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Commodity terms of trade volatility and industry growth

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Abstract

The rising volatility of commodity terms of trade (CTOT) is associated with a high cost of capital and a low credit supply for producers in commodity-dependent countries. In this paper, we examine how volatile CTOT influences various industries' growth performance based on sector-level panel data for countries specializing in commodity exports. We find robust evidence that CTOT volatility causes a more significant growth loss in manufacturing sectors facing tighter credit constraints. The adverse growth effects operate through lower total factor productivity in industries heavily reliant on external finance for long-term investments and through lower capital accumulation in industries with high liquidity needs for short-term working capital. Our findings offer a complementary explanation for the "resource curse" through the credit constraint channel.

Keywords: Commodity terms of trade volatility; Cost of capital; Credit constraints; Industry growth

JEL classification: F43; O11; O13; O47

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1. Introduction

The economic fortunes of emerging and developing economies with a comparative advantage in the production of commodities are closely tied to fluctuations in international commodity prices and, more generally, to terms of trade. For example, Argentina, an important global supplier of soybeans, corn, and wheat, is notorious for its volatile inflation and unpredictable currency. Its export performance depends not only on local production and weather patterns but also on global market conditions.

The “resource curse” literature establishes that while commodity booms have positive short-term impacts on output, their long-term effects, especially when combined with poor governance, tend to be negative (Collier and Goderis, 2012). Departing from the primary focus of the existing literature on aggregate economic outcomes, we investigate exogenous commodity terms of trade (CTOT) volatility as a critical force behind the slow growth of industrial sectors in commodity-abundant developing countries.

Three stylized facts motivate this paper. First, as evidenced in Fig. 1, commodity-exporting countries face greater TOT fluctuations than their manufacturing counterparts (Panel A), suggesting that trade revenues are highly volatile in commodity-rich economies. Equivalently, TOT volatility is positively related to a country’s degree of commodity dependence measured by the commodity share of total exports (Panel B). The observed patterns are consistent with the notion that the prices of commodity products are typically more volatile than those of manufactured goods (Jacks et al., 2011).

Second, sizeable TOT volatility is associated with a high cost of capital. Fig. 2 reveals such a relationship using the risk premium on lending, defined as the lending rate minus the Tbill rate, as a proxy for the cost of domestic private debt.[1] This positive connection makes sense; one consequence of exposure to higher TOT volatility and a resulting increase in uncertainty on dollar export revenue and aggregate economy could be the higher risk premium economic agents have to pay for their credit.

Third, domestic credit to the private sector provided by financial corporations is likely to shrink as a result of rising CTOT volatility. Fig. 3 shows supporting evidence in commodity-exporting countries using a private credit growth regression while controlling for other variables such as (lagged) annual inflation, real GDP growth, world GDP growth, and financial openness.

The above three observations naturally lead to the following questions: Does volatile CTOT play a central role in depressing the growth of industrial sectors in commodity-rich economies? If so, what are the channels by which volatility affects industry growth? How persistent are the damaging effects of CTOT volatility? This paper studies these questions by analyzing the industry-level panel data for commodity-exporting countries from 1969 to 2018. Among the several possible channels, our emphasis is particularly on the effects of country-specific CTOT volatility on the growth performance of credit-constrained industries.

It is conceivable that industries differ in their outside capital needs due to the technological features of the manufacturing process inherent in a sector. For instance, some industries experience a longer lag between the time when they incur upfront costs and the time when they realize revenues. We quantify such industry differences with two widely used credit constraint indicators.

[1] Relatedly, Hilscher and Nosbusch (2010) document that the cost of U.S. dollar-denominated sovereign debt, proxied by the Emerging Market Bond Index Plus (EMBI+) spread, increases with TOT volatility even when controlling for the effect of country-specific fundamentals and global factors.

The first is *external finance dependence.* This measure is proposed by Rajan and Zingales (1998) and defined as $(\text{Capital expenditures} - \text{Cash flow})/\text{Capital expenditures}$, where Cash flow = cash flow from operations + decreases in inventories + decreases in receivables + increases in payables. Rajan and Zingales construct the index using the Compustat data on publicly traded U.S. firms under the following assumptions. Since capital markets in the U.S. are the most advanced with little friction, the degree of external dependence of large U.S. firms without binding credit constraints can serve as a relatively pure measure of their technological demand for external financing. In addition, the differences in technological demand persist over time across countries.[2] The industry median value of the firm ratios is selected to represent each sector's level of external dependence and reflect its funding needs for long-term investment.

The second is *liquidity needs*, measured by inventories over sales for ISIC industries. An industry needs more external liquidity when a smaller fraction of inventory investment can be financed by ongoing revenue. Applying the methodology of Rajan and Zingales (1998), Raddatz (2006) computes the liquidity needs index using the U.S. firm-level data from Compustat to recognize an industry's intrinsic need for working capital to satisfy both short-term debt payments and ongoing operational expenses. Some industries demand relatively more working capital than others for technological reasons, such as the length of the production process and the mode of operation.

Despite their conceptual similarities, the pairwise correlation between the two indicators is 0.01, implying that they address quite different aspects of the sector's credit constraints. Using these two proxies, we test whether CTOT volatility triggers a more significant decline in the

[2] Since industry-level data needed for construction of credit constraint indices are typically unavailable for low-income countries, the U.S.-based measures provide a useful benchmark for our industry-level analysis across countries while also mitigating endogeneity issues. See Section 2.2 for more details.

growth of industries with tighter financial constraints and explore the underlying channels for the growth impact.

To identify differential growth effects of country-specific CTOT volatility across industries, our estimation procedure closely follows the work of Samaniego and Sun (2015) and Iacovone et al. (2019) in the spirit of Rajan and Zingales (1998).[3] This approach allows the growth effects to differ depending on an industry's credit needs while considerably reducing potential endogeneity biases by using an extensive set of interacted fixed effects in a three-dimensional panel of countries and sectors.

The main results from the five-year panel regressions show that CTOT volatility disproportionately dampens the growth of manufacturing industries facing tighter credit constraints in commodity-exporting countries. More specifically, our estimates suggest that a one-standard-deviation increase in CTOT volatility leads to a 1.68 percentage point lower growth in real value-added in the Chemical Products industry at the 75^{th} percentile of external finance dependence, relative to the Non-metallic Mineral Products industry at the 25^{th} percentile. Likewise, an industry at the 75^{th} percentile of liquidity needs, such as Motor Vehicles, would decline further by 1.35 percentage points than the Paper Products industry at the 25^{th} percentile. These results align with the economic intuition that higher borrowing costs and lower funding availability during volatile times raise the likelihood of industries having binding credit constraints.

We then explore underlying channels for the main results and uncover interesting heterogeneity for production factor responses across industries. First of all, in sectors more

[3] Dell'Ariccia et al. (2008) and Igan et al. (2020) also rely on the same estimation strategy.

reliant on external finance, the damaging effects operate through a fall in total factor productivity (TFP). A plausible reason for this finding is that since heightened uncertainty arising from volatile CTOT increases the chances of facing a liquidity shock, externally dependent industries may experience difficulties financing desired long-term investments, such as an R&D project or adopting new technology. Our result also reveals a decrease in newly established firms, which are typically more in need of external funds (Rajan and Zingales, 1998). To the extent that starting up a new business is the source of ideas, CTOT volatility may discourage the innovative activities and knowledge spillovers necessary for the further expansion of sectors with external dependence.[4]

In sectors with insufficient liquidity, on the other hand, lower physical capital accumulation is found to be a key operating channel. This result suggests that a higher cost of capital and lower credit supply due to increasing CTOT volatility are likely to limit liquidity-constrained industries' ability to fund short-term working capital, thereby forcing them to cut expenses for fixed capital investment.

To examine the dynamic responses of industries with different degrees of credit constraints over the long run, we employ Jordà's (2005) local projection methods and estimate impulse response functions. We find that a persistently negative output effect of CTOT volatility is more pronounced in industries with high external finance dependence than those with high liquidity needs. The industries relying on external financing suffer from lower production and employment in the long run, with a prolonged moderate loss in TFP. In the sectors with high

[4] Based on our findings, we can infer that industries with a high degree of external finance dependence, such as Computing Machinery or Communication and Medical Equipment, may be subject to more severe value-added and TFP losses in fuel-exporting countries (e.g., Kuwait and Qatar) due to their excessive CTOT volatility.

liquidity needs, the detrimental effects seem relatively short-lived, although there is clear evidence of decreased capital accumulation over a sustained period.

To justify the main results, we perform a battery of robustness checks. First, we use a recently developed Hamilton (2018) filter to calculate CTOT growth using the trend components and volatility using the standard deviation of the cyclical components. The extended specification includes both the CTOT growth and volatility variables. Second, we control for a group of relevant global and domestic macroeconomic conditions and country-specific crisis episodes while having them interact with our measures of financial constraints. Third, we reestimate the baseline model using alternative proxies for credit constraints, namely the degree of asset tangibility and R&D intensity. In addition, we check whether countries with marginal manufacturing sectors (i.e., the average share of manufacturing value added in GDP less than 15 percent) drive the main results by excluding them from the sample. Lastly, we investigate whether the baseline results are sensitive to the CTOT indices constructed with time-varying commodity trade weights instead of fixed weights. The results from these exercises verify that our main conclusion remains the same.

This paper deserves attention for the following three reasons. First, our results offer a complementary explanation for the resource curse by showing novel evidence of the interaction between CTOT volatility and credit constraints. There is a wealth of evidence documenting the poor growth experiences of resource-abundant economies in the “resource curse” literature (see Sachs and Warner (1995) for a pioneering empirical study and van der Ploeg (2011) for an extensive survey). One theoretical justification is the “Dutch disease,” according to which resource booms crowd out non-resource tradable sectors through increased input prices and currency appreciation.[5] If one of these lagging tradable sectors is manufacturing, slow growth may arise due to forgone opportunities for learning-by-doing and knowledge spillovers. Other justifications include bad institutions (Mehlum et al., 2006), reduced investment in human capital (Gylfason et al., 1999), and rent-seeking (Tornell and Lane, 1999; Torvik, 2002).

In comparison, some recent studies report a negative growth effect of volatility in commodity-dependent countries. For example, van der Ploeg and Poelhekke (2009) point out the volatility of unanticipated output growth as a source of the resource curse, independent of resource abundance. Bleaney and Greenaway (2001) show that GDP growth in sub-Saharan African countries is negatively linked to the terms of trade volatility. Cavalcanti et al. (2015) emphasize the importance of the second moments of CTOT and document the negative impact of CTOT volatility on GDP per capita growth using a cross-country regression approach. They attribute this result to a lower accumulation of physical and human capital, with virtually no effects on productivity.[6] Relative to these studies, we analyze the sector-level data to propose credit constraints as a crucial channel that magnifies the adverse impact of CTOT volatility on industry growth. This sector-level analysis helps uncover significant and persistent production factor responses depending on an industry's long-term or short-term funding needs.

Second, this paper adds to the literature that connects the growth effects of uncertainty with credit constraints. Some recent theoretical contributions to this strand of literature include Alfaro et al. (2018) and Arellano et al. (2019), and empirical contributions include Caldara et al.

[5] For theoretical developments on the Dutch disease, see Corden and Neary (1982), van Wijnbergen (1984), Krugman (1987), Matsuyama (1992), Acosta et al. (2009), van der Ploeg and Venables (2013), and Alberola and Benigno (2017), among others. Empirical evidence related to this topic is presented in Ismail (2010), Bjørnland and Thorsrud (2016), Harding and Venables (2016), and Allcott and Keniston (2018).

[6] For the earlier literature studying a negative association between TOT volatility and economic growth beyond a commodity country sample, see Mendoza (1997), Turnovsky and Chattopadhyay (2003), and Blattman et al. (2007).

(2016) and Choi et al. (2018).[7] One notable theoretical work is by Aghion et al. (2010), who show that the share of long-term productivity-enhancing investment becomes procyclical under sufficiently tight credit constraints inducing a higher likelihood of such investment being interrupted by a liquidity shock. In support of this theory, Aghion et al. (2012) report more procyclical R&D investment for French firms facing tighter credit constraints. We introduce to the literature CTOT volatility, a critical concern for commodity exporters but underexplored in the context of financial constraints. In particular, our static and dynamic approaches investigate how tight credit conditions can amplify the painful volatility effects over time using various proxies for credit constraints.

Third, our sector-level approach has clear advantages compared to the traditional country-level analysis. The major strength is that the micro-level data make it possible to explore a causal link from country-specific CTOT volatility to industry growth, with the direction of the causality flow unlikely to be reversed. Specifically, it allows us to discover the underlying channels by examining how the growth of production factors, such as labor, capital, and TFP, responds to the interaction between CTOT volatility and the financing needs of industries. Another strength is that the three-dimensional panel permits a rich set of fixed effects in estimation at the country-time, industry-time, and industry-country levels, limiting the risk of omitted variable bias and simultaneity concerns.

The next section describes the data used for empirical analysis and the identification strategy. Section 3 reports the main estimation results and their robustness using panel regressions and investigates the channels whereby CTOT volatility might affect the growth of

[7] A related policy-relevant work is Levchenko et al. (2009), documenting that financial liberalization increases both the growth and the volatility of industry production, with a particularly significant effect in financially dependent sectors.

financially constrained industries. Section 4 displays the dynamic responses of industry-level outcome variables based on local projections. Finally, Section 5 concludes.

2. Data and identification strategy

2.1. Data

We use the United Nations Industrial Development Organization (UNIDO, 2020) Industrial Statistics Database, which provides annual output, value-added, gross fixed capital formation, employment, and the number of establishments for all manufacturing industries according to the 2-digit ISIC Revision 3 classification. The raw data are reported in U.S. dollars, so we convert them into constant international dollars. Since the industry-level deflators are unavailable for the vast majority of the sample countries, we deflate output, value-added, and gross fixed capital formation using the price level of GDP (output-side) and the price level of capital formation from the Penn World Table, version 10.0 (Feenstra et al., 2015).

Following the data screening process of Rajan and Zingales (1998) and Wurgler (2000), we drop industry-year observations for which the absolute value of the annual growth rate in real value added is greater than one or 100 percent.[8] In addition, we exclude country-year observations with data for fewer than 10 industries and country observations with fewer than 10 years of data. The United States is removed because it serves as an industry benchmark, as discussed earlier.

[8] In this paper, all the annual growth variables are defined using the log differences. The log specifications help mitigate the possible impact of outliers and restrictions placed on the distribution underlying the errors.

The resulting data set contains 22 distinct industries (excluding a recycling sector with ISIC code 37) for an unbalanced panel of 100 countries over the 50 years between 1969 and 2018 in the best cases.[9] However, nearly all of our empirical analysis relies on 51 commodity-exporting countries. Following Cavalcanti et al. (2015), we define commodity exporters as those countries with primary commodities, such as agricultural products, food, fuel, and minerals, representing more than 50 percent of their total exports on average during the sample period.[10] We convert the annual data into non-overlapping five-year averages so we can focus on the long-run impact of CTOT volatility by filtering out business cycle effects (Aghion et al., 2009).

Country-specific CTOT data come from Gruss and Kebhaj (2019), who provide the annual frequency information covering our sample period. They use the commodity trade information from the United Nations' Comtrade and the IMF's Primary Commodity Prices databases for up to 40 individual commodities.

The annual weight of each commodity used in the construction of CTOT is given by the net exports-to-GDP ratio: $w_{cj,\tau} = \left(x_{cj,\tau} - m_{cj,\tau}\right)/GDP_{j\tau}$, where $x_{cj,\tau}$ and $m_{cj,\tau}$ respectively denote the export and import values (in U.S. dollars) of commodity c in country j in year τ, and $GDP_{j\tau}$ is country j's GDP in dollars. Using net exports as a weight for each commodity accounts for price changes in imported commodities for which the weight would take a negative value. For baseline estimations, we use CTOT indices constructed using fixed commodity weights based on the average net export share over the years 1980–2015.

[9] See Table A.1 in Appendix for the list of all sample countries with relevant trade statistics. The average share of manufacturing value added in GDP is 15.8 percent in all countries and 14.4 percent in commodity-exporting countries, ranging from 4.7 percent in Ethiopia to 37.6 percent in Algeria.

[10] These countries are commodity exporters on net; that is, their average commodity exports are greater than imports. We also confirm that the results (available upon request) are very similar in their magnitude and statistical significance to our baseline results when using 40 or 60 percent of commodity export share as a threshold to define commodity exporters.

Our empirical analysis exploits two sector-level proxies for credit constraints.[11] First is external finance dependence (EFD), defined as the share of capital expenditures not financed with internal funds from operations. It is intended to capture outside funding needs for long-term investment projects. The second proxy is liquidity needs (LIQ), constructed as the ratio of inventories to sales, reflecting the short-term working capital needs. The information for EFD and LIQ at the 2-digit level of ISIC Revision 3 classification comes from Choi et al. (2022).

2.2. Identification strategy

To study whether an increase in CTOT volatility leads to lower growth in industries that are more financially constrained, we follow the identification strategy used by Samaniego and Sun (2015) and Iacovone et al. (2019) in the spirit of Rajan and Zingales (1998) and estimate the baseline model in Eq. (1):

$$g_{ij,t}^{y} = \alpha_1\left(\sigma_{jt}^{CTOT} \times FIN_i\right) + \alpha_2 s_{ij,0} + \theta_{ij} + \theta_{it} + \theta_{jt} + \varepsilon_{ij,t}, \tag{1}$$

where y is the log of the real value added so that $g_{ij,t}^{y}$ is the average annual growth rate of real value added of industry i in country j over each five-year period t; σ_{jt}^{CTOT} is CTOT volatility measured by the standard deviation of the annual CTOT growth over each period t; FIN_i refers to a time-invariant industry-level measure of financial constraints, either EFD or LIQ; $s_{ij,0}$ is the beginning-of-period share of the sector in a country's total manufacturing value added, which serves as a proxy for growth potential; θ_{ij}, θ_{it}, and θ_{jt} are industry-country, industry-time, and country-time fixed effects, respectively; and $\varepsilon_{ij,t}$ is a disturbance term.

[11] The summary statistics of the credit constraint proxies are available in Appendix Table A.2.

An exhaustive set of fixed effects allows us to control for a wide array of unobserved factors that might affect industry growth. For example, country-time fixed effects θ_{jt} implicitly capture changes in monetary and fiscal policies, financial development, macroeconomic volatility, episodes of political instability, and domestic crisis events. Industry-time fixed effects θ_{it} absorb industry-level factors over time across all countries, such as sector-specific global supply and demand disruptions or technological innovations. Finally, industry-country fixed effects θ_{ij} are dummies aimed at controlling for industry characteristics within each country, such as the differences in industry-level factor endowments across countries.[12] Thus, identification comes purely from a simultaneous variation of industry, country, and time, such as our interaction variable.

The specification in Eq. (1), which controls for the most stringent possible set of fixed effects, enables us to test the differential impact of CTOT volatility across sectors. The key parameter of interest is α_1. We expect it to be negative and economically significant, supporting our hypothesis that increasing CTOT volatility disproportionately reduces the growth of sectors with a high level of EFD or LIQ relative to the ones with a low level. We cluster the standard errors at the industry-country level to correct for any remaining serial correlation in the error term.

Since our credit constraint measures are built on the U.S. firm-level data and CTOT volatility is driven largely by global market conditions, the interaction variable in Eq. (1) is likely exogenous to the industry growth in a country other than the U.S., reducing the scope for

[12] Note that as we control for industry-country fixed effects, the industry-specific credit constraint measures cannot be included separately. More generally, time-invariant industry-specific and country-specific fixed effects (θ_i and θ_j, respectively) and time-fixed effects θ_t are all absorbed in our baseline specification.

reverse causality.[13] Finally, identification does not depend on the condition that sector-level credit constraint is identical between the U.S. and our sample countries but rather that their ordinal rank remains relatively stable across countries.

3. Panel regression results

3.1. Main results

Table 1 summarizes the results of our baseline regression (1), estimated using OLS. From the results in columns (1) and (2), which use the information from all countries in our sample, we find a statistically significant and negative coefficient for the interaction term for both measures of credit constraints. In general, more financially constrained industries seem to be worse off to a greater extent when a country is hit by a sizeable CTOT volatility change. Furthermore, we see an expected negative sign for the initial industry share, verifying that the more established industries tend to grow slowly.

Our next analysis focuses on 49 non-commodity or manufacturing exporters. As seen in columns (3) and (4), there is no significant evidence consistent with our hypothesis. This result is

[13] It is well known that the world commodity price changes are primarily determined by global supply and demand conditions and can serve as an important source of an exogenous terms-of-trade shock to the majority of commodity exporters (Chen et al., 2010). Nevertheless, as a robustness check, we follow Chen and Lee (2018) and identify a few sample countries holding 25% or more of the world export share of their specific commodities. These countries include Argentina (soybean meal, soybean oil, and sunflower oil), Australia (coal, iron, uranium, and wool), Brazil (iron and soybean meal), Chile (copper), Cote d'Ivoire (cocoa), Indonesia (palm kernel oil), Morocco (phosphate rock), and New Zealand (wool). When dropping these countries and reestimating the baseline model, we find that the main results remain unaltered.

not surprising given that non-commodity exporters generally have highly diversified export and import baskets and therefore are better insured against large commodity price swings.[14]

As shown in columns (5) and (6), restricting the sample to 51 commodity-exporting countries strengthens the results, increasing both the size of the point estimates and the probability of rejecting the null. In this sample, a one-standard-deviation increase in CTOT volatility (= 0.028) is predicted to decrease the annual value-added growth by 1.91 (0.23) percentage points in an industry at the 75th (25th) percentile level of EFD. In other words, the growth of the more external finance–dependent sectors (e.g., Chemical Products) appears to underperform by 1.68 percentage points compared to the growth of the less dependent sectors (e.g., Non-metallic Mineral Products). This growth differential is remarkable, given that the average annual growth rate of value added in all manufacturing industries in the commodity exporter sample is 3.04 percent.

A similar analysis reveals that the value-added growth is expected to decline by 4.86 (3.51) percentage points in a sector with LIQ at its 75th (25th) percentile, representing a growth differential of 1.35 percentage points between the sectors with large and small liquidity needs (e.g., Motor Vehicles versus Paper Products). Comparing the growth differentials across different country groups reported in Table 1, we observe that they are much more pronounced in countries specializing in commodity exports than the others.

We conduct an additional exercise by including both EFD- and LIQ-interaction variables in the same specification. Column (7) shows that our results remain very robust, validating that

[14] Note that if we define commodity importers in the same way as we do for commodity exporters, Japan will be the only commodity-importing country with a commodity share greater than 50 percent of its total imports.

the two industry-specific proxies, EFD and LIQ, capture considerably different dimensions of the credit constraints.

Our commodity-exporter sample includes 11 fuel exporters for which the share of fuel (e.g., coal, petroleum, natural gas, and related materials) represents more than 50 percent of their total exports. Fuel exporters typically experience excessive CTOT volatility, as summarized in the last column of Table A.1.

Estimating Eq. (1) based on the fuel-exporter sample, we find that the interaction coefficients keep the consistently negative signs. Their magnitude, however, is much larger than those found in the broader commodity-exporter sample despite the smaller sample size for fuel exporters decreasing statistical power. Excluding fuel-exporting countries continues to produce results qualitatively similar to our baseline results.[15]

Overall, the results in Table 1 demonstrate a negative effect of CTOT volatility on the development of credit-constrained industries, primarily in commodity-abundant economies.[16] This industry-level evidence complements the existing "resource curse" literature (e.g., Cavalcanti et al., 2015) which documents a harmful growth effect of CTOT volatility at an aggregate level.[17] In what follows, we will restrict our attention to the sample of commodity-exporting countries.

[15] These results are available in Appendix Table A.3.

[16] Though not reported, the core results stay unchanged when real output is used in place of real value added for computing industry growth.

[17] Although it is not a primary objective of this paper, we also attempt to evaluate the overall impact of CTOT volatility on industry growth. In fact, when CTOT volatility is included in the specification with various combinations of fixed effects but the country-time specific effect and interaction variable of interest, the CTOT volatility coefficient is small and not statistically different from zero even at the 15% level. This version of the model, however, may not be free from an omitted variable bias in the absence of country-time fixed effect. When

3.2. Robustness checks

In this subsection, we introduce various alternative specifications to establish the robustness of our main results.

3.2.1. Controlling for CTOT growth

In the baseline estimation, we use the standard deviation of CTOT growth rates as a measure of volatility. This approach may be subject to critique in that a surge in CTOT in the last year can raise both the average CTOT growth and its volatility during the five-year period. In other words, the baseline regression may encounter misspecification, suggesting the need to control for CTOT growth as well as its volatility (Blattman et al., 2007).

Before introducing the CTOT growth rate to the estimation procedure, we follow standard practice and employ the Hamilton filter to separate the annual CTOT series into trend and stationary cyclical components.[18] Then, we calculate CTOT growth using the trend components and volatility using the standard deviation of the cyclical components.

We extend the main specification in Eq. (1) and estimate the following CTOT growth-augmented model:

$$g_{ij,t}^{y} = \alpha_0 \left(g_{jt}^{CTOT} \times FIN_i \right) + \alpha_1 \left(\sigma_{jt}^{CTOT} \times FIN_i \right) + \alpha_2 s_{ij,0} + \theta_{ij} + \theta_{it} + \theta_{jt} + \varepsilon_{ij,t}, \qquad (2)$$

where g_{jt}^{CTOT} is the average annual growth rate of CTOT in country *j* over each five-year period *t* and all other variables are as defined in Eq. (1).

CTOT volatility and its interaction with credit constraint measures are included together, there is almost no change in the interaction coefficients, reassuring our main results.

[18] The Hamilton filter is preferred because it addresses the HP filter's problem of introducing "spurious dynamic relations that are purely an artifact of the filter and have no basis in the true data-generating process" (Hamilton, 2018). Nevertheless, we confirm that the results remain robust when CTOT is decomposed using the HP filter.

The estimation results are summarized in Table 2. Columns (1) and (2) document the results when we obtain the CTOT volatility from the Hamilton-filtered cyclical components. We continue to find a negative coefficient on the CTOT volatility interaction terms consistent with the baseline results in columns (5) and (6) of Table 1, regardless of the measure of credit constraints.

Columns (3) and (4) show the results when the specification controls for the financial constraint interaction with both CTOT volatility and growth variables. The main message that emerges from the results in those fuller specifications is that CTOT volatility, rather than CTOT growth, is a major driving force in eroding the growth of credit-constrained industries.[19]

3.2.2. Introducing additional controls

Our stringent possible specification may not wholly resolve simultaneity problems at the industry-country-time level. Missing potentially relevant factors, especially if they are highly correlated with CTOT volatility and affect industry growth through financial constraints, would make our main results biased. We therefore introduce an indicator of the financial crisis and some other measures of local or global macroeconomic conditions, including inflation, RGDP growth, and the world GDP growth. In particular, we consider the interaction between these variables and credit constraint proxies.

The crisis variable captures country-level banking crises and the 2008–09 global financial crisis. The information for the crisis years between 1970 and 2017 is taken from Laeven and Valencia (2013, 2018). They define a banking crisis as an event characterized by significant bank runs, bank losses or liquidations, and active policy interventions in response to losses in the

[19] The conclusion does not change when controlling for CTOT growth and its volatility without filtering the series. The relevant results are available in Appendix Table A.4.

banking system. Local inflation and domestic and world growth rates are calculated using the annual data on the consumer price index (2010 = 100) and RGDP (constant 2010 US$) from the World Bank's World Development Indicator.

We would anticipate negative coefficients of interaction variables that involve a crisis dummy and inflation to the extent that more financially dependent industries are hurt more in the presence of banking-sector disruptions and capital misallocation resulting from inflation. On the other hand, a positive coefficient of interaction between our measure of credit constraints and domestic growth (or world growth) would reflect industries' limited access to external sources of financing during local (or global) downturns.

As shown in Table 3, columns (1) and (2), the main result is not affected when the crisis interaction variables are added, with statistically robust and economically significant support for a negative growth effect of CTOT volatility through the credit-constraint channel. The crisis interaction terms retain a negative sign but are not significant.

The coefficients of our interest remain significant when world growth interactions are included in columns (3) and (4) and when domestic inflation and growth interactions are included in columns (5) and (6). Yet, the point estimates and statistical significance slightly decrease in the latter case. These results provide further confidence that simultaneity is not a major issue. We also note that additional local and global interaction variables exhibit consistent signs in the industry growth regressions.

3.2.3. Alternative proxies for credit constraints

Since our credit constraint indicators may involve measurement errors, we consider two additional proxies often used in the literature: *asset tangibility*, measured as the median across all firms in a given industry of the ratio of fixed assets (net property, plant, and equipment) to total book-value assets, and *R&D intensity*, defined as R&D expenditures over total capital expenditures. The updated information for these two measures based on the Compustat data is from Samaniego and Sun (2015).

As long as intangible assets are less desirable as collateral (Hart and Moore, 1994), an industry with fewer tangible assets (i.e., a lower value of the *asset tangibility*) is likely to be more credit-constrained. Moreover, R&D-intensive sectors are presumably more constrained due to their considerable startup funding needs and the intangible nature of the R&D asset.

Table 4, Panel A presents the estimation results when our credit constraint indicators are substituted with the alternative proxies. As shown in column (1), the *asset tangibility* interaction coefficient is positive and statistically significant at the 11% level (*p*-value = 0.104), suggesting that sectors with fewer tangible assets tend to shrink more following an increase in CTOT volatility. This result reflects that intangible assets are difficult to collateralize, making it more challenging to raise funds during volatile times.

Furthermore, the significantly negative interaction coefficient in column (2) indicates that R&D-intensive sectors appear more sensitive to volatile CTOT because these sectors tend to draw on external funds and rely on less durable assets. Overall, the findings in Table 4, Panel A, offer further confidence in the relevance of our credit constraint indicators.

3.2.4. Excluding small manufacturing countries

To check whether the sample countries with small manufacturing industries might be driving our results, we conduct an additional robustness test by estimating the baseline model using a panel of countries with relatively large manufacturing sectors. As shown in Table 4, Panel B, the interaction coefficients remain negative and significant when restricting the sample to countries whose average share of manufacturing value added in GDP is greater than 15 percent (note that the median share is 16 percent in the full sample). Thus, we conclude that our main results are not driven exclusively by countries with marginal manufacturing sectors.

3.2.5. Alternative CTOT indices

Thus far, we use CTOT indices that are built using fixed weights based on average trade flows; that is, the average weight of an individual commodity used in the construction of CTOT indices is its net exports as a share of GDP. Alternatively, one can build the CTOT indices using the average weight defined as net exports of individual commodities over the trade of all commodities. In this case, the annual weight of each commodity is given by $(x_{cj,\tau} - m_{cj,\tau})/\left(\sum_{c=1}^{C} x_{cj,\tau} + \sum_{c=1}^{C} m_{cj,\tau}\right)$, where $x_{cj,\tau}$ and $m_{cj,\tau}$ respectively stand for the export and import dollar values of commodity c in country j in year τ.

On the other hand, while we prefer to use CTOT indices based on fixed weights in order to eliminate the quantity effect from the price index calculation and keep them as an exogenous external shock measure, they have some drawbacks. The volume of commodity exports and imports does respond to the development of their global prices, and the fixed weights may not well represent the relative importance of certain commodities in a given time period. For this reason, we also consider CTOT indices constructed with time-varying weights based on three-year rolling averages of commodity trade values and output. The information for CTOT indices built with commodity-trade and time-varying weights is available from Gruss and Kebhaj (2019).

In Table 5, we report the results using a CTOT measure constructed with commodity-trade weights $\left(\text{CTOT}^{\text{comtrade}}\right)$ in columns (1) and (2) and time-varying weights $\left(\text{CTOT}^{\text{rolling}}\right)$ in columns (3) and (4). The main results hold regardless of the weighting schemes used in creating the CTOT indices, demonstrating that the endogenous responses in the volume of the commodity trade do not have any noticeable impacts on our findings.

3.3. Operating channels

This subsection explores potential operating channels whereby CTOT volatility might affect the growth performance of credit-constrained industries. In particular, we emphasize heterogeneous production factor responses across sectors that differ by the nature of outside funding needs.

3.3.1. Impact on establishments

We first test whether the interaction between CTOT volatility and credit constraints is negatively related to the entry of new firms. We do this by estimating Eq. (1) with the growth rate of the number of establishments as a dependent variable. Table 6 displays the regression results for industries with EFD in Panel A and those with LIQ in Panel B. Also reported is the industry differential in establishment growth between high (at the 75^{th} percentile) and low (at the 25^{th} percentile) levels of financing needs following a one-standard-deviation rise in CTOT volatility.

As shown in column (1), the effect of CTOT volatility on firm establishments is strongly negative in more externally dependent industries, while the sectors with greater liquidity needs seem to have no significant entry effects. Since heightened uncertainty can raise the cost of external capital and make access to it more difficult, CTOT volatility appears to work as an entry barrier to new firms, whose establishment generally requires considerable external financing for long-term productivity-enhancing investments. Accordingly, high-EFD industries experience disproportionately low establishment growth through reduced entry or increased exit.

3.3.2. Impact on the factors of production

We now turn our attention to the standard growth accounting framework using a simple growth model based on a Cobb-Douglas production function so that the growth in output increases with labor employment (*L*), physical capital (*K*), and *TFP*. We examine the impact of CTOT volatility on each of these components using the regression model specified below:

$$g^{\boldsymbol{z}}_{ij,t} = \beta_1\left(\sigma^{CTOT}_{jt} \times FIN_i\right) + \beta_2 s_{ij,0} + \theta_{ij} + \theta_{it} + \theta_{jt} + e_{ij,t}, \quad (3)$$

where $\boldsymbol{z} \in \{L, K, TFP\}$ and all other variables are as defined in Eq. (1) with *i* denoting industry, *j* country, and *t* each five-year period.

Note that the UNIDO provides the information for labor employment and investment but not for capital stock and TFP. Thus, we build physical capital stock in each year τ using the perpetual inventory method $K_{ij,\tau} = (1-\delta)K_{ij,\tau-1} + I_{ij,\tau}$, where δ is the depreciation rate, set to 8 percent, and $I_{ij,\tau}$ is real investment. We assume that the initial period corresponds to the steady state, and hence the initial value of capital is equal to $K_{ij,0} = I_{ij,0}/\delta$. The industry-level total factor productivity is given by $TFP_{ij,\tau} = Y_{ij,\tau}/\left(L_{ij,\tau}\right)^{\gamma}\left(K_{ij,\tau}\right)^{1-\gamma}$, where $Y_{ij,\tau}$ is real output and γ is the labor share, equal to 0.7.

Table 6 displays the coefficient estimates of Eq. (3), along with the industry differential in factor growth between high and low financing needs. According to the results in Panel A, columns (2) and (4), CTOT volatility lowers the growth rate of employment and TFP to a greater extent in industries more reliant on external finance. Intuitively, high-EFD industries may struggle more with volatile CTOT due to decreased innovative activities that may require long-term funding, such as R&D investment.[20] Suppressed entry of new firms, as reported in column (1), could also contribute to the TFP decline to the extent that starting up a new business stimulates innovation and encourages technology adoption. As a result, given CTOT volatility, high-EFD industries may experience more persistent stress, which we revisit in Section 4. The insignificant interaction coefficient in column (3) indicates that the growth differential is unlikely caused by an excessive capital loss in externally dependent industries.[21]

On the contrary, as presented in Panel B, column (3), CTOT volatility is more disruptive to capital accumulation for high-LIQ industries. Also, a negative interaction coefficient in column (2) shows suggestive evidence of an adverse employment effect (*p*-value = 0.108). For an industry undergoing more significant liquidity shortages, a rise in CTOT volatility and a resulting decrease in domestic credit disproportionately discourage the sector's capital investment, thereby deterring its further expansion.[22] However, as demonstrated by the insignificant point estimate in column (4), TFP growth does not react more significantly to CTOT volatility changes in sectors with considerable liquidity needs.

3.4. Marginal effects

To fully exploit the information from a continuous measure of financial constraints, we look at the marginal effects of CTOT volatility as a function of credit constraints using the models in Eqs. (1) and (3), that is, $\alpha_1 FIN_i$ and $\beta_1 FIN_i$. We also discuss the marginal effects on

[20] Supporting this view, the correlation between the EFD and R&D intensity, introduced in Section 3.2.3, reaches almost 70 percent at the conventional level of statistical significance.
[21] Also, we find reinforcing evidence for the insignificant interaction coefficient from the investment regression. This result is available in Appendix Table A.5, Panel A.
[22] In fact, as shown in Appendix Table A.5, Panel B, the LIQ interaction coefficient is significantly negative in the investment regression as well.

the growth of firm establishments. The resulting fitted values are depicted in Fig. 4, along with the 90% confidence intervals. Panel A displays the estimates for industries with different levels of EFD and Panel B for those with varying levels of LIQ.

The charts in the first row illustrate the marginal effects on value-added growth as a function of credit constraints. The tighter an industry's credit constraint (i.e., a higher value of EFD or LIQ), the more pronounced the negative marginal effect of CTOT volatility. These results lend support to our main finding that CTOT volatility disproportionately hampers the development of more financially constrained industries.

Interestingly, the marginal effect on value-added growth turns out to be positive when EFD is in its 1st (Tobacco Products) and 5th (Leather and Footwear) percentiles because of the negative values of EFD at which an industry's internal cash flows are greater than its capital expenditures. Nevertheless, we should not conclude that the tobacco and leather industries are highly resilient against a CTOT volatility shock, as these are among the sectors with the largest liquidity needs (i.e., LIQ greater than the 90th percentile).

Another notable point is that sectors that may use commodities as primary intermediate inputs do not necessarily suffer more from volatile CTOT through the credit constraint channel. Sectors such as Food and Beverages (ISIC code 15); Wood Products (20); Paper Products (21); Coke, Refined Petroleum Products, and Nuclear Fuel (23); and Basic Metals (27) have a modest level of EFD or LIQ and do not exhibit disproportionately large output losses.

The establishment growth responses are shown in the second row. As expected, exit is significantly associated with CTOT volatility only in industries with high EFD. In industries with

LIQ, the marginal effects seem pretty flat across various levels of LIQ and are not statistically different from zero.

The third row presents the marginal effects on employment growth, which look much like the marginal effects on value-added growth. In general, labor employment deteriorates more in industries with tighter credit constraints in response to increasing CTOT volatility.

Moving to the next row, we find significant evidence for a negative marginal effect on physical capital growth in sectors with LIQ but not those with EFD. In fact, CTOT volatility does little to affect capital growth in sectors with all levels of EFD.

From the last row, we observe that volatile CTOT significantly reduces the TFP growth of high-EFD industries, which may require outside funding for their innovative long-term investment. The TFP growth of high-LIQ industries is not subject to a significant CTOT volatility shock, consistent with the result in Table 6.

4. Dynamic responses

In this section, we investigate whether there is a chance that CTOT volatility has a long-lasting effect by estimating the impulse responses of industry-level outcome variables over 20 years. To assess the cumulative effects for horizon h, we adopt the local projection approach (Jordà, 2005) and modify Eqs. (1) and (3) as follows:

$$\Delta_h y_{ij,t-1} = \alpha_1^h\left(\sigma_{jt}^{CTOT} \times FIN_i\right) + \alpha_2^h s_{ij,0} + \theta_{ij}^h + \theta_{it}^h + \theta_{jt}^h + \varepsilon_{ij,t+h}, \tag{4}$$

$$\Delta_h \boldsymbol{z}_{ij,t-1} = \beta_1^h\left(\sigma_{jt}^{CTOT} \times FIN_i\right) + \beta_2^h s_{ij,0} + \theta_{ij}^h + \theta_{it}^h + \theta_{jt}^h + e_{ij,t+h}, \tag{5}$$

where $\Delta_h y_{ij,t-1} = y_{ij,t+h} - y_{ij,t-1}$ denotes the change in industry *i*'s value-added from the base period $t - 1$ up to period $t + h$ with $h = 0, 1, \ldots, H$; $\Delta_h \mathbf{z}_{ij,t-1} = \mathbf{z}_{ij,t+h} - \mathbf{z}_{ij,t-1}$ represents the change in industry *i*'s factors of production, such as *L*, *K*, and *TFP*; and subscript *j* denotes country and *t* each five-year period.[23] Here, CTOT volatility, σ_{jt}^{CTOT}, is standardized to facilitate its interpretation. Standard errors are clustered at the industry-country level to account for any remaining autocorrelation.

Fig. 5 illustrates the local projection coefficients, α_1^h's and β_1^h's, in Eqs. (4) and (5) with their 95% confidence intervals. Panel A displays the estimates for industries with high EFD (i.e., the subsample in the top quartile of EFD) and Panel B for industries with low EFD (i.e., the subsample in the bottom quartile of EFD).

Comparing the charts in the first row, we see that a one-standard-deviation shock to CTOT volatility initially results in about a 0.5-percent decrease in the value-added of high-EFD industries. Conversely, there is little initial decline in the low-EFD industries. The dynamic pattern indicates that the negative impact of the initial volatility shock keeps building over time but with different degrees of persistence, conditional on the level of EFD. In the high-EFD subsample, by year 15, there is about a 1.7-percent decrease in value-added. The negative effect continues to exist over the rest of the response horizon. However, in the low-EFD subsample, value-added declines up to about 0.7 percent by year 5 but gradually rebounds afterward, making the impulse responses statistically indifferent from zero after 10 years.

The employment dynamics illustrated in the second row show more salient changes in industries with a higher degree of EFD. While there is a cumulative 1.2-percent drop in

[23] We cannot obtain a reliable estimate for the impulse responses of the number of establishments due to insufficient observations, and therefore it is not presented.

employment for less dependent sectors after 20 years, the cumulative decline for more dependent sectors is much larger, reaching 2.2 percent by year 20.

Proceeding to the third row, we find that for both subsamples in Panels A and B, physical capital adjusts slowly, with a lag of about 10 years in externally dependent industries. Moreover, for most horizons, the impulse responses are not statistically different from zero. These response patterns suggest that diminishing capital accumulation is unlikely to be the main channel driving the negative output responses in industries with EFD.

The dynamic responses of TFP are displayed in the last row. Not surprisingly, the response paths in more externally dependent industries show about a 0.4-percent initial contraction of TFP, followed by sustained negative swings over the next 20 years. By contrast, the cumulative paths of TFP in the less dependent industries are mostly insignificant for the first 15 years and show an upward trajectory thereafter.

We now look at the local projection coefficients for industries with liquidity shortages. The corresponding impulse responses are portrayed in Fig. 6, along with the 95% confidence intervals. Panel A shows the coefficients for industries with large LIQ (i.e., the subsample in the top quartile of LIQ) and Panel B for industries with small LIQ (i.e., the subsample in the bottom quartile of LIQ).

From the charts in the first row, we find that a one-standard-deviation shock to CTOT volatility decreases the value-added of high-LIQ industries by 1.7 percent upon impact, followed by relatively persistent adverse effects that peak at 3.4 percent after 15 years. On the other hand, the cumulative responses for low-LIQ industries stay positive for most projection horizons.

The cumulative effects on employment, presented in the second row, reflect a more detrimental impact in industries with high LIQ than in those with low LIQ, although they are not robustly significant. Indeed, low-LIQ industries experience only minor employment adjustments, which are statistically insignificant for most horizons.

Reviewing the charts in the third row, we verify a persistently negative impact of the CTOT volatility shock on the physical capital in more liquidity-scarce industries, with a substantial cumulative drop of up to 9 percent by year 20. Industries with a low level of LIQ are much less affected, with the effects on physical capital indistinguishably different from zero over the entire response path.

From the last row, we see that the 2-percent initial drop in TFP in high-LIQ industries appears to be short-lived; in fact, it becomes difficult to distinguish the cumulative response from zero after five years due to the wide confidence bands. In addition, there is virtually no evidence for a negative and persistent TFP effect of CTOT volatility in low-LIQ industries.

In sum, the damaging impact of CTOT volatility is expected to continue in the long run, with the persistent effect more apparent in industries with high dependence on external finance relative to those with large liquidity needs. Output and employment in sectors with high EFD do not fully recover even after 20 years. The underlying driver of this prolonged effect seems to be slow TFP progress in those sectors. On the other hand, decreased capital accumulation contributes to sustained output drop in the liquidity-lacking sectors. The dynamic response patterns bolster our point estimate results of the growth model reported in Section 3.

5. Conclusion

Volatile commodity prices are a critical source of macroeconomic fluctuations in commodity-exporting countries. Cross-country evidence reveals that sizeable CTOT volatility is associated with a high cost of capital and lower domestic credit to the private sector, which can deter the development of industries in economies with financial frictions.

Guided by these observations, we argue that volatile CTOT might interact with credit constraints to hamper the long-run growth of industries in commodity-exporting countries. To test this hypothesis, we collect sector-level panel data for countries specializing in commodity exports and analyze them using the five-year panel regressions for the long-run growth effects and local projection approaches for their dynamic responses over time.

The three-dimensional panel data make it possible to explore a causal link between country-specific CTOT volatility and industry growth and identify the underlying channels for such a link. Moreover, a comprehensive set of fixed effects helps control for a wide array of omitted variables that might affect industry growth.

We find robust evidence in favor of our hypothesis. CTOT volatility causes a disproportionately large growth loss in manufacturing sectors with tighter credit constraints in commodity-exporting countries. However, we do not find the same result in the non-commodity or manufacturing exporter sample. Unlike commodity exporters, manufacturing exporters typically have highly diversified export and import baskets and therefore are better insured against large commodity price swings.

When analyzing the negative growth effects across industries, we also discover that it is important to distinguish among different financial constraints, as not all sectors suffer from the same channel. For example, the destructive effects operate through reduced firm entry and lower

TFP in industries heavily reliant on external finance for long-term investments and through lower capital accumulation in industries with high liquidity needs for short-term working capital. Due to the adverse TFP effect, the persistent decline appears more salient in sectors with high external finance dependence than those with liquidity needs.

Micro-level evidence in this paper provides a complementary explanation for the resource curse through the credit constraint channel that amplifies the undesirable effect of CTOT volatility. Moreover, it also offers a lesson for policymakers in commodity-dependent developing countries to promote industrialization by smoothing CTOT volatility effects. Strengthening the resilience of the financial market through financial development with less financing frictions and active management of international reserves or sovereign wealth funds could be policy options to alleviate the detrimental impact of CTOT volatility on local industry growth.

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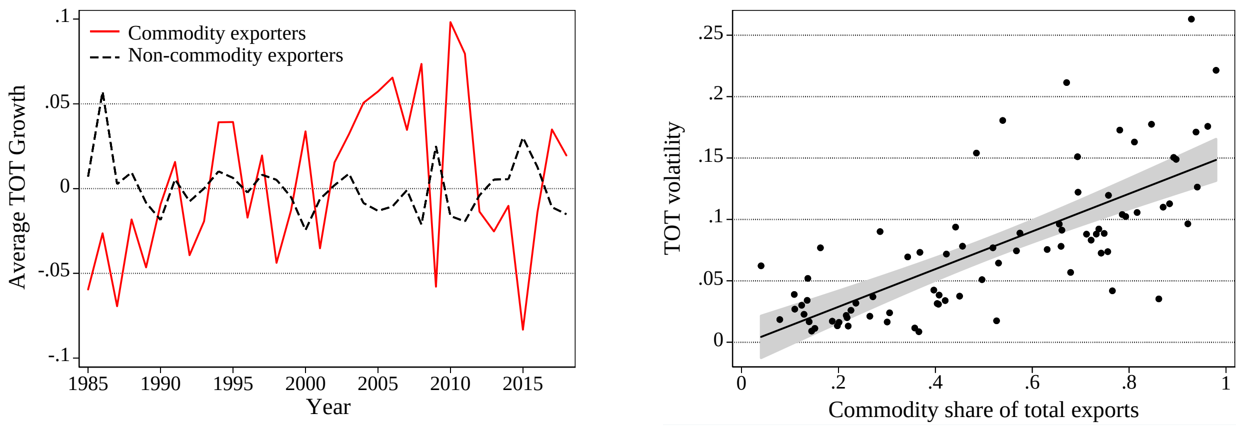
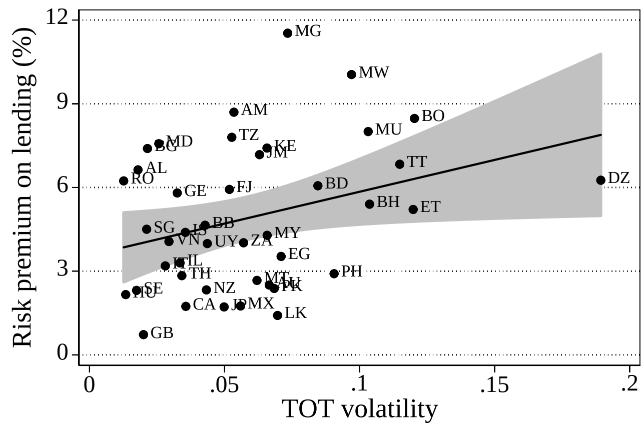


A. TOT growth across country groups

B. Increasing TOT volatility with commodity dependency

Fig. 1. Commodity dependency and TOT volatility, 1985–2018.

Notes: TOT growth is defined as the logarithmic annual differences in terms-of-trade in each country and TOT volatility as the moving five-year standard deviations (in $t-4$ through t) of the TOT growth. In Panel A, commodity exporters refer to 51 countries for which primary commodities represent more than 50 percent of their total exports on average from 1985 to 2018. Non-commodity exporters are the rest of the sample countries that specialize in manufacturing exports. See Appendix Table A.1 for a full set of countries considered in this figure. In Panel B, the figure depicts the OLS-fitted linear relation between the commodity share of total exports and TOT volatility, with the 95% confidence intervals shown in gray. Data source: OECD and the World Bank's World Development Indicator.



coef. = 22.82, (robust) s.e. = 8.75, t = 2.61

Fig. 2. TOT volatility and the cost of borrowing, 1971–2018.

Notes: The figure depicts the OLS-fitted linear relation between TOT volatility and the cost of domestic private debt, with the 95% confidence intervals shown in gray. Due to the data availability, the figure relies on 42 countries. TOT volatility is defined as the standard deviation of TOT growth. The labels in the figure correspond to the two-digit ISO code of each country. Data source: OECD and the World Bank's World Development Indicator.

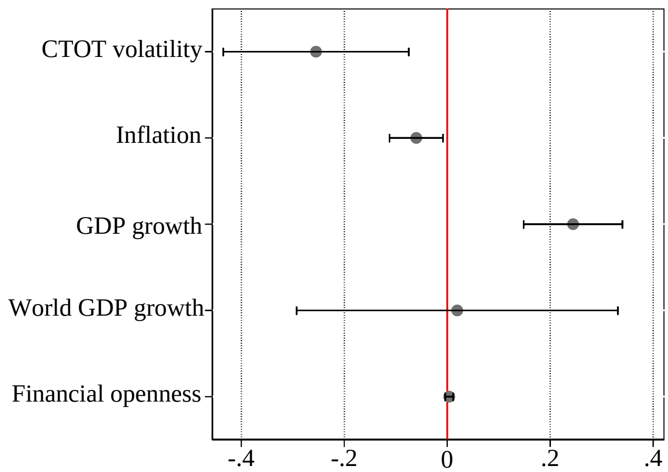
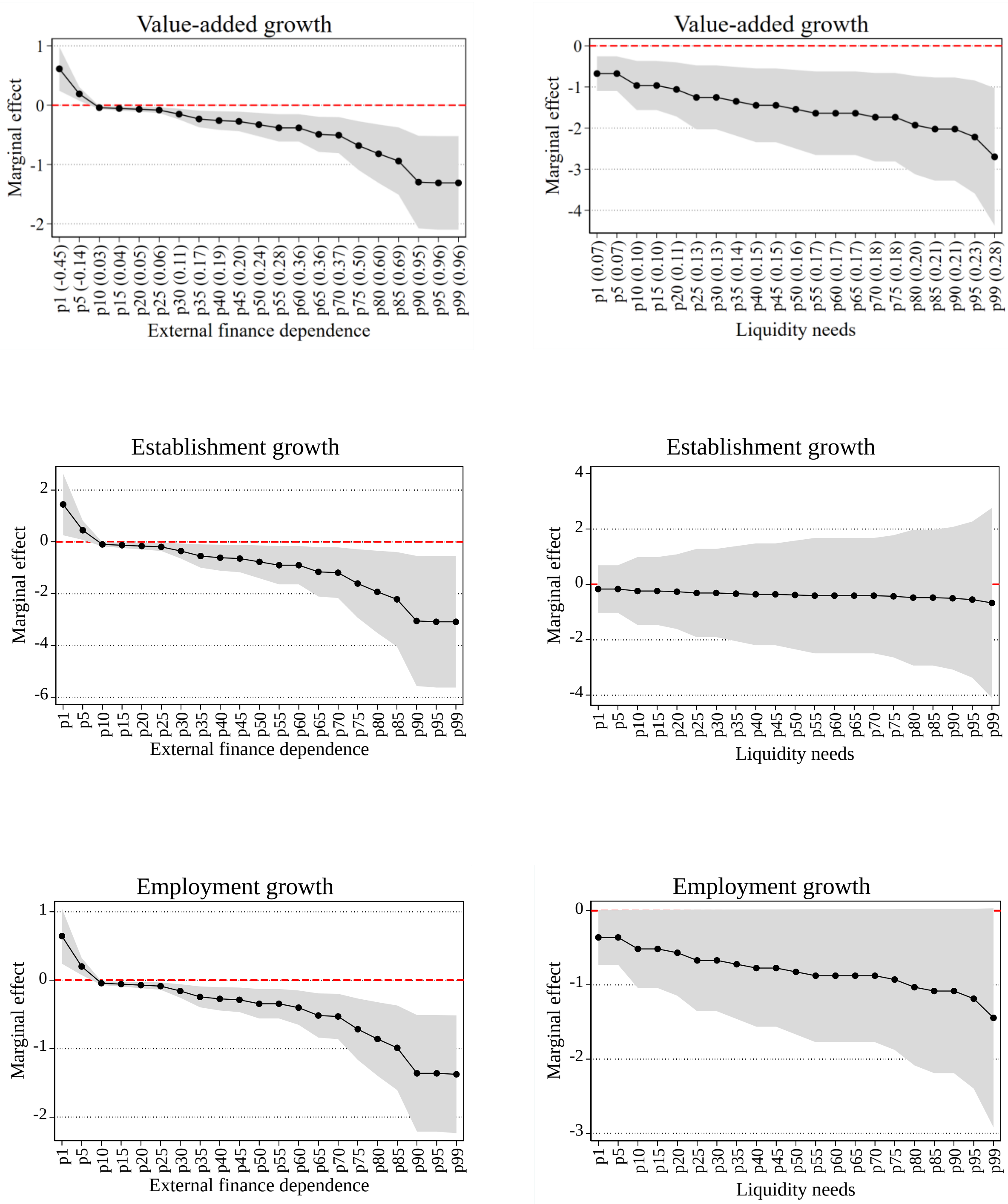


Fig. 3. Determinants of private credit growth in commodity exporters, 1969-2018.

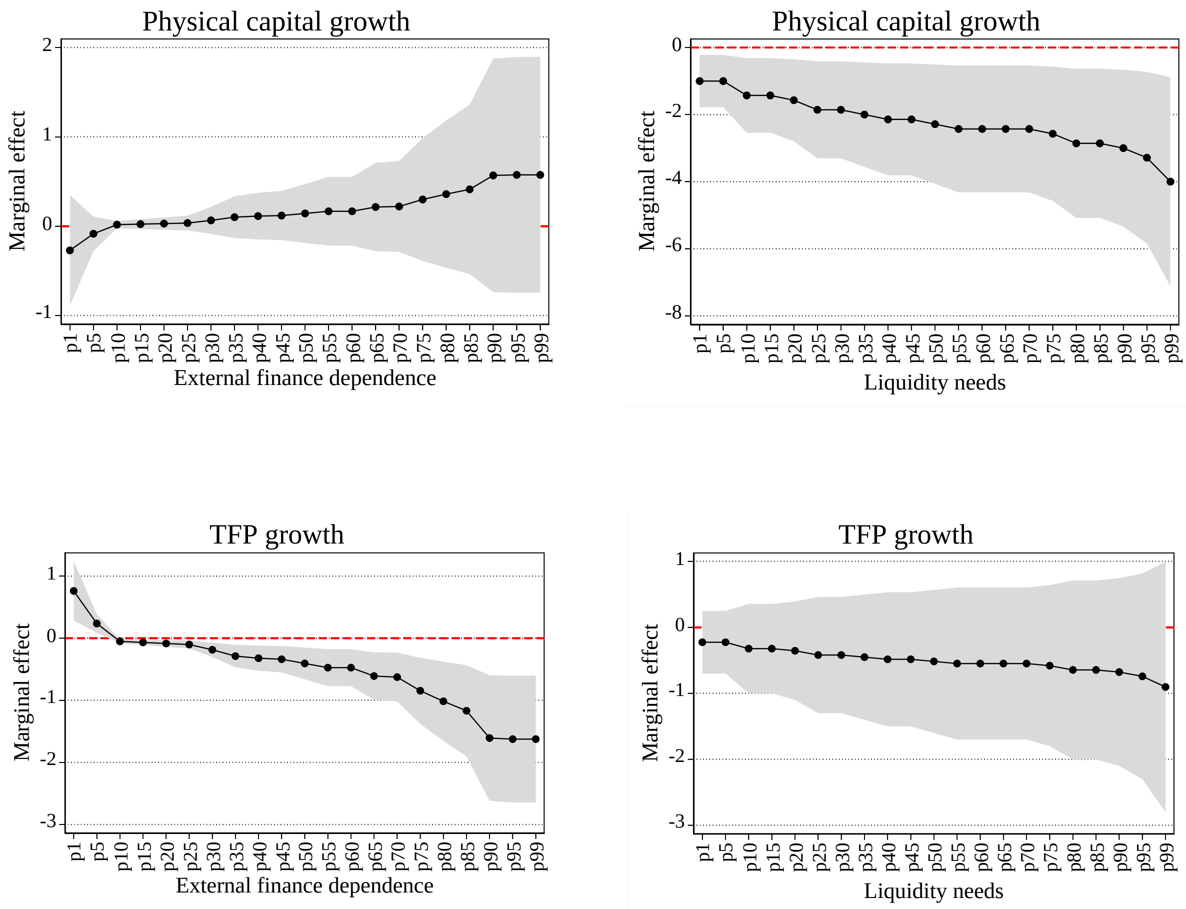
Notes: The figure plots point estimates of coefficients along with the 90% confidence intervals using capped spikes based on the panel fixed-effect regression with clustered standard errors by country. The dependent variable is the annual growth rate of domestic credit to the private sector as a share of GDP. Control variables include the CTOT volatility, defined as the standard deviation of the CTOT growth in the past five years from $t-5$ to $t-1$; lagged CPI inflation; lagged GDP growth; lagged world GDP growth; and lagged de jure financial openness. Commodity exporters refer to 51 countries for which primary commodities represent more than 50 percent of their total exports on average during the sample period. See Appendix Table A.1 for a full set of countries considered in this figure. Data source: Chinn and Ito (2006), Gruss and Kebhaj (2019), and the World Bank's World Development Indicator.



A. Marginal effects as a function of EFD

B. Marginal effects as a function of LIQ

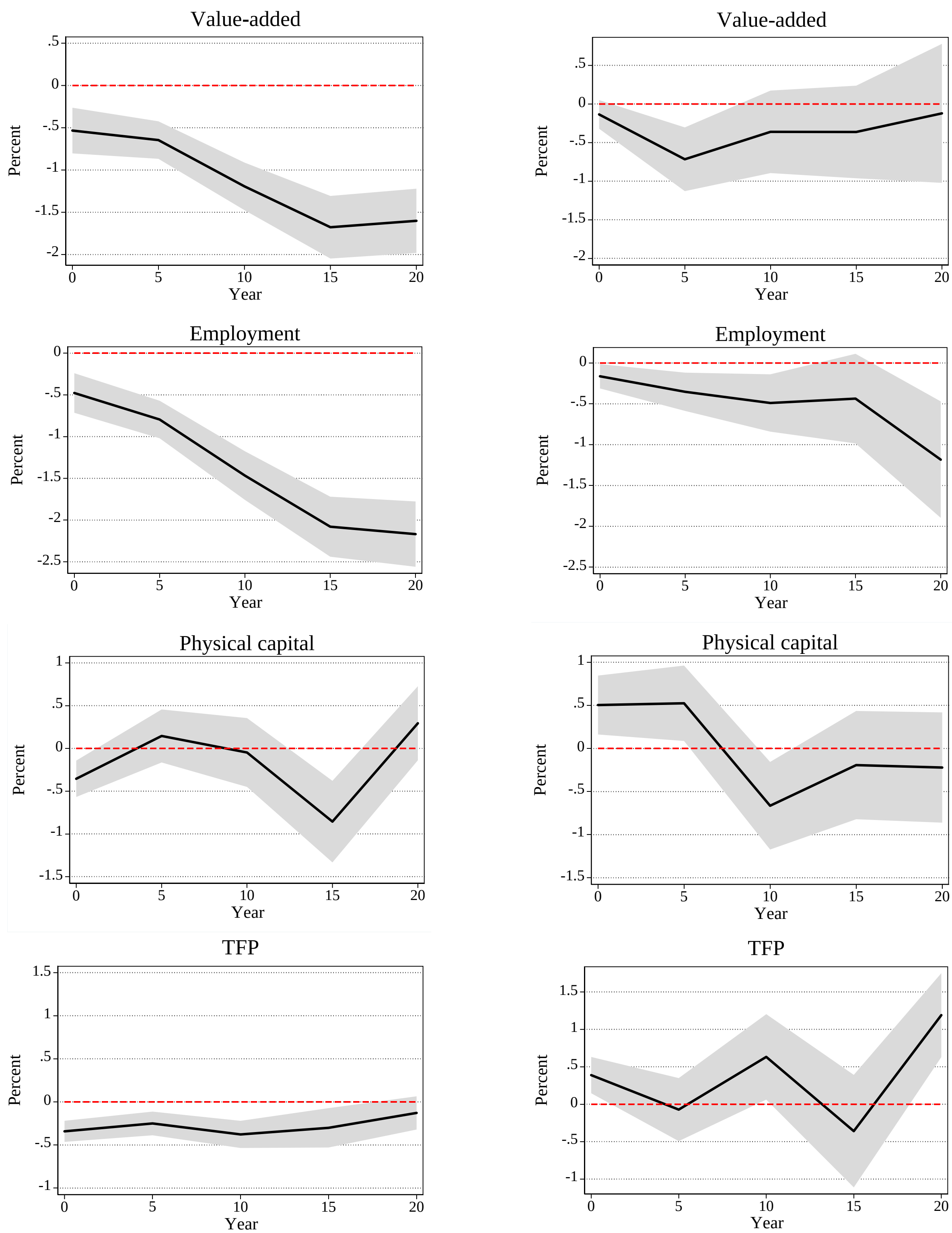
Fig. 4. Marginal effects of an increase in CTOT volatility. The 90% confidence intervals are shown in gray.



A. Marginal effects as a function of EFD

B. Marginal effects as a function of LIQ

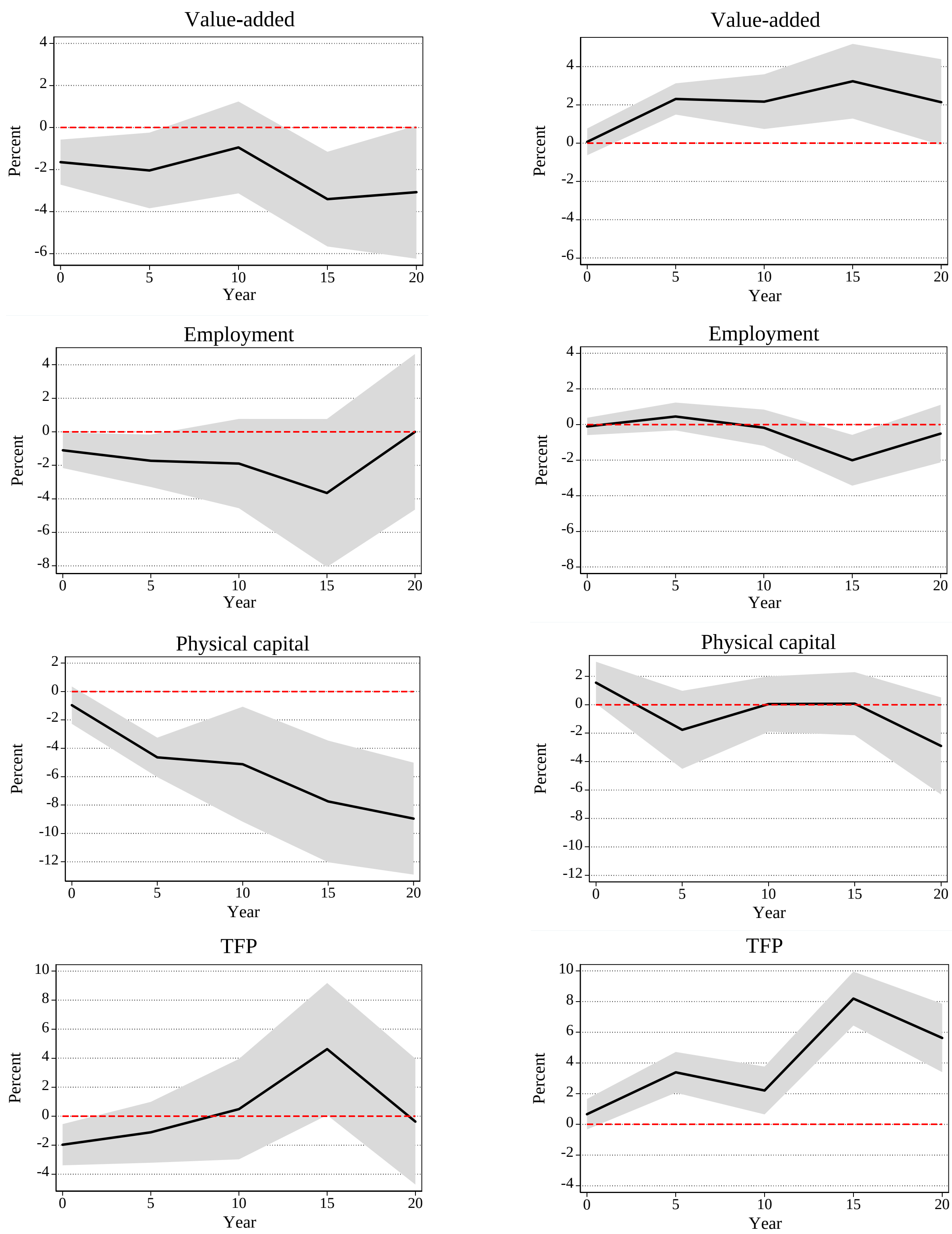
Fig. 4. (continued) Marginal effects of an increase in CTOT volatility. The 90% confidence intervals are shown in gray.



A. Top quartile of EFD

B. Bottom quartile of EFD

Fig. 5. Cumulative effects of a one-S.D. shock to CTOT volatility. The 95% confidence intervals are shown in gray.



A. Top quartile of LIQ

B. Bottom quartile of LIQ

Fig. 6. Cumulative effects of a one-S.D. shock to CTOT volatility. The 95% confidence intervals are shown in gray.

Table 1
CTOT volatility and industry growth: across different country groups.

Dependent variable: Value-added growth	All countries		Non-commodity exporters		Commodity exporters		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CTOT volatility × External dependence	**-1.166****		**0.708**		**-1.365*****		**-1.216****
	(0.465)		(1.186)		(0.499)		(0.472)
CTOT volatility × Liquidity needs		**-8.768*****		**4.332**		**-9.641*****	**-8.696*****
		(3.180)		(6.009)		(3.631)	(3.221)
Initial industry share	-0.117***	-0.117***	-0.186***	-0.184***	-0.089*	-0.089*	-0.086*
	(0.037)	(0.037)	(0.061)	(0.061)	(0.047)	(0.047)	(0.047)
Number of countries	100	100	49	49	51	51	51
Observations	13,809	13,809	7,077	7,077	6,729	6,729	6,729
R-squared	0.459	0.459	0.499	0.499	0.451	0.451	0.452
Average value-added growth (%)	2.79		2.56		3.04		
Diff. in value-added growth (ppt)	-1.08	-0.92	-0.36	-0.43	-1.68	-1.35	

Notes: This table presents the estimates of Eq. (1) based on the sector-level semi-decade data. All specifications include country-time fixed effects, sector-time fixed effects, and sector-country fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the sector-country level. *, **, ***: Statistically different from zero with 90%, 95%, and 99% certainty, respectively. Using Eq. (1), the differential in value-added growth appearing in the last row is calculated by $\alpha_1 \times \text{S.D.}(\sigma_{jt}^{CTOT}) \times (FIN_{\text{p75}} - FIN_{\text{p25}})$, where FIN is either external dependence or liquidity needs.

Table 2
CTOT volatility and industry growth: controlling for CTOT growth.

Dependent variable: Value-added growth				
	(1)	(2)	(3)	(4)
CTOT volatility × External dependence	**-0.007****		**-0.008****	
	(0.004)		(0.005)	
CTOT volatility × Liquidity needs		**-0.053****		**-0.065****
		(0.029)		(0.032)
CTOT growth × External dependence			-0.147	
			(0.499)	
CTOT growth × Liquidity needs				-4.559
				(3.182)
Initial industry share	-0.091*	-0.091*	-0.091*	-0.091*
	(0.047)	(0.047)	(0.047)	(0.047)
Observations	6,729	6,729	6,729	6,729
R-squared	0.450	0.451	0.450	0.451

Notes: This table presents the estimates of Eq. (2) based on the sector-level semi-decade data. We decompose CTOT using the Hamilton filter and calculate CTOT growth using the trend components and volatility using the standard deviation of the cyclical components. All specifications include country-time fixed effects, sector-time fixed effects, and sector-country fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the sector-country level. *, **: Statistically different from zero with 90% and 95% certainty, respectively.

Table 3

CTOT volatility and industry growth: additional controls.

Dependent variable: Value-added growth	Add crisis events		Add world growth		Add macro conditions	
	(1)	(2)	(3)	(4)	(5)	(6)
CTOT volatility × External dependence	**-1.381*****		**-1.390*****		**-1.175****	
	(0.497)		(0.494)		(0.535)	
CTOT volatility × Liquidity needs		**-9.736*****		**-9.618*****		**-7.322***
		(3.641)		(3.660)		(4.281)
Crisis × External dependence	-0.035					
	(0.028)					
Crisis × Liquidity needs		-0.259				
		(0.181)				
World growth × External dependence			3.184**			
			(1.398)			
World growth × Liquidity needs				16.116**		
				(6.395)		
Inflation × External dependence					-0.127**	
					(0.064)	
Inflation × Liquidity needs						-0.382
						(0.367)
GDP growth × External dependence					0.852***	
					(0.211)	
GDP growth × Liquidity needs						3.489**
						(1.432)
Initial industry share	-0.088*	-0.089*	-0.089*	-0.089*	-0.068	-0.072
	(0.047)	(0.047)	(0.047)	(0.047)	(0.050)	(0.051)
Observations	6,729	6,729	6,729	6,729	5,999	5,999
R-squared	0.452	0.452	0.453	0.453	0.450	0.448

Notes: This table presents point estimates based on the sector-level semi-decade data. All specifications include country-time fixed effects, sector-time fixed effects, and sector-country fixed effects. Their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the sector-country level. *, **, ***: Statistically different from zero with 90%, 95%, and 99% certainty, respectively.

Table 4
CTOT volatility and industry growth: alternative credit constraints and excluding outliers.

Dependent variable: Value-added growth		
	(1)	(2)
	Panel A. Alternative credit constraint proxies	
CTOT volatility × Asset tangibility	**2.377**†	
	(1.460)	
CTOT volatility × R&D intensity		**-1.183****
		(0.495)
Initial industry share	-0.090*	-0.087*
	(0.047)	(0.047)
Observations	6,729	6,729
R-squared	0.451	0.451
Diff. in value-added growth (ppt)	-1.07	-0.80
	Panel B. Manufacturing value added/GDP > 0.15	
CTOT volatility × External dependence	**-1.229***	
	(0.729)	
CTOT volatility × Liquidity needs		**-7.147***
		(3.778)
Initial industry share	-0.023	-0.024
	(0.066)	(0.066)
Number of countries	23	23
Observations	3,259	3,259
R-squared	0.425	0.425
Diff. in value-added growth (ppt)	-1.51	-1.00

Notes: This table presents the estimates of Eq. (1) based on the sector-level semi-decade data. All specifications include country-time fixed effects, sector-time fixed effects, and sector-country fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the sector-country level. †, *, **: Statistically different from zero with 89%, 90%, and 95% certainty, respectively. Using Eq. (1), the differential in value-added growth is calculated by $\alpha_1 \times \text{S.D.}\left(\sigma_{jt}^{CTOT}\right) \times \left(FIN_{\text{p75}} - FIN_{\text{p25}}\right)$, where FIN is asset tangibility, R&D intensity, external dependence, or liquidity needs.

Table 5
CTOT volatility and industry growth: alternative CTOT indices.

Dependent variable: Value-added growth				
	X = $\text{CTOT}^{\text{comtrade}}$		X = $\text{CTOT}^{\text{rolling}}$	
	(1)	(2)	(3)	(4)
X volatility × External dependence	**-0.337****		**-0.712****	
	(0.135)		(0.282)	
X volatility × Liquidity needs		**-2.374*****		**-5.909*****
		(0.893)		(2.197)
Initial industry share	-0.090*	-0.091*	-0.092*	-0.092**
	(0.047)	(0.047)	(0.047)	(0.047)
Observations	6,729	6,729	6,729	6,729
R-squared	0.451	0.451	0.451	0.451

Notes: This table presents the estimates of Eq. (1) based on the sector-level semi-decade data using a CTOT measure constructed with commodity-trade weights ($\text{CTOT}^{\text{comtrade}}$) and time-varying weights ($\text{CTOT}^{\text{rolling}}$). All specifications include country-time fixed effects, sector-time fixed effects, and sector-country fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the sector-country level. *, **, ***: Statistically different from zero with 90%, 95%, and 99% certainty, respectively.

Table 6
Operating channels of the CTOT volatility effects: growth accounting.

Dependent variable is the growth of:	Establishments	Employment	Physical capital	TFP
	(1)	(2)	(3)	(4)
	Panel A. Industries with external finance dependence			
CTOT volatility × External dependence	**-3.213****	**-1.432*****	**0.599**	**-1.692*****
	(1.607)	(0.545)	(0.836)	(0.647)
Initial industry share	-0.036	-0.032	0.131	-0.366***
	(0.076)	(0.036)	(0.110)	(0.092)
Observations	4,091	6,117	4,057	4,014
R-squared	0.478	0.424	0.341	0.433
Average factor growth (%)	1.03	1.70	3.48	0.75
Diff. in factor growth (ppt)	-3.96	-1.76	0.74	-2.09
	Panel B. Industries with liquidity needs			
CTOT volatility × Liquidity needs	**-2.388**	**-5.157**†	**-14.285****	**-3.228**
	(7.452)	(3.202)	(6.763)	(4.120)
Initial industry share	-0.046	-0.034	0.137	-0.370***
	(0.076)	(0.036)	(0.109)	(0.091)
Observations	4,091	6,117	4,057	4,014
R-squared	0.474	0.423	0.342	0.432
Average factor growth (%)	1.03	1.70	3.48	0.75
Diff. in factor growth (ppt)	-0.33	-0.72	-2.00	-0.45

Notes: This table presents the estimates of Eq. (3) based on the sector-level semi-decade data. All specifications include country-time fixed effects, sector-time fixed effects, and sector-country fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the sector-country level. †, **, ***: Statistically different from zero with 89%, 95%, and 99% certainty, respectively. Using Eq. (3), the differential in factor growth is calculated by $\beta_1 \times \text{S.D.}\left(\sigma_{jt}^{CTOT}\right) \times \left(FIN_{\text{p75}} - FIN_{\text{p25}}\right)$, where FIN is either external dependence or liquidity needs.

Appendix

Table A.1

Country characteristics: average from 1969 to 2018.

Country	CEX/EX	CIM/IM	MEX/EX	MIM/IM	FEX/EX	FIM/IM	MVA/Y	σ^{CTOT}
Albania	0.314	0.319	0.618	0.622	0.087	0.097	0.050	0.004
Algeria	0.979	0.283	0.021	0.717	0.949	0.022	0.376	0.058
Argentina	0.712	0.204	0.268	0.792	0.068	0.083	0.238	0.006
Armenia	0.558	0.414	0.382	0.548	0.042	0.181	0.100	0.033
Australia	0.742	0.180	0.183	0.790	0.192	0.092	0.100	0.007
Austria	0.145	0.236	0.837	0.757	0.020	0.092	0.185	0.006
Bahrain	0.792	0.451	0.189	0.534	0.507	0.287	0.153	0.023
Bangladesh	0.163	0.387	0.811	0.606	0.011	0.108	0.135	0.006
Barbados	0.453	0.361	0.540	0.626	0.039	0.131	0.084	0.012
Belarus	0.409	0.457	0.560	0.500	0.271	0.308	0.270	0.014
Belgium	0.220	0.318	0.747	0.670	0.065	0.130	0.150	0.010
Bolivia	0.883	0.204	0.084	0.787	0.301	0.051	0.132	0.019
Brazil	0.575	0.367	0.406	0.630	0.043	0.229	0.199	0.004
Bulgaria	0.398	0.331	0.561	0.593	0.106	0.168	-	0.004
Burundi	0.539	0.337	0.060	0.656	0.005	0.138	0.093	0.015
Cameroon	0.897	0.326	0.085	0.670	0.285	0.125	0.136	0.012
Canada	0.420	0.189	0.547	0.787	0.150	0.073	0.126	0.006
Chile	0.870	0.308	0.113	0.676	0.010	0.160	0.178	0.027
China	0.137	0.267	0.835	0.693	0.045	0.094	0.308	0.003
Colombia	0.732	0.210	0.250	0.775	0.294	0.053	0.175	0.009
Congo, Dem. Rep.	0.938	0.308	0.054	0.685	0.022	0.093	0.145	0.007
Costa Rica	0.567	0.226	0.412	0.753	0.005	0.102	0.179	0.014
Cote d'Ivoire	0.846	0.400	0.134	0.593	0.140	0.194	0.131	0.031
Croatia	0.302	0.285	0.694	0.707	0.109	0.142	0.146	0.006
Cyprus	0.508	0.336	0.457	0.657	0.047	0.144	0.106	0.014
Denmark	0.357	0.273	0.602	0.705	0.047	0.096	0.143	0.002
Dominican Rep.	0.442	0.367	0.443	0.631	0.019	0.182	0.179	0.011
Ecuador	0.941	0.216	0.053	0.780	0.458	0.095	0.187	0.022
Egypt	0.656	0.409	0.313	0.565	0.344	0.076	0.158	0.005
El Salvador	0.485	0.318	0.445	0.648	0.022	0.135	0.181	0.018
Estonia	0.301	0.273	0.671	0.690	0.089	0.117	0.146	0.010
Ethiopia	0.816	0.283	0.113	0.717	0.002	0.150	0.047	0.011
Fiji	0.793	0.391	0.173	0.589	0.000	0.191	0.112	0.033
Finland	0.216	0.313	0.770	0.667	0.040	0.161	0.203	0.006
France	0.218	0.313	0.770	0.686	0.030	0.142	0.152	0.005
Gabon	0.962	0.213	0.036	0.785	0.782	0.026	0.088	0.100
Georgia	0.553	0.404	0.399	0.577	0.062	0.196	0.112	0.019
Germany	0.110	0.316	0.858	0.644	0.023	0.128	0.205	0.005
Ghana	0.722	0.311	0.064	0.668	0.081	0.132	0.093	0.011
Greece	0.526	0.362	0.459	0.634	0.132	0.175	0.087	0.006
Guatemala	0.671	0.293	0.327	0.705	0.032	0.154	0.160	0.012
Honduras	0.811	0.311	0.171	0.687	0.013	0.154	0.176	0.019
Hungary	0.198	0.227	0.661	0.631	0.029	0.103	0.189	0.002
Iceland	0.861	0.287	0.107	0.711	0.008	0.111	0.112	0.033
India	0.343	0.450	0.644	0.485	0.067	0.270	0.161	0.007
Indonesia	0.694	0.318	0.294	0.679	0.414	0.145	0.227	0.011
Iran	0.880	0.217	0.101	0.726	0.816	0.019	0.127	0.049
Ireland	0.265	0.231	0.695	0.726	0.008	0.083	0.232	0.007
Israel	0.124	0.258	0.847	0.731	0.004	0.125	0.146	0.009
Italy	0.135	0.394	0.850	0.576	0.037	0.160	0.164	0.006
Jamaica	0.718	0.439	0.281	0.546	0.071	0.239	0.091	0.025
Japan	0.040	0.577	0.930	0.408	0.007	0.287	0.214	0.006
Kenya	0.756	0.369	0.235	0.628	0.119	0.221	0.104	0.013
Korea, Rep.	0.109	0.414	0.885	0.579	0.037	0.210	0.242	0.015
Kuwait	0.853	0.187	0.143	0.747	0.837	0.007	0.076	0.104
Lithuania	0.404	0.385	0.586	0.595	0.188	0.231	0.168	0.009
Luxembourg	0.151	0.269	0.810	0.678	0.006	0.081	0.074	0.012

Table A.1 (continued)

Country	CEX/EX	CIM/IM	MEX/EX	MIM/IM	FEX/EX	FIM/IM	MVA/Y	σ^{CTOT}
Madagascar	0.737	0.349	0.247	0.646	0.041	0.174	-	0.011
Malawi	0.921	0.261	0.076	0.734	0.001	0.120	0.124	0.009
Malaysia	0.496	0.252	0.494	0.725	0.149	0.092	0.230	0.020
Malta	0.146	0.304	0.851	0.689	0.072	0.127	0.182	0.016
Mauritius	0.456	0.354	0.533	0.635	0.002	0.119	0.166	0.035
Mexico	0.423	0.190	0.568	0.781	0.209	0.046	0.187	0.007
Moldova	0.698	0.385	0.300	0.590	0.004	0.229	0.133	0.029
Morocco	0.530	0.416	0.468	0.583	0.028	0.174	0.174	0.014
Nepal	0.289	0.324	0.566	0.628	0	0.151	0.060	0.010
Netherlands	0.366	0.333	0.580	0.629	0.121	0.145	0.151	0.003
New Zealand	0.765	0.241	0.216	0.754	0.022	0.113	0.179	0.009
Nicaragua	0.781	0.316	0.178	0.676	0.007	0.160	0.138	0.021
Norway	0.661	0.220	0.311	0.774	0.460	0.060	0.109	0.035
Oman	0.886	0.246	0.098	0.695	0.843	0.058	0.081	0.097
Pakistan	0.286	0.442	0.711	0.550	0.025	0.219	0.138	0.010
Panama	0.749	0.269	0.244	0.728	0.101	0.160	0.130	0.010
Paraguay	0.892	0.303	0.104	0.696	0.194	0.166	0.164	0.014
Peru	0.786	0.292	0.116	0.707	0.086	0.106	0.167	0.011
Philippines	0.368	0.306	0.530	0.633	0.016	0.164	0.238	0.010
Poland	0.236	0.246	0.756	0.739	0.060	0.109	0.165	0.004
Portugal	0.226	0.350	0.762	0.644	0.038	0.135	0.132	0.009
Qatar	0.887	0.166	0.080	0.825	0.888	0.008	0.169	0.105
Romania	0.206	0.296	0.779	0.688	0.077	0.161	0.225	0.001
Russia	0.693	0.216	0.204	0.694	0.568	0.018	0.133	0.039
Senegal	0.659	0.491	0.304	0.506	0.156	0.197	0.182	0.014
Singapore	0.306	0.311	0.631	0.654	0.177	0.198	0.224	0.019
Slovak Rep.	0.140	0.237	0.856	0.761	0.050	0.124	0.189	0.012
Slovenia	0.129	0.260	0.869	0.733	0.031	0.101	0.204	0.011
South Africa	0.406	0.199	0.422	0.712	0.083	0.099	0.180	0.004
Spain	0.271	0.389	0.716	0.607	0.046	0.183	0.135	0.007
Sri Lanka	0.519	0.400	0.467	0.592	0.029	0.158	0.163	0.014
Sweden	0.187	0.265	0.782	0.715	0.039	0.125	0.176	0.005
Switzerland	0.079	0.195	0.875	0.760	0.008	0.064	0.186	0.004
Syrian Arab Rep.	0.831	0.406	0.158	0.566	0.623	0.182	0.137	0.023
Tanzania	0.631	0.355	0.163	0.643	0.013	0.213	0.085	0.012
Thailand	0.450	0.279	0.528	0.686	0.022	0.157	0.251	0.013
Trinidad and Tobago	0.757	0.456	0.241	0.540	0.702	0.299	0.174	0.048
Tunisia	0.408	0.306	0.591	0.690	0.220	0.113	0.146	0.004
Turkey	0.397	0.306	0.589	0.644	0.025	0.175	0.185	0.006
United Kingdom	0.201	0.290	0.749	0.671	0.091	0.092	0.121	0.001
Uruguay	0.679	0.367	0.314	0.632	0.011	0.210	0.179	0.011
Venezuela	0.928	0.191	0.063	0.792	0.873	0.016	0.160	0.059
Vietnam	0.385	0.238	0.599	0.742	0.150	0.102	0.168	0.007
Summary statistics for all countries								
Average:	0.521	0.311	0.443	0.667	0.160	0.137	0.158	0.018
Median:	0.513	0.308	0.451	0.676	0.055	0.133	0.160	0.011
Minimum:	0.040	0.166	0.021	0.408	0.000	0.007	0.047	0.001
Maximum:	0.979	0.577	0.930	0.825	0.949	0.308	0.376	0.105
Std. Dev.:	0.269	0.080	0.272	0.079	0.238	0.064	0.054	0.021
Summary statistics for 51 commodity-exporting countries								
Average:	0.752	0.312	0.210	0.674	0.250	0.135	0.144	0.026
Median:	0.756	0.311	0.183	0.679	0.086	0.145	0.137	0.014
Minimum:	0.508	0.166	0.021	0.506	0.000	0.007	0.047	0.004
Maximum:	0.979	0.491	0.468	0.825	0.949	0.299	0.376	0.105
Std. Dev.:	0.132	0.084	0.128	0.082	0.303	0.073	0.053	0.026

Notes: CEX = commodity exports; CIM = commodity imports; EX = total exports; FEX = fuel exports; FIM = fuel imports; IM = total imports; MEX = manufacturing exports; MIM = manufacturing imports; MVA = manufacturing value added; Y = GDP; σ^{CTOT} = CTOT volatility. Commodity exporters are indicated with bold text. Data source: Gruss and Kebhaj (2019) and the World Bank's World Development Indicator.

Table A.2
Industry-level proxies for credit constraints.

ISIC code	Sector name	EFD	LIQ	RND	TAN
15	Food and beverages	0.11	0.10	0.07	0.37
16	Tobacco products	-0.45	0.28	0.22	0.19
17	Textiles	0.19	0.17	0.14	0.35
18	Wearing apparel, fur	0.03	0.21	0.02	0.13
19	Leather, leather products, and footwear	-0.14	0.23	0.18	0.14
20	Wood products (excl. furniture)	0.28	0.11	0.03	0.31
21	Paper and paper products	0.17	0.13	0.08	0.47
22	Printing and publishing	0.20	0.07	0.10	0.26
23	Coke, refined petroleum products, nuclear fuel	0.04	0.08	0.08	0.55
24	Chemicals and chemical products	0.50	0.15	1.18	0.29
25	Rubber and plastics products	0.69	0.14	0.17	0.37
26	Non-metallic mineral products	0.06	0.13	0.11	0.46
27	Basic metals	0.05	0.15	0.08	0.40
28	Fabricated metal products	0.24	0.16	0.15	0.27
29	Machinery and equipment n.e.c.	0.60	0.17	0.93	0.20
30	Office, accounting, and computing machinery	0.96	0.20	0.81	0.21
31	Electrical machinery and apparatus	0.95	0.20	0.81	0.21
32	Radio, television, and communication equipment	0.96	0.20	0.81	0.21
33	Medical, precision, and optical instruments	0.96	0.21	1.19	0.18
34	Motor vehicles, trailers, semi-trailers	0.36	0.18	0.32	0.26
35	Other transport equipment	0.36	0.18	0.32	0.26
36	Furniture; manufacturing n.e.c.	0.37	0.17	0.21	0.25
Summary statistics for 51 commodity-exporting countries					
Average:		0.30	0.16	0.32	0.30
25th percentile:		0.06	0.13	0.08	0.21
Median:		0.24	0.16	0.15	0.27
75th percentile:		0.50	0.18	0.32	0.37
Minimum:		-0.45	0.07	0.02	0.13
Maximum:		0.96	0.28	1.19	0.55
Std. Dev.:		0.33	0.05	0.37	0.11

Notes: EFD = external finance dependence; LIQ = liquidity needs; RND = R&D intensity; TAN = asset tangibility. Data source: Choi et al. (2022) and Samaniego and Sun (2015).

Table A.3
CTOT volatility and industry growth: fuel versus non-fuel commodity exporters.

Dependent variable: Value-added growth				
	Fuel exporters		Non-fuel commodity exporters	
	(1)	(2)	(3)	(4)
CTOT volatility × External dependence	**-1.942***		**-1.483***	
	(1.003)		(0.803)	
CTOT volatility × Liquidity needs		**-15.595***		**-12.013****
		(8.031)		(4.952)
Initial industry share	-0.043	-0.036	-0.101*	-0.099*
	(0.071)	(0.072)	(0.058)	(0.058)
Number of countries	11	11	40	40
Observations	1,249	1,249	5,478	5,478
R-squared	0.573	0.574	0.440	0.441
Average value-added growth (%)	3.97		2.83	
Diff. in value-added growth (ppt)	-3.50	-3.20	-0.72	-0.66

Notes: This table presents the estimates of Eq. (1) based on the sector-level semi-decade data. All specifications include country-time fixed effects, sector-time fixed effects, and sector-country fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the sector-country level. *, **: Statistically different from zero with 90% and 95% certainty, respectively. Using Eq. (1), the differential in value-added growth appearing in the last row is calculated by $\alpha_1 \times \text{S.D.}(\sigma_{jt}^{CTOT}) \times (FIN_{\text{p75}} - FIN_{\text{p25}})$, where FIN is either external dependence or liquidity needs.

Table A.4
CTOT volatility and industry growth: controlling for CTOT growth without filtering.

Dependent variable: Value-added growth		
	(1)	(2)
CTOT volatility × External dependence	**-1.369*****	
	(0.499)	
CTOT volatility × Liquidity needs		**-9.638*****
		(3.630)
CTOT growth × External dependence	0.124	
	(0.412)	
CTOT growth × Liquidity needs		-0.095
		(2.516)
Initial industry share	-0.089*	-0.089*
	(0.047)	(0.047)
Observations	6,729	6,729
R-squared	0.451	0.451

Notes: This table presents the estimates of Eq. (2) based on the sector-level semi-decade data. All specifications include country-time fixed effects, sector-time fixed effects, and sector-country fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the sector-country level. *, ***: Statistically different from zero with 90% and 99% certainty, respectively.

Table A.5
Operating channels of the CTOT volatility effects: investment growth.

Dependent variable is the growth of:	Investment
	(1)
	Panel A. Industries with external finance dependence
CTOT volatility × External dependence	**-1.013**
	(1.219)
Initial industry share	-0.225
	(0.166)
Observations	4,057
R-squared	0.405
Average investment growth (%)	3.28
Diff. in investment growth (ppt)	-1.25
	Panel B. Industries with liquidity needs
CTOT volatility × Liquidity needs	**-18.772****
	(7.828)
Initial industry share	-0.222
	(0.166)
Observations	4,057
R-squared	0.406
Average investment growth (%)	3.28
Diff. in investment growth (ppt)	-2.63

Notes: This table presents the estimates of Eq. (3) based on the sector-level semi-decade data, with real investment growth as a dependent variable. All specifications include country-time fixed effects, sector-time fixed effects, and sector-country fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the sector-country level. **: Statistically different from zero with 95% certainty. Using Eq. (3), the differential in investment growth is calculated by $\beta_1 \times \text{S.D.}\left(\sigma_{jt}^{CTOT}\right) \times \left(FIN_{\text{p75}} - FIN_{\text{p25}}\right)$, where FIN is either external dependence or liquidity needs.