Commodity terms of trade volatility and industry growth

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Abstract

Commodity terms of trade (CTOT) volatility is positively associated with sovereign credit spreads, leading to a higher cost of capital for producers in commodity-dependent countries. In this paper, we examine how volatile CTOT influences industries' growth performance based on sector-level panel data for countries specializing in commodity exports. We find robust evidence that CTOT volatility causes slow growth in manufacturing sectors more prone to financial vulnerabilities due to tight credit constraints. The adverse growth effects operate through lower total factor productivity in industries heavily reliant on external finance for long-term investments and lower physical capital accumulation in industries requiring external funds to finance their liquidity needs. 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

This paper shows how the rising volatility of commodity terms of trade (CTOT) erodes the growth of credit-constrained industries in countries that specialize in commodity exports. The adverse growth effects of CTOT volatility remain robust when controlling for the growth rate of CTOT and using alternative measures of CTOT and credit constraints. Therefore, we conclude that exogenous CTOT volatility is a critical force behind the unbalanced sectoral growth in commodity-abundant developing countries.

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

The second motivating observation is that sizeable TOT volatility is associated with a high cost of capital. Fig. 2 provides supporting evidence using the annual Emerging Market Bond Index Plus (EMBI+) spread provided by J.P. Morgan, which serves as a proxy for the cost of sovereign debt. For emerging and developing countries, there is significant evidence that the cost of external borrowing increases with TOT volatility.[1] This positive relation makes sense; one consequence of exposure to higher TOT volatility and a resulting increase in uncertainty on

[1] Hilscher and Nosbusch (2010) also document a similar finding even when controlling for the effect of country-specific fundamentals and global factors. For the related literature highlighting the role of other global factors, such as U.S. interest rates and stock returns, as a determinant of sovereign credit spreads, see Uribe and Yue (2006) and Longstaff et al. (2011).

dollar export revenue could be the higher risk premium economic agents have to pay for their external credit.

The above two stylized facts 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 output effects of CTOT volatility? This paper addresses 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 heterogenous effects of country-specific CTOT volatility on the growth performance of industries that face financial constraints.

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. The first is *external finance dependence*, 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 is *liquidity needs*, constructed as the ratio of inventories to sales, reflecting the working capital needed to satisfy both short-term debt payments and ongoing operational expenses. Despite their conceptual similarities, the pairwise correlation between the two is 0.01, with no statistical significance at the conventional level, implying that they address quite different aspects of the sector's credit constraints. Using these two proxies, we test whether CTOT volatility triggers a relatively larger decline in the growth of industries with tighter financial constraints and explore the underlying channels for the growth impact.

The empirical result from static regressions shows that CTOT volatility dampens the growth of manufacturing industries more prone to financial vulnerabilities due to tight credit constraints. For example, in response to rising CTOT volatility, an industry such as Chemicals and Chemical Products, which depends considerably on external finance, would contract relatively more than Non-metallic Mineral Products, which requires little external finance. Likewise, an industry such as Motor Vehicles, Trailers, and Semi-trailers would decline relatively more than Paper and Paper Products because of the former's greater liquidity needs. These results are consistent with the economic intuition that higher borrowing costs and risk aversion due to increased aggregate uncertainty raise the likelihood of industries having binding credit constraints.

We also uncover that the damaging effects operate through a fall in total factor productivity in sectors more reliant on external finance. A plausible reason for this result is that since heightened uncertainty arising from CTOT volatility 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 that there is 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.

Another operating channel we discover is lower physical capital accumulation in sectors with insufficient liquidity. This result suggests that the increased risk aversion and cost of capital following higher CTOT volatility is likely to limit liquidity-constrained industries' ability to fund short-term working capital, thereby forcing them to cut expenses for fixed capital investment.

To study 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. Supporting the static regression results, we find a persistently negative effect of CTOT uncertainty only in industries with high external finance dependence. These industries suffer from lower production and employment in the long run, with a prolonged moderate loss in total factor productivity. In the sectors with high liquidity needs, the detrimental effects seem relatively short-lived, although there is significant 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 standard HP (Hodrick and Prescott, 1997) filter and the more 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 investigate whether the main results are sensitive to the CTOT indices constructed with time-varying commodity trade weights instead of fixed weights. In addition, we reestimate the model using alternative proxies for credit constraints, namely the degree of asset tangibility and R&D intensity. Lastly, we check whether countries with tiny manufacturing sectors drive the main results by excluding them from the sample. We confirm that the main conclusion remains the same.

This paper deserves attention for the following four 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.[2] 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), most closely related to this paper, emphasize the importance of the second moments of CTOT and document the negative impact of CTOT volatility on GDP per capita growth. They attribute this result to a lower accumulation of physical and human capital, with virtually no effects on

[2] 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).

productivity.[3] Relative to these studies, we analyze the sector-level data to propose financial constraints as a crucial channel that magnifies the adverse impact of CTOT volatility on industry growth. This sector-level analysis enables us to identify a significantly and persistently negative productivity response in an external finance–dependent industry, which is not addressed by Cavalcanti et al. (2015).

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. (2016) and Choi et al. (2018).[4] One notable theoretical work is by Aghion et al. (2010), who show that tighter credit constraints depress long-term productivity-enhancing investments that are subject to liquidity risk. 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 uncertainty, a critical concern for commodity exporters but underexplored in the context of credit constraints. In particular, our static and dynamic approaches investigate how tight credit conditions can amplify the effects of uncertainty over time using various proxies for credit constraints.

Third, this paper attempts to extend the literature on commodity-sovereign risk dependence. Unlike the previous literature that relates the volatile commodity prices to sovereign risk in the form of the greater cost of capital or external debt (Hilscher and Nosbusch, 2010; Arezki and Brückner, 2012; Boehm et al., 2021), we stress the real-economy consequences of

[3] 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).
[4] 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 more pronounced effect in financially dependent sectors.

commodity-sovereign risk dependence for commodity-exporting countries by evaluating the growth performance of the industrial sectors in response to a rise in CTOT volatility.

Lastly, 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 identify the underlying channels by examining how the growth of production factors, such as labor, capital, and productivity, responds to the interaction between CTOT volatility and the financial constraints 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 country-industry 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 static panel regressions and explores the channels whereby CTOT volatility might affect the growth of 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.[5] 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 below.

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.[6] However, the majority of our empirical analysis relies on 51 commodity-exporting countries. Commodity exporters are 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.[7] We convert the annual data into non-overlapping

[5] 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.

[6] See Table A1 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.

[7] We confirm that these countries are commodity exporters on net; that is, their average commodity exports are greater than imports.

five-year averages so we can focus on the long-run effects 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 represent the export and import values (in U.S. dollars) of commodity c of 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.

Our analysis exploits two sector-level proxies for financial constraints.[8] First is external finance dependence (EFD). This measure is proposed by Rajan and Zingales (1998) and defined as $\text{EFD} = (\text{Capital expenditures} - \text{Cash flow})/\text{Capital expenditures}$, 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. The industry median value of the firm ratios is selected to represent each

[8] The summary statistics of the credit constraint proxies are available in Appendix Table A2.

sector's level of EFD and reflect its financing needs for long-term investment. The updated information for EFD is collected from Choi et al. (2022).

The second proxy is liquidity needs (LIQ), 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 LIQ index using the U.S. firm-level data from Compustat to identify an industry's intrinsic need for short-term working capital. 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.

2.2. Identification strategy

To study the growth effects of CTOT volatility in credit-constrained industries, we follow the identification strategy specified in Samaniego and Sun (2015) 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 real growth rate of value added in industry i of country j over each five-year period t; σ_{jt}^{CTOT} is CTOT volatility measured by the standard deviation of the annual CTOT growth, as in Cavalcanti et al. (2015); FIN_i refers to a time-invariant industry-level measure of financial constraints, either EFD or LIQ; $s_{ij,0}$ is the initial share of a sector in a country's total manufacturing value added in each period, 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.[9]

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

The key parameter of interest in Eq. (1) is α_1, and we expect it to be negative and economically significant, supporting our hypothesis that CTOT volatility hinders industry growth to a greater degree for credit-constrained industries with a higher value of EFD or LIQ. We cluster the standard errors at the country-industry level to control any remaining autocorrelations.

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 to be exogenous to the industry growth of a country other than the U.S., reducing the scope

[9] The volatility of annual CTOT growth over the sample period for each country is summarized in the last column of Table A1.

for reverse causality.[10] Finally, identification does not depend on the condition that sector-level financial vulnerability is identical between the U.S. and our sample countries but rather that their ordinal rank remains relatively stable across countries.

3. Static 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 not surprising given that non-commodity exporters typically have highly diversified export and import baskets and therefore are better insured against large commodity price swings.

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

[10] It is well known that the world commodity price changes are driven mostly by global supply and demand conditions and can serve as an important source of an exogenous terms-of-trade shock to the vast majority of commodity exporters (Chen et al., 2010).

probability of rejecting the null.[11] 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., Chemicals and 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, Trailers, and Semi-trailers versus Paper and Paper Products).

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

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.[12]

[11] Our commodity-exporter sample includes 14 fuel exporters for which the share of fuel represents more than 40 percent of their total exports, encompassing former OPEC members such as Ecuador and Indonesia as well as Norway. From estimation based on the fuel exporter sample, we find mixed evidence; although the LIQ interaction term turns out to be marginally significant with the expected sign, the EFD interaction term is statistically insignificant (results available in Appendix Table A3). These findings verify that our main results are not driven primarily by the fuel exporters.

[12] Though not reported, we find qualitatively similar results when real output is used in place of real value added for computing industry growth.

This industry-level evidence complements the existing "resource curse" literature (e.g., Cavalcanti et al., 2015) documenting a harmful growth effect of CTOT volatility at an aggregate level. In what follows, we will restrict our attention to the sample of commodity-exporting countries.

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 the growth rate of CTOT 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 be subject to 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 use the HP filter to separate the annual CTOT series into trend and stationary cyclical components.[13] Then, we calculate CTOT growth using the trend components and volatility using the standard deviation of the cyclical components. As an alternative decomposition method, we also employ the Hamilton filter, which 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).

[13] We set the HP smoothing parameter to be 6.25, as suggested by Ravn and Uhlig (2002) for annual data.

We extend the baseline model 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).

The estimation results are summarized in Table 2. Columns (1) and (2) report the results when we obtain the CTOT volatility from the HP-filtered cyclical components, and columns (5) and (6) report the results when we get it from the Hamilton-filtered series. Comparing the results with those in columns (5) and (6) of Table 1, we find a consistently negative coefficient of the CTOT interaction term, regardless of the measure of credit constraints and the choice of the filtering techniques. The growth differential shown in the last row of the table remains at around one percentage point or slightly lower.

Columns (3), (4), (7), and (8) show the results when the specification controls for the CTOT growth rate.[14] The main message that emerges from the results in those fuller specifications is that CTOT volatility, rather than CTOT growth, is a key driving force in deterring the growth of credit-constrained manufacturing sectors.[15]

3.2.2. Alternative CTOT indices

[14] When the CTOT growth variable is present in the estimation of Eq. (2), the differential in value-added growth is calculated by $\left[\left\{\hat{\alpha}_0 \times \text{mean}\left(g_{jt}^{CTOT}\right)\right\} + \left\{\hat{\alpha}_1 \times \text{S.D.}\left(\sigma_{jt}^{CTOT}\right)\right\}\right] \times \left(FIN_{\text{p75}} - FIN_{\text{p25}}\right)$, where FIN is either EFD or LIQ.

[15] The conclusion does not change when controlling for CTOT growth and its volatility without filtering the series. Results are available in Appendix Table A4.

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 represent the export and import values (in U.S. dollars) of commodity *c* in country *j* in year τ.

Additionally, 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. Gruss and Kebhaj's (2019) database also provides CTOT indices constructed with time-varying weights based on three-year rolling averages of commodity trade values and output.

In Table 3, we report results using a commodity trade–weighted CTOT measure $\left(\mathrm{CTOT}^{\mathrm{comtrade}}\right)$ in columns (1) and (2), and a time-varying weight–based CTOT measure $\left(\mathrm{CTOT}^{\mathrm{rolling}}\right)$ in columns (3) and (4). Our 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 major impacts on our findings.

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 taken 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 measure) is likely to be more credit-constrained. Moreover, R&D-intensive sectors are presumably credit-constrained due to their considerable startup funding needs and the intangible nature of the R&D asset.

The results in Table 4, Panel A, show that more financially fragile sectors with fewer tangible assets and higher R&D intensity tend to shrink more severely following an increase in CTOT volatility, providing empirical support for our core results.

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, our results remain stable 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).

3.3. Operating channels

This section explores potential operating channels whereby CTOT volatility might affect the growth performance of industries facing different degrees of financial constraints.

3.3.1. Commodity export versus import prices

While the data strongly support the negative growth effect of CTOT volatility, it is worth checking whether the volatility of export prices or import prices drives the result. Therefore, we consider the volatility of commodity export and import price indices separately in our estimation. These indices are constructed by weighting the individual commodity prices with the export- or import-to-GDP ratios and are taken from Gruss and Kebhaj (2019).

Table 5 presents the results using the volatility of commodity export prices (CXP) and commodity import prices (CMP). We find statistically and economically significant interaction coefficients in columns (1) and (2) and insignificant coefficients in columns (3) and (4), certifying that the volatility of commodity export rather than import prices is what matters for the growth of financially vulnerable manufacturing sectors. These results correspond to a much higher share of commodities in total exports relative to imports (75 percent versus 31 percent) for commodity-rich countries.

3.3.2. Impact on establishments

We next 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 for those with LIQ in Panel B.

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 larger liquidity needs seem to have no entry effects. Since the increased uncertainty can make access to external funds more difficult, CTOT volatility seems to work as an entry barrier to new firms, whose establishment generally requires external financing for long-term productivity-enhancing investments.

3.3.3. Growth accounting

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 total production increases with labor employment, physical capital accumulation, and productivity. We examine the impact of CTOT volatility on each of these components using the regression model specified below:

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

where $\boldsymbol{z} \in \{L, K, TFP\}$, with L denoting employment, K physical capital, and *TFP* total factor productivity, 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). According to the results in Panel A, columns (2) and (4), CTOT volatility lowers the growth rate of employment and TFP in external finance–dependent industries. Intuitively, high-EFD industries may struggle with CTOT volatility due to decreased innovative activities that may require long-term funding, such as R&D investment.[16] As a result, given the CTOT uncertainty shock, external finance–dependent industries may experience persistent stress, which we revisit in Section 4. The insignificant interaction coefficient in column (3) indicates that the growth effects of CTOT volatility are not channeled through capital accumulation in externally dependent industries.[17]

On the contrary, as presented in Panel B, column (3), CTOT volatility is disruptive to capital accumulation for high-LIQ industries. Moreover, column (2) shows suggestive evidence of an adverse employment effect. For industries undergoing liquidity shortages, high CTOT uncertainty and the associated increases in risk aversion and the cost of capital discourage their capital investment, thereby deterring the industries' further expansion.[18,19]

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

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[16] Supporting this view, the correlation between the EFD and R&D intensity, introduced in Section 3.2.3, reaches almost 70 percent, with the conventional level of statistical significance.

[17] We find reinforcing evidence of the insignificant interaction coefficient from the investment regression (results available in Appendix Table A5, Panel A).

[18] In fact, as shown in Appendix Table A5, Panel B, the LIQ interaction coefficient is significantly negative in the investment regression.

[19] As an additional exploration, we estimate the impact of CTOT volatility on export growth and find no meaningful evidence (see Appendix Table A6).

models in Eqs. (1) and (3), that is, $\hat{\alpha}_1 FIN_i$ and $\hat{\beta}_1 FIN_i$. We also discuss the marginal effects on the growth of firm establishments. The resulting fitted values are depicted in Fig. 3, along with the 90 percent confidence intervals. Panel A displays the results 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 of CTOT volatility 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 vulnerable 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, Leather Products, and Footwear) percentiles because of the negative values of EFD at which internal cash flows are greater than 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 major intermediate inputs do not necessarily suffer more from volatile CTOT. Sectors such as Food and Beverages (ISIC code 15); Wood Products (20); Paper and 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 losses.[20]

[20] See Appendix Table A2 for EFD and LIQ statistics across industries.

The establishment growth responses are shown in the second row. As expected, exit is significantly associated with CTOT volatility only in financially fragile 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. Labor employment deteriorates more in industries with higher financing needs in response to increasing CTOT volatility.

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

From the last row, we observe that CTOT volatility 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 results in Table 6.

4. Local projection 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 30 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:

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

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

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, …, H; $\Delta_h \boldsymbol{z}_{ij,t-1} = z_{ij,t+h} - z_{ij,t-1}$ 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. Here, CTOT volatility, σ_{jt}^{CTOT}, is standardized to facilitate its interpretation.[21] Standard errors are clustered at the country-industry level.

Fig. 4 illustrates the local projection coefficients, α_1^h's and β_1^h's, in Eqs. (4) and (5) with their 95 percent confidence intervals. Panel A displays the results 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 0.4-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 effect 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 1.3-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 by up to about 0.6 percent by year 5 but gradually rebounds afterward, making the impulse responses statistically indifferent from zero after 10 years.

[21] 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.

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 employment for less dependent sectors after 25 years, the cumulative decline for more dependent sectors is much larger, reaching 2 percent by year 30.

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 more externally dependent industries and about 20 years in less dependent sectors. These response patterns indicate that capital accumulation is unlikely to be the main channel driving the negative output responses in industries with EFD.

The dynamic responses of TFP are summarized in the last row. Not surprisingly, the response paths in more externally dependent industries show about a 0.3-percent initial contraction of TFP, followed by sustained negative swings over the next 30 years. On the other hand, the cumulative paths of TFP in the less dependent industries are mostly insignificant at least 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. 5, along with the 95 percent confidence intervals. Panel A shows the results 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 see that a one-standard-deviation shock to CTOT volatility decreases the value-added of industries with low available liquidity by 1.3 percent upon impact, followed by relatively persistent adverse effects that peak at 2.7 percent after 15 years.

The impulse responses are not statistically different from zero after 20 years. In contrast, the cumulative responses for liquidity-abundant industries stay positive for most projection horizons.

The cumulative effects on employment, summarized in the second row, reflect a more detrimental impact in industries with high LIQ than in those with low LIQ, although they are not highly significant. Indeed, liquidity-sufficient industries experience only minor employment responses, which are indistinguishably different from zero for most horizons.

Reviewing the charts in the third row, we verify that there is a persistently negative impact of the CTOT volatility shock on the physical capital in liquidity-scarce industries, with a substantial cumulative drop of up to 7 percent by year 20. Liquidity-abundant industries are much less affected, with the effects statistically insignificant over the entire response path.

From the last row, we find that the 1.5-percent initial drop in TFP in high-LIQ industries appears to be short-lived; the cumulative response returns to zero after 10 years. In addition, there is virtually no evidence of a negative and persistent TFP effect of CTOT volatility in low-LIQ industries.

In sum, the destructive output effect of CTOT uncertainty is expected to continue in the long run, with the effect being more persistent in industries with high dependence on external finance relative to those with liquidity needs. Output and employment in sectors with high EFD do not fully recover even after 30 years. The underlying driver of this prolonged effect is 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

This paper is motivated by two observations. First, CTOT is usually more volatile than manufacturing TOT. Second, sizeable CTOT volatility is associated with a high cost of capital. Guided by these two observations, we hypothesize that volatile CTOT might play a critical role in hampering the long-run growth of industrial sectors in commodity-exporting countries. We test this hypothesis using sector-level panel data over the past five decades.

We find that CTOT volatility is negatively related to the growth of credit-constrained manufacturing sectors in commodity-rich economies. We then go on to identify underlying channels. The destructive effect operates through the reduced firm entry and lower TFP in industries reliant on external finance for long-term investments and lower capital accumulation in industries with high liquidity needs. Due to the adverse TFP effect, the sectoral decline appears to be more persistent in industries 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 negative 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 local financial market through financial development, active management of international reserves or sovereign wealth funds, and effective macroprudential regulations could be policy options to mitigate the harmful growth effects of CTOT volatility.

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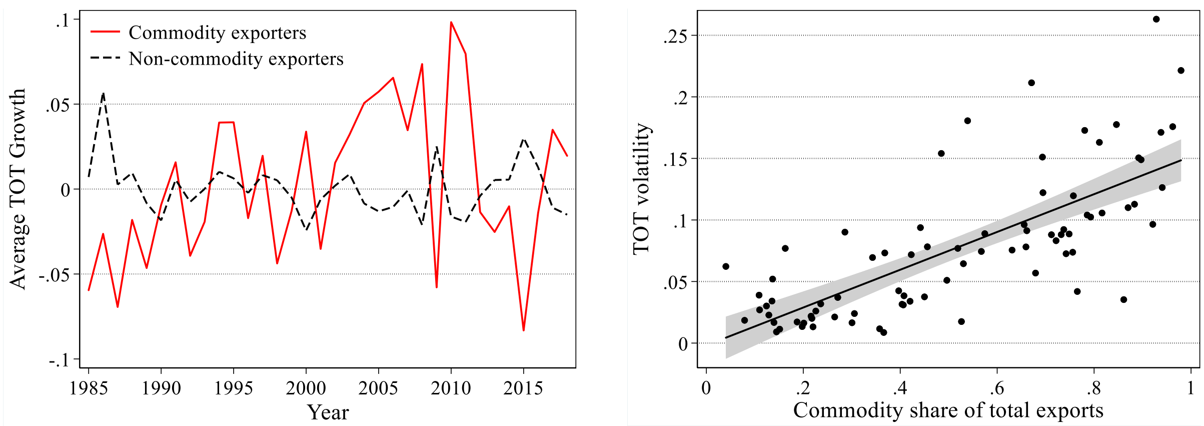


A. TOT growth across country groups   B. Increasing TOT volatility with commodity exports

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

Notes: TOT growth is defined as the logarithmic annual differences in terms of trade in each country and volatility as the moving five-year standard deviations (in t – 4 through t) of TOT growth. See Appendix Table A1 for a full set of countries considered in this figure. In Panel A, commodity exporters are countries for which primary commodities represent more than 50% 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. In Panel B, the figure depicts the OLS fitted linear relation between commodity share of total exports and TOT volatility, with the 95% confidence interval shown in grey. Data source: OECD and the World Bank's World Development Indicator.

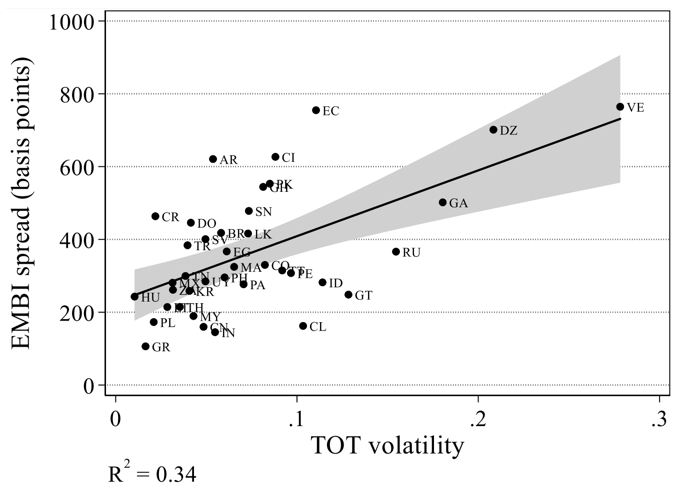
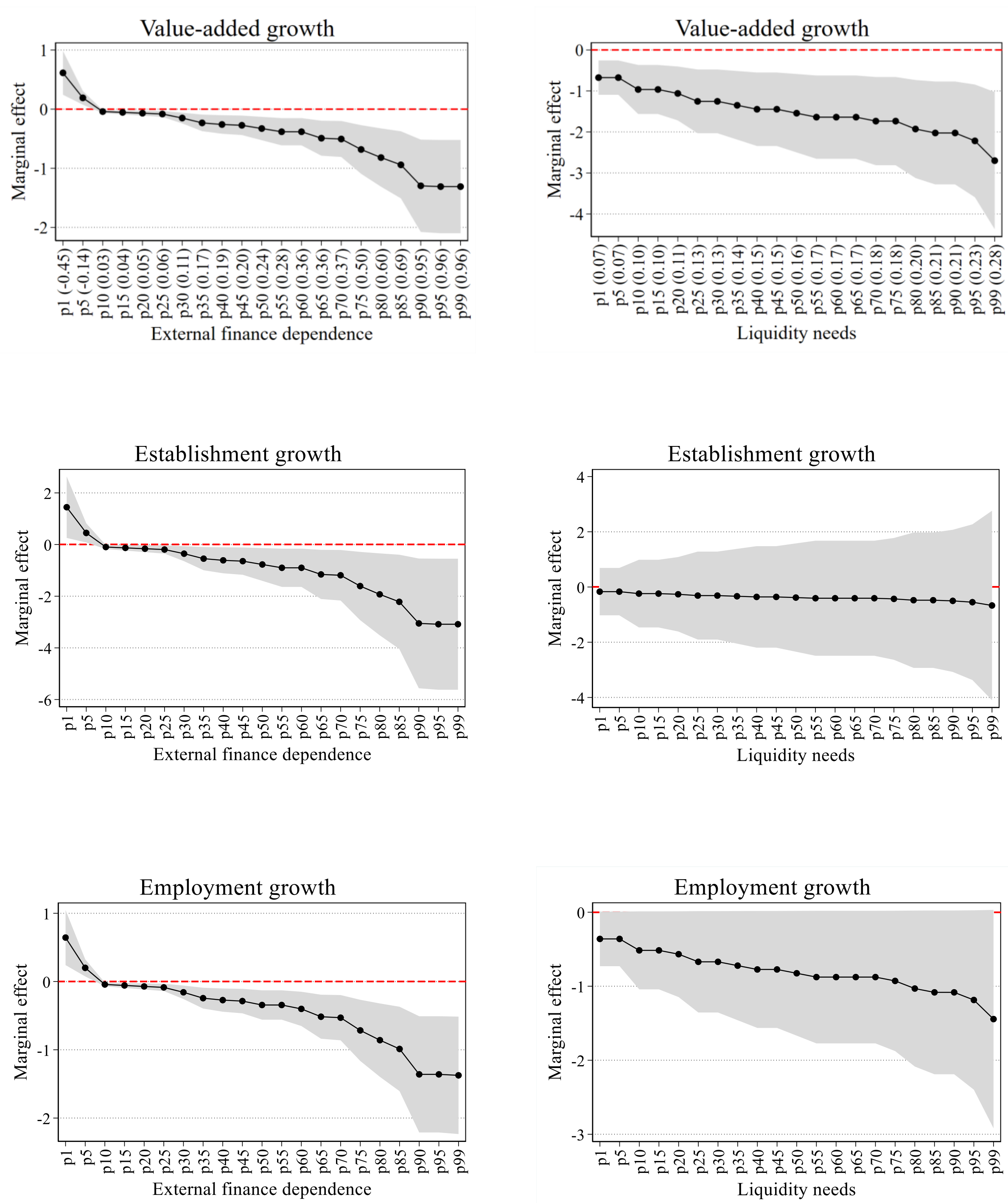


Fig. 2. TOT volatility and sovereign spread, 1997–2018.

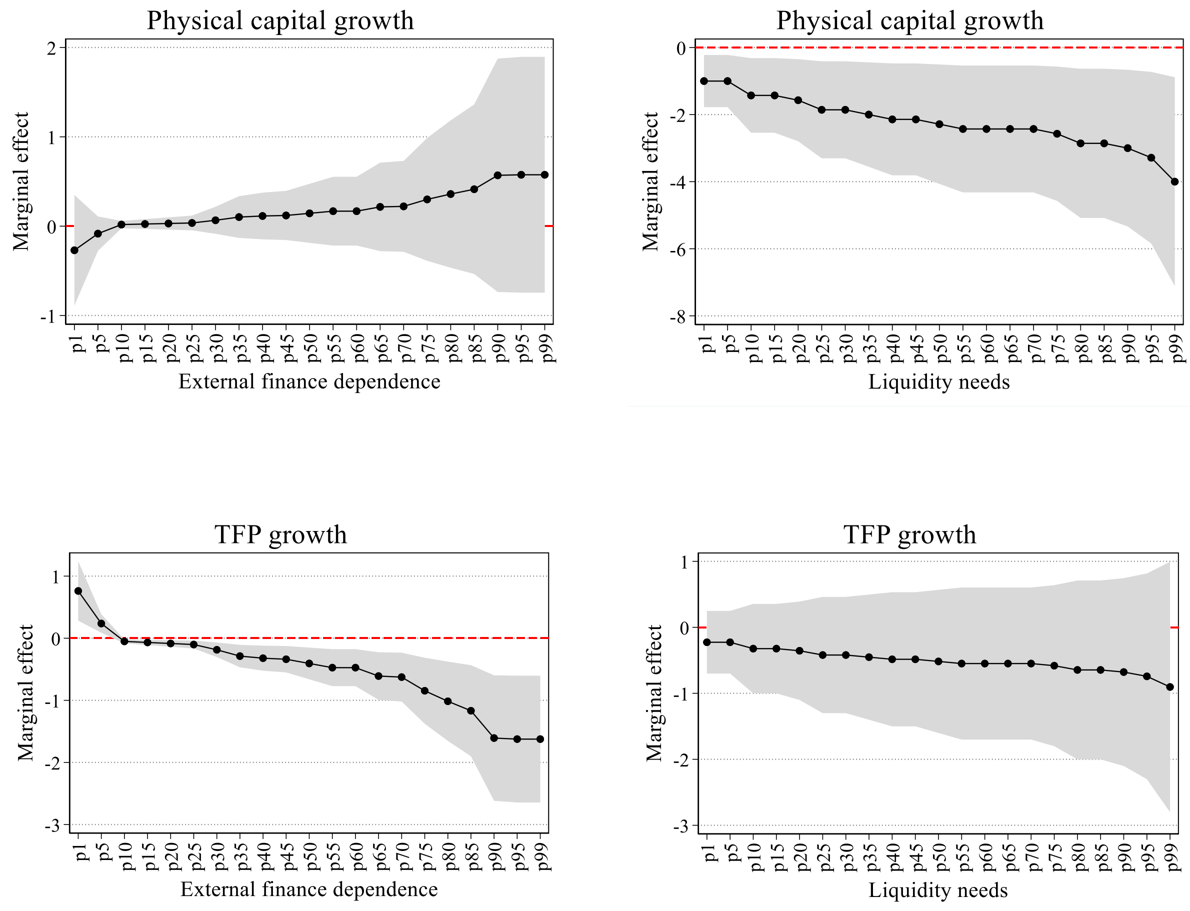
Notes: The figure depicts the OLS fitted linear relation between TOT volatility and EMBI spread, with the 95% confidence interval shown in grey. TOT volatility is defined as the moving five-year standard deviations (in t – 4 through t) of TOT growth. The labels in the figure correspond to the two-digit ISO code of each country. Due to the data availability of EMBI spread, the figure relies on 39 sample countries, including Algeria, Argentina, Brazil, Chile, China, Colombia, Costa Rica, Côte d'Ivoire, the Dominican Republic, Ecuador, Egypt, El Salvador, Gabon, Ghana, Greece, Guatemala, Hungary, India, Indonesia, Korea, Lithuania, Malaysia, Mexico, Morocco, Pakistan, Panama, Peru, the Philippines, Poland, Russia, Senegal, South Africa, Sri Lanka, Thailand, Trinidad and Tobago, Tunisia, Turkey, Uruguay, and Venezuela. Data source: OECD and the World Bank's World Development Indicator and Global Economic Monitor.



A. Marginal effects as a function of EFD

B. Marginal effects as a function of LIQ

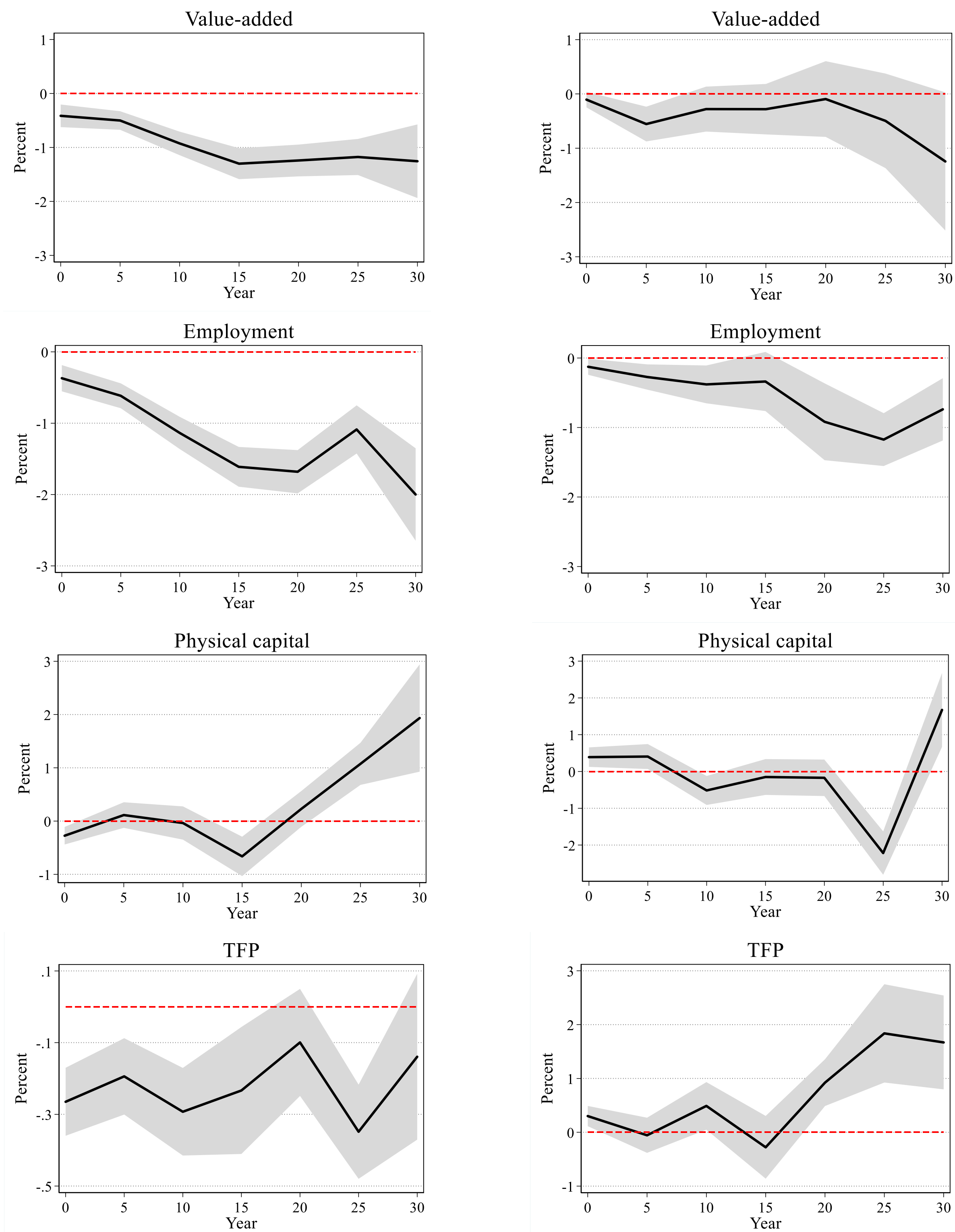
Fig. 3. Marginal effects of an increase in CTOT volatility. The 90% confidence interval is shown in grey.



A. Marginal effects as a function of EFD

B. Marginal effects as a function of LIQ

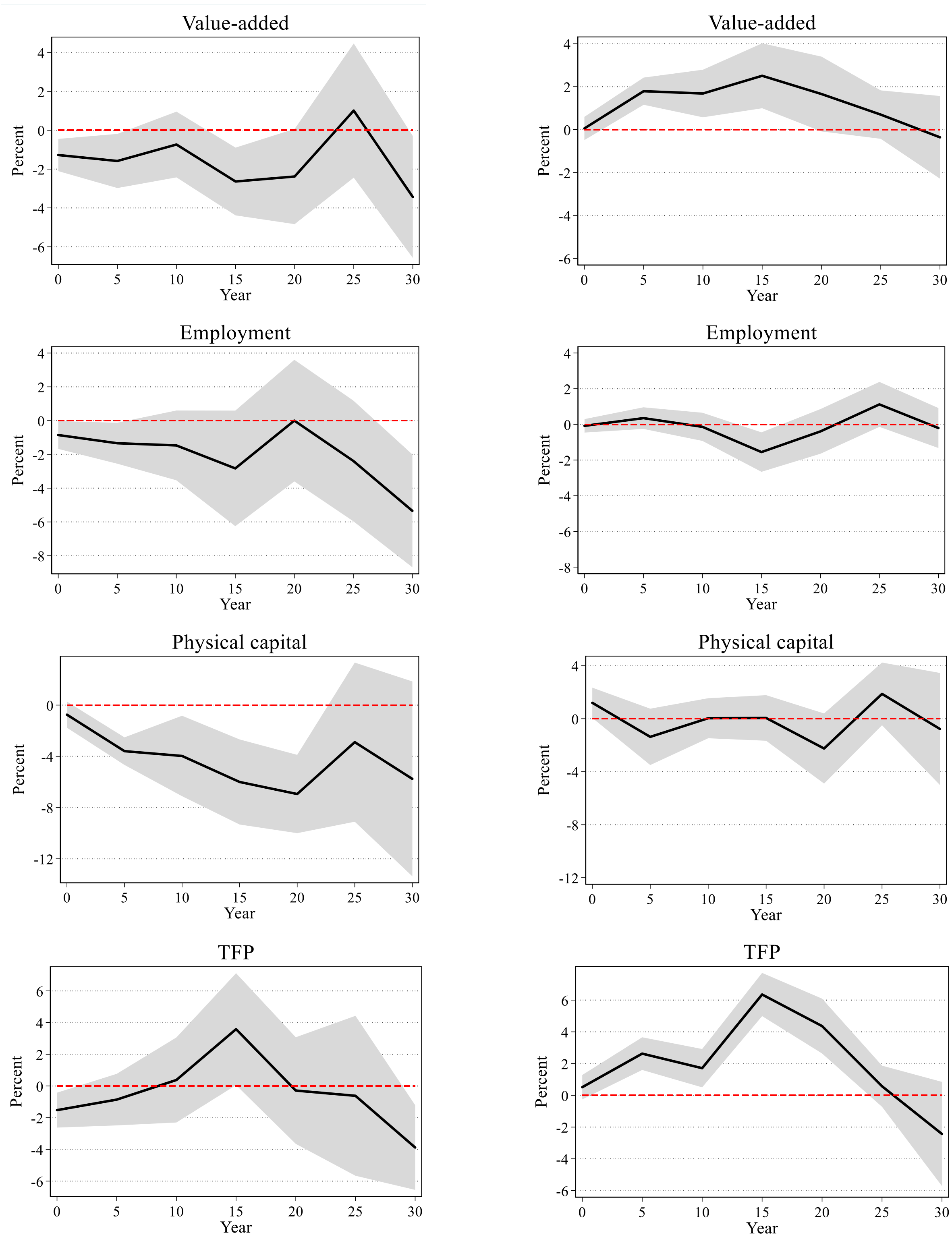
Fig. 3. (continued) Marginal effects of an increase in CTOT volatility. The 90% confidence interval is shown in grey.



A. Top quartile of EFD

B. Bottom quartile of EFD

Fig. 4. Cumulative effects of a one-S.D. shock to CTOT volatility. The 95% confidence interval is shown in grey.



A. Top quartile of LIQ

B. Bottom quartile of LIQ

Fig. 5. Cumulative effects of a one-S.D. shock to CTOT volatility. The 95% confidence interval is shown in grey.

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)
No. 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		
Differential in value-added growth (ppt)	-1.08	-0.92	-0.36	-0.43	-1.68	-1.35	

Notes: This table presents estimates of Eq. (1) based on the sector-level semi-decade data. All specifications include country-time fixed effects, sector-time fixed effects, and country-sector fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the country-sector level. *, **, ***: Statistically different from zero with 90%, 95%, and 99% certainty, respectively. The differential in value-added growth is calculated by $\hat{\alpha}_1 \times \text{S.D.}(\sigma_{jt}^{CTOT}) \times (FIN_{\text{p75}} - FIN_{\text{p25}})$, 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								
	CTOT decomposed using the HP filter				CTOT decomposed using the Hamilton filter			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CTOT volatility × External dependence	**-0.017****		**-0.016****		**-0.007***		**-0.008***	
	(0.008)		(0.008)		(0.004)		(0.005)	
CTOT volatility × Liquidity needs		**-0.136*****		**-0.138*****		**-0.053***		**-0.065****
		(0.049)		(0.050)		(0.029)		(0.032)
CTOT growth × External dependence			0.295				-0.147	
			(0.546)				(0.499)	
CTOT growth × Liquidity needs				-0.663				-4.559
				(3.228)				(3.182)
Initial industry share	-0.090*	-0.091*	-0.090*	-0.091*	-0.091*	-0.091*	-0.091*	-0.091*
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)
Observations	6,729	6,729	6,729	6,729	6,729	6,729	6,729	6,729
R-squared	0.451	0.451	0.451	0.451	0.450	0.451	0.450	0.451
Differential in value-added growth (ppt)	-1.04	-0.95	-0.96	-0.96	-0.71	-0.61	-0.82	-0.77

Notes: This table presents estimates of Eq. (2) based on the sector-level semi-decade data. We 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 country-sector fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the country-sector level. *, **, ***: Statistically different from zero with 90%, 95%, and 99% certainty, respectively. When the CTOT growth variable is present in the estimation, the differential in value-added growth is calculated by $\left[\left\{\hat{\alpha}_0 \times \text{mean}\left(g_{jt}^{CTOT}\right)\right\} + \left\{\hat{\alpha}_1 \times \text{S.D.}\left(\sigma_{jt}^{CTOT}\right)\right\}\right] \times \left(FIN_{\text{p75}} - FIN_{\text{p25}}\right)$, where FIN is either external dependence or liquidity needs.

Table 3
CTOT volatility and industry growth: alternative CTOT indices.

Dependent variable: Value-added growth				
	X = $\mathrm{CTOT}^{\mathrm{comtrade}}$		X = $\mathrm{CTOT}^{\mathrm{rolling}}$	
	(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
Differential in value-added growth (ppt)	-1.02	-0.81	-0.98	-0.92

Notes: $\mathrm{CTOT}^{\mathrm{comtrade}}$ is a commodity trade–weighted CTOT measure and $\mathrm{CTOT}^{\mathrm{rolling}}$ is a time-varying weight–based CTOT measure. This table presents estimates of Eq. (1) based on the sector-level semi-decade data. All specifications include country-time fixed effects, sector-time fixed effects, and country-sector fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the country-sector level. *, **, ***: Statistically different from zero with 90%, 95%, and 99% certainty, respectively. The differential in value-added growth is calculated by $\hat{\alpha}_1 \times \mathrm{S.D.}\left(\sigma_{jt}^{CTOT}\right) \times \left(FIN_{\mathrm{p75}} - FIN_{\mathrm{p25}}\right)$, where FIN is either external dependence or liquidity needs.

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
Differential in value-added growth (ppt)	-1.07	-0.80
	Panel B. Countries with MVA/GDP > 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)
No. countries	23	23
Observations	3,259	3,259
R-squared	0.425	0.425
Differential in value-added growth (ppt)	-1.51	-1.00

Notes: This table presents estimates of Eq. (1) based on the sector-level semi-decade data. All specifications include country-time fixed effects, sector-time fixed effects, and country-sector fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the country-sector level. †, *, **: Statistically different from zero with 85%, 90%, and 95% certainty, respectively. The differential in value-added growth is calculated by $\hat{\alpha}_1 \times \text{S.D.}\left(\sigma_{jt}^{CTOT}\right) \times \left(FIN_{\text{p75}} - FIN_{\text{p25}}\right)$, where FIN is external dependence, liquidity needs, asset tangibility, or R&D intensity.

Table 5
Operating channels of the CTOT volatility effects: commodity export vs. import prices.

Dependent variable: Value-added growth	X = CXP		X = CMP	
	(1)	(2)	(3)	(4)
X volatility × External dependence	**-1.207*****		**0.233**	
	(0.466)		(1.395)	
X volatility × Liquidity needs		**-7.606****		**-0.253**
		(3.268)		(8.162)
Initial industry share	-0.090*	-0.091*	-0.093*	-0.093*
	(0.047)	(0.047)	(0.047)	(0.047)
Observations	6,729	6,729	6,729	6,729
R-squared	0.451	0.451	0.450	0.450
Differential in value-added growth (ppt)	-1.28	-0.91	0.12	-0.02

Notes: CXP is a commodity export price index and CMP is a commodity import price index. This table presents estimates of Eq. (1) based on the sector-level semi-decade data. All specifications include country-time fixed effects, sector-time fixed effects, and country-sector fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the country-sector level. *, **, ***: Statistically different from zero with 90%, 95%, and 99% certainty, respectively. The differential in value-added growth is calculated by $\hat{\alpha}_1 \times$ S.D.$\left(\sigma_{jt}^{CTOT}\right) \times \left(FIN_{\mathrm{p75}} - FIN_{\mathrm{p25}}\right)$, where FIN is either external dependence or liquidity needs.

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
Differential 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
Differential in factor growth (ppt)	-0.33	-0.72	-2.00	-0.45

Notes: This table presents estimates of Eq. (3) based on the sector-level semi-decade data. All specifications include country-time fixed effects, sector-time fixed effects, and country-sector fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the country-sector level. †, **, ***: Statistically different from zero with 85%, 95%, and 99% certainty, respectively. The differential in factor growth is calculated by $\hat{\beta}_1 \times \text{S.D.}\left(\sigma_{jt}^{CTOT}\right) \times \left(FIN_{\text{p75}} - FIN_{\text{p25}}\right)$, where FIN is either external dependence or liquidity needs.

Appendix

Table A1

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 A1 (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 A2
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), Raddatz (2006), and Samaniego and Sun (2015).

Table A3
CTOT volatility and industry growth: fuel exporters.

Dependent variable: Value-added growth		
	(1)	(2)
CTOT volatility × External dependence	**-1.151**	
	(0.846)	
CTOT volatility × Liquidity needs		**-11.015***
		(5.958)
Initial industry share	-0.026	-0.022
	(0.078)	(0.079)
No. countries	14	14
Observations	1,821	1,821
R-squared	0.533	0.534
Average value-added growth (%)	4.45	
Differential in value-added growth (ppt)	-2.03	-2.20

Notes: This table presents estimates of Eq. (1) based on the sector-level semi-decade data. All specifications include country-time fixed effects, sector-time fixed effects, and country-sector fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the country-sector level. *, **, ***: Statistically different from zero with 90%, 95%, and 99% certainty, respectively. The differential in value-added growth is calculated by $\hat{\alpha}_1 \times \text{S.D.}\left(\sigma_{jt}^{CTOT}\right) \times \left(FIN_{\text{p75}} - FIN_{\text{p25}}\right)$, where FIN is either external dependence or liquidity needs.

Table A4
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
Differential in value-added growth (ppt)	-1.68	-1.35

Notes: This table presents estimates of Eq. (2) based on the sector-level semi-decade data. All specifications include country-time fixed effects, sector-time fixed effects, and country-sector fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the country-sector level. *, **, ***: Statistically different from zero with 90%, 95%, and 99% certainty, respectively. When the CTOT growth variable is present in the estimation, the differential in value-added growth is calculated by $\left[\left\{\hat{\alpha}_0 \times \text{mean}\left(g_{jt}^{CTOT}\right)\right\} + \left\{\hat{\alpha}_1 \times \text{S.D.}\left(\sigma_{jt}^{CTOT}\right)\right\}\right] \times \left(FIN_{\text{p75}} - FIN_{\text{p25}}\right)$, where FIN is either external dependence or liquidity needs.

Table A5
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
Differential in factor 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
Differential in factor growth (ppt)	-2.63

Notes: This table presents estimates of Eq. (3) based on the sector-level semi-decade data, with the growth of real investment as a dependent variable. All specifications include country-time fixed effects, sector-time fixed effects, and country-sector fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the country-sector level. **: Statistically different from zero with 95% certainty. The differential in factor growth is calculated by $\hat{\beta}_1 \times \text{S.D.}\left(\sigma_{jt}^{CTOT}\right) \times \left(FIN_{\text{p75}} - FIN_{\text{p25}}\right)$, where FIN is either external dependence or liquidity needs.

Table A6
Operating channels of the CTOT volatility effects: export growth.

Dependent variable:	Growth of export/output		Growth of export/value-added	
	(1)	(2)	(3)	(4)
CTOT volatility × External dependence	**0.011***		**0.020**	
	(0.006)		(0.021)	
CTOT volatility × Liquidity needs		**0.078**		**0.209**
		(0.069)		(0.161)
Initial industry share	-0.001	-0.001	-0.00002	-0.0001
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	3,307	3,307	3,307	3,307
R-squared	0.295	0.295	0.241	0.241

Notes: This table presents estimates of Eq. (3) based on the sector-level semi-decade data, with export growth as a dependent variable. All specifications include country-time fixed effects, sector-time fixed effects, and country-sector fixed effects, but their coefficient estimates are omitted to save space. Standard errors in parentheses are clustered at the country-sector level. The information for sector-specific exports between 1988 and 2018 is extracted from the World Bank's World Integrated Trade Solution database. *: Statistically different from zero with 90% certainty.