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Emerging Economies' Vulnerability to Changes in Capital Flows: The Role of Global and Local Factors*

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Abstract

This study uses panel quantile regression to examine the risk of capital outflows in times of stress (capital flows-at-risk, CFaR) for 16 emerging economies. Our analysis shows that changes in financial conditions in advanced economies and in the monetary policy stance of the United States affect the risk of large capital outflows for some countries. In particular, we find that tighter financial conditions in advanced economies during a phase when the U.S. monetary policy stance is changing significantly affect emerging economies' CFaR. Further, using government debt as a measure of emerging economies' structural vulnerability, we find that an increase in government debt substantially raises the risk of capital outflows in times of stress. Moreover, while in the case of debt investment, CFaR tend to be greater the higher the level of government debt, in the case of other investment (consisting mainly of bank lending), CFaR tend to increase when financial conditions in advanced economies deteriorate.

JEL classification: E52, F32, F34, F37

Keywords: Risk of Capital Outflows (CFaR: Capital Flows-at-Risk), Global Factors, Local Factors, Panel Quantile Regression, Relative Entropy

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1. Introduction

Capital flows to emerging economies have played an important role in promoting the economic growth of these economies. On the other hand, as shown in Figure 1, emerging economies have experienced large and rapid capital outflows during times of stress such as the global financial crisis (GFC) of 2008–09, the taper tantrum in 2013, the Chinese Renminbi crash in 2015, and the outbreak of the COVID-19 pandemic in 2020, and the amplification of shocks through large swings in capital flows has become a major risk factor facing emerging economies.

Capital flows to emerging economies are regarded to be affected by both global factors such as global financial conditions and investors' risk sentiment as well as local factors such as economic conditions and debt developments in individual emerging economies.[1] Since the global financial crisis, there have been many indications that the influence of global factors on capital flows to emerging economies has been increasing as a result of investors' search for yield against the backdrop of the prolonged low-growth, low-interest-rate environment in advanced economies. On the other hand, the view that the capital inflows to and outflows from individual countries essentially depend on country-specific fundamentals remains deep-rooted. Against this background, there are indications since the outbreak of the pandemic of growing vulnerabilities in some emerging economies, such as increasing government debt, and attention has focused on the potential impact of such vulnerabilities on capital flows.

Based on these considerations, this study examines the risks to capital flows to emerging economies by (1) modeling the conditional predicted distribution of future capital flows using panel quantile regression, and (2) examining the impact of global and local factors on capital flows – distinguishing between debt investment and other investment (which consists mainly of bank lending) – at different quantiles of the predicted distribution that correspond to, for example, times of stress or normal times. The reason for using panel quantile regressions is that, as pointed out by Gelos et al. (2019) and Eguren-Martin et al. (2020b), it is important to understand the link between capital flows and their various determinants for different quantiles of the distribution other than the mean. Capital flows to emerging economies differ substantially in normal

[1] In this study, we use the IMF's Balance of Payments Statistics (BOPS) for data on capital flows, and when referring to "capital flows" we mean portfolio investment flows (especially debt investment) and other investment flows, excluding direct investment. Direct investment lies outside the scope of the analysis in this study since, as also pointed out by Koepke (2019), it is not possible to clearly capture the determinants of such investments within a global push and local pull factor framework.

times and in times of stress, in that emerging economies (on average) tend to register net inflows in normal times but sharp outflows when a shock occurs. For this reason, when analyzing capital flows, it is important to pay attention not only to the average relationship between capital flows and their determinants but also to the left-tail of the predicted distribution showing developments in capital flows in times of stress (referred to as capital flows-at-risk, CFaR, below). Since emerging economies that experience rapid capital outflows suffer substantial negative consequences, such as a long-term decline in economic growth and financial system instability, considering CFaR is also important from a social welfare perspective.

Empirical research on CFaR in emerging economies using quantile regression has been growing rapidly since the seminal studies by Gelos et al. (2019) and Eguren-Martin et al. (2020b), and in addition to CFaR being regularly monitored in the IMF's Global Financial Stability Report (2019, 2020a and b, 2021), the concept of CFaR is being used in the Bank of England's Financial Stability Papers (e.g., Eguren-Martin et al., 2020a) and other reports. However, these previous studies on CFaR do not incorporate the monetary policy stance in advanced economies (especially the United States) as a determinant, which studies such as those by Miranda-Agrippino and Rey (2020) and Avdjiev et al. (2020) highlight as the most important risk factors.

Against this background, one contribution of the present study is that it explicitly incorporates the Federal Reserve's monetary policy stance as a global factor into the model and quantitatively shows the impact of monetary tightening by the Federal Reserve on CFaR. Moreover, using panel quantile regression, the present study also empirically examines factors that increase the risk of capital outflows in times of stress that have not been sufficiently explored in previous studies and quantitatively compares the effects of global and local factors. Another contribution of this study is that it examines differences in the factors strongly affecting CFaR in the case of debt investment and other investment.

The remainder of this study is organized as follows. Section 2 provides a review of the extant literature, positions the present study in this literature, and outlines the nature of the analysis. Section 3 then describes the data and empirical approach used in the empirical analysis. Next, Section 4 presents the estimation results and identifies the factors that are important for capital flows to emerging economies. Section 5 concludes.

2. Literature Review

As highlighted by Obstfeld (2012), Mendoza (2010), and others, with the advances in globalization in both trade and finance, capital flows to emerging economies have come to play an important role in the financial stability of emerging economies. In this context, the pioneering studies categorizing the risks surrounding capital flows to emerging economies into global and local factors are the empirical studies conducted by Calvo et al. (1993) and Fernandez-Arias (1996), with a comprehensive review of empirical studies regarding capital flows to emerging economies being provided by Koepke (2019) and Hannan (2018), so that a large amount of research has been accumulated. Within this literature, the present study is mainly related to the following two strands of research.

The first strand focuses on the examination of the risks and vulnerabilities linked to capital flows to emerging economies. Standard analyses to date set ad hoc thresholds for extreme phenomena such as a "sudden stop" or a "bonanza/surge" of capital flows from non-residents and examine the probability of these phenomena occurring using non-linear regression models such as probit models (e.g., Calvo et al., 2004; Forbes and Warnock, 2012; Ghosh et al., 2016). In contrast, following the growth-at-risk approach developed by Adrian et al. (2019) to examine the risk to GDP growth posed by financial vulnerability, scholars such as Gelos et al. (2019) and Eguren-Martin et al. (2020b) have started to employ panel quantile regression to model the conditional predicted distribution of capital flows and use this to analyze CFaR. This paper essentially follows these previous studies on CFaR but extends them in several respects. The first extension is that this study separately examines capital flows related to debt investment and other investment, which, as shown in Figure 2, together have accounted for about 90 percent of capital flows in recent years (excluding direct investment) and which have seen large fluctuations.[2] A study using similar variables as ours is that by Avdjiev et al. (2020). The second extension is that the emerging economies examined in this study include China, which has had a major impact on the global economy in terms of both trade activities and capital transactions since joining the WTO in 2001.[3] The third extension is that this study explicitly incorporates as one of the explanatory variables the Federal Reserve's monetary

[2] Gelos et al. (2019) only examine portfolio investment (the sum of debt and equity investment) in their country-level panel quantile regressions due to the declining share of other investment over the observation period. On the other hand, while Eguren-Martin et al. (2020b) include direct investment, portfolio investment, and other investment in their analysis, they do not examine equity and debt investment separately for portfolio investment.

[3] While Gelos et al. (2019) include 18 countries (in their panel quantile regression analysis controlling for integration with global financial markets) and Eguren-Martin et al. (2020b) include 13 countries in their analysis, neither study includes China.

policy stance, which, as highlighted by, for example, Miranda-Agrippino and Rey (2020) and Avdjiev et al. (2020) is the most important global factor affecting capital flows to/from emerging economies. We incorporate the Federal Reserve's monetary policy stance by using the shadow federal funds (FF) rate as a proxy.[4]

The second strand of the literature to which this study is related is research on the determinants of capital flows to emerging economies focusing on global and local factors from a new angle. As highlighted by Koepke (2019), while there is a general consensus on the (global and local) factors affecting capital flows and hence on the explanatory variables to be taken into account in empirical analyses, there is no consensus on the quantitative sensitivity of capital flows to these factors. For instance, Buono et al. (2020) point out that the global financial crisis and the taper tantrum have led to changes in the sensitivity of capital flows to risk factors in emerging economies. Moreover, using Bank for International Settlements (BIS) data on debt securities and bank lending, Avdjiev et al. (2020) find that since the global financial crisis (1) the rise in the lending market share of banks with high capital ratios has reduced the impact of global factors on international bank lending (corresponding to other investment in our analysis), and (2) amid the convergence of monetary policy stances in advanced economies, the impact of the Federal Reserve's monetary policy stance on capital flows has declined.

Moreover, regarding developments in international lending to emerging economies, Shim and Shin (2021) highlight that since international lending is affected by financial stress in lender countries, banks' lending behavior has changed in the wake of the global financial crisis. Furthermore, with regard to non-bank activities, Financial Stability Board (2020) points out that both the presence and the influence of non-banks have increased due to tighter banking regulations. Consequently, amid the ongoing structural changes in the financial system since the global financial crisis, clarifying the causes of changes in capital flows by type (debt investment and other investment) is an important empirical topic, and this study provides quantitative evidence, albeit partial, on these important issues. In particular, while all of the above studies are limited to analyzing the average relationship between capital flows and various factors at the same point in time (the relationship in normal times), this study examines the risk of capital outflows in times of

[4] Gelos et al. (2019) use the U.S. corporate BBB spread and U.S. real GDP growth (detrended) as explanatory variables representing global factors and do not include the Fed's monetary policy stance. Meanwhile, Eguren-Martin et al. (2020b) represent global factors by an index, the Financial Conditions Index (FCI), so that they do not analyze the effect of the Federal Reserve's monetary policy stance on its own.

stress, thus complementing existing analyses from a new angle.

3. Data and Empirical Approach

This section begins by presenting summary statistics of the data used in the empirical analysis and then outlines the empirical approach. Capital flows to emerging economies are characterized by (1) extreme volatility in times of stress in the time series dimension and (2) large cross-sectional variation among countries in the cross-sectional dimension. Therefore, when examining the summary statistics, it is necessary to evaluate the characteristics of each variable while taking the impact of outliers into account.

3.1 Outline of Data and Summary Statistics

The analysis in this study uses unbalanced panel data for 16 emerging economies (see Table 1 for details) for the period from 1996/Q4 to 2019/Q2. The frequency of the data is quarterly.

Table 2 presents summary statistics for debt investment and other investment flows, which are used as the dependent variables in the empirical analysis. Starting with the panel for the entire observation period, this shows that there is no significant difference between the mean and median for the sum of total debt and other investment. However, when looking at debt and other investment separately, the mean is larger than the median for both debt investment and other investment, reflecting the influence of some countries with large capital inflows. Moreover, looking at the time-series data in Figure 3, we find that while the global financial crisis led to a decline in capital flows to advanced economies (as indicated by the period averages of the median across countries depicted by the broken green line), emerging economies experienced an increase in debt investment (in terms of the period averages of both the median and the 20th and 80th percentiles across countries), while inflows of other investment can be regarded to have remained more or less unchanged in terms of the period averages of the median.[5] Returning to Table 2, the summary statistics for the subperiods before and after the global

[5] The dataset used for the analysis in this study is an unbalanced panel consisting of 16 countries in the cross-sectional dimension and about 80 quarters in the time-series dimension, meaning that a key feature of our dataset is the large number of observations in the time-series dimension. We therefore check for the presence of unit roots using panel unit root tests before conducting our fixed effects estimation. See Appendix 1 for details.

financial crisis show that the means and medians for both debt investment and other investment have increased. This suggests that dummy variables to control for changes in the level of capital flows after the global financial crisis need to be included in the regression analysis.

Next, we examine the variables used as explanatory variables in more detail. As one of the variables representing global factors, we use the shadow FF rate as a proxy for the Federal Reserve's monetary policy stance.[6] For the shadow FF rate, we use estimates obtained following the approach of Wu and Xia (2016). The reason for using the shadow FF rate is that, in addition to setting the policy rate, the Fed has been implementing unconventional policies such as government bond purchases, and using the shadow FF rate makes it possible to capture this policy stance.[7] Meanwhile, the spread on BBB-rated corporate bonds in the United States is used as a proxy variable for financial conditions in advanced economies. As shown in Table 2, the median shadow FF rate (one quarter difference) at -0.01 percent is very close to zero. As for the U.S. corporate BBB spread, the average is higher than the median, showing that while spreads are calm in normal times, they widen sharply during times of stress.[8]

To represent local factors, we use emerging economies' real GDP growth rate as an indicator of their economic performance and the outstanding amount of government debt as a ratio of nominal GDP (government debt-to-GDP ratio) as a proxy for their underlying creditworthiness. As shown in Figure 4, the government debt-to-GDP ratio of emerging economies has been on an upward trend in all regions since the global financial crisis and is particularly high in Latin America and Asia. Most recently, it has risen further in emerging economies, partly because of the increase in fiscal spending in response to the economic downturn caused by the COVID-19 pandemic. As shown in Table 2, the standard deviation of the government debt-to-GDP ratio is quite large, and the variation among countries is extremely large. Moreover, in Table 3, for the 16 emerging economies, we divide the sample into two groups below and above the median in terms of the government debt-to-GDP ratio and the real GDP growth rate respectively, and look at

[6] We use the shadow FF rate in periods when the effective lower bound is binding and the FF rate in other periods.
[7] To check the robustness of our results, in addition to the shadow FF rate based on Wu and Xia (2016), we also conducted regression analyses using, for example, the spread between short- and long-term yields on the U.S. Treasury yield curve, which also indicates the Fed's monetary policy stance. However, the results remained essentially unchanged.
[8] The correlation between the U.S. corporate BBB spread and the shadow FF rate (one-quarter difference) is about -0.3, so perfect multicollinearity is not an issue even if both are included in the regression model at the same time.

debt investment and other investment by quantile. The results show that for countries with a high government debt-to-GDP ratio and low real GDP growth, both types of capital flows tend to register large outflows around the lower quantiles, i.e., the risk of capital outflows in times of stress is high. Thus, even these relatively simple summary statistics show that local factors in emerging economies affect capital flows.

3.2 Empirical Approach

In this study, we model the impact of the various factors (explanatory variables) discussed in the previous section on the risk of capital outflows from emerging economies to obtain the conditional predicted distribution of capital flows. In order to do so, we conduct the following two-step estimation: (1) we estimate the impact of each factor at each quantile using panel quantile regression (controlling for unobservable heterogeneity across countries using fixed effects), and (2) approximate the estimated quantile function (the empirical inverse cumulative distribution function) with a skewed t-distribution. CFaR, the key concept for analyzing the risk to capital flows, are then defined as the tail risk that capital flows may fall below the α^{th} percentile of the skewed t-distribution described above.[9] We calculate CFaR by setting α to 5 percent and 10 percent (denoted as $CFaR_5$ and $CFaR_{10}$, respectively).

<u>Step 1</u>

To start with, we consider the following panel quantile regression model. To estimate the panel quantile regression, we use a fixed effects estimator (see Koenker, 2004).[10] Moreover, to ensure robust standard errors, we also examine confidence intervals generated by simulation using the block bootstrap strategy.[11]

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[9] Gelos et al. (2019) set the 5th and 10th percentiles of the conditional predicted distribution of capital flows as CFaR, while Eguren-Martin et al. (2020b) also set the 5th percentile as CFaR. However, as pointed out by Gelos et al. (2019), what quantile should be regarded as CFaR is not set a priori and should be decided based on the purpose of the analysis and the judgment of the policy authority.

[10] In the fixed effects model presented by Koenker (2004), the fixed effects do not depend on the quantile. It is well known that fixed effects estimators with quantile regression models can be used in practice when the panel data structure is such that the number of observations in a time-series dimension is sufficiently large relative to the number of observations in the cross-sectional dimension (Besstremyannaya and Golovan, 2019). However, it is not easy to obtain an estimate of the asymptotic variance-covariance matrix because it contains the conditional density function of the unobservable error term. Therefore, in order to ensure the robustness of our results, we also use confidence intervals calculated using a block bootstrap strategy to evaluate the statistical significance of the marginal effects.

[11] We calculate the confidence intervals through simulation using the block bootstrap strategy in order

$$
\begin{aligned}
Q(\tau;\overline{Flow}_{j,i,t+2}) = \beta^{\tau}_{0,j}Flow_{j,i,t} + \beta^{\tau}_{1,j}BBB\_spread_t + \beta^{\tau}_{2,j}\Delta Shadow\_rate_t \\
+\ \beta^{\tau}_{3,j}BBB\_spread_t \cdot \Delta Shadow\_rate_t \\
+\ \beta^{\tau}_{4,j}\overline{RGDP}_{i,t} + \beta^{\tau}_{5,j}\overline{G\_debt}_{i,t} + \beta^{\tau}_{6,j}GFC_t + \mu_{j,i}
\end{aligned}
$$

where subscript j denotes the type of capital flow (1=debt investment, 2=other investment), i represents the country, and t is the point in time (quarter), while superscript τ (=0.05,0.1,0.2,...,0.90,0.95) denotes the quantile. Table 4 provides an overview of the definitions and expected signs of the variables used in the analysis.

The dependent variable $\overline{Flow}^{\tau}_{j,i,t+2}$ represents future capital flows and, as in Avdjiev et al. (2020), we conduct our estimations for debt investment and other investment separately.[12] The reason is to take into account that, as also pointed out by Cerutti et al. (2019), debt investment and other investment have different investor groups, so that the factors influencing fluctuations in debt and other investment may also differ. The estimates from the panel quantile regression ($\hat{Q}(\tau;\overline{Flow}_{j,i,t+2})$) are quantiles conditional on the realized values of the vector of explanatory variables ($X_{j,i,t}$) and can be expressed as follows:

$$
\hat{Q}\left(\tau;\overline{Flow}_{j,i,t+2}\middle|X_{j,i,t}\right) = X_{j,i,t}\hat{\beta}^{\tau}_{j}
$$

Next, we explain our independent variables. To represent global factors, we use BBB_spread_t, the U.S. corporate BBB spread, as a proxy for financial conditions in advanced economies, and $\Delta Shadow\_rate_t$, the shadow FF rate (one-quarter difference), as a proxy for the Fed's monetary policy stance, as mentioned in the previous section. In addition, we use the interaction term of BBB_spread_t and $\Delta Shadow\_rate_t$ as an explanatory variable. The reason is that the impact of the Fed's monetary policy on capital flows to emerging economies may vary depending on the financial conditions in advanced economies at the time. For example, in times of serious stress in financial markets, such as the global financial crisis or the recent coronavirus shock, the Fed's actions as the market maker of last resort may have a more positive impact on capital flows than in

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to resample the panel data without changing the cross-sectional structure while retaining the temporal dependence structure in the time series dimension (for details, see Lahiri, 2003, and Kapetanios, 2008). Further, following Adrian et al. (2018), we also resample the rows of data from the temporal dimension of each emerging economy 10,000 times, considering block widths of four consecutive quarters and allowing for overlap. The overlapping block bootstrap procedure has been shown to provide heteroskedasticity and autocorrelation consistent (HAC) standard errors for panel quantile regressions (Fitzenberger, 1998).

[12] While the study by Avdjiev et al. (2020) is similar to ours in that it uses cross-border bank lending and international debt securities (and the sum of the two) as the dependent variables, it differs in that they use different data, namely, the BIS Locational Banking Statistics (LBS) and the BIS International Debt Securities Statistics (IDSS).

normal times. Conversely, if a change in the monetary policy stance is perceived as unexpected by the financial market, as was the case during the taper tantrum, and financial conditions in advanced economies become much tighter, this may have a substantial negative impact on capital flows. Regarding these global factors, a widening of BBB_spread_t (i.e., a tightening of financial conditions in advanced economies) and an increase in $\Delta Shadow\_rate_t$ (i.e., a tightening of the Fed's monetary policy) are expected to put downward pressure on capital flows to emerging economies. However, a widening of BBB_spread_t (i.e., a tightening of financial conditions in advanced economies) at upper quantiles of the conditional predicted distribution of capital flows to emerging economies may also encourage a shift of funds from risky emerging economies to relatively low-risk emerging economies, so that the sign may also be positive.

To represent local factors, we use $\overline{RGDP_{i,t}}$, which is the real GDP growth rate of emerging economy *i* and is used as a proxy for cyclical economic performance. $\overline{G\_debt_{i,t}}$ represents the ratio of outstanding government debt to nominal GDP in emerging economy i and is used as a proxy for countries' underlying creditworthiness. Since a higher $\overline{RGDP_{i,t}}$ (strong economic growth) encourages inflows of investment funds, coefficient $\beta^{\tau}_{4,j}$ is expected to be positive; on the other hand, since a higher $\overline{G\_debt_{i,t}}$ (implying higher country risk) reduces investors' willingness to invest in the country, coefficient $\beta^{\tau}_{5,j}$ is expected to be negative. However, an increase in $\overline{G\_debt_{i,t}}$ may also indicate strong government demand for funds against the background of high growth expectations. In this case, the sign of $\beta^{\tau}_{5,j}$ could also be positive since at upper quantiles of the conditional predicted distribution of capital flows to emerging economies an increase in $\overline{G\_debt_{i,t}}$ may encourage capital inflows. In order to capture structural changes in capital flows to emerging countries after the global financial crisis, a dummy (GFC_t) which takes a value of 1 for the period after the global financial crisis, a lag term ($Flow_{j,i,t}$)[13] to capture autocorrelation, and country fixed effects ($\mu_{j,i}$) are added as control variables.

[13] In panel regression analysis, strict exogeneity of the error term is assumed. Therefore, in the case of dynamic panel regressions, since there is correlation between the explanatory variables (lag terms) and the error term, it is common to employ the Arellano-Bond estimator using the instrumental variable method. However, while the Arellano-Bond estimator is used when the number of observations in the time-series dimension is small, in the analysis in this study, there are a sufficient number of data points in the time-series dimension, about 80, so that we do not use instrumental variables (for details on fixed effects estimators in dynamic panel quantile regression, see Galvao, 2011).

Step 2

The results of the above panel quantile regressions show the partial effect of each explanatory variable on the conditional predicted distribution of capital flows, making it difficult to intuitively grasp the overall change in the conditional distribution. Therefore, we next calibrate the smooth conditional predicted distribution of capital flows from the results of the quantile regression. In practice, due to estimation noise and approximation errors, it is generally difficult to obtain a smooth probability density function from the empirical distribution directly estimated from quantile regression. We therefore use a similar approach as in the growth-at-risk analysis by Adrian et al. (2019) and obtain the probability density function by fitting the skewed t-distribution.[14] Specifically, we use the skewed t-distribution based on Azzalini and Capitanio (2003) to recover a smooth probability density function from the empirical quantile function. The skewed t-distribution à la Azzalini and Capitanio is part of a family of flexible distribution functions characterized by the following four moments:

$$f(y;\mu,\sigma,\alpha,\nu)=\frac{2}{\sigma}t\left(\frac{y-\mu}{\sigma};\nu\right)T\left(\alpha\frac{y-\mu}{\sigma}\sqrt{\frac{\nu+1}{\nu+\frac{y-\mu}{\sigma}}};\nu+1\right)$$

where $t(\cdot)$ and $T(\cdot)$ respectively denote the probability density function and the cumulative distribution function of Student's t-distribution. Further, μ is the location parameter, σ is the scale parameter, α is the shape parameter, and ν is the fatness parameter. Intuitively, it can be seen that the distribution is the base probability density function $t((y-\mu)/\sigma\,;\nu)$ weighted by the cumulative distribution function with the rescaling parameter (α).[15] We use the algorithm proposed by Azzalini (2021) for calculating the skewed t-distribution.

To calibrate the parameters $\{\mu,\sigma,\alpha,\nu\}$ of the skewed t probability density function *f*, we set the minimization problem such that the square distance between the estimated quantile function and the quantile function $F^{-1}(\tau;\mu,\sigma,\alpha,\nu)$ of the skewed t-distribution

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[14] Although the approximated conditional distribution has become a standard analytical tool in the literature, there are issues; namely, (1) issues arising from estimation errors in the empirical quantile function obtained from the quantile regression estimator (e.g., the distribution function does not satisfy monotonicity), and (2) issues arising from approximation errors to the skewed t-distribution. Therefore, although analyses using approximated conditional distributions are useful in terms of aiding intuitive interpretation, quantitative interpretations should be based on the statistical and economic significance of the estimates.

[15] Meanwhile, when $\alpha=0$, the distribution becomes Student's t-distribution, and when $\alpha=0,\ \nu\to\infty$, the distribution becomes the normal distribution with mean μ and standard deviation σ.

is minimized, i.e.:[16]

$$\{\hat{\mu}, \hat{\sigma}, \hat{\alpha}, \hat{\nu}\} = \underset{\mu,\sigma,\alpha,\nu}{\operatorname{argmin}} \sum_{\tau} \left(\hat{Q}(\tau; \overline{Flow}_{j,i,t+2} | X_{j,i,t}) - F^{-1}(\tau; \mu, \sigma, \alpha, \nu) \right)^2$$

4. Empirical Results

In this section, we first examine the impact of changes in global and local factors on debt and other investment at each quantile and then visually show the effect of each factor on the entire predicted distribution of capital flows using the probability density function. We then examine how the impact of U.S. monetary policy on capital flows varies with the state of financial conditions in advanced economies. Finally, using relative entropy (the Kullback-Leibler divergence), we rigorously compare the impact of the factors considered in this study on debt investment and other investment. Note that technical issues such as the estimation results of the panel quantile regressions and the approximation error between the empirical distribution obtained from the panel quantile regressions and the skewed t quantile function are summarized in Appendix 2.

4.1 Debt Investment

To start with, in Figures 5(a) and (b) we examine the impact on debt investment of a one standard deviation adverse shock to each of the factors (a tightening of financial conditions or monetary policy in the case of the U.S. corporate BBB spread and the shadow FF rate, a decline in the real GDP growth rate, and an increase in the government debt-to-GDP ratio). Note that in the case of the global factors (the U.S. corporate BBB spread and the shadow FF rate), the impact of each depends on the relative level of the two to each other, since the estimation equation includes an interaction term. We therefore do not assess the impact of shocks on capital flows in terms of the coefficient on each variable but in terms of the marginal effect including the impact through the interaction term. On the other hand, in the case of local factors, since no interaction term is included, we assess the impact in terms of the coefficient.

[16] When fitting the empirical conditional distribution to the skewed t-distribution, the approximation error and the shape of the fitted conditional distribution differ substantially depending on the number of quantiles to be approximated, so in this regard, too, care must be taken when performing analyses and interpreting the results using only the approximated conditional distribution. In the present study, minimization is performed for the following seven quantiles: $\tau =$ 0.05, 0.10, 0.30, 0.50, 0.70, 0.90, 0.95.

Starting with global factors, Figure 5(a) indicates that the marginal effect of a widening of the U.S. corporate BBB spread (BBB_spread_t) is not large at the median quantile but is about -1.0 percent and hence fairly large at the lower quantiles. This implies that a widening of corporate bond spreads increases the risk of debt investment outflows in times of stress.[17] Similarly, an increase in the shadow FF rate ($\Delta Shadow\_rate_t$) has little impact at the median quantile; on the other hand, the impact appears to be slightly negative at the lower quantiles (representing times of stress), although it is not statistically significant and smaller than the impact of a widening of corporate bond spreads. However, the impact of the shadow FF rate seen here is premised on the average level of corporate bond spreads. How the impact of the shadow FF rate changes when the level of corporate bond spreads changes will be discussed later. Note that Avdjiev et al. (2020) and Buono et al. (2020) find that, on average, the Fed's monetary policy stance has no contemporaneous impact on debt investment, which is consistent with the result for the median quantile in this study. However, as mentioned above, the analysis in this study shows a negative relationship between the two at the lower quantiles. This illustrates the benefits of using quantile regressions, which allow us to analyze not only the average relationship but also explicitly the relationship in times of stress.

Next, Figure 5(b) examines the impact of local factors. The marginal effect of a decline in the real GDP growth rate ($\overline{RGDP_{i,t}}$) of emerging economies on capital flows is negative below the 80th percentile, indicating that a lower growth rate increases the probability of debt investment outflows. However, the impact is small and statistically insignificant. On the other hand, the marginal effect of an increase in the government debt-to-GDP ratio ($\overline{G\_debt_{i,t}}$) on capital flows is negative below the 40th percentile, and this negative impact at the lower quantiles, at –3.0 percent, is quite large. In other words, an increase in the government debt-to-GDP ratio is a major factor that increases the risk of capital outflows in times of stress.[18] An interesting upshot of the results for local factors is that structural vulnerabilities such as government debt, rather than cyclical factors such as the business cycle, increase the risk of debt investment outflows in times of stress.

[17] The impact of corporate bond spreads is difficult to interpret, as the results for the upper quantiles suggest that when spreads widen, capital inflows increase. One interpretation is that when financial conditions deteriorate in advanced economies, global investors move capital from advanced economies or risky emerging countries to emerging countries where conditions are better. Further research is needed to determine whether this mechanism is actually at work.

[18] What is difficult to explain is the sign on $\overline{G\_debt_{i,t}}$ at upper quantiles. This suggests that at upper quantiles, an increase in $\overline{G\_debt_{i,t}}$ is associated with an increase in capital inflows. One possible interpretation is that countries with a high expected growth rate have a substantial demand for capital and attract funds from foreign investors.

While so far we have looked at the marginal effects of global and local factors, we now examine the impact of each factor on the overall predicted distribution of capital flows in the form of changes in the conditional probability density function. In Figure 6, the red solid line shows the probability density function when each factor is subjected to a one standard deviation adverse shock (relative to the mean value represented by the blue solid line). Whereas the median value does not change much for any of the factors, $CFaR_{10}$ and $CFaR_5$, which represent the risk of capital outflows in times of stress, shift to the left. As shown by the marginal effects discussed above, shocks to the U.S. corporate BBB spread and government debt significantly shift $CFaR_{10}$ and $CFaR_5$ to the left, visually indicating that they are important risk factors that increase the risk of capital flow outflows in times of stress.

4.2 Other Investment

Next, in Figures 7(a) and (b) we examine the impact of each factor on other investment.

Starting with global factors, the marginal effect of a widening of the U.S. corporate BBB spread has a negative sign below the 60^{th} quantile, and the impact at lower quantiles is extremely large at –5.0 percent. This indicates that in times of stress, a widening of corporate bond spreads substantially increases the risk of outflows of other investment. On the other hand, a tightening of the shadow FF rate has hardly any impact at the median quantile and a limited and statistically insignificant impact at lower quantiles. However, as with debt investment, the impact of the shadow FF rate varies depending on the level of the U.S. corporate BBB spread, which is something that we examine in more detail below.

Next, Figure 7(b) shows the impact of local factors. Looking at the marginal effect of a decline in emerging economies' real GDP growth rate, the sign is negative at all quantiles. When economic growth falls, the probability of outflows of other investment increases almost across the board, regardless of other conditions, although the extent is small. On the other hand, the sign of the marginal effect of an increase in the government debt-to-GDP ratio is negative from the median and below, and the impact around the lower quantiles, with –2.0 percent, is quite large. These results for local factors imply that, as in the case of debt investment, structural factors such as government debt are more important than cyclical factors such as the business cycle in increasing the risk of capital outflows in times of stress.

The conditional probability density function for other investment, shown in Figure 8, indicates that, as in the case of debt investment, for shocks other than those to the real GDP growth rate, $CFaR_{10}$ and $CFaR_5$ shift to the left, although the median does not change much. On the other hand, in response to a shock to the real GDP growth rate, the median shifts substantially to the left. Other investment, which mainly consists of bank lending, has relatively short maturities, and global banks may consider the real GDP growth rate as an important factor when making lending decisions, even in normal times, as it may affect borrowers' short-term financial capacity for repayment.

4.3 Interconnectedness of Global Factors: The Fed's Monetary Policy and Financial Conditions

The panel quantile regression model in this study includes an interaction term of the U.S. corporate BBB spread (BBB_spread_t) and the change in the shadow FF rate ($\Delta Shadow\_rate_t$). In other words, the model incorporates that the impact of the Fed's monetary policy stance on capital flows to emerging economies may vary depending on the level of the U.S. corporate BBB spread, which represents financial conditions in advanced economies. That is, the model assumes that even if the Fed tightens monetary policy, the impact on emerging economies may differ depending on how tight financial conditions in advanced economies are at that time (or how tight they have become as a result of monetary tightening).

In order to examine this interconnectedness, we consider the impact of the Fed's monetary policy stance on capital flows to emerging economies by varying the level of the U.S. corporate BBB spread. We begin with Figure 9(a), which shows the impact of the shadow FF rate on debt investment. The chart on the left shows the results for the median, which can be interpreted as the impact during normal times. It indicates that even if the Fed's monetary tightening were to lead to tighter financial conditions in advanced economies, this would have little impact on the probability of debt investment outflows during normal times, which correspond to the median. One of the reasons is that when monetary policy is tight, this usually means that advanced economies, led by the United States, are in an expansionary phase, and emerging economies benefit from this through, for example, increased exports to advanced economies (i.e., the trade channel).

However, looking at the chart on the right for the risk of capital outflows at the 10^{th} percentile, which can be interpreted as representing a time of stress, this suggests that if monetary tightening by the Fed were to lead to a tightening of financial conditions in advanced economies, this would have quite a substantial impact on debt investment. While the standard error in our estimates increases as corporate bond spreads widen, so that our results should be interpreted with a degree of caution, they suggest that if a tightening of monetary policy by the Fed leads to tighter financial conditions in advanced economies, this could increase the risk of capital outflows from emerging economies at a time when these are already under stress. Conversely, if the Fed were to ease monetary policy when financial conditions in advanced economies are tight, this could reduce the risk of capital outflows from emerging economies.

Next, Figure 9(b) shows the impact of the shadow FF rate on other investment. Looking at the results for the median in the left chart, this shows that if the Fed's monetary tightening were to result in a tightening of financial conditions in advanced economies, this would have quite a large impact on other investment even during normal times, which correspond to the median. This is different from the result for debt investments. Further, looking at the chart on the right for the 10^{th} percentile, this shows that if monetary tightening by the Fed were to lead to tighter financial conditions in advanced economies, the risk of outflows of other investment in times of stress would be substantially higher than in the case of debt investment. This can be interpreted as the natural result of the fact that other investment mainly consists of bank lending and the mechanism that monetary tightening by the Fed has a direct impact on global banks' dollar liquidity management (see, e.g., Cetorelli and Goldberg, 2012) and leverage cycle (Bruno and Shin, 2015) through higher dollar funding costs.

4.4 Comparison of the Impact by Type of Capital Flow

So far, we have examined the effects of changes in various factors on capital flows separately for debt investment and other investment. Next, we try to measure the difference in the impact of each factor on debt investment and other investment. In doing so, it is not appropriate to simply compare the marginal effects on debt investment and other investment, since the levels of these two investments differ. Therefore, following Adrian et al. (2019) and Eguren-Martin et al. (2020b), we measure the impact of each factor through relative entropy (see Appendix 3 for the specific procedure). Relative entropy quantifies the divergence between the conditional distribution induced by a one standard deviation adverse shock and the original conditional distribution in a particular region of the distribution (in this study, the 10^{th} percentile and below). Intuitively, it represents the extent to which the risk of capital outflows increases in response to an adverse shock to each of the factors.

Figure 10 shows the 10 percent downside relative entropy (the increase in the probability of capital outflows in times of stress) by factor. Starting with global factors, we find that these have a stronger impact on other investment than on debt investment. In particular, the impact of a widening of the U.S. corporate BBB spread on other investment is quite large. Local factors, on the other hand, have a stronger impact on debt investment. In particular, an increase in government debt substantially increases the risk of debt investment outflows.[19]

Finally, using relative entropy, we compare the impact of a tightening of the shadow FF rate between the two types of capital flows for different levels of the U.S. corporate BBB spread. As can be seen in Figure 11, the point estimate of the impact of a tightening of the shadow FF rate is larger for other investment than debt investment regardless of the level of the corporate bond spread. However, it should be noted that the larger the corporate bond spread, the larger the estimation error becomes, so that the estimates regarding the impact should be interpreted with care.

A possible explanation for these findings is as follows. Other investment, which consists mainly of bank lending, (1) has relatively short maturities and (2) is likely to be subject to capital adequacy and liquidity ratio constraints under tighter regulations such as Basel III. Therefore, when there are adverse developments in global factors, this may give rise to outflows of other investment as banks refrain from rolling over their loans. On the other hand, in the case of debt investment, (1) institutional and other investors with a relatively long investment horizon account for a large share of such investment, and (2) investors may struggle to sell debt instruments in times of stress due to the low liquidity of bond markets in emerging countries. Therefore, it is likely that global bond investors invest their funds while paying attention to emerging economies' credit risk, which represents their structural vulnerabilities such as their government debt. While quantitatively examining banks' and investors' behavior in these regards is beyond the scope of the present study, from the perspective of emerging economies it has important implications for the management of capital flows and macroprudential policy, and we hope to focus on this issue in future research, including through the use of creditor-side data.

[19] In order to check whether the downside relative entropy is nonlinear, we also examined the 5 percent downside relative entropy, which shows the behavior of the tail under more severe stress, and found that it is generally similar to the 10 percent downside relative entropy. This suggests that there does not appear to be strong nonlinearity in the risk to capital outflows in times of stress.

5. Conclusion

In this study, we estimated the conditional predicted distribution of capital flows using panel quantile regression and examined the capital flows at risk (CFaR) in times of stress by type of capital flow (debt investment and other investment). Moreover, using relative entropy, we compared the impacts of the different factors on debt investment and other investment. In these analyses, we explicitly incorporated into the model the monetary policy stance of the U.S., which has not been fully taken into account in previous studies. Doing so shows that the impact of changes in the U.S. monetary policy stance on the risk of capital outflows in emerging economies differs substantially depending on financial conditions in advanced economies.

Emerging economies are facing increased risk of capital outflows in times of stress, as government debt has grown due to the deterioration in fiscal balances as a result of addressing the COVID-19 pandemic. It should be noted that the risk of capital outflows, particularly in vulnerable countries, may increase further if the economic recovery in advanced economies gathers pace and financial conditions in advanced economies tighten. Emerging economies will need to increase their robustness to global shocks by addressing their structural vulnerabilities, such as increases in government debt, over the medium to long term, while taking into account the current economic downturn due to the pandemic.

Finally, some limitations of the analysis in this study should be mentioned. One is that the analysis focuses on the short-term impact of global and local factors on capital flows. In order to examine the impact of structural vulnerabilities on capital flows in emerging economies, a medium- to long-term perspective is also important, and this is a topic we hope to address in future research. Moreover, while using relative entropy enabled us to compare the impact of the different factors on debt investment and other investment, we were not able to examine differences in the behavior of investors and banks and mechanisms that likely underlie these differences. Furthermore, the structure of the financial system has also changed since the global financial crisis. The impact of these aspects on capital flows to emerging economies is another topic for future research.

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Appendix 1: Testing for the Stationarity of Variables

In order to check the stationarity of the panel data used in this paper, we conducted panel unit root tests using (1) the Levin-Lin-Chu (LLC) test and (2) the Im-Pesaran-Shin (IPS) test. Multiple methods were applied to ensure robustness. The tests were performed on the time series data of the dependent and explanatory variables. For the shadow FF rate, we tested the level and the first difference. The results of the tests are shown in Appendix Table A1.1. In the LLC and IPS tests, the null hypothesis is rejected at the 1 percent significance level for all variables, meaning that the variables can be judged to be stationary.

Appendix 2: Panel Quantile Regressions, Validity of the Approximation Through the Skewed t-Distribution, and Estimation Results of the Panel Regressions

In this appendix, we present the estimation results of panel quantile regressions, the validity of the approximation through the skewed t-distribution, and the estimation results of the panel regressions.[20]

A2.1 Estimation Results of the Panel Quantile Regressions

Debt Investment

Table A2.1 presents the estimation results of the panel quantile regressions. Starting with global factors, we find that the coefficient of changes in the shadow FF rate ($\Delta Shadow\_rate_t$) is statistically significant for lower quantiles (10th to 30th percentiles) but not for the other quantiles, while the coefficient of the U.S. corporate BBB spread (BBB_spread_t) is statistically significant for lower quantiles (5th to 30th percentiles) and upper quantiles (60th to 95th percentiles). In addition, the coefficient of the interaction term between the two ($BBB\_spread_t * \Delta Shadow\_rate_t$) is statistically significant for lower quantiles (10th to 40th percentiles). Therefore, the impact of global factors is generally statistically significant with respect to the lower quantiles, which are important in the risk assessment of capital flows, and confidence in the quantitative impact of the marginal effects can be considered to be ensured. Next, turning to local factors, the coefficient on emerging economies' real GDP growth rate ($\overline{RGDP}_{i,t}$) is statistically

[20] Note that the standard errors described in the estimation results of the panel quantile regressions in this appendix are asymptotic standard errors that do not take the cluster or autocorrelation structure of the data into account.

significant for intermediate quantiles (30th and 40th percentiles) but not for other quantiles. On the other hand, the coefficient of the government debt-to-GDP ratio ($\overline{G\_debt_{i,t}}$) is statistically significant for lower quantiles (5th to 30th percentiles) and upper quantiles (70th to 95th percentiles). The results therefore suggest that the government debt-to-GDP ratio ($\overline{G\_debt_{i,t}}$) has an important impact on the risk of debt investment outflows in times of stress.

<u>Other Investment</u>

Table A2.2 presents the panel quantile regression results for other investment. The table shows that for global factors, the coefficients of the shadow FF rate ($\Delta Shadow\_rate_t$), the U.S. corporate BBB spread (BBB_spread_t), and their interaction term ($BBB\_spread_t * \Delta Shadow\_rate_t$) are statistically significant across a wide range from low to intermediate quantiles (5th to 50th percentile). Therefore, the impact of global factors is generally statistically significant with respect to the lower quantiles, which are important in the risk assessment of capital flows, and confidence in the quantitative impact of marginal effects can be considered to be ensured. Next, turning to local factors, while the coefficient on emerging economies' real GDP growth rate ($\overline{RGDP_{i,t}}$) is insignificant for lower quantiles (5th and 10th percentile), it is significant for all the other quantiles (from the 20th to the 95th percentile). On the other hand, the coefficient on the government debt to GDP ratio ($\overline{G\_debt_{i,t}}$) is not statistically significant except for the higher quantiles (90th and 95th quantiles). The results therefore suggest that, in terms of local factors, emerging economies' real GDP growth rate ($\overline{RGDP_{i,t}}$) has an important impact on other investment flows in times of stress.

A2.2 Validity of the Approximation Through the Skewed t-Distribution

When we fit the quantile function (empirical distribution) estimated through panel quantile regression to the skewed t-distribution, there is a possibility of non-negligible error caused by the approximation method. For this reason, we here examine the approximation error. Figure A2.1 shows, for the conditional probability density function of debt investment, the behavior of the estimated quantile function (blue line with diamond markers) and the approximated skewed t quantile function (red line) when each risk factor is subjected to an adverse shock of one standard deviation from the mean.

Similarly, Figure A2.2 shows the behavior of the conditional probability density function for other investment when a similar shock is applied. Comparing these quantile functions, the errors between the empirical distribution and the approximated skewed t quantile function are small, suggesting that the analysis using the fitted conditional probability density function of capital flows and the interpretation of the results are valid.

A2.3 Estimation Results of the Panel Regression Analysis

In specifying the model for the panel quantile regression used in the main analysis in the text, we also estimated the following panel regression equation:

$$\begin{gathered}\overline{Flow}_{j,i,t+2} = \beta_{0,j} Flow_{j,i,t} + \beta_{1,j} BBB\_spread_t + \beta_{2,j} \Delta Shadow\_rate_t \\ +\beta_{3,j} BBB\_spread_t \cdot \Delta Shadow\_rate_t \\ +\beta_{4,j} \overline{RGDP}_{i,t} + \beta_{5,j} \overline{G\_debt}_{i,t} + \beta_{6,j} GFC_t + \mu_{j,i} + \varepsilon_{j,i,t}\end{gathered}$$

The definitions of the variables are the same as for the panel quantile regression equation described above, while $\varepsilon_{j,i,t}$ is an error term that satisfies the usual assumptions.

The estimation results for the different specifications are shown in Table A2.3. Column (i) shows the results for the fixed effects estimation without the interaction term ($BBB\_spread_t * \Delta Shadow\_rate_t$) and without the dummy for the period after the GFC, while column (ii) shows the same estimation but with the post-GFC dummy included. In both columns, the only statistically significant variable is the real GDP growth rate ($\overline{RGDP}_{i,t}$). Next, column (iii) shows the fixed effects estimation with the interaction term ($BBB\_spread_t * \Delta Shadow\_rate_t$). The results indicate that both the shadow FF rate ($\Delta Shadow\_rate_t$) and the U.S. corporate BBB spread (BBB_spread_t) are statistically significant. Furthermore, in (iv), we add the post-GFC dummy and find that the statistical dominance of global factors increases. In (v), fixed effects estimation was conducted without the lag terms; however, the statistical significance of the explanatory variables remains unchanged.

Moreover, we conducted fixed effects estimations using the same model as in column (iv) but for the two types of investment flow separately. Column (vi) shows the estimation results with debt investment as the dependent variable. Only the government debt-to-GDP ratio GDP ($\overline{G\_debt}_{i,t}$) is statistically significant, while all the other explanatory variables are insignificant. Finally, column (vii) shows the estimation results with other investment as the dependent variable; we find that all explanatory variables except for the government debt-to-GDP ratio ($\overline{G\_debt}_{i,t}$) are statistically significant. In the panel quantile regression, the empirical analysis is conducted using the same model as in (iv), based on the results for the fixed effects estimator (average effect).

Appendix 3: Comparison of Impact Using Relative Entropy

When comparing the impact of each factor (explanatory variable) on the different types of capital flows (debt investment and other investment), it is not possible to simply compare them directly because of differences in levels. For this reason, we introduce relative entropy (Kullback-Leibler divergence) as an indicator to quantify the degree to which the conditional predicted distribution of capital flows differs in response to changes in each factor.

Intuitively, relative entropy quantifies the divergence between the conditional distribution brought about by an adverse shock to each of the factors and the original conditional distribution in the tail region. Assuming that $\hat{g}(y|\bar{x};\hat{\mu},\hat{\sigma},\hat{\alpha},\hat{v})$ is an approximate probability density function (of the skewed t-distribution) with all explanatory variables conditional on the mean values, and $\hat{f}(y|\dot{x},\hat{\mu},\hat{\sigma},\hat{\alpha},\hat{v})$ is the approximate probability density function (of the skewed t-distribution) conditional on any of the factors (explanatory variables) being shifted by a one standard deviation adverse shock, the α% downside relative entropy of $\hat{g}(y|\bar{x};\hat{\mu},\hat{\sigma},\hat{\alpha},\hat{v})$ is expressed by the following equation:

$$\mathcal{L}^D\left(\hat{f}_{y|x};\hat{g}_{y|x}\right) = -\int_{-\infty}^{\hat{G}_{y|x}^{-1}(\alpha\%|\bar{x})} \left(\log \hat{g}_{y|x}(y|\bar{x}) - \log \hat{f}_{y|x}(y|\dot{x})\right)\hat{f}_{y|x}(y|\dot{x})\, dy,$$

Note that $\hat{G}_{y|x}^{-1}(\cdot\,|\bar{x})$ is the quantile function with all explanatory variables conditioned on the mean (of the skewed t-approximation probability density function) and shows the quantiles in terms of percentiles.

Table 1: Overview of Data for the 16 Emerging Economies

Debt investment		Other investment	
Country	Period	Country	Period
Argentina	04/Q1-19/Q2	Argentina	04/Q1-19/Q2
Brazil	98/Q2-19/Q2	Brazil	98/Q2-19/Q2
Chile	98/Q2-19/Q2	Chile	98/Q2-19/Q2
China	05/Q1-19/Q2 （excluding 05/Q3-06/Q4）	China	05/Q1-19/Q2
Hungary	96/Q4-19/Q2	Hungary	96/Q4-19/Q2
India	97/Q1-19/Q2 （excluding 98/Q3-07/Q4）	India	96/Q4-19/Q2
Indonesia	02/Q1-19/Q2	Indonesia	02/Q1-19/Q2
South Korea	96/Q4-19/Q2	South Korea	96/Q4-19/Q2
Malaysia	02/Q1-19/Q2	Malaysia	01/Q1-19/Q2
Mexico	96/Q4-19/Q2	Mexico	96/Q4-19/Q2
Philippines	96/Q4-19/Q2	Philippines	96/Q4-19/Q2
Poland	00/Q1-19/Q2	Poland	00/Q1-19/Q2
Russia	00/Q1-19/Q2	Russia	00/Q1-19/Q2
South Africa	96/Q4-19/Q2	South Africa	96/Q4-19/Q2
Thailand	97/Q2-19/Q2	Thailand	97/Q2-19/Q2
Turkey	01/Q2-19/Q2	Turkey	01/Q2-19/Q2

Table 2: Summary Statistics

Full observation period

	Average	Mean	Std. dev.	Min.	Max.	No. of obs.
Dependent variables						
Debt investment + Other investment (as a ratio of nominal GDP in %, average over next 2 quarters)	1.63	1.67	4.31	-28.49	18.90	1,249
Debt investment (as a ratio of nominal GDP in %, average over next 2 quarters)	0.95	0.69	2.35	-14.13	14.16	1,249
Other investment (as a ratio of nominal GDP in %, average over next 2 quarters)	0.72	0.67	3.32	-28.17	19.69	1,298
Explanatory variables (global factors)						
Shadow FF rate (1-quarter difference, percentage points)	-0.03	-0.01	0.46	-1.67	0.89	1,249
Corporate BBB spread (bps)	208.49	192.00	109.04	75.00	766.00	1,249
Explanatory variables (local factors)						
Real GDP growth rate (q-o-q, %, 2-quarter backward moving average)	0.98	1.08	1.08	-5.04	5.64	1,249
Government debt (as a ratio of nominal GDP in %, 2-quarter backward moving average)	42.19	40.40	20.71	3.80	124.70	1,249

Before GFC (until 2009/Q1)

	Average	Mean	Std. dev.	Min.	Max.	No. of obs.
Dependent variables						
Debt investment + Other investment (as a ratio of nominal GDP in %, average over next 2 quarters)	1.32	1.27	5.25	-28.49	18.90	593
Debt investment (as a ratio of nominal GDP in %, average over next 2 quarters)	0.72	0.42	2.49	-14.13	11.20	593
Other investment (as a ratio of nominal GDP in %, average over next 2 quarters)	0.69	0.58	4.12	-28.17	19.69	642
Explanatory variables (global factors)						
Shadow FF rate (1-quarter difference, percentage points)	-0.10	-0.01	0.56	-1.67	0.66	593
Corporate BBB spread (bps)	213.44	159.00	147.67	75.00	766.00	593
Explanatory variables (local factors)						
Real GDP growth rate (q-o-q, %, 2-quarter backward moving average)	0.99	1.14	1.19	-5.04	4.71	593
Government debt (as a ratio of nominal GDP in %, 2-quarter backward moving average)	41.01	40.75	22.20	3.80	124.70	593

After GFC (from 2009/Q2)

	Average	Mean	Std. dev.	Min.	Max.	No. of obs.
Dependent variables						
Debt investment + Other investment (as a ratio of nominal GDP in %, average over next 2 quarters)	1.90	1.97	3.20	-14.38	18.50	656
Debt investment (as a ratio of nominal GDP in %, average over next 2 quarters)	1.15	0.86	2.20	-7.45	14.16	656
Other investment (as a ratio of nominal GDP in %, average over next 2 quarters)	0.75	0.73	2.29	-11.52	8.55	656
Explanatory variables (global factors)						
Shadow FF rate (1-quarter difference, percentage points)	0.04	-0.01	0.32	-0.53	0.89	656
Corporate BBB spread (bps)	204.02	198.00	53.89	128.00	402.00	656
Explanatory variables (local factors)						
Real GDP growth rate (q-o-q, %, 2-quarter backward moving average)	0.97	1.03	0.96	-3.71	5.64	656
Government debt (as a ratio of nominal GDP in %, 2-quarter backward moving average)	43.25	39.98	19.21	8.25	94.40	656

Sources: IMF, IIF, Atlanta Fed, Bloomberg, ICE Data Indices, CEIC, Haver Analytics.

Table 3: Summary Statistics of the Relationship between Capital Flows and Local Factors

(a) Subsamples based on government debt-to-GDP ratio

(i) Debt investment flows (as a ratio of nominal GDP, %)

		Quantiles								
		10%	20%	30%	40%	50%	60%	70%	80%	90%
Median of debt-to-GDP ratio	Below	-0.8	-0.2	0.1	0.4	0.8	1.2	1.6	2.2	3.1
	Above	-1.7	-0.8	-0.2	0.1	0.6	1.0	1.7	2.7	4.4

(ii) Other investment flows (as a ratio of nominal GDP, %)

		Quantiles								
		10%	20%	30%	40%	50%	60%	70%	80%	90%
Median of debt-to-GDP ratio	Below	-2.2	-0.9	-0.4	0.1	0.5	0.9	1.4	2.2	3.5
	Above	-2.4	-1.1	-0.4	0.3	0.9	1.6	2.4	3.1	4.5

(b) Subsamples based on real GDP growth rate

(i) Debt investment flows (as a ratio of nominal GDP, %)

		Quantiles								
		10%	20%	30%	40%	50%	60%	70%	80%	90%
Median of GDP growth rate	Above	-0.9	-0.3	0.0	0.3	0.7	1.1	1.5	2.0	3.0
	Below	-1.4	-0.5	0.0	0.4	0.7	1.2	1.7	2.5	4.0

(ii) Other investment flows (as a ratio of nominal GDP, %)

		Quantiles								
		10%	20%	30%	40%	50%	60%	70%	80%	90%
Median of GDP growth rate	Above	-1.6	-0.5	0.2	0.7	1.2	2.0	2.7	3.5	4.6
	Below	-2.9	-1.4	-0.7	-0.2	0.3	0.8	1.3	2.1	3.5

Sources: IIF, IMF, CEIC.

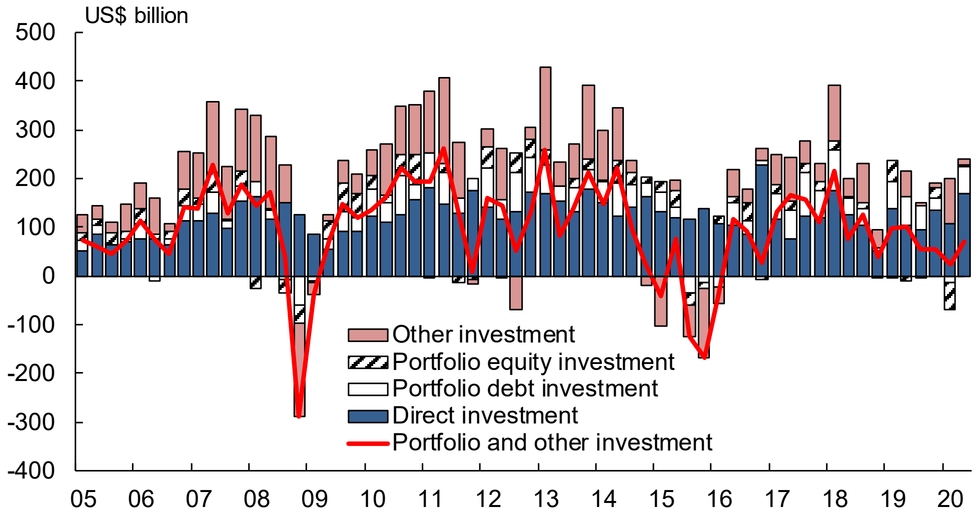
Table 4: Dependent and Explanatory Variables and Expected Signs

Variable		Source	Description
Dependent variables			
Debt investment (average over next 2 quarters)	$\overline{Flow}_{1,i,t+2}$	IMF, CEIC	Portfolio investment liabilities (debt), as a ratio of nominal GDP, %, average over next 2 quarters
Other investment (average over next 2 quarters)	$\overline{Flow}_{2,i,t+2}$	IMF, CEIC	Other investment liabilities, as a ratio of nominal GDP, %, average over next 2 quarters
Explanatory variables (global factors)			
Shadow FF rate	$\Delta Shadow\_rate_t$	Atlanta Fed	1-quarter difference, percentage points, quarterly average of end-of-month values
Corporate BBB spread	BBB_spread_t	Bloomberg, ICE Data Indices	Option-adjusted spread of U.S. BBB-rated corporate bonds vis-à-vis Treasuries, bps, end of quarter
Explanatory variables (local factors)			
Real GDP growth rate	$\overline{RGDP}_{i,t}$	HAVER	Q-o-q real GDP growth rate, %, 2-month backward moving average
Government debt	$\overline{G\_debt}_{i,t}$	IIF	As a ratio of nominal GDP, %, 2-month backward moving average
Control variables			
Debt investment (current quarter)	$\overline{Flow}_{1,i,t}$	IMF, CEIC	Portfolio investment liabilities (debt), as a ratio of nominal GDP, %
Other investment (current quarter)	$\overline{Flow}_{2,i,t}$	IMF, CEIC	Other investment liabilities, as a ratio of nominal GDP, %
Post-GFC dummy	GFC_t		A dummy that takes value 1 for the period after the global financial crisis (2009/Q2 onward) and 0 otherwise

		Debt investment (average over next 2 quarters)			Other investment (average over next 2 quarters)		
		Quantiles			Quantiles		
		Lower	Intermediate	Upper	Lower	Intermediate	Upper
Global factors	Shadow FF rate (including interaction term)	–	–	–	–	–	–
	Corporate BBB spread (including interaction term)	–	–	±	–	–	±
Local factors	Real GDP growth rate	+	+	+	+	+	+
	Government debt	–	–	±	–	–	±

Positive sign expected
Negative sign expected
Either positive or negative

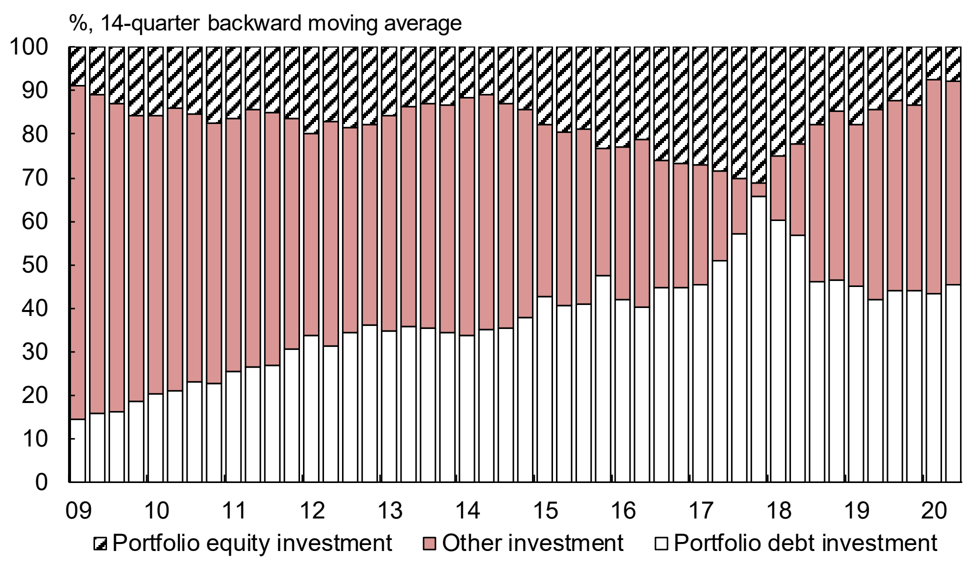
Figure 1: Capital Flows to Emerging Economies (by Type)



Notes: The most recent period is 2020/Q2. The data are for the following 16 emerging economies: Argentina, Brazil, Chile, China, Hungary, India, Indonesia, South Korea, Malaysia, Mexico, the Philippines, Poland, Russia, South Africa, Thailand, and Turkey. The same applies below.

Sources: IMF, CEIC.

Figure 2: Capital Flows to Emerging Economies (by Share of Type)



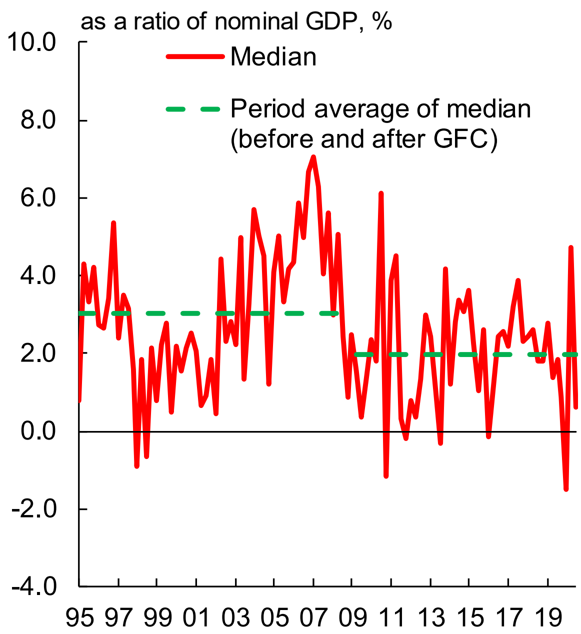
Note: The most recent period is 2020/Q2.

Sources: IMF, CEIC.

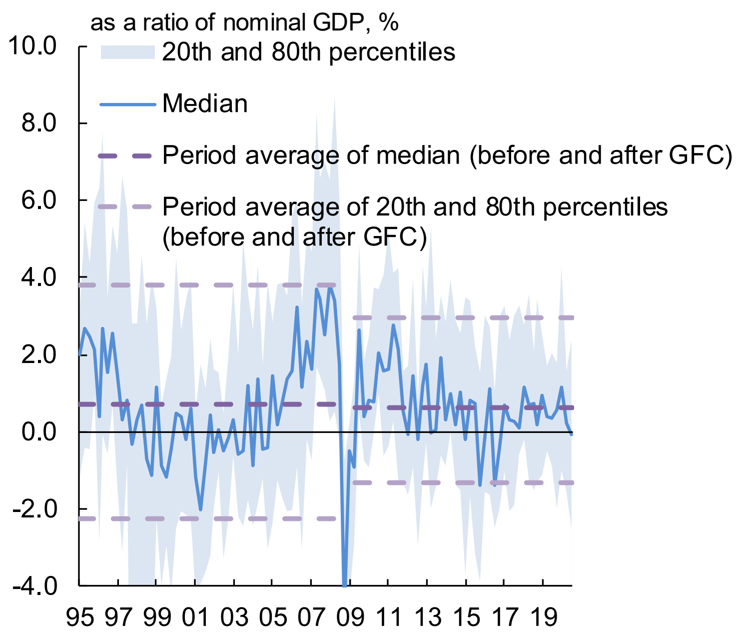
Figure 3: Time-Series Characteristics of Capital Flows

(a) Debt investment flows

Advanced economies

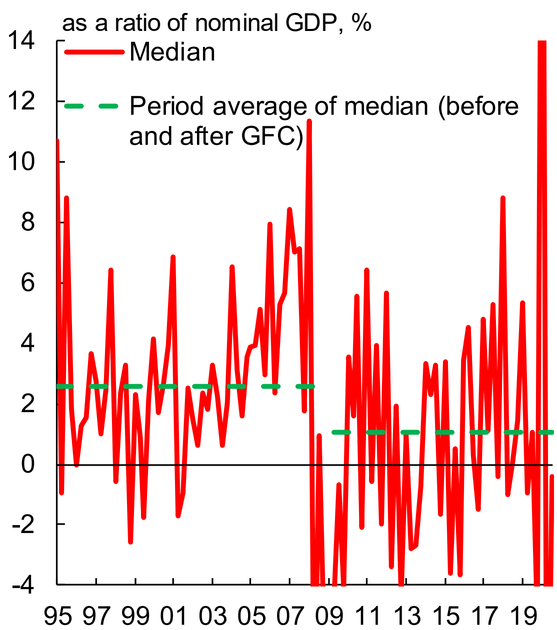


Emerging economies

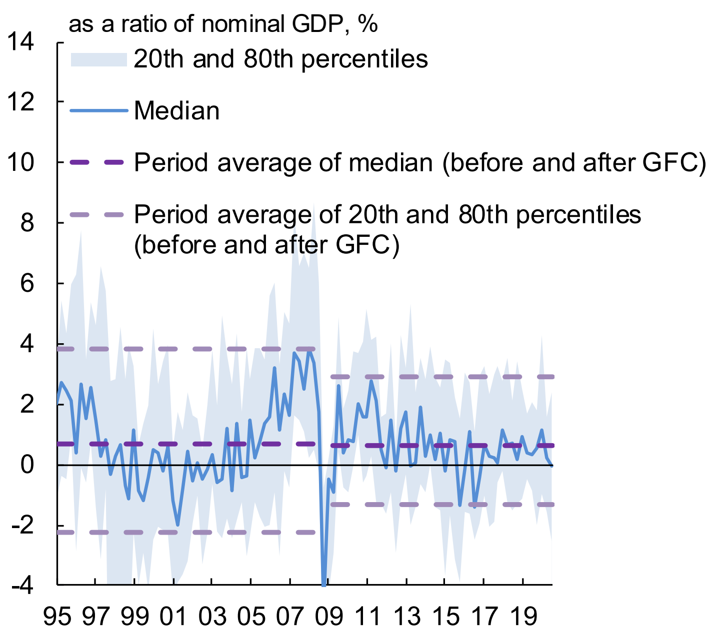


(b) Other investment flows

Advanced economies



Emerging economies

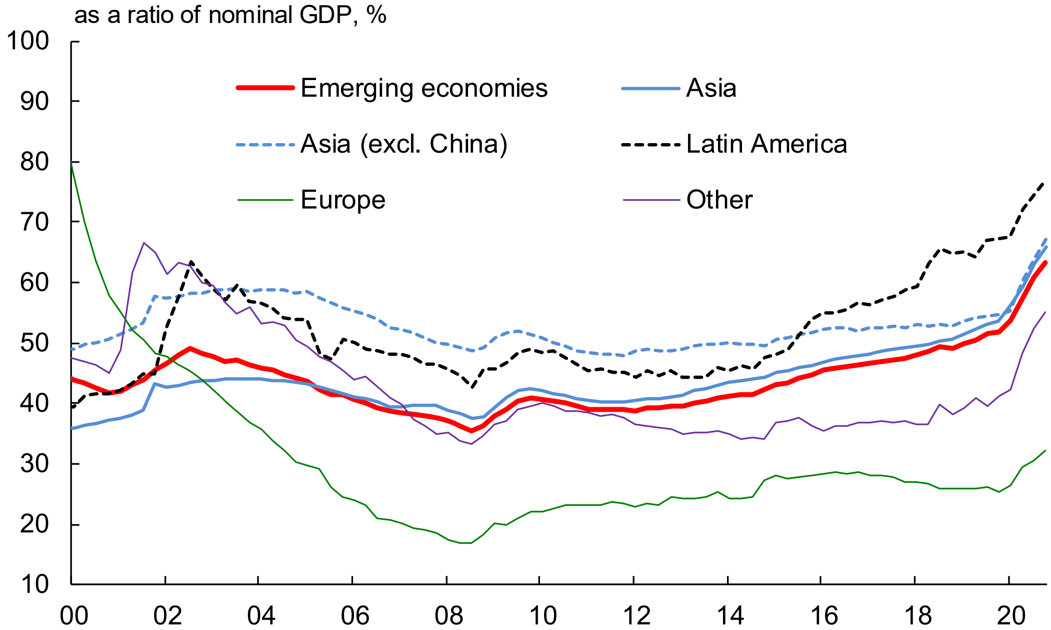


Notes: 1. The most recent period is 2020/Q3. The period before the GFC is 1995/Q1–2009/Q1, while the period after the GFC is 2009/Q2–2020/Q3.

2. The charts respectively show the aggregates for four advanced economies or regions (United States, United Kingdom, Euro area, Japan) and the 16 emerging countries.

Sources: IMF, CEIC, OECD.

Figure 4: Emerging Economies' Government Debt



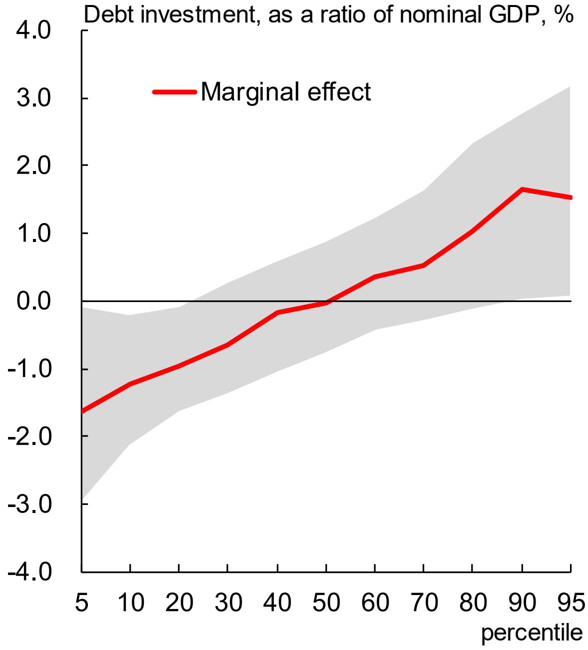
Notes: 1. The most recent period is 2020/Q4.
2. The line for emerging economies shows the weighted average of the government debt (as a ratio of nominal GDP) of the 16 emerging countries published by the IIF using economies' GDP weights calculated by the IMF as weights.

Sources: IIF, IMF.

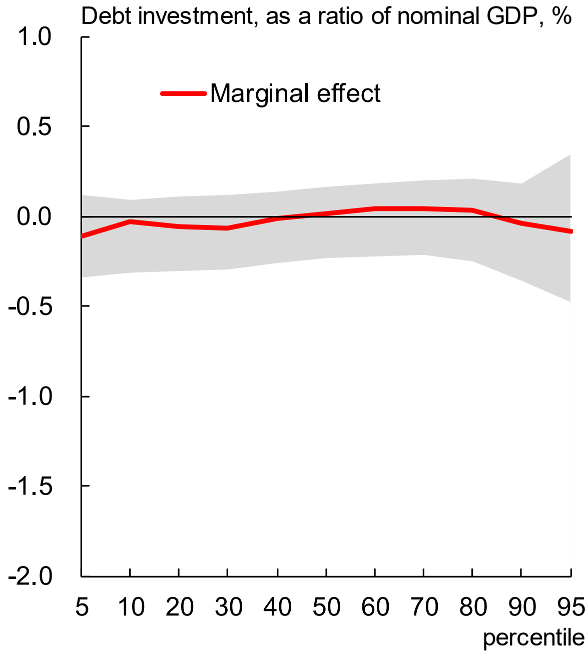
Figure 5: Marginal Effect of Each Risk Factor on Debt Investment Flows

(a) Global factors

Corporate BBB spread

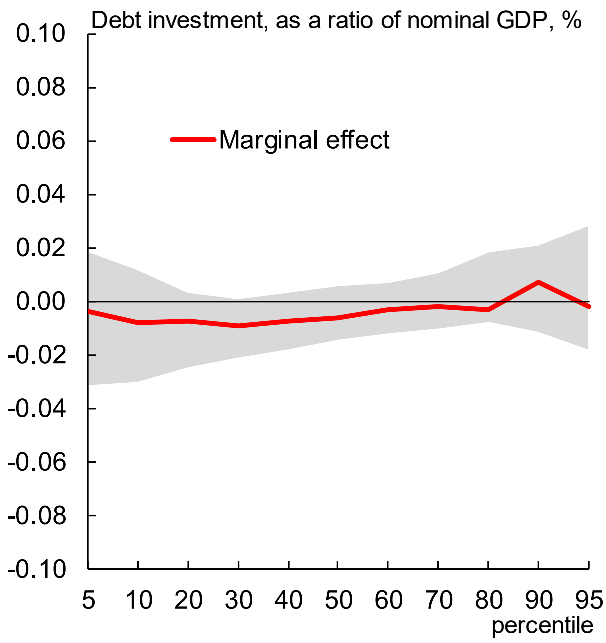


Shadow FF rate

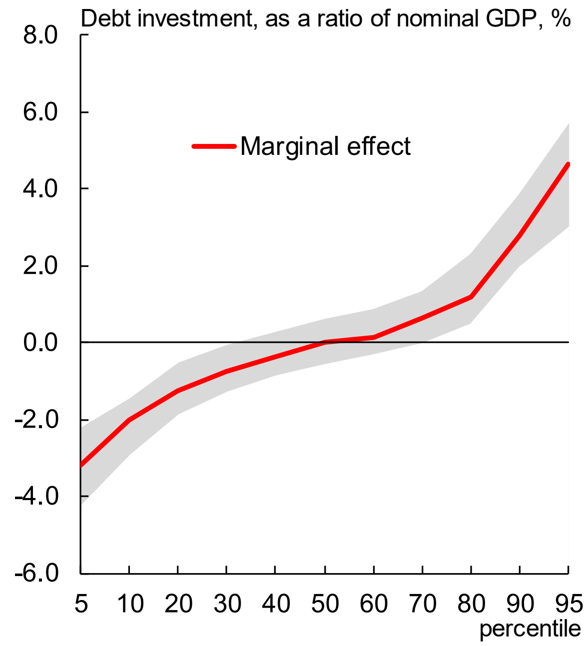


(b) Local factors

Real GDP growth rate



Government debt



Notes: 1. The marginal effects are calculated based on the assumption of a positive one standard deviation shock to the period average for 1996/Q4–2019/Q2 in the case of global factors and a positive or negative one standard deviation shock to the average of all observations (both in a cross-section and a time-series dimension) in the case of local factors.

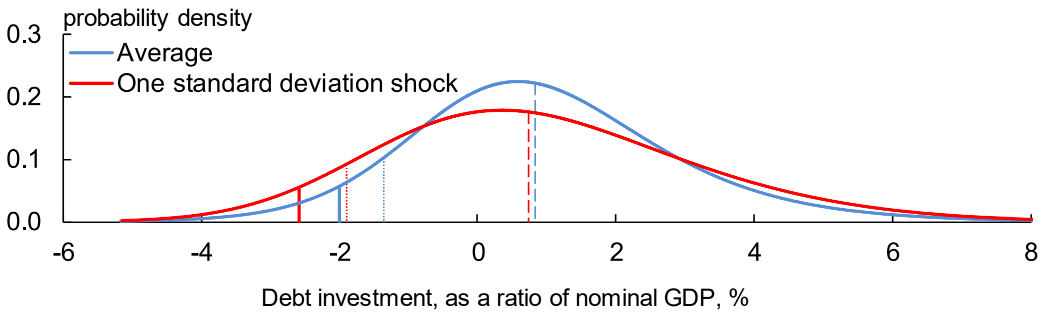
2. For the calculation of the marginal effect of the interaction term of the global factors, the other explanatory variables are set to their median values for 1996/Q4–2019/Q2. The marginal effects of the local factors are equal to the values of the coefficient estimates multiplied by the adverse shock since they do not include interaction terms.

3. The shaded areas show the 5 to 95 percent confidence interval obtained using the block bootstrap method.

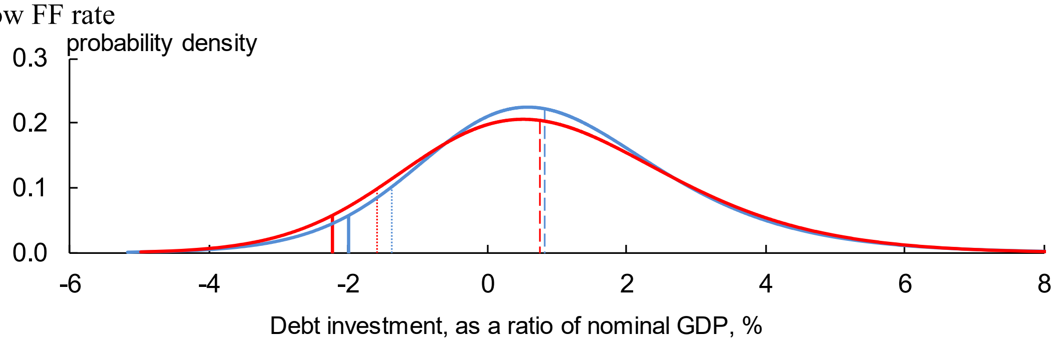
Figure 6: Changes in the Conditional Predicted Distribution of Debt Investment Flows (Response to a One Standard Deviation Shock)

(a) Global factors

Corporate BBB spread

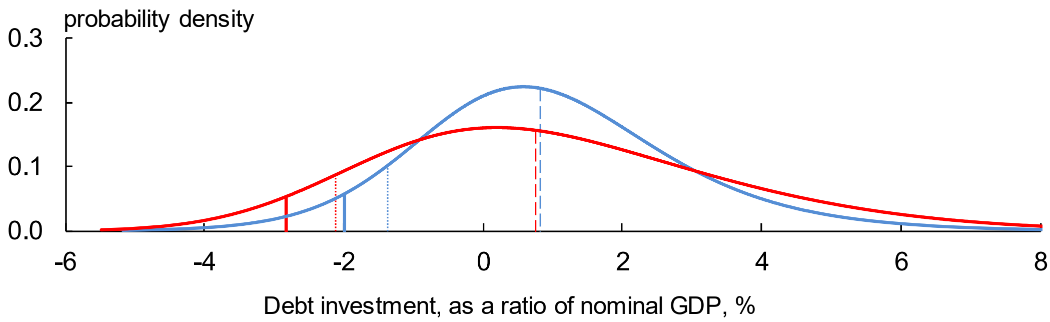


Shadow FF rate

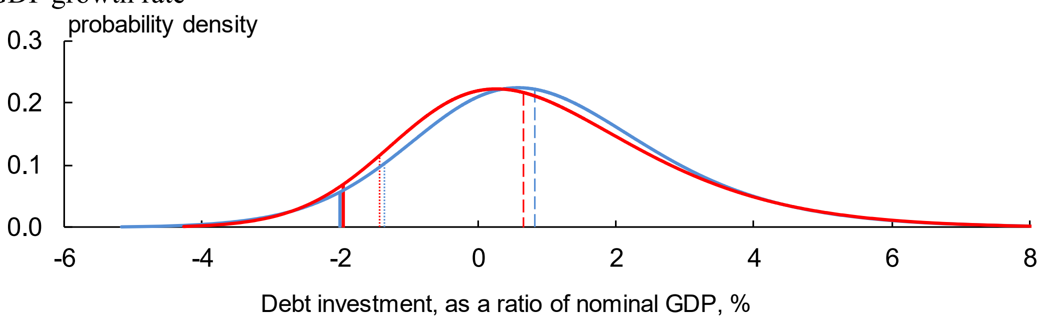


(b) Local factors

Government debt



Real GDP growth rate



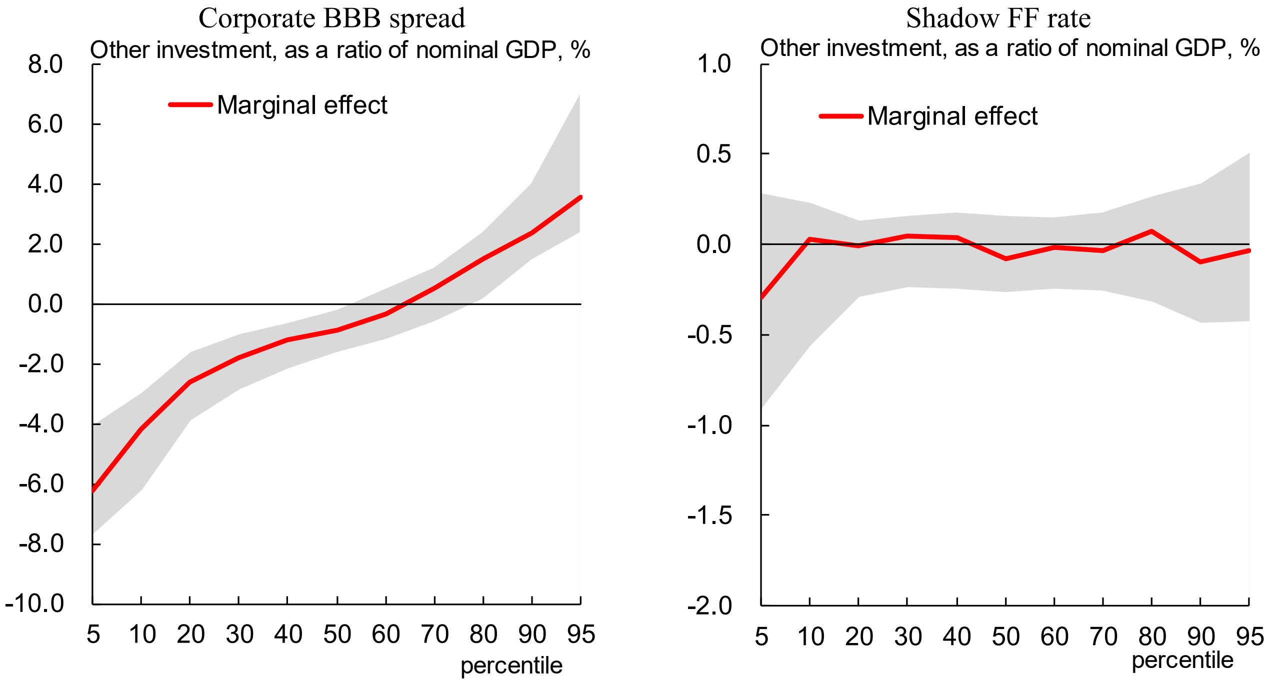
Notes: 1. The distribution is the probability density function of debt investment flows (as a share of nominal GDP, %, average over next 2 quarters).

2. A positive one standard deviation shock is assumed, except in the case of the real GDP growth rate, where a negative one standard deviation shock is assumed.

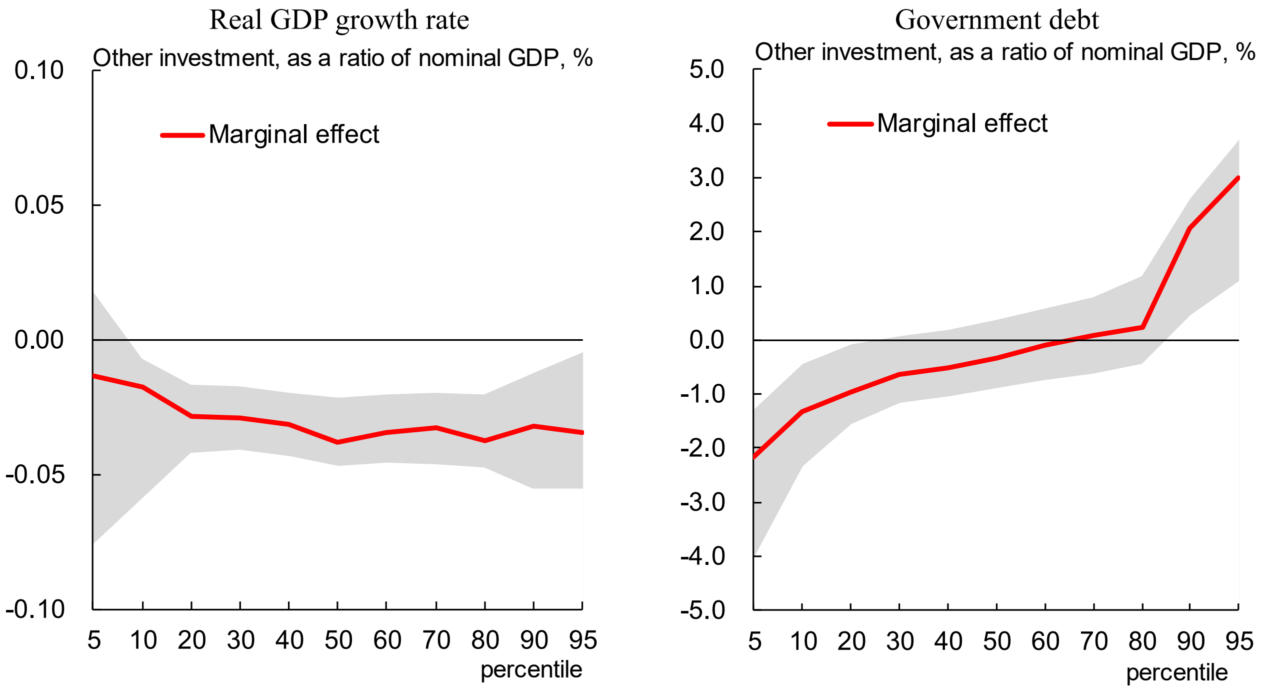
3. The vertical dashed line in each chart shows the median, the vertical dotted line the 10th percentile, and the vertical solid line the 5th percentile.

Figure 7: Marginal Effect of Each Risk Factor on Other Investment Flows

(a) Global factors



(b) Local factors



Notes: 1. The marginal effects are calculated based on the assumption of a positive one standard deviation shock to the period average for 1996/Q4–2019/Q2 in the case of global factors and a positive or negative one standard deviation shock to the average of all observations (both in a cross-section and a time-series dimension) in the case of local factors.

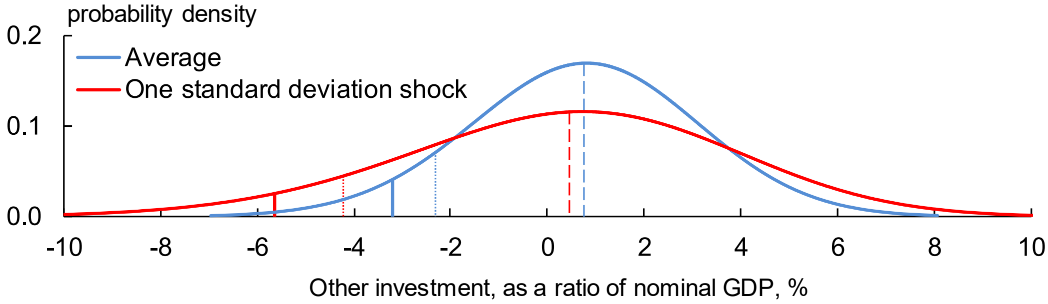
2. For the calculation of the marginal effect of the interaction term of the global factors, the other explanatory variables are set to their median values for 1996/Q4–2019/Q2. The marginal effects of the local factors are equal to the value of the coefficient estimate multiplied by the adverse shock since they do not include interaction terms.

3. The shaded areas show the 5 to 95 percent confidence interval obtained using the block bootstrap method.

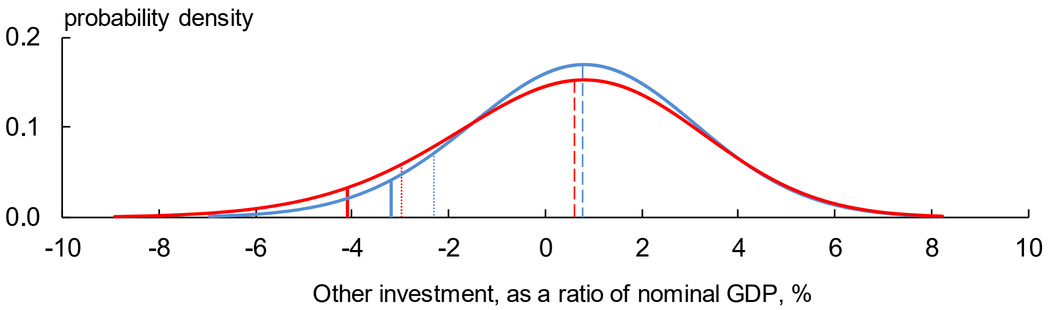
Figure 8: Changes in the Conditional Predicted Distribution of Other Investment Flows (Response to a One Standard Deviation Shock)

(a) Global factors

Corporate BBB spread

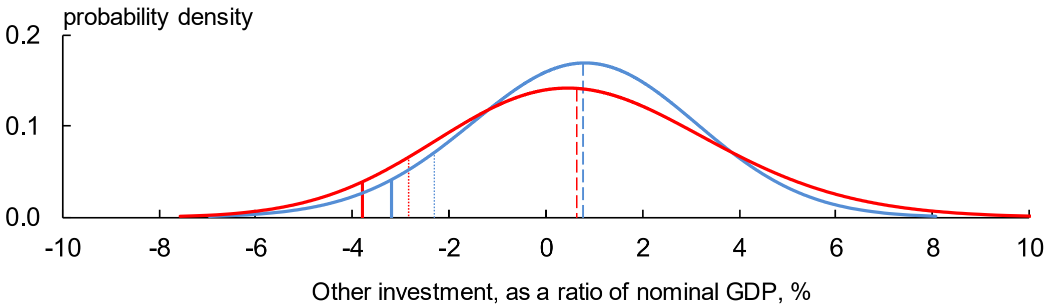


Shadow FF rate

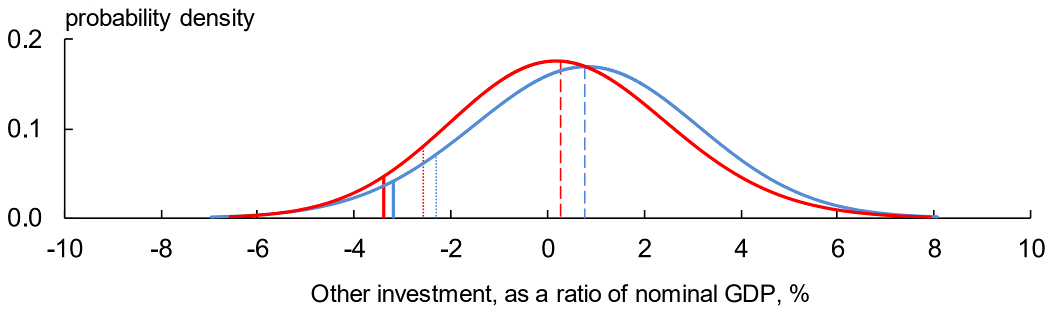


(b) Local factors

Government debt



Real GDP growth rate



Notes: 1. The distribution is the probability density function of debt investment flows (as a share of nominal GDP, %, average over next 2 quarters).

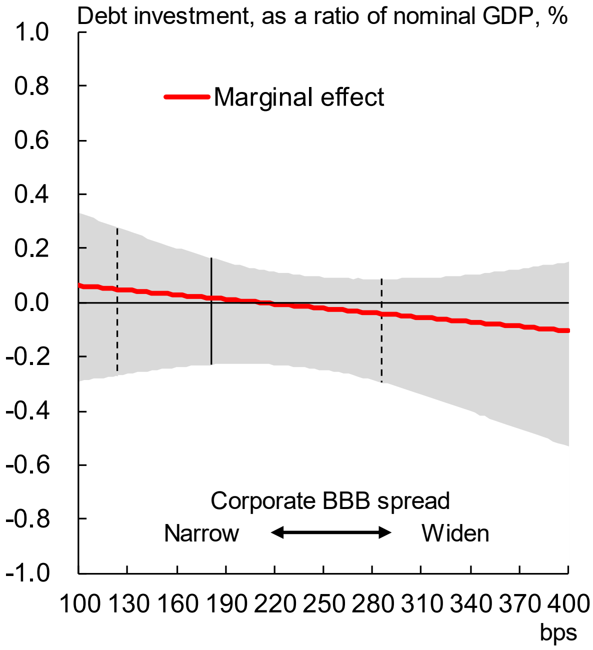
2. A positive one standard deviation shock is assumed, except in the case of the real GDP growth rate, where a negative one standard deviation shock is assumed.

3. The vertical dashed line in each chart shows the median, the vertical dotted line the 10th percentile, and the vertical solid line the 5th percentile.

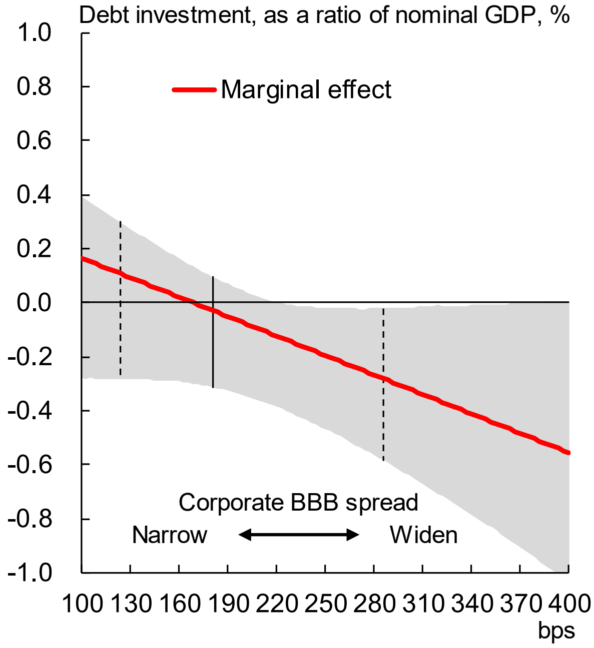
Figure 9: Impact of the Shadow FF Rate at the Median and the 10th Percentile across Different Levels of the Corporate BBB Spread

(a) Debt investment flows

Median

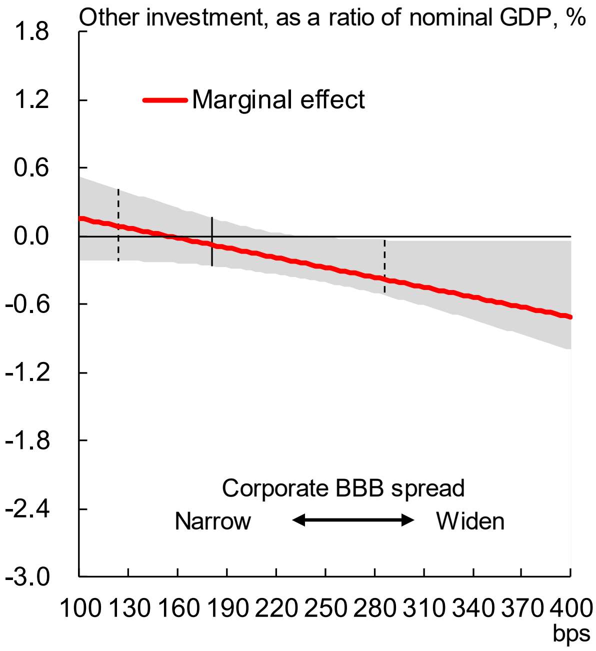


10th percentile

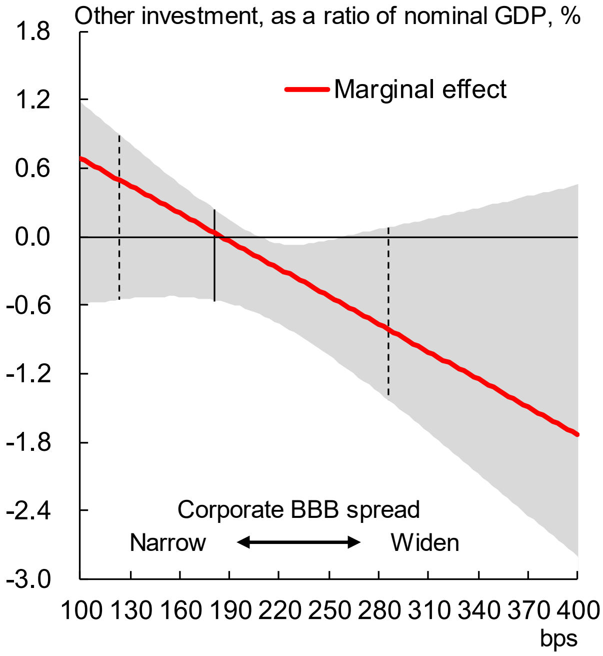


(b) Other investment flows

Median

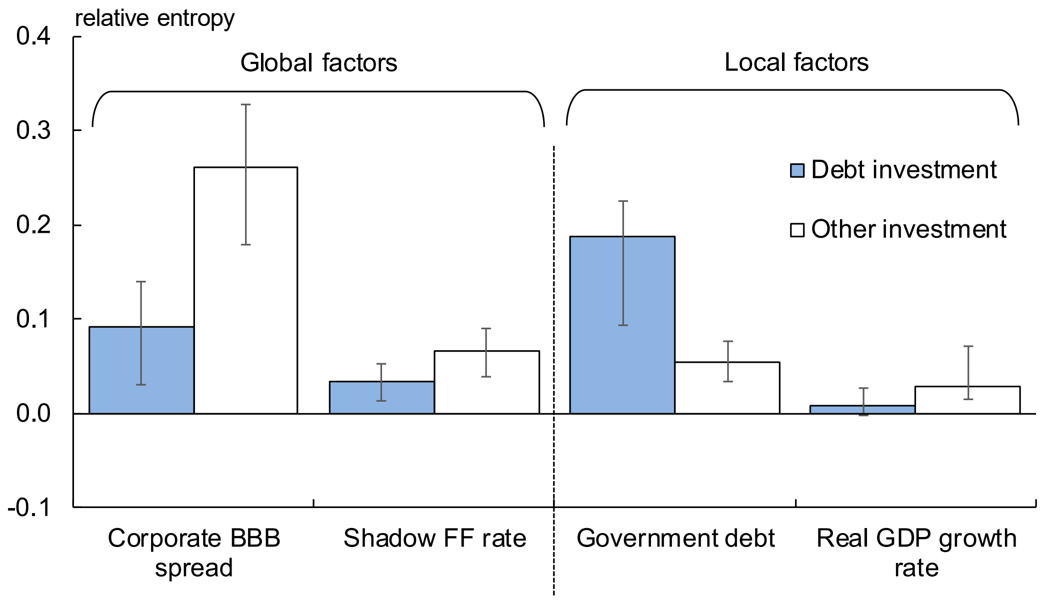


10th percentile



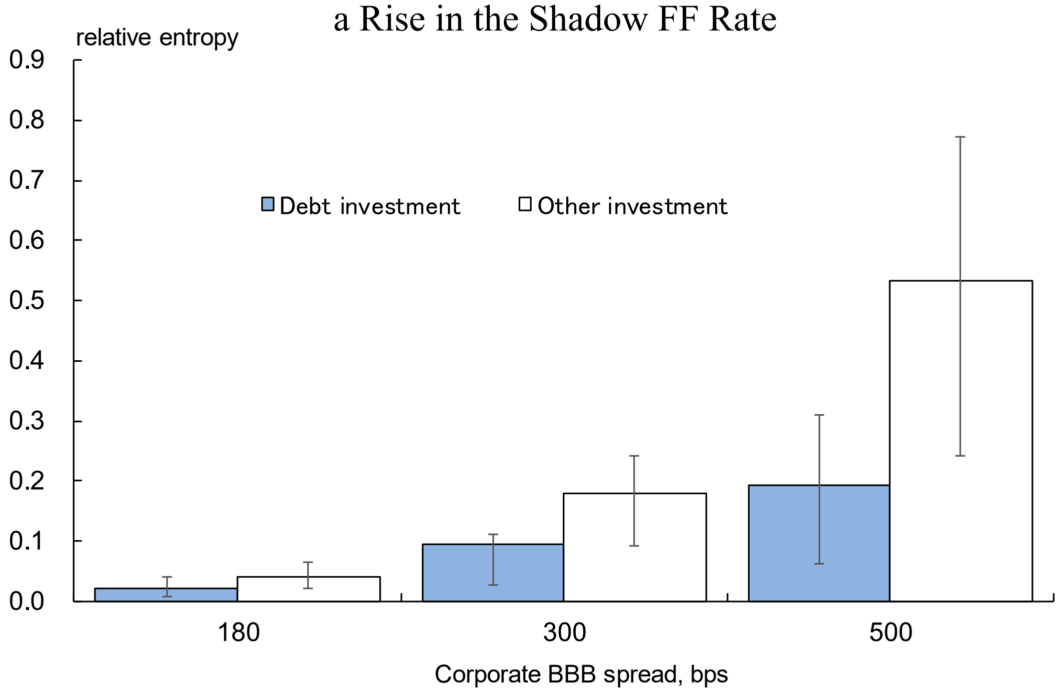
Notes: 1. The marginal effect of the shadow FF rate is calculated assuming a one standard deviation shock to the period average for 1996/Q4–2019/Q2.
2. The vertical dotted lines represent the 16th and 84th percentiles of the U.S. corporate BBB spread in 1996/Q4–2019/Q2, while the vertical solid lines represent the median.
3. The shaded areas show the 5 to 95 percent confidence interval obtained using the block bootstrap method.

Figure 10: Downside Relative Entropy



Note: The bars show the downside relative entropy (divergence in mass to the left of the 10th percentile) given a one standard deviation adverse shock to each of the risk factors shown on the horizontal axis. The bands show the 16 to 84 percent confidence intervals based on the block bootstrap method.

Figure 11: Downside Relative Entropy with Respect to a Rise in the Shadow FF Rate



Note: The bars show the downside relative entropy (divergence in mass to the left of the 10th percentile) given a one standard deviation adverse shock to the shadow FF rate for the different corporate BBB spreads shown on the horizontal axis. The bands show the 16 to 84 percent confidence intervals based on the block bootstrap method.

Appendix Table A1.1: Panel Unit Root Test

Variable	Test	p-value	No. of obs.	Standard (S) Nonstandard (NS)
Dependent variables				
Bond investment	LLC	0.00 ***	1,243	S
	IPS	0.00 ***	1,243	S
Other investment	LLC	0.00 ***	1,292	S
	IPS	0.00 ***	1,292	S
Global factors				
Shadow FF rate (level)	LLC	0.00 ***	1,292	S
	IPS	0.00 ***	1,292	S
Shadow FF rate (1-quarter difference)	LLC	0.00 ***	1,292	S
	IPS	0.00 ***	1,292	S
Corporate BBB spread	LLC	0.00 ***	1,292	S
	IPS	0.00 ***	1,292	S
Local factors				
Real GDP growth rate	LLC	0.00 ***	1,292	S
	IPS	0.00 ***	1,292	S
Government debt	LLC	0.00 ***	1,296	S
	IPS	0.00 ***	1,296	S

Notes: 1. The LLC (Levin, Lin, and Chu, 2002) test and the IPS (Im, Pesaran, and Shin, 2003) test use the null hypothesis that all panels include a unit root.
2. *** denotes statistical significance at the 1 percent level.

Appendix Table A2.1: Panel Quantile Regression (Debt Investment Flows)

Dependent variables

Debt investment (as a ratio of nominal GDP, %, average over next 2 quarters)

Estimation results

	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%	95%
Global factors											
Shadow FF rate	0.89	0.94 **	0.91 **	0.63 **	0.37	0.28	0.09	-0.09	-0.51	-1.00	-1.15
Corporate BBB spread	-0.01 ***	-0.00 ***	-0.00 ***	-0.00 ***	-0.00	-0.00	0.00 *	0.00 **	0.00 ***	0.01 ***	0.01 **
Shadow FF rate × Corporate BBB spread (interaction term)	-0.01	-0.01 **	-0.01 ***	-0.00 ***	-0.00 **	-0.00	0.00	0.00	0.00	0.01 **	0.01
Local factors											
Real GDP growth rate	0.04	0.08	0.08	0.10 ***	0.07 *	0.07	0.03	0.02	0.03	-0.07	0.02
Government debt	-0.05 ***	-0.03 ***	-0.02 **	-0.01 *	-0.01	0.00	0.00	0.01 **	0.02 **	0.04 ***	0.07 ***
Dynamic estimation						Yes					
Post-GFC dummy						Yes					
Country fixed effects						Yes					
No. of obs.						1,249					
No. of quarters						97					

Notes: ***, **, and * denote statistical significance at the 1, 5, and10 percent levels, respectively. Standard errors are calculated using asymptotic standard errors that do not take the cluster or autocorrelation structure of the data into account. The number of quarters is for the largest number of quarters in the unbalanced panel.

Appendix Table A2.2: Panel Quantile Regression (Other Investment Flows)

Dependent variables

Other investment (as a ratio of nominal GDP, %, average over next 2 quarters)

Estimation results

	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%	95%
Global factors											
Shadow FF rate	3.27 **	3.50 ***	2.27 ***	1.83 ***	1.62 ***	1.04 **	1.32 **	0.67	0.57	-0.72	-1.48
Corporate BBB spread	-0.02 ***	-0.01 ***	-0.01 ***	-0.01 ***	-0.00 ***	-0.00 ***	-0.00	0.00	0.00 ***	0.01 ***	0.01 ***
Shadow FF rate × Corporate BBB spread (interaction term)	-0.02 ***	-0.02 ***	-0.01 ***	-0.01 ***	-0.01 ***	-0.01 ***	-0.01 ***	-0.00 **	-0.00	0.00	0.01
Local factors											
Real GDP growth rate	0.18	0.23	0.38 ***	0.39 ***	0.42 ***	0.51 ***	0.47 ***	0.44 ***	0.50 ***	0.43 **	0.47 **
Government debt	-0.03	-0.02	-0.01	-0.01	-0.01	-0.01	-0.00	0.00	0.00	0.03 **	0.05 ***
Dynamic estimation						Yes					
Post-GFC dummy						Yes					
Country fixed effects						Yes					
No. of obs.						1,298					
No. of quarters						97					

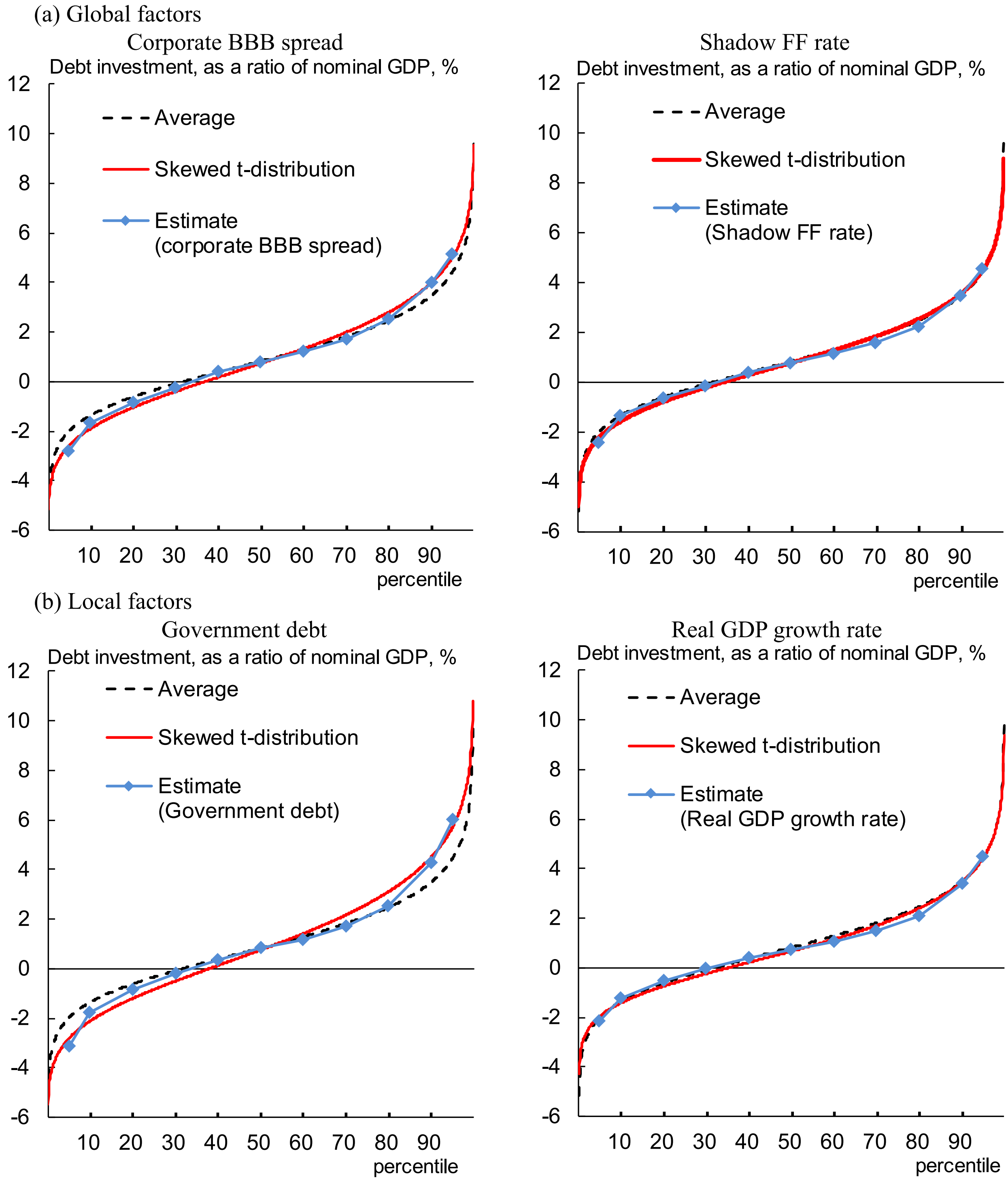
Notes: ***, **, and * denote statistical significance at the 1, 5, and10 percent levels, respectively. Standard errors are calculated using asymptotic standard errors that do not take the cluster or autocorrelation structure of the data into account. The number of quarters is for the largest number of quarters in the unbalanced panel.

Appendix Table A2.3: Panel Regression Estimation Results

Dependent variables	(i) Debt investment +Other investment	(ii) Debt investment +Other investment	(iii) Debt investment +Other investment	(iv) Debt investment +Other investment	(v) Debt investment +Other investment	(vi) Debt investment	(vii) Other investment
Global factors							
Shadow FF rate	-0.26	-0.32	1.72 *	2.10 ***	1.84 **	0.36	1.58 ***
Corporate BBB spread	0.00	0.00	-0.00 *	-0.00 ***	-0.01 ***	-0.00	-0.00 ***
Shadow FF rate× Corporate BBB spread (interaction term)			-0.01 **	-0.01 ***	-0.01 ***	-0.00	-0.01 ***
Local factors							
Real GDP growth rate	0.33 ***	0.35 ***	0.35 ***	0.38 ***	0.62 ***	0.02	0.38 ***
Government debt	-0.03	-0.03	-0.03	-0.03	-0.05	-0.02 *	-0.01
Control variable							
Debt investment (current period) + Other investment (current period)	0.34 ***	0.33 ***	0.34 ***	0.33 ***		0.15 ***	0.33 ***
Post-GFC dummy	No	Yes	No	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	1,249	1,249	1,249	1,249	1,249	1,249	1,298
No. of quarters	97	97	97	97	97	97	97

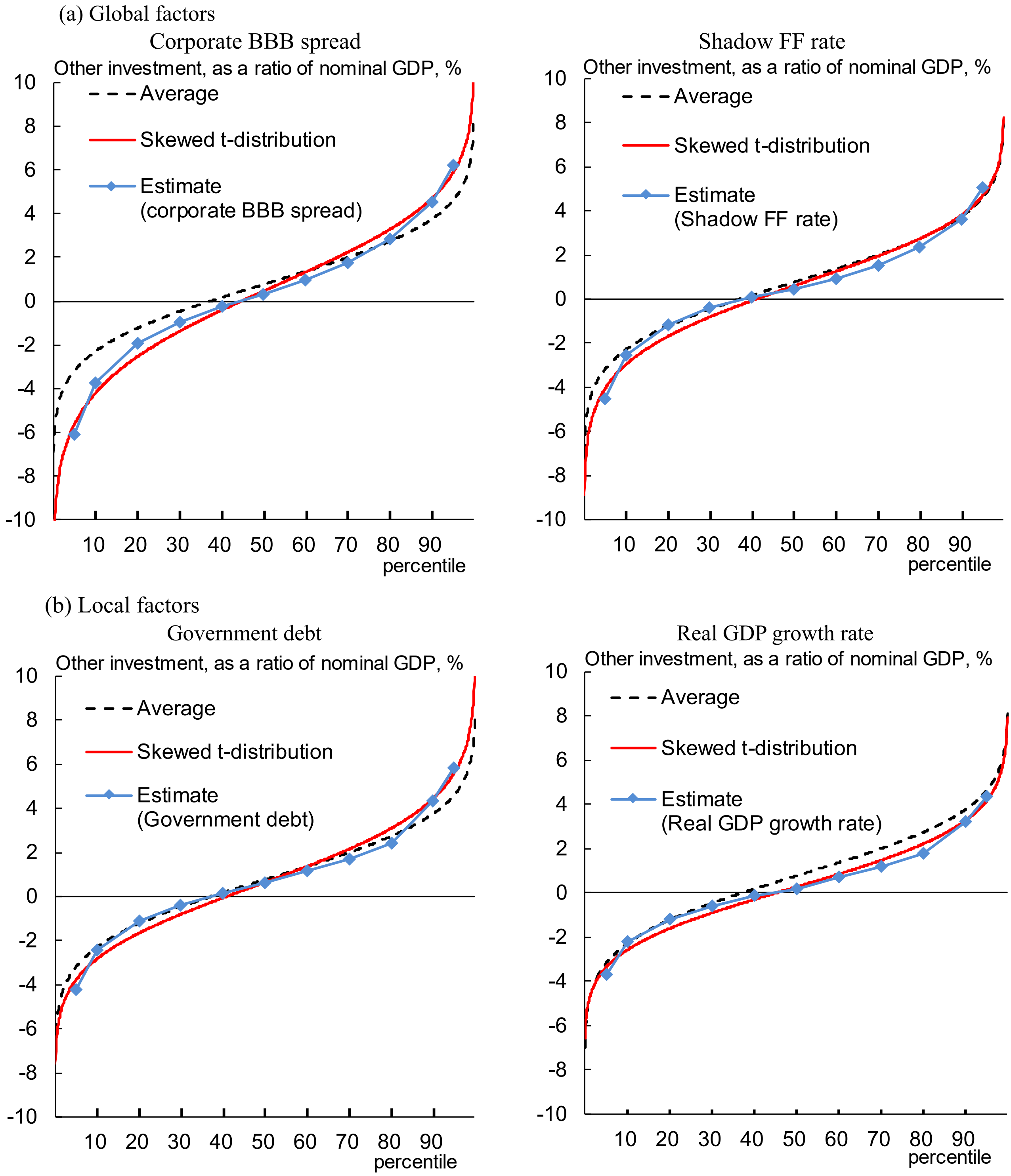
Notes: 1. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively. Standard errors are calculated using robust standard errors that take the cluster structure of the data into account. The number of quarters is for the largest number of quarters in the unbalanced panel.
2. All dependent variables are the averages over the next 2 quarters.
3. The control variable in column (vi) is "Debt investment (current period)." The control variable in column (vii) is "Other investment (current period)."

Appendix Figure A2.1: Quantile Function of Debt Investment Flows
(Empirical Quantiles and Fitted Skewed t Quantiles)



Note: The blue lines with diamond markers show the conditional quantiles when the risk factor described in each chart is subjected to an adverse shock of one standard deviation from the mean. The red lines show the skewed t-inverse cumulative distribution functions obtained by fitting the empirical quantiles. The black dashed lines show the fitted skewed t-inverse cumulative distribution functions conditional on the average of each factor.

Appendix Figure A2.2: Quantile Function of Other Investment Flows (Empirical Quantiles and Fitted Skewed t Quantiles)



Note: The blue lines with diamond markers show the conditional quantiles when the risk factor described in each chart is subjected to an adverse shock of one standard deviation from the mean. The red lines show the skewed t-inverse cumulative distribution functions obtained by fitting the empirical quantiles. The black dashed lines show fitted skewed t-inverse cumulative distribution functions conditional on the average of each factor.