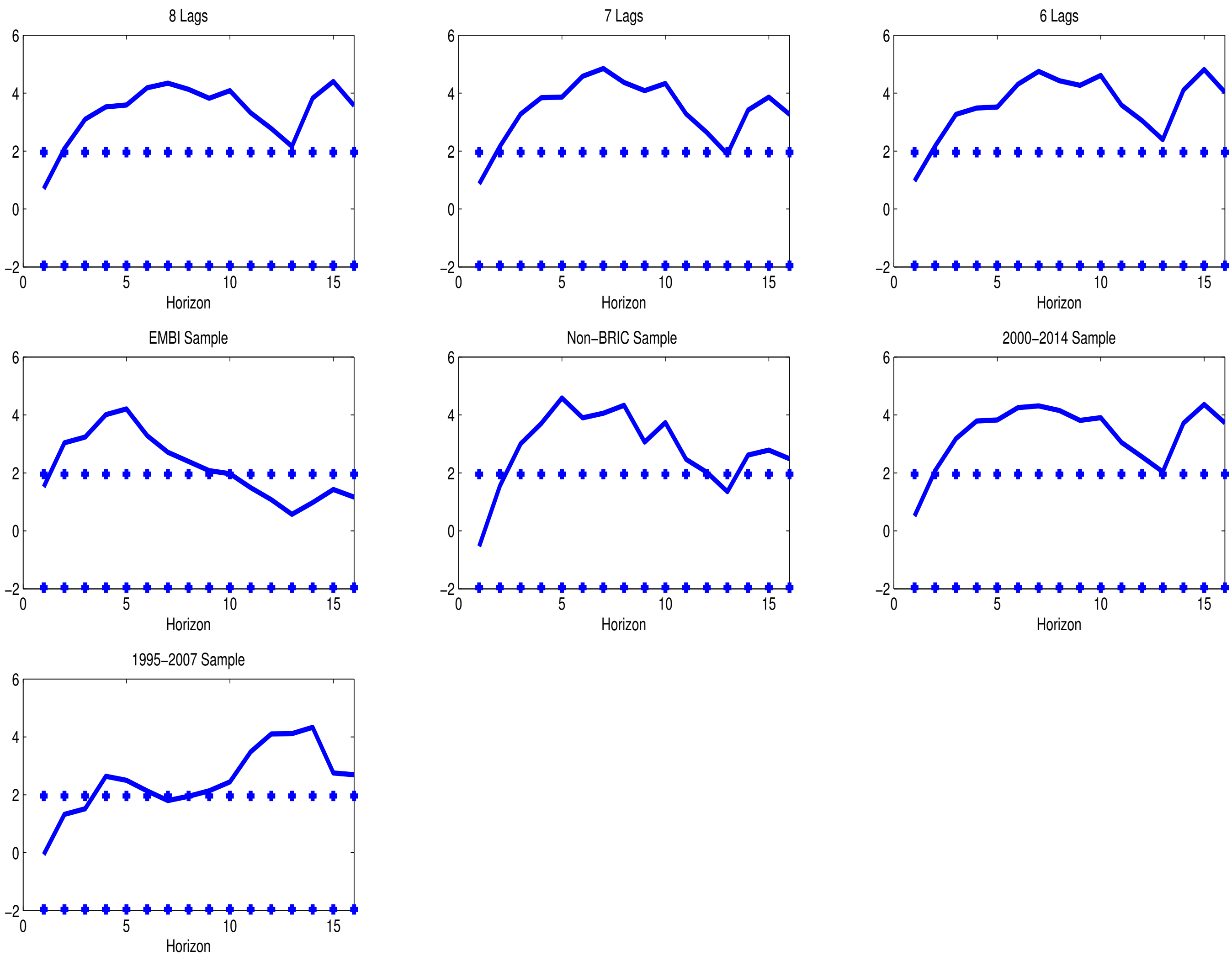
Notes: This figure presents the impulse responses of output to a one standard deviation credit supply shock from the linear model and non-linear model, where the annual capital controls series are interpolated into quarterly values via a cubic splining procedure rather than being converted into quarterly series by assuming within-year constancy as in the baseline case. In the first sub-figure the solid lines show the responses in the light capital controls state and the dashed lines are the responses in the strict capital controls state. The next two sub-figures present the impulse responses to the two state dummies along with Driscoll and Kraay (1998) 95% confidence bands. The last sub-figure shows the t-statistic of the difference between the responses in the strict capital controls state and the light controls state, where for convenience the 2.5% significance levels (±1.96) are added. The responses are shown in terms of percentage deviations from pre-shock values. Horizon is in quarters.

Figure 18: **Capital Inflow Controls' Effect on Output's Sensitivity to Credit Supply Shocks: Alternatives to the 0.75 Percentile Threshold**.



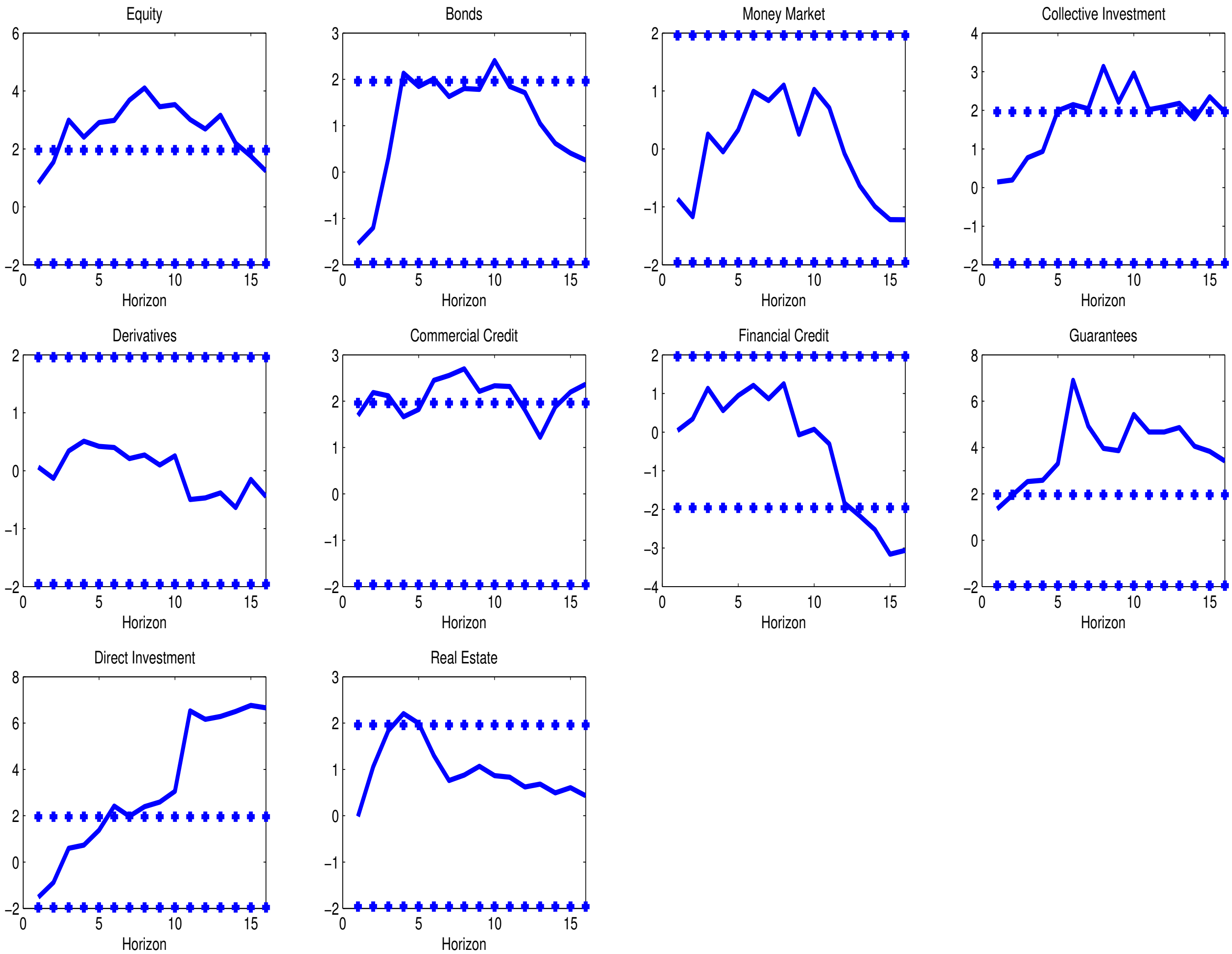
Notes: This figure shows the t-statistics of the difference between output responses in the strict capital controls state and the light controls state for various alternative percentile thresholds as well as the t-statistics from estimation of a continuous interaction based specification (Equation (5)), where the latter relate to the additional effect of the interaction term comprising of the capital controls index and EBP. For convenience, the 2.5% significance levels (± 1.96) are added. The responses are shown in terms of percentage deviations from pre-shock values. Horizon is in quarters.

Figure 19: **Capital Inflow Controls' Effect on Output's Sensitivity to Credit Supply Shocks: Alternatives Lag and Sub-Sample Specifications**.



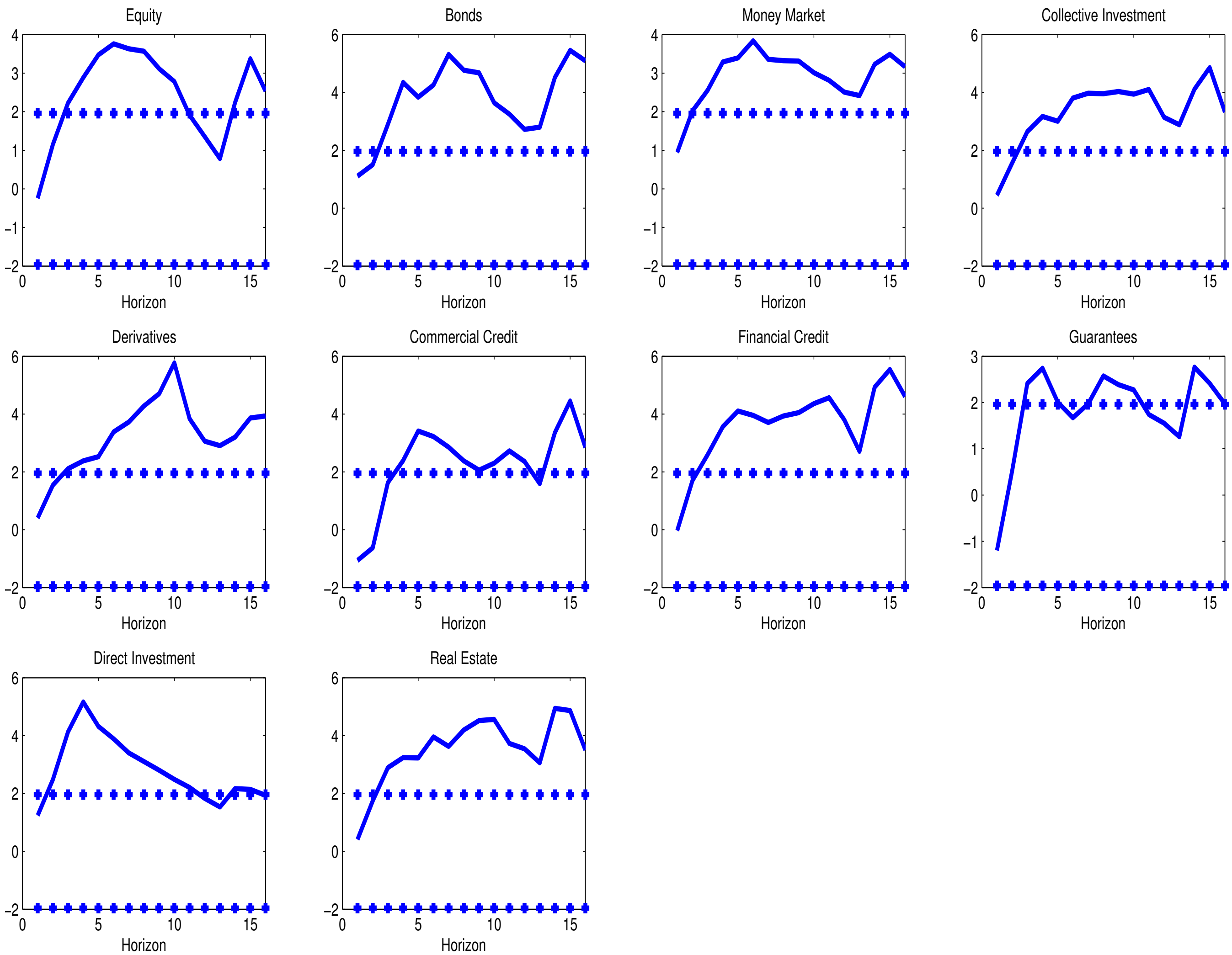
Notes: This figure shows the t-statistics of the difference between output responses in the strict capital controls state and the light controls state for various alternative lag and sub-sample specifications. For convenience, the 2.5% significance levels (±1.96) are added. The responses are shown in terms of percentage deviations from pre-shock values. Horizon is in quarters.

Figure 20: **Individual Asset Controls' Effect on Output's Sensitivity to Credit Supply Shocks**.



Notes: This figure shows the t-statistics of the difference between output responses in the strict capital controls state and the light controls state for all inflow controls indices, where the latter include the 10 different sub-components of the total inflow controls index: 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. For convenience, the 2.5% significance levels (±1.96) are added. The responses are shown in terms of percentage deviations from pre-shock values. Horizon is in quarters.

Figure 21: **Capital Inflow Controls' Effect on Leverage's Sensitivity to Credit Supply Shocks: Conditioning on the Effects of Individual Asset Controls**.



Notes: This figure shows the t-statistics of the difference between output responses in the strict capital controls state and the light controls state for the total, baseline inflow controls index, while conditioning on the 10 different sub-components of the total inflow controls index. Each sub-figure corresponds to a model (Specification (4)) in which conditioning on the category corresponding to the sub-figure title was made. For convenience the 2.5% significance levels (± 1.96) are added. The responses are shown in terms of percentage deviations from pre-shock values. Horizon is in quarters.