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Heterogenous Gains from Countercyclical Fiscal Policy: New Evidence from International Industry-level Data

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Abstract

Empirical evidence to date suggests a positive relationship between fiscal policy countercyclicality and growth. But do all industries gain equally from countercyclical fiscal policy? What are the channels through which countercyclical fiscal policy affects industry-level growth? We answer these questions by applying a difference-in-difference approach to an unbalanced panel of 22 manufacturing industries for 55 countries—including both advanced and developing economies—during the period 1970-2014. Among the nine industry characteristics that we consider based on different theoretical channels, we find that the credit constraint channel—proxied by asset fixity—identifies the best transmission mechanism through which countercyclical fiscal policy enhances growth. This channel becomes stronger during periods of weak economic activity when credit constraints are more likely to bind.

Keywords: countercyclical fiscal policy; time-varying coefficients; industry growth, technologies of production, credit constraints

JEL codes: E62; H50; H60.

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I. INTRODUCTION

The growth slowdown since the Global Financial Crisis across the world, including both advanced and developing economies, has triggered a debate on whether this phenomenon would become a new normal (IMF, 2015). While the binding zero-lower-bound in advanced economies stimulated a stream of research on the role of fiscal policy as an alternative policy tool (Christiano et al., 2011; Eggertsson, 2011; DeLong and Summers, 2012), fiscal policy has also become increasingly constrained due to high debt-to-GDP ratios (Teles and Mussolini, 2014). Against this background, there has been a renewed interest in examining how countercyclical fiscal policy can spur growth.

Countercyclical fiscal policy can enhance growth by reducing the volatility of business cycles or uncertainty of the aggregate economy to the extent that volatility (uncertainty) and growth are inversely related (see, Ramey and Ramey, 1995; Acemoglu and Zilibotti, 1997; Martin and Rogers, 1997).[1]

If investors are risk-averse or financial frictions exist, the negative effect of volatility on growth could be amplified via an increased cost of external financing or a decline in funds available to the economy.[2] For example, Aghion et al. (2010) propose credit constraints as a key channel through which fiscal policy countercyclicality affects long-run growth: the countercyclical fiscal policy that reduces aggregate volatility would have larger effects on productivity-enhancing investment in more credit-constrained industries, particularly in bad times—when borrowing constraints are more likely to be binding. Aghion et al. (2014) and Furceri and Jalles (2018) empirically confirm these predictions for advanced economies using the Rajan and Zingales' (1998) difference-in-difference methodology.

However, credit constraints may not be the only channel through which countercyclical fiscal policy affects growth. For example, the real option values theory (Bernanke, 1983; Bloom, 2009) would predict that industries that are subject to higher irreversibility or

[1] See Bakas et al. (2018) for a comprehensive meta analysis of the relationship between volatility and growth.

[2] Recent studies have highlighted the role of financial constraints in amplifying the adverse effect of uncertainty shocks on the economy (Baum et al., 2010; Christiano et al., 2014; Samaniego and Sun, 2016; Alfaro et al., 2018; Choi et al., 2018).

adjustment costs benefit more from countercyclical fiscal policy. In contrast, the so-called Oi-Hartman-Abel effect (convexity channel) would predict that volatility (i.e., less fiscal policy countercyclicality) can foster growth if the economy is characterized by perfect competition, a constant-returns-to-scale technology, and asymmetric adjustment costs. Thus, identifying the main channel through which countercyclical fiscal policy enhances growth is ultimately an empirical question.

This paper contributes to the literature by extending existing studies along several dimensions. First, it considers a comprehensive set of industry-specific characteristics. We choose nine industry-specific characteristics guided by three theoretical channels (credit constraints, real options, and convexity) explaining the link between volatility and growth.[3] Second, we extend Aghion et al. (2014) by constructing a time-varying measure of fiscal policy countercyclicality for each country in the sample, which allows us to consider a three-dimensional (country-industry-year) panel. Thus, our estimates capture the within-variation of the fiscal policy countercyclicality over time, thereby identifying cyclical sensitivity of industry-level growth to country-level fiscal policy countercyclicality. The cyclicality of fiscal policy has typically been captured by a unique time-invariant parameter in previous studies using the Rajan and Zingales' (1998) methodology, making it difficult to discern the effects of countercyclical fiscal policy from unobserved cross-country heterogeneity.

Third, this paper extends the analysis to a broad set of developing economies. To the extent to which fiscal policy in many developing economies has escaped from the procyclicality trap and has become countercyclical recently (Frankel et al., 2013), a study of these economies provides an additional opportunity to examine the causal link between countercyclical fiscal policy and growth. Lastly, it examines the effects of fiscal policy countercyclicality on the sources of growth: labor, capital, and productivity. This decomposition allows for a more meaningful evaluation of the growth effect of the fiscal policy compared to previous studies.

[3] As discussed by Samaniego and Sun (2016), to the extent to which certain industry characteristics interact systematically with output volatility or uncertainty, countercyclical fiscal policy may have differential growth effects across industries depending on the differences in these characteristics.

We apply Rajan and Zingales' (1998) difference-in-difference methodology to an unbalanced panel of 22 manufacturing industries for 55 advanced and developing economies from 1970 to 2014.[4] While the original Rajan and Zingales' (1998) approach does not consider a time dimension, the advantage of having a three-dimensional (i industries, c countries, and t periods) panel dataset is twofold:[5]

First, it allows controlling for various unobserved factors by including country-time (c, t), industry-country (i, c), and industry-time (i, t) fixed effects. The inclusion of country-time (c, t) fixed effect is particularly important, as it allows controlling for any unobserved cross-country heterogeneity in the macroeconomic shocks that affect industry growth. In a pure cross-country analysis, this control would not be possible, leaving open the possibility that the impact attributed to fiscal policy countercyclicality would be due to other unobserved macro shocks.

Second, it mitigates concerns about reverse causality. While it is typically difficult to identify causal effects using aggregate data, it is much more likely that fiscal policy countercyclicality affects industry-level outcomes than the other way around. This is because when one controls for country-time fixed effect—and, therefore, aggregate growth, reverse causality implies that differences in growth across sectors influence fiscal policy countercyclicality at the aggregate level. Moreover, our main independent variable is the interaction between fiscal policy countercyclicality and industry-specific technological characteristics obtained from the U.S. firm-level data, which makes it even less plausible that causality runs from industry-level growth to this composite variable.

Our main findings indicate that there exist heterogeneous gains across industries from countercyclical fiscal policy depending on their intrinsic characteristics. The credit constraint channel is the most robust transmission channel explaining the effect of countercyclical fiscal

[4] Industry-level data from many developing economies are only available from the 1990s.

[5] Although Braun and Larrain (2005) is the first one to exploit the time dimension using the Rajan and Zingales' (1998) approach, they do not use a complete set of fixed effects. Instead, we follow Dell'Ariccia et al. (2008) and Samaniego and Sun (2015) and use three kinds of two-way fixed effects, which mitigates endogeneity concerns substantially.

policy on industry growth, followed by the real options channel to a lesser extent. In contrast, we do not find strong empirical support for the convexity channel.

We find robust evidence that industries that have higher external financial dependence and fewer tangible assets as collateral benefit more from countercyclical fiscal policy. We also find that industries that are subject to higher irreversibility or higher cost of waiting for the resolution of uncertainty benefit more from countercyclical fiscal policy, which is consistent with the prediction of the real options channel. To the extent to which our finding answers which kind of industries are expected to gain more by escaping from the procyclicality trap, it also sheds light on economy-wide gains from enhancing fiscal policy countercyclicality. For example, countercyclical fiscal policy is expected to be more growth-enhancing in an economy with a larger share of credit-constrained industries.

While the effects of countercyclical fiscal policy are typically larger in developing economies, they are less precisely estimated in these countries—possibly due to poor data quality and shorter time series. Finally, the differential effect of countercyclical fiscal policy tends to be larger during recessions—this is particularly true in the case of financially constrained industries. These results are robust to alternative measures of industry growth and fiscal policy countercyclicality as well as to the inclusion of the interactions between various macroeconomic variables (that are known to be associated with fiscal policy countercyclicality) and the industry technological characteristics.

The remainder of the paper is organized as follows. Section II outlines the theoretical channels through which countercyclical fiscal policy has differential effects on industry growth. Section III develops the econometric methodology to test the main hypotheses. Section IV describes the underlying country- and industry-level data, including industry-specific proxies for the theoretical mechanisms, used in the empirical analysis. Section V presents the main results and a battery of robustness exercises. The last section concludes and provides some policy implications.

II. COUNTERCYCLICAL FISCAL POLICY AND GROWTH: THEORETICAL ARGUMENTS

What are the potential channels through which countercyclical fiscal policy can have differential effects on industry growth? We summarize three theoretical arguments (credit constraint, real options, and convexity) based on a group of existing theoretical studies, which will be empirically tested by employing the nine industry-specific technological characteristics. See Appendix A for the analytical derivation of the testable hypotheses.

Credit constraint. Aghion et al. (2014) argue that a larger stabilizing role attributed to fiscal policy affects industry growth positively, and it is likely to operate by relaxing credit constraints. This mechanism implies that countercyclical fiscal policy would increase growth, particularly in industries that are more financially constrained. The intuition of the model is that the precautionary motive of credit-constrained firms results in a sub-optimal level of productivity-enhancing investment when the future economic condition is volatile.

Suppose there are two types of investment projects (long- vs. short-term), where the former is riskier but more productive than the latter. If a firm is not constrained (can borrow freely from an outside lender up to the present discounted value of its long-term project when hit by a liquidity shock), it will invest in each project at the optimal scale. However, a credit-constrained firm which cannot borrow from an outside lender needs to generate its cash flows via short-term investment to cope with liquidity risk, thus ending up investing at a sub-optimal level. As a result, a decline in the volatility of future productivity shocks achieved via more countercyclical fiscal policy mitigates this problem by encouraging constrained firms to engage in long-term investment.[6] This growth-enhancing effect is expected to be stronger during recessions when financial constraints are more likely binding. The existing literature has proxied the degree of credit constraints by external financial dependence (Rajan and Zingales, 1998) and asset fixity (Hart and Moore, 1994).

[6] With a mean preserving spread in the distribution of a productivity shock, long-term investment is less likely to be successful, making a constrained firm effectively risk averse.

Real options. This theory (e.g., Bernanke, 1983) also predicts a positive relationship between fiscal policy countercyclicality and growth, especially for industries with higher irreversibility or higher cost of waiting for the resolution of uncertainty. The real options channel relies on the irreversibility in firms' investment or hiring decisions. Intuitively, when economic conditions are more uncertain or volatile, firms become cautious and pursue "wait-and-see" strategies by letting the economic environment unfold before making decisions. In the short run, this wait-and-see strategy, which is optimal for individual firms, could cause a recession that is followed by a rebound once uncertainty is resolved (Bloom, 2009). When their investment or production decision is more irreversible, the adverse effect on growth from the volatile environment will also be larger. Thus, countercyclical fiscal policy is expected to enhance growth, particularly for industries subject to higher irreversibility, proxied by input specificity and investment lumpiness.

When waiting is costly, firms are forced to make suboptimal decisions in the form of either premature investment in a new project or premature exit (Samaniego and Sun, 2019), which also hampers growth. For example, when capital depreciates fast, not exercising the option results in a rapid decline in the capital stock, and therefore it is more costly to wait in such industries. As a result, industries subject to a higher cost of waiting are expected to gain more from a stable environment achieved by countercyclical fiscal policy. We proxy the cost of waiting by physical and economic depreciation.

Convexity. Countercyclical fiscal policy may reduce growth if growth options or the so-called Oi-Hartman-Abel effect are the dominant force.[7] If firms can readily respond to booms (downturns) by increasing (decreasing) their inputs of production, they can benefit from a more volatile economic environment. Without any irreversibility or adjustment costs, firms' profit function becomes convex in the size of underlying shocks, so firms act as if they are risk-lovers.

According to this theoretical mechanism, countercyclical fiscal policy is expected to reduce growth, especially in industries with more flexibility in their investment and hiring decisions, which can exploit upside risk from the volatile environment. For example, if labor

[7] See Bloom (2014) for further details on how these channels shape the relationship between uncertainty and growth.

is more readily adjustable than capital in response to a shock, labor-intensive industries are expected to grow slower than capital-intensive industries when fiscal policy countercyclicality increases, everything else equal. Following the literature, we gauge the degree of "convexity" using labor intensity (Lee and Shin, 2000) and R&D intensity (Weeds, 2002).

The left panel of Table 1 summarizes the different theoretical predictions on the interaction between fiscal policy countercyclicality and each industry-specific characteristic. While the credit constraint channel and the real options channel are not contradictory to each other, the convexity channel often predicts an opposite sign of the interaction effects from others. For example, capital depreciation, labor intensity, and R&D intensity would have different interaction effects on industry growth depending on the underlying theoretical channels. Thus, we pay special attention to the internal consistency amongst the proposed channels when we discuss our estimation results.

III. METHODOLOGY

To assess the relevant channel of countercyclical fiscal policy effects on industry growth, we apply the methodology proposed by Rajan and Zingales (1998) to a three-dimensional panel setup. Specifically, the following specification is estimated for an unbalanced panel of 55 countries and 22 manufacturing industries over the period 1970-2014:

$$Y_{i,c,t} = \alpha_{i,c} + \alpha_{i,t} + \alpha_{c,t} + \beta X_i FC_{c,t} + \gamma Size_{i,c,t-1} + \varepsilon_{i,c,t}, \tag{1}$$

where i denotes industries, c countries, and t years. Y is a measure of industry growth; X is a measure of an industry characteristic for industry i; FC is our time-varying measure of fiscal policy countercyclicality for each country c; $\alpha_{i,c}$, $\alpha_{i,t}$, and $\alpha_{c,t}$ are industry-country, industry-time, and country-time fixed effects, respectively; $Size$ is the share of industry i in country c's total manufacturing sector value-added. Because the effect of the average size of each industry in a given country is already controlled for with the industry–country fixed effects, the coefficient of this variable captures the growth effects of abnormal industry size.

The most closely related papers to ours in terms of the empirical setup are Dell'Ariccia et al. (2008) and Samaniego and Sun (2015) that use a full set of these two-way fixed effects in the panel setup. The inclusion of these three types of fixed effects provides important advantages compared to the cross-country analysis: (i) industry-country fixed effects allow controlling for industry-specific factors, including for instance cross-country differences in the growth of certain sectors that could arise from differences in comparative advantages and the initial condition of a specific industry-country pair (i.e., controlling for catch-up effects); (ii) industry-time fixed effects allow controlling for any global-level variation common to each industry, such as an industry-specific demand shock or a commodity price shock; and (iii) country-time fixed effects allow controlling for any variation that is common to all sectors of a country's economy, including macroeconomic shocks. Thus, β captures the differential impact of industry characteristic X_i on industry growth when fiscal policy countercyclicality is high.

As discussed in the previous section, most of our industry characteristics are measured using only U.S. firm-level data. One potential problem with this approach is that U.S. industry characteristics may not be representative of the whole sample—that is, U.S. measures may be affected by its specific regulations or sectoral patterns. While this issue is unlikely to be important for advanced economies, extending it to developing economies requires caution. Nevertheless, using country-specific industry-level characteristics, even if such measures are available, does not necessarily improve identification. For example, it is plausible that growth in the textile industry in China systematically affects its own set of characteristics than the characteristics of the U.S. textile industry. It is important to note that U.S. measures of industry characteristics are assumed to represent technological characteristics in a frictionless environment, thereby serving as a conceptual benchmark for our analysis.

Following Dell'Ariccia et al. (2008), equation (1) is estimated using OLS—and standard errors are clustered by country and industry—as the inclusion of two-way fixed effects is likely to address the endogeneity concerns related to omitted variable bias.[8] It is important to note that reverse causality issues are unlikely. First, related to the measures of industry characteristics, it is hard to conceive that individual sectoral growth in other countries can influence the U.S. industry's characteristics. Second, it is even more unlikely that

[8] Our main findings are robust to clustering standard errors by country and year, using heteroskedasticity-autocorrelation robust standard errors, and Driscoll-Kraay standard errors (Driscoll and Kraay, 1998). See Table B.3 in Appendix for details.

individual sectoral growth can influence aggregate measures of fiscal policy countercyclicality. While, in principle, this could be the case if output growth would co-move across all sectors, we address this concern by including industry-country fixed effects. In other words, claiming reverse causality is equivalent to arguing that differences in growth across sectors lead to changes in the degree of fiscal policy countercyclicality—which we believe to be unlikely.

However, a remaining possible concern in estimating equation (1) with OLS is that other macroeconomic variables could affect sectoral output growth when interacted with industries' certain characteristics, and they are also correlated with our fiscal policy countercyclicality measure. For example, to the extent to which fiscal policy responds to underlying economic conditions in a systematic way, our findings might have simply captured the well-known differential industry-level growth during recessions (Braun and Larrain, 2005; Samaniego and Sun, 2015). This concern could also be the case for financial development—the original channel assessed by Rajan and Zingales (1998)—and for inflation and the size of government. We address this issue in the subsection devoted to robustness checks.

IV. Data

A. Industry technological characteristics

In this section, we lay out various industry technological characteristics that are expected to interact with fiscal policy countercyclicality through the theoretical channels outlined above and describe how we measure them using U.S. data.

External financial dependence (EFD). External financial dependence proxies the degree of credit constraints, and this is the main channel of countercyclical fiscal policy considered in the literature (Aghion et al., 2014; Furceri and Jalles, 2018). Following Rajan and Zingales (1998), the degree of dependence on external finance in each industry is measured as the median across all U.S. firms, in each industry, of the ratio of total capital expenditures minus the current cash flow to total capital expenditures.[9] According to the credit constraint channel,

[9] The updated data have been kindly provided by Hui Tong. For details, see Tong and Wei (2011).

we expect a positive sign on the interaction term between the degree of external finance and our time-varying measure of fiscal policy countercyclicality.

Asset fixity (FIX). Similar to external financial dependence, asset fixity measures the degree of credit constraints faced by firms. The reason is that non-fixed assets are typically intangible, and therefore it is harder to use them as collateral (Hart and Moore, 1994). Thus, an industry with less tangible capital has more difficulty in raising external funds. Consequently, an increase in the fiscal policy countercyclicality would be more beneficial to such an industry. We take industry-level asset fixity values from Samaniego and Sun (2015) that are measured by the ratio of fixed assets to total assets using the Compustat data.

Input specificity (SPEC) and investment lumpiness (LMP). Both input specificity and investment lumpiness measure the degree of irreversibility. To the extent to which a given industry relies on specific inputs, resale prices of input will be lower than its purchase prices (Abel and Eberly, 1996). Thus, it will be more expensive for firms to adjust when economic conditions change. As a result, firms will adjust capital in a "lumpy" manner (Caballero et al., 1999). Hart and Moore (1994) also argue that specific inputs are less suitable as collateral because the secondary market for such an asset is likely to be illiquid; therefore, transferring such inputs is more costly. Thus, countercyclical fiscal policy would be more beneficial in industries characterized by greater input specificity or investment lumpiness, according to both the credit constraint and real options channels. Nunn (2007) measures the relationship-specific input usage with the proportion of inputs that are not sold at an organized exchange nor reference-priced in a trade publication. The lumpiness of investment is defined as the average number of investment spikes per firm during a decade in each industry, computed using Compustat data.[10] Both are taken from Samaniego and Sun (2015).

Capital depreciation (DEP). Capital depreciation can be used to test the relevance of all three theoretical channels described above. First, more durable capital stocks tend to be more readily collateralizable, and industries with durable capital stocks require less frequently new investment to replace depreciated capital. Thus, industries that are characterized by higher rates

[10] A spike is defined as an annual capital expenditure exceeding 30% of the firm's stock of fixed assets.

of depreciation are likely to benefit more from countercyclical fiscal policy according to the credit constraint channel.

Second, the real options channel also suggests that countercyclical fiscal policy may favor industries with a higher depreciation rate. The irreversibility of investment induces caution in investment decisions when uncertainty is high, and greater uncertainty pushes more firms near the adjustment thresholds where firms operate under the inefficient scales of production. Because firms tend to be closer to the adjustment thresholds in high-depreciation industries, they should experience relatively slow growth in the presence of volatile economic conditions (Samaniego and Sun, 2019).

Third, unlike the case of input specificity and investment lumpiness, high-depreciation industries are expected to grow slower under the countercyclical fiscal policy if the depreciation rate is sufficiently high. For example, investment irreversibility becomes irrelevant under full depreciation because firms set the level of capital equal to their optimal values, which makes the production function convex in productivity. Thus, firms enjoy faster growth under a more volatile economic environment. We adopt the industry-level indicators from Samaniego and Sun (2015), who construct the indicators using the BEA industry-level capital flow tables.[11]

Investment-specific technological change (ISTC). Investment-specific technological change works similarly to deprecation, as it captures the economic depreciation of capital goods due to technological obsolescence. Waiting is particularly costly for the industries with faster technological obsolescence, so they may be forced to act inefficiently before the uncertainty has been resolved. Thus, we would expect a positive effect of the interaction between investment-specific technological change and fiscal policy countercyclicality on industry growth according to the real options channel. The degree of investment-specific technological change is measured by the rate of decline in the quality-adjusted price of capital goods used by each industry relative to the price of consumption and services. Here, we adopt the industry-level investment-specific technical progress index from Samaniego and Sun (2015).

[11] Both physical and economic depreciation are considered.

Labor intensity (LAB). Labor intensity may have different interaction effects on industry growth, depending on the underlying theoretical channels. First, following the same logic applied to asset fixity, labor-intensive industries will gain more from the countercyclical fiscal policy because labor input cannot be used as effective collateral. Second, to the extent that labor is a more variable input than capital, labor-intensive industries can be more flexible in exploiting the larger volatility of underlying shocks. In other words, we should expect a negative interaction effect if the convexity channel is a dominant force in this relationship.[12] Thus, determining whether labor intensity mitigates or amplifies the effect of countercyclical fiscal policy on growth helps sort out the most relevant theoretical channel. We take the industry-level indicators from Samaniego and Sun (2015), who measure labor intensity as the ratio of total wages and salaries over the total value added in the United States, using UNIDO data.

Skilled labor (HC). In addition to the overall importance of labor for production, a type of labor may be an important channel through which fiscal policy countercyclicality affects growth. For example, skilled labor entails high irreversibility due to the accumulation of firm- or task-specific knowledge, resulting in higher labor adjustment costs when the volatility of the economic environment is high. Thus, the real options channel predicts a positive interaction effect between the share of skilled labor and fiscal policy countercyclicality. Following Mulligan and Sala-i-Martin (1997), we measure the share of skilled labor using the average wage bill (wages divided by the number of employees). We take the industry-level indicators from Samaniego and Sun (2015).

R&D intensity (RND). R&D intensity can have either a positive or negative interaction effect depending on the underlying theoretical channels. If the convexity channel is the dominant force in this relationship, we may expect a negative sign on the interaction term because firms can exploit a volatile economic environment. This is because decisions taking R&D investment are often motivated by upside, not downside risk. However, to the extent which intangible capital is more difficult to be used as collateral, we should expect that countercyclical fiscal

[12] Theoretical work by Lee and Shin (2000) also notes that "as uncertainty increases, the convexity effect due to labor eventually dominates the option-value effect so that increased uncertainty raises the level of the optimal investment from zero to a positive value."

policy would have larger growth-enhancing effects in industries that are more R&D intensive. We adopt the industry-level values from Samaniego and Sun (2015), who measure R&D intensity as R&D expenditures over total capital expenditure using the Compustat data.

Table 2 reports the indicators of nine industry characteristics for the 22 manufacturing industries, which are constructed from U.S. data. INDSTAT2 industry classification used in this paper is similar to that of INDSTAT3 used in other studies (Braun and Larrain, 2005; Dell'Ariccia et al., 2008; Ilyina and Samaniego, 2011; Samaniego and Sun, 2015), with a minor exception.[13] For example, whereas "manufacture of food products and beverages" (ISIC 16) is the first industry appearing in the INDSTAT2 dataset, the INDSTAT3 dataset disaggregates them into the "manufacture of food products" (ISIC 311) and "manufacture of beverages" (ISIC 313). In this case, we take the weighted average of the industry characteristics for ISIC 311 and ISIC 313 with the average value-added share from the United States as a weight, to obtain the value for ISIC 16. If two datasets share the same industry, we simply use the values of INDSTAT3. Table B.1 in Appendix compares the industry classification between INDSTAT2 and INDSTAT3.

Table 3 presents the correlation matrix amongst these variables. The correlations amongst industry characteristic measures are intuitive and consistent with the existing studies. For example, as described in Choi et al. (2018), an industry that relies more heavily on external finance also tends to have higher rates of depreciation and R&D intensity. Similarly, an industry characterized by large input specificity is also the one with a high depreciation rate and lumpy investment (Samaniego and Sun, 2019). Given the high correlation between several industry characteristics, one should take caution in interpreting the estimation results. We also test the robustness of the interaction effects by including them in the single regression.

B. Fiscal Policy Countercyclicality

We discuss how our measure of time-varying fiscal policy countercyclicality is constructed. Assessment of how fiscal policy affects aggregate demand is required to measure the stabilizing effect of fiscal policy. As discussed by Blanchard (1993) in a static setting, the

[13] There are 28 manufacturing industries in INDSTAT3.

budget balance-to-GDP ratio can be used as a proxy for the effect of fiscal policy on aggregate demand, which implies that the response of the budget balance to changes in economic activity gives a good approximation of the stabilizing effects of fiscal policy: (i) a relatively high level of government spending when private demand is low (i.e., the more countercyclical government spending) will stabilize aggregate demand; (ii) if taxes fall more than output when output falls (i.e., the more progressive taxes), then taxes contribute to stabilizing household's disposable income.

Within this conceptual framework, we assess the fiscal policy countercyclicality in each country c by estimating the following regression:

$$b_c = \alpha_c + FC_c \Delta y_c + \varepsilon_c \tag{2}$$

where b is the budget balance-to-GDP ratio, Δy is GDP growth, and FC measures the fiscal policy countercyclicality, with larger values of the coefficient denoting higher countercyclicality.

We generalize equation (2) by allowing for the regression coefficients (FC) to vary over time. Time-varying measures of fiscal policy countercyclicality ($FC_{c,t}$) are then estimated from the following equation:

$$b_{c,t} = \alpha_{c,t} + FC_{c,t} \Delta y_{c,t} + \varepsilon_{j,t}. \tag{3}$$

The coefficient FC is assumed to follow a random walk, with its expected value being equal to its past value. Although more general AR(1) process can be considered, we adopt a random walk specification to reduce the number of coefficients to be estimated because of the relatively short time-series data, especially from developing economies. The change of the coefficient is denoted by $v_{c,t}$, which is assumed to be normally distributed with expectation zero and variance σ_c^2:

$$FC_{c,t} = FC_{c,t-1} + v_{c,t}. \tag{4}$$

Equations (3) and (4) are jointly estimated using the Varying-Coefficient model proposed by Schlicht (1985) and Schlicht and Ludsteck (2006). In this approach, the variances σ_c^2 are calculated by a method-of-moments estimator that coincides with the maximum-likelihood estimator for large samples (see Schlicht, 1985 and Schlicht and Ludsteck, 2006 for more details). The model described in equation (3) and (4) is a generalized version of equation (2) that is obtained as a particular case when the variance of the disturbances in equation (4) approaches zero.

According to Aghion and Marinescu (2008), This method has several advantages over other approaches to compute time-varying coefficients such as rolling windows and Gaussian methods. First, it mitigates reverse causality problems when fiscal policy countercyclicality is used as an explanatory variable because fiscal policy countercyclicality depends on the past, not the present. Second, the methodology is consistent with persistence in fiscal policy and accounts for the fact that changes in policy are typically slow. Third, changes in the fiscal policy countercyclicality in each year come from innovations in the same year, rather than from shocks occurring in neighboring years. Lastly, it allows using all observations in the sample to estimate the degree of fiscal policy countercyclicality each year, thereby enhancing the efficiency of estimation. This is not possible in the rolling windows approach.

In Figure 1, we first present the median level and the time path of the coefficient of fiscal policy countercyclicality estimated in equation (3) and (4) for our sample of 55 countries, for which we have data for at least 23 consecutive years—that is, between 1994 and 2016. As a first observation, it is worth noting that the time-median fiscal policy countercyclicality coefficient is positive (about 0.2), which is consistent with the fact that the budget balance is overall countercyclical, especially in the recent decades (Aghion and Marinescu, 2008; Frankel et al., 2013).

Second, fiscal policy countercyclicality has increased over time, particularly in advanced economies, but less so in developing countries (see Figure 2). A closer inspection of the latter group suggests that a large fraction of low-income countries still remain in the procyclicality trap—dragging down the improvement made by other countries in this group—likely due to a persistently weak institutional environment (Lane and Tornell, 1998). In contrast, fiscal policy countercyclicality in emerging market economies increased at a similar pace of advanced economies. Figure B.1 in Appendix shows that the average increase in the estimated fiscal policy countercyclicality coefficient has been accompanied by an increase in the t-statistics associated, suggesting that this increase over time can be considered as statistically significant.

Supporting the growth-enhancing effect of the countercyclical fiscal policy argued by Aghion and Marinescu (2008) and Aghion et al. (2014), more countercyclical fiscal policy is, on average, associated with lower output volatility. Figure 3 shows a strong negative relationship between the average of our time-varying fiscal policy countercyclicality measure and the standard deviation of real GDP growth during the full sample period.

C. Industry-level outcomes

Industry-level outcomes are taken from the United Nations Industrial Development Organization (UNIDO) database. While Aghion et al. (2014) and Furceri and Jalles (2018) use the KLEMS database in their analysis of advanced economies, the UNIDO database allows us to extend our analysis to developing economies. The extension of the analysis towards developing economies is particularly meaningful for the econometric setup in our study. Although our three-dimensional panel dataset with pairs of fixed effects substantially mitigates the endogeneity issues raised in Aghion et al. (2014)—by controlling for unobserved heterogeneity and reducing the chance of reverse causality—, successful identification hinges on variations in the measure of fiscal policy countercyclicality over time.

Given that the fiscal policy in many emerging market economies has become more countercyclical in recent times (Frankel et al., 2013), a study of these economies provides an additional opportunity to examine heterogeneous gains from countercyclical fiscal policy across both industries and countries. In addition to broader country coverage, UNIDO provides information on more disaggregated manufacturing industries compared to KLEMS.

We measure industry growth by value-added growth. To further shed light on a specific channel through which fiscal policy countercyclicality affects short-term growth, we also study growth in labor, investment, and labor productivity at the industry level. The top and bottom one percent of the growth variables are eliminated from the sample to avoid the influence of outliers. All nominal variables are deflated by the Consumer Price Index taken from the World

Economic Outlook database. All these variables are reported for 22 manufacturing industries based on the INDSTAT2 2016, ISIC Revision 3.[14]

Our final sample comprises an unbalanced panel of 55 countries, among which 21 are advanced, and 34 are developing countries. While the advanced country sample typically starts between the late 1970s and the mid-1980s, the developing country sample mostly starts between the late 1980s and the early 1990s.[15] Table B.2 in Appendix summarizes the final country coverage and the number of observations used in the analysis. We do not include the United States in the final sample since the industry characteristics are measured using the U.S. firm-level data. To the extent that U.S. fiscal policies influence U.S. firms from different industries in a systemic way, the inclusion of the United States would bias the result.

V. RESULTS

A. Baseline results

Table 4 present the baseline results obtained by estimating equation (1) using the full sample. The coefficients on the lagged value-added share are always negative and statistically significant, suggesting a strong convergence effect at the industry level (Braun and Larrain, 2005; Samaniego and Sun, 2015). The industry characteristic variables are normalized to have a zero mean and unit standard deviation to ease comparison.

The baseline results are consistent with the findings of Aghion et al. (2014) that industries with a relatively heavy reliance on external finance or lower asset tangibility tend to grow faster in the long run in countries where fiscal policies are more countercyclical. To gauge the economic magnitude of each channel and facilitate the comparison with the existing studies, we measure differential growth effects from an increase in the fiscal policy countercyclicality from the 25th to the 75th percentile of its distribution for an industry with a

[14] While the original INDSTAT2 database includes 23 manufacturing industries, we exclude the “manufacture of recycling” industry due to insufficient observations.

[15] One might be concerned about the relevance of using the industry characteristics computed from the 1970-2000 average values in Samaniego and Sun (2015) for a subset of the sample (mostly developing economies) starting after the 1980s. However, Ilyina and Samaniego (2011) confirm that the industry characteristics are stable over time. The correlation among the decade averages often exceeds 0.9, further supporting the inherency of these characteristics.

relatively low value of each characteristic (at the 25th percentile of the distribution) compared to an industry with a relatively high value (at the 75th percentile).

The magnitude of the differential effects of the countercyclical fiscal policy ranges from 0.16 to 1.49 percentage points in an absolute term depending on the technological characteristics under consideration. Among the five statistically significant characteristics, asset fixity has the strongest differential effect (1.49), followed by investment lumpiness (1.03), external financial dependence (0.60), input specificity (0.50), and labor intensity (0.41). The magnitude of the effect via external financial dependence, while economically and statistically significant, is smaller than the one found by Aghion et al. (2014) using cross-sectional data (between 1.1 and 2.2 percentage points). This is because our differential effects only capture the within-country variation of fiscal policy countercyclicality given the inclusion of country-time fixed effects. Nevertheless, it is worth noting that increasing the degree of fiscal policy countercyclicality from the 25th to the 75th percentile of the distribution corresponds to quite a dramatic change in the design of fiscal policy over the cycle. As illustrated in Figures 1 and 2, changes in the degree of fiscal policy countercyclicality within a country are typically small and occur only gradually over time.

The full sample results may mask potential heterogeneity between advanced and developing economies. The way countercyclical fiscal policy affects industry growth is not necessarily the same for countries with a different level of economic development. Moreover, because industry characteristics are constructed from U.S. data, extending them to developing economies can be subject to larger measurement errors. Whereas cross-country differences are likely to persist in the sample of advanced economies given the slow growth convergence process in advanced economies, it may not necessarily be the case for developing economies. Therefore, we re-estimate equation (1) by splitting the sample into advanced economies (21 countries) and developing economies (34 countries).

The results of this analysis are reported in Table 5. The interaction effects are larger for developing economies, but they are more precisely estimated for advanced economies—presumably due to larger measurement errors in the data for developing economies. While external financial dependence is not statistically significant for developing economies, asset fixity is highly statistically significant for both groups. The differential effect implied from asset fixity is 0.58 (2.23) percentage points for advanced (developing) economies. Other robust interaction variables for both advanced and developing economies are investment lumpiness and labor intensity. Despite the weaker statistical evidence for developing economies, the larger differential effects imply potentially substantial growth gains from the countercyclical fiscal policy for this group.

In the right panel of Table 1, we compare the signs of the interaction terms with those predicted by alternative theoretical channels. In sum, we find that countercyclical fiscal policy increases growth in industries that are more credit constrained and subject to higher irreversibility or the cost of waiting, thereby supporting the credit constraint channel and the real options channel. In contrast, we do not find empirical support for the convexity channel. More specifically, the positive and statistically significant signs of external finance, capital depreciation, and labor intensity and the negative and statistically significant sign of asset fixity are all fully consistent with the credit constraint channel. The positive and statistically significant signs of capital depreciation, lumpiness, and input specificity, in turn, support the real options channel, although the negative and statistically significant sign of skilled labor does not. The positive and statistically significant signs of capital depreciation and labor intensity clearly reject the theoretical prediction of the convexity channel. In the following section, we run several sensitivity tests to confirm that our findings are robust to changes in the baseline econometric specification.

B. Robustness checks

This section presents several robustness checks to the main findings, including using a lagged specification, employing alternative measures of fiscal counter-cyclicality and industry growth, accounting for uncertainty in the measure of fiscal counter-cyclicality, and controlling for possible omitted variables.

Lagged specification. Following Braun and Larrain (2005), Dell'Ariccia et al. (2008), and Samaniego and Sun (2015), our baseline estimation is based on a static equation (4). Although the inclusion of two-way fixed effects (especially country-time fixed effects) alleviates the omitted variable bias problem, one may still argue that this specification cannot fully disentangle the causal effect of countercyclical fiscal policy on growth from the short-term demand-side interpretation because fiscal policy often takes time to ameliorate firms' constraints. While we believe the use of annual data largely mitigates this concern, we still test the robustness of our findings using a lag of our fiscal policy countercyclicality variable in the interaction term. Panel A of Table 6 shows that our findings hardly change, suggesting that our static framework—when applied to the three-dimensional panel—is an appropriate tool to investigate the effect of countercyclical fiscal policy on short-term sectoral growth.

Alternative fiscal policy countercyclicality estimates. While using the budget balance to GDP ratio has the main advantage to be available for many countries over an extended period, it may not capture the actual degree of fiscal policy countercyclicality. As discussed by Kaminsky et al. (2004), the reason is that such a ratio could change upwards or downwards even if government spending or tax policy (e.g., effective tax rates) does not change. It could be driven by changes in the interest payment over the business cycle or changes in the budget due to automatic stabilizers—that is, automatic changes in the budget, driven by changes in economic conditions.

To address this issue and check the robustness of the results, we have re-estimated equation (3) using the cyclically-adjusted balance to GDP ratio—net of automatic changes in the budget.[16] Unfortunately, data on the cyclically-adjusted balance to GDP ratio is not necessarily available for all countries considered in the baseline. While this measure is positively correlated with the baseline measure in most countries (the average correlation is 0.36), they are negatively correlated in some cases, implying that the alternative measure captures a different dimension of fiscal policy countercyclicality. The results obtained by estimating equation (1) with this alternative measure of the fiscal policy countercyclicality are reported in Panel B of Table 6. Although the coefficients are less precisely estimated in most cases, probably due to the smaller sample size, they show the statistically significant effects of countercyclical fiscal policy on industry growth via asset fixity with a negative sign and labor intensity with a positive sign, confirming that the credit constraint channel is the most robust channel through which countercyclical fiscal policy affects industry growth.

Alternative growth measure. Unlike value-added, gross output measures the overall production at market prices. Thus, the difference between gross output and value-added of an

[16] Data on the cyclically-adjusted balanced-to-GDP ratio are taken from the IMF FAD database.

industry is intermediate inputs. To the extent that the intensity of intermediate inputs varies across countries within the same industry, our growth measure based on value-added might not necessarily provide the same picture as a gross output measure. To check this possibility, we repeat our analysis using the growth rate of gross output. Gross output is also deflated using the CPI to obtain real values. Panel C of Table 6 confirms that the sign, size, and statistical significance of the interaction effects using gross output are largely consistent with those using value-added, lending support to our baseline results. The only difference is that external financial dependence and input specificity are no longer statistically significant when using gross output.

Uncertainty in fiscal policy countercyclicality estimates. A possible limitation of the baseline analysis is that our measure of fiscal policy countercyclicality is not directly observed but estimated. It implies that the above findings could just reflect the possibility that the standard errors around the estimates are not adequately considered. To address this limitation, we re-estimate equation (1) using Weighted Least Squares (WLS), with weights given by the inverse of the standard error of the estimated time-varying coefficients. The results of this exercise are reported in Panel D of Table 6. The estimated parameters are similar from those obtained using OLS, suggesting that baseline results are unlikely biased due to a generated regressor.

Different factors and omitted variable bias. As discussed before, a possible concern in estimating equation (1) is that our findings could be biased due to the omission of macroeconomic variables affecting industry growth through a specific channel that is correlated with our measure of fiscal policy countercyclicality at the same time. For example, Braun and Larrain (2005) and Samaniego and Sun (2015) find that industries that are more dependent on external finance are hit harder during recessions. This finding implies that—to the extent that governments respond to the period of low growth by increasing spending—our fiscal policy countercyclicality measure might simply capture the well-known recession channel instead. Although, if anything, this bias only goes against finding our results, we still augment equation (1) by interacting each additional country-specific variable $Z_{c,t}$ with the industry characteristics X_i to check whether the inclusion of other macroeconomic variables alters our findings. The parameter θ in equation (5) aims to capture this additional interaction effect.

$$Y_{i,c,t} = \alpha_{i,c} + \alpha_{i,t} + \alpha_{c,t} + \beta X_i FC_{c,t} + \gamma Size_{i,c,t-1} + \theta X_i Z_{c,t} + \varepsilon_{i,c,t}. \quad (5)$$

As already mentioned, the first obvious candidate to consider is real GDP growth that captures the state of business cycles. To the extent that fiscal policies affect the GDP by boosting aggregate demand, the interaction effect we found earlier might have simply captured different elasticities of industry growth to business cycles, as argued by Braun and Larrain (2005) and Samaniego and Sun (2015). Second, we control for the size of government, which is known to be correlated with output volatility and growth (Fátas and Mihov, 2001; Debrun et al., 2008; Afonso and Furceri, 2010). We measure the government size by the ratio of government expenditure to GDP. These two control variables help disentangle the stabilizing effect of fiscal policy countercyclicality from the first-order effect of expansionary fiscal policies.

The third one is the level of financial development, as discussed by Rajan and Zingales (1998). Due to the lack of financial depth, emerging and developing economies are often forced to run procyclical fiscal policy (Caballero and Krishnamurthy, 2004). Acemoglu and Zilibotti (1997) also claim that low financial development as a factor that could reduce long-run growth and increase the volatility of the economy. To the extent to which our measure of fiscal policy countercyclicality increases with financial depth over time, controlling for the level of financial development corrects this bias in our estimates. Following Rajan and Zingales (1998), we use the ratio of private bank credit to GDP.

Another potential variable that may affect industry growth and also correlated with the degree of fiscal policy countercyclicality is inflation. Inflation may lead to capital misallocation (Fischer and Modigliani, 1978; Mondino et al., 1996), and to the extent that some industries are more vulnerable to capital misallocation, it may have larger negative effects on these industries. Moreover, our sample includes the period of the Great Moderation, during which our measure of fiscal policy countercyclicality, on average, also increases. Thus, our result may simply capture the reduced business cycles' volatility, rather than the effect of increased fiscal policy countercyclicality. The inclusion of the interaction between the industry technological characteristics and inflation mitigates this concern.

Table 7 shows that the interaction effect of fiscal policy countercyclicality and the industry-specific characteristics, such as asset fixity, input specificity, investment lumpiness, and labor intensity, remains statistically significant across the specifications. Thus, our baseline results are largely free of omitted variable bias.

C. Decomposition of industry growth

So far, we have studied the relevance of various theoretical channels through which countercyclical fiscal policy affects industry growth, based on two measures of output. In this section, we try to shed further light on mechanisms through which countercyclical fiscal policy affects industry growth by examining the effects on labor, investment, and productivity, respectively. Based on the standard neoclassical production function, our new dependent variables are the growth rate of industry-level employment, gross fixed capital formation, and labor productivity. We also deflate the gross fixed capital formation by using a country-level CPI because many developing economies in our sample do not have capital good price deflators. Due to large measurement errors in estimating total factor productivity, we use labor productivity instead. Labor productivity is defined as the ratio of real value added to the number of employees.

Table 8 shows the results of using employment, gross fixed capital formation, and labor productivity as an alternative dependent variable. The results on employment are consistent with the value-added growth regarding the sign and statistical significance of the interaction variables. If anything, the coefficients are more precisely estimated than in the baseline using value-added. For example, the interaction term on depreciation becomes statistically significant.

However, the results on investment growth present somewhat different pictures. Most importantly, asset fixity and labor intensity—the most robust characteristics considered so far—are no longer statistically significant. Although external financial dependence is still statistically significant, this finding somewhat weakens the relevance of the credit constraint channel in explaining the effect of fiscal policy countercyclicality on investment growth. Interestingly, the coefficient on skilled labor switches its sign and becomes economically and statistically significant. Together with the significance of the input specificity, this finding suggests that the most relevant theoretical mechanism for investment is the real options channel. Nevertheless, we cannot rule out the possibility that larger measurement errors due to the absence of capital good price deflators drive these results. Arguably, deflating gross fixed capital formation by CPI is more problematic than deflating value-added or gross output by CPI.

The results on labor productivity growth are qualitatively consistent with the baseline results, although statistical significance is reduced. For example, labor intensity—one of the most robust characteristics—is not statistically significant anymore, whereas investment-specific technological change becomes statistically significant. However, one should note that the size of the differential effects are not comparable across different dependent variables, as their mean and standard deviations are different.[17]

D. Recessions vs. expansions

To assess whether the effect of countercyclical fiscal policy on industry growth differs between good and bad times, we adopt the smooth transition approach proposed by Auerbach and Gorodnichenko (2012) and estimate the following regression:

$$Y_{i,c,t} = \alpha_{i,c} + \alpha_{i,t} + \alpha_{c,t} + \beta^L X_i F(s_{c,t}) FC_{c,t} + \beta^H X_i \big(1 - F(s_{c,t})\big) FC_{c,t} + \varepsilon_{i,c,t} \qquad (6)$$

$$\text{with } F\big(s_{c,t}\big) = \frac{exp(-\theta s_{c,t})}{1+exp(-\theta s_{c,t})}, \quad \theta > 0,$$

where s is an indicator of the state of the economy normalized to have zero mean and unit variance, and $F(s_{c,t})$ is the corresponding smooth transition function between the states. While Auerbach and Gorodnichenko (2012) use a seven-quarter moving average of real GDP growth, our analysis uses annual real GDP growth as a measure of the state of the economy.[18]

This approach is equivalent to the smooth transition autoregressive model developed by Granger and Terasvirta (1993). The advantage of this approach is twofold. First, compared with a model in which the fiscal policy countercyclicality variable interacts with business cycle

[17] The average (standard deviation) sectoral growth of value-added, employment, gross fixed capital formation, and labor productivity is 0.92 (20.31), 0.04 (12.90), 0.11 (57.48), and 0.89 (18.77) respectively.

[18] Our main results are robust to using a two-year moving average of annual real GDP growth instead.

proxies, this approach tests directly whether the effect of fiscal policy countercyclicality varies across different regimes such as recessions and expansions. Second, compared with estimating structural VARs for each regime, it allows the effects of countercyclical fiscal policy to change smoothly between recessions and expansions by considering a continuum of states to compute the impact, thus making the resulting estimate more precise. We choose $\theta = 1.5$ following Auerbach and Gorodnichencko (2012) and calibrate the mean of $s_{c,t}$ so that the economy spends about 20 percent of the time in recessions. The parameter $\theta > 0$ governs the smoothness of transition from a recession to an expansion regime. As θ increases, the transition becomes more abrupt between the regimes, while setting $\theta = 0$ is equivalent to the linear specification.

The results reported in Table 9 suggest that the effects of countercyclical fiscal policy on industry growth vary across economic regimes. Interestingly, we find that countercyclical fiscal policy has larger effects on industry growth during recessionary periods—that is when credit conditions are likely to be more tightening—especially for industries that are more credit constrained (with higher external financial dependence and R&D intensity and lower asset fixity). This finding reinforces the importance of the credit constraint channel as the main transmission mechanism of the effect of countercyclical fiscal policy on industry growth. On the other hand, the interaction effects of labor intensity and skilled labor channels are stronger during expansions when financial conditions are relaxed.

E. Robust channels

Our findings suggest that several industry characteristics can amplify the effect of countercyclical fiscal policy on industry growth. However, given that these variables are correlated with each other, as shown in Table 3, an interesting question is which of these channels survive when all the statistically significant variables are included simultaneously in the regression. The results for this horserace using value-added growth as an indicator of industry growth are presented in Table 10. Table 10 shows that asset fixity is the most robust determinant for both advanced and developing economies, which confirms that the credit constraint channel is the most relevant mechanism through which countercyclical fiscal policy affects industry growth.

VI. CONCLUSION

By applying a difference-in-difference approach to annual industry-level panel data, including both advanced and developing economies, this paper has examined whether there exist heterogeneous gains from countercyclical fiscal policy. We estimate the interaction effect of various industry technological characteristics to examine the relevant theoretical channels through which countercyclical fiscal policy fosters short-run growth. Consistent with Aghion et al. (2014) regarding the effect of fiscal policy countercyclicality on long-run productivity growth, we find that the credit constraint channel is the most robust transmission mechanism for short-term growth. Moreover, we find that the importance of the credit constraint channel is larger during recessions than expansions.

The real options channel is also consistent with industry-level evidence, albeit to a lesser extent than the credit constraint channel. In contrast, we do not find empirical support for the convexity channel. These findings are robust to controlling for the interaction between the industry characteristics and a broad set of macroeconomic variables (such as inflation, financial development, and the size of government), which may affect the cyclical dynamics of fiscal policy. Most importantly, they are robust to controlling for the interaction of the characteristics with real GDP growth, suggesting that our findings do not simply pick up different sensitivities of industry growth to the state of aggregate business cycles. Our results also hold when we focus on discretionary fiscal policy (by controlling for automatic changes in the budget due to business cycle fluctuations).

Identifying policies that could lift growth is crucial at this juncture. Our results suggest that in addition to structural reforms, fiscal policy countercyclicality can play an important role in spurring growth. Because our findings answer which kind of industries can benefit more by enhancing the degree of fiscal policy countercyclicality, it also helps estimate economy-wide gains by examining the industrial structure of each economy. An important avenue for further research is then the investigation of the underlying determinants of fiscal policy countercyclicality and the assessment of which specific components of fiscal policy (revenues versus expenditures) can deliver greater stabilization.

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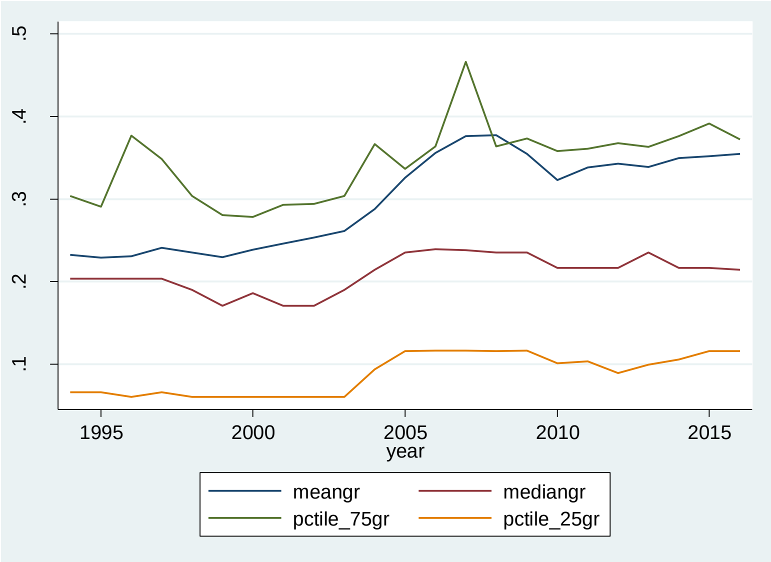
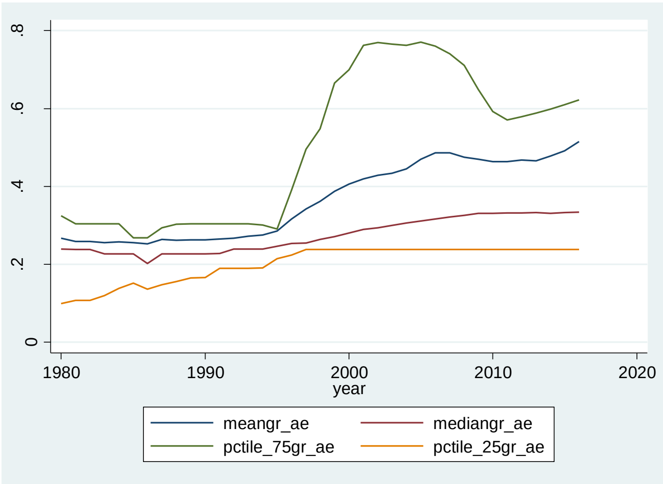
Figure 1. Fiscal policy countercyclicality over time, all countries, 1994-2016



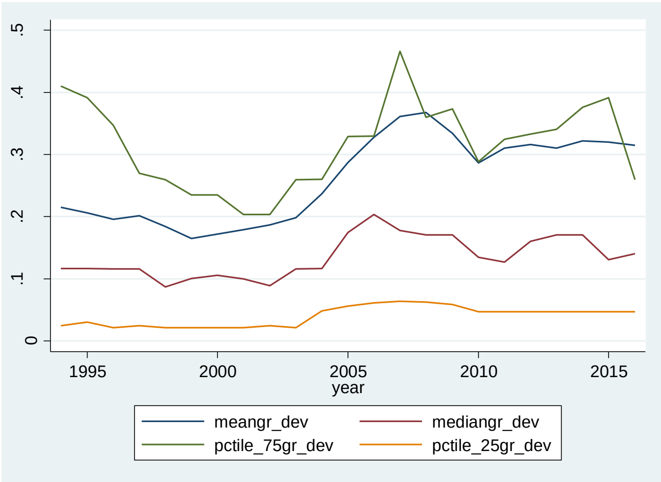
Note: This figure displays the time profile of the time-varying coefficient (TVC) estimates for the entire sample. It includes 55 countries with at least 23 consecutive observations.

Figure 2. Fiscal policy countercyclicality over time—within sample interquartile ranges

A) Advanced Economies: 1980-2016

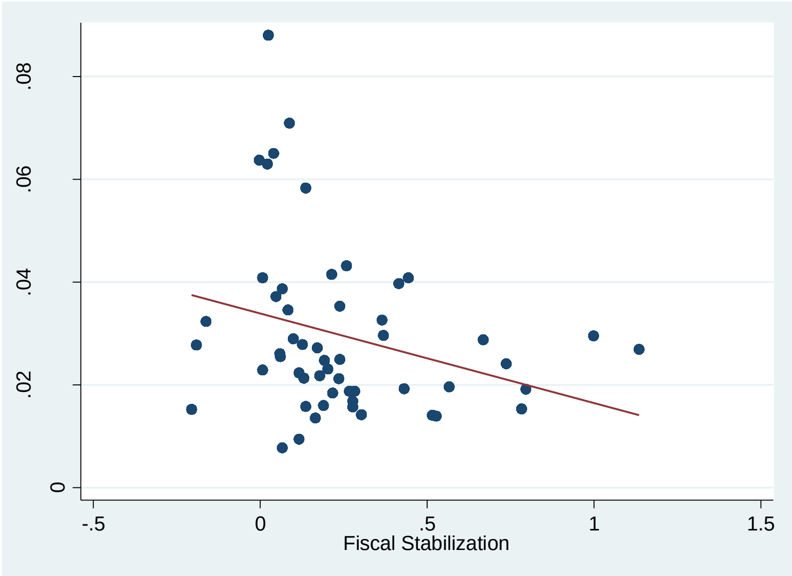


B) Developing Economies: 1994-2016



Note: This figure displays the interquartile and the mean evolution of the time-varying coefficient (TVC) estimates for the two groups, advanced and developing economies. Panel A) includes the sub-sample of 21 advanced economies with at least 36 observations; panel B) includes the sub-sample of 34 developing economies with at least 23 consecutive observations.

Figure 3. Fiscal policy countercyclicality and output volatility: Evidence across countries



Note: This figure displays the correlation between the average of our fiscal policy countercyclicality measure and the standard deviation of real GDP growth.

Table 1. The effect of countercyclical fiscal policy on industry growth: Theories vs. findings

	Theories			Findings		
Channel	Credit constraint	Real option	Convexity	Full sample	Advanced economies	Developing economies
EFD	+			+*	+*	+
FIX	–			– *	–*	–*
SPEC		+		+*	+	+
LMP		+		+*	+*	+*
DEP	+	+	–	+	+	+
ISTC		+		+	–	+
LAB	+		–	+*	+*	+*
HC		+		–	–*	–
RND	+		–	+	+	+

Note: + (–) in theory column indicates positive (negative) interaction effects from existing theories. +* (–*) sign in findings column indicates statistically significant (at 10 percent) positive (negative) interaction effects, whereas + (–) sign indicates positive (negative), but insignificant interaction effects. EFD (external financial dependence), FIX (asset fixity), SPEC (input specificity), LMP (investment lumpiness), DEP (depreciation), ISTC (Investment-specific technical change), LAB (labor intensity), HC (skilled labor intensity), RND (R&D intensity).

Table 2. Industry-specific technological characteristics

ISIC code	Industry	EFD	FIX	SPEC	LMP	DEP	ISTC	LAB	HC	R&D
15	Food products and beverages	0.11	0.37	0.61	1.21	7.09	3.95	0.28	1.86	0.07
16	Tobacco products	-0.45	0.19	0.48	0.82	5.25	3.98	0.12	2.64	0.22
17	Textiles	0.19	0.35	0.82	1.23	7.67	3.91	0.46	1.46	0.14
18	Wearing apparel; dressing and dyeing of fur	0.03	0.13	0.98	2.00	6.44	4.37	0.45	1.08	0.02
19	Tanning and dressing of leather	-0.14	0.14	0.88	2.04	8.81	4.02	0.44	1.33	0.18
20	Wood and of products of wood and cork, except furniture	0.28	0.31	0.67	1.72	9.53	3.93	0.47	1.62	0.03
21	Paper and paper products	0.17	0.47	0.89	0.90	8.63	3.25	0.36	2.41	0.08
22	Publishing, printing and reproduction of recorded media	0.20	0.26	1.00	1.67	9.75	4.41	0.41	1.97	0.10
23	Coke, refined petroleum products and nuclear fuel	0.04	0.55	0.79	0.82	6.78	3.94	0.20	3.25	0.08
24	Chemicals and chemical products	0.50	0.29	0.92	1.77	8.16	4.64	0.23	2.73	1.18
25	Rubber and plastics products	0.69	0.37	0.97	1.47	10.07	3.19	0.41	1.87	0.17
26	Other non-metallic mineral products	0.06	0.46	0.96	1.13	8.10	4.68	0.39	2.09	0.11
27	Basic metals	0.05	0.40	0.66	1.08	6.06	3.44	0.45	2.55	0.08
28	Fabricated metal products, except machinery and equipment	0.24	0.27	0.95	1.37	7.04	3.42	0.46	2.02	0.15
29	Machinery and equipment n.e.c.	0.60	0.20	0.98	2.69	8.83	5.15	0.43	2.39	0.93
30	Office, accounting and computing machinery	0.96	0.21	0.98	2.70	9.38	4.31	0.41	2.27	0.81
31	Electrical machinery and apparatus n.e.c.	0.95	0.21	0.96	2.70	9.38	4.31	0.41	2.27	0.81
32	Radio, television and communication equipment and apparatus	0.96	0.21	0.96	2.70	9.38	4.31	0.41	2.27	0.81
33	Medical, precision and optical instruments, watches and clocks	0.96	0.18	0.98	2.79	9.21	4.46	0.38	2.55	1.19
34	Motor vehicles, trailers and semi-trailers	0.36	0.26	0.99	1.61	10.56	3.85	0.44	2.81	0.32
35	Other transport equipment	0.36	0.26	0.99	1.61	10.56	3.85	0.44	2.81	0.32
36	Furniture; manufacturing n.e.c.	0.37	0.25	0.89	1.51	8.97	3.65	0.46	1.59	0.21

Note: The manufacturing industry classification follows INDSTAT2 2016, ISIC Revision 3. EFD (external financial dependence), FIX (asset fixity), SPEC (relationship-specific investment), LMP (investment lumpiness), DEP (depreciation), ISTC (Investment-specific technical change), LAB (labor intensity), HC (skilled labor intensity), RND (R&D intensity).

Table 3. Correlation matrix of industry-level characteristics

	EFD	FIX	SPEC	LMP	DEP	ISTC	LAB	HC	R&D
EFD	1								
FIX	-0.26	1							
SPEC	0.59*	-0.24	1						
LMP	0.78*	-0.70*	0.55*	1					
DEP	0.62*	-0.19	0.64*	0.49*	1				
ISTC	0.25	-0.38	0.28	0.57*	0.07	1			
LAB	0.31	-0.24	0.51*	0.37	0.49*	-0.10	1		
HC	0.14	0.32	-0.04	-0.11	0.02	0.05	-0.51*	1	
RND	0.74*	-0.43*	0.38	0.75*	0.30	0.59*	-0.10	0.36	1

Note: * indicates statistical significance at the 5 percent level. EFD (external financial dependence), FIX (asset fixity), SPEC (input specificity), LMP (investment lumpiness), DEP (depreciation), ISTC (Investment-specific technical change), LAB (labor intensity), HC (skilled labor intensity), RND (R&D intensity).

Table 4. The effect of countercyclical fiscal policy on industry growth: Baseline

Explanatory variable	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
Lagged share in manufacturing value-added	-0.030*** (0.010)	-0.030*** (0.010)	-0.030*** (0.010)	-0.030*** (0.010)	-0.030*** (0.010)	-0.030*** (0.010)	-0.030*** (0.010)	-0.030*** (0.010)	-0.030*** (0.010)
Interaction (EFD)	2.373* (1.427)								
Interaction (FIX)		-4.534*** (1.163)							
Interaction (SPEC)			2.127* (1.144)						
Interaction (LMP)				3.861** (1.529)					
Interaction (DEP)					2.376 (1.464)				
Interaction (ISTC)						1.022 (1.206)			
Interaction (LAB)							2.417** (1.114)		
Interaction (HC)								-1.715 (1.383)	
Interaction (RND)									1.137 (1.496)
Differential effects (in percentage point)	0.602	-1.488	0.504	1.032	0.816	0.349	0.405	-0.483	0.161
Obs	22,655	22,655	22,655	22,655	22,655	22,655	22,655	22,655	22,655
R-squared	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.323

Note: The first column indicates each specific channel interacting with a fiscal policy countercyclicality measure when estimating equation (1). T-statistics based on clustered standard errors at the industry-country level are reported in parenthesis. *, **, *** denote significance at 10, 5, and 1 percent, respectively. EFD (external financial dependence), FIX (asset fixity), SPEC (input specificity), LMP (investment lumpiness), DEP (depreciation), ISTC (Investment-specific technical change), LAB (labor intensity), HC (skilled labor intensity), RND (R&D intensity). Differential effects are computed for an industry whose characteristics would increase from the 25th percentile to the 75th percentile of the distribution when fiscal policy countercyclicality would increase from the 25th to the 75th percentile.

Table 5A. The effect of countercyclical fiscal policy on industry growth: Advanced economies

Explanatory variable	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
Lagged share in manufacturing value-added	-0.023** (0.011)	-0.023** (0.011)	-0.023** (0.011)	-0.023** (0.011)	-0.023** (0.011)	-0.023** (0.011)	-0.023** (0.011)	-0.023** (0.011)	-0.023** (0.011)
Interaction (EFD)	1.776* (0.950)								
Interaction (FIX)		-2.393** (1.036)							
Interaction (SPEC)			1.064 (0.755)						
Interaction (LMP)				1.901** (0.960)					
Interaction (DEP)					0.783 (0.874)				
Interaction (ISTC)						-0.321 (0.593)			
Interaction (LAB)							2.253** (1.141)		
Interaction (HC)								-1.744* (1.054)	
Interaction (RND)									0.707 (0.698)
Differential effects (in percentage point)	0.332	-0.578	0.185	0.374	0.198	-0.081	0.278	-0.361	0.069
Obs	12,465	12,465	12,465	12,465	12,465	12,465	12,465	12,465	12,465
R-squared	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403	0.403

Note: The first column indicates each specific channel interacting with a fiscal policy countercyclicality measure when estimating equation (1). T-statistics based on clustered standard errors at the industry-country level are reported in parenthesis. *, **, *** denote significance at 10, 5, and 1 percent, respectively. EFD (external financial dependence), FIX (asset fixity), SPEC (input specificity), LMP (investment lumpiness), DEP (depreciation), ISTC (Investment-specific technical change), LAB (labor intensity), HC (skilled labor intensity), RND (R&D intensity). Differential effects are computed for an industry whose characteristics would increase from the 25th percentile to the 75th percentile of the distribution when fiscal policy countercyclicality would increase from the 25th to the 75th percentile.

Table 5B. The effect of countercyclical fiscal policy on industry growth: Developing economies

Explanatory variable	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
Lagged share in manufacturing value-added	-0.028*** (0.010)	-0.028*** (0.010)	-0.028*** (0.010)	-0.028*** (0.010)	-0.028*** (0.010)	-0.028*** (0.010)	-0.028*** (0.010)	-0.028*** (0.010)	-0.028*** (0.010)
Interaction (EFD)	2.449 (2.798)								
Interaction (FIX)		-6.344*** (1.986)							
Interaction (SPEC)			2.550 (1.994)						
Interaction (LMP)				5.213* (2.857)					
Interaction (DEP)					3.389 (2.530)				
Interaction (ISTC)						1.794 (1.928)			
Interaction (LAB)							2.902* (1.689)		
Interaction (HC)								-1.973 (2.238)	
Interaction (RND)									0.935 (2.650)
Differential effects (%)	0.685	-2.293	0.665	1.535	1.282	0.676	0.536	-0.612	0.137
Obs	10,184	10,184	10,184	10,184	10,184	10,184	10,184	10,184	10,184
R-squared	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342	0.342

Note: The first column indicates each specific channel interacting with a fiscal policy countercyclicality measure when estimating equation (1). T-statistics based on clustered standard errors at the industry-country level are reported in parenthesis. *, **, *** denote significance at 10, 5, and 1 percent, respectively. EFD (external financial dependence), FIX (asset fixity), SPEC (input specificity), LMP (investment lumpiness), DEP (depreciation), ISTC (Investment-specific technical change), LAB (labor intensity), HC (skilled labor intensity), RND (R&D intensity). Differential effects are computed for an industry whose characteristics would increase from the 25th percentile to the 75th percentile of the distribution when fiscal policy countercyclicality would increase from the 25th to the 75th percentile.

Table 6. The effect of countercyclical fiscal policy on industry growth: Robustness checks

	A) Lagged regressors (N=21,735)			B) Cyclically-adjusted balance to GDP (N=13,377)		
Channel	Coef	S.E	Differential effects (%)	Coef	S.E	Differential effects (%)
EFD	2.703*	1.435	0.686	0.033	0.661	0.007
FIX	-3.647***	1.255	-1.197	-1.435**	0.652	-0.379
SPEC	1.606*	0.956	0.380	0.235	0.624	0.045
LMP	3.599**	1.644	0.962	1.107	0.753	0.238
DEP	2.190**	1.072	0.752	0.114	0.699	0.032
ISTC	0.168	1.265	0.057	0.163	0.631	0.045
LAB	3.459***	1.195	0.580	1.248*	0.714	0.169
HC	-3.202***	1.155	-0.901	-1.649**	0.672	-0.374
RND	0.364	1.576	0.048	-0.169	0.706	-0.018
	C) Gross output (N=22,581)			D) Weighted Least Squares (N=22,655)		
Channel	Coef	S.E	Differential effects (%)	Coef	S.E	Differential effects (%)
EFD	1.328	1.418	0.337	2.846**	1.412	0.722
FIX	-2.989***	1.053	-0.981	-3.533***	1.284	-1.159
SPEC	1.336	0.990	0.316	1.686*	1.018	0.399
LMP	2.601*	1.464	0.695	4.055**	1.806	1.083
DEP	1.352	1.132	0.464	1.500	1.192	0.515
ISTC	0.870	1.153	0.297	0.914	1.626	0.313
LAB	1.850**	0.877	0.310	3.551***	1.207	0.595
HC	-1.242	1.034	-0.350	-2.702**	1.150	-0.760
RND	0.360	1.468	0.048	1.130	1.843	0.150

Note: The first column indicates each specific channel interacting with a fiscal policy countercyclicality measure when estimating equation (1). T-statistics based on clustered standard errors at the industry-country level are reported in parenthesis. *, **, *** denote significance at 10, 5, and 1 percent, respectively. EFD (external financial dependence), FIX (asset fixity), SPEC (input specificity), LMP (investment lumpiness), DEP (depreciation), ISTC (Investment-specific technical change), LAB (labor intensity), HC (skilled labor intensity), RND (R&D intensity). Differential effects are computed for an industry whose characteristics would increase from the 25th percentile to the 75th percentile of the distribution when fiscal policy countercyclicality would increase from the 25th to the 75th percentile.

Table 7. The effect of countercyclical fiscal policy on industry growth: Omitted variable bias

	A) Real GDP growth (N=22,655)			B) Government expenditure/GDP (N=18,791)		
Channel	Coef	S.E	Differential effects (%)	Coef	S.E	Differential effects (%)
EFD	2.493*	1.430	0.633	3.071**	1.556	0.779
FIX	-4.805***	1.171	-1.577	-4.997***	1.224	-1.640
SPEC	2.535**	1.124	0.600	2.677**	1.268	0.634
LMP	4.099***	1.560	1.095	4.673***	1.665	1.249
DEP	2.661*	1.405	0.914	2.508	1.686	0.861
ISTC	1.028	1.191	0.352	1.565	1.234	0.535
LAB	2.976**	1.167	0.499	2.222**	1.108	0.372
HC	-2.161*	1.307	-0.608	-1.207	1.563	-0.340
RND	1.085	1.489	0.144	2.372	1.493	0.315
	C) Private credit/GDP (N=21,273)			D) Inflation (N=22,655)		
Channel	Coef	S.E	Differential effects (%)	Coef	S.E	Differential effects (%)
EFD	1.980	1.482	0.503	2.393*	1.431	0.607
FIX	-4.569***	1.213	-1.499	-4.636***	1.163	-1.521
SPEC	2.086*	1.206	0.494	2.151*	1.144	0.509
LMP	3.532**	1.577	0.944	3.895**	1.534	1.041
DEP	2.617*	1.552	0.899	2.421*	1.464	0.831
ISTC	0.926	1.256	0.317	1.011	1.206	0.346
LAB	2.549**	1.213	0.427	2.463**	1.146	0.413
HC	-1.517	1.471	-0.427	-1.752	1.383	-0.493
RND	0.819	1.540	0.109	1.152	1.499	0.153

Note: The first column indicates each specific channel interacting with a fiscal policy countercyclicality measure when estimating equation (1). T-statistics based on clustered standard errors at the industry-country level are reported in parenthesis. *, **, *** denote significance at 10, 5, and 1 percent, respectively. EFD (external financial dependence), FIX (asset fixity), SPEC (input specificity), LMP (investment lumpiness), DEP (depreciation), ISTC (Investment-specific technical change), LAB (labor intensity), HC (skilled labor intensity), RND (R&D intensity). Differential effects are computed for an industry whose characteristics would increase from the 25th percentile to the 75th percentile of the distribution when fiscal policy countercyclicality would increase from the 25th to the 75th percentile.

Table 8. The effect of countercyclical fiscal policy on industry growth: Labor, investment, and productivity

	Employment (N=22,655)			Gross fixed capital formation (N=15,734)			Labor productivity (N=22,655)		
Channel	Coef	S.E	Differential effects (%)	Coef	S.E	Differential effects (%)	Coef	S.E	Differential effects (%)
EFD	2.144**	1.022	0.544	6.953*	4.221	1.626	0.628	0.890	0.159
FIX	-2.065**	0.869	-0.678	-3.497	4.391	-1.057	-2.468***	0.839	-0.810
SPEC	1.539**	0.701	0.364	8.833**	4.221	1.927	0.588	0.869	0.139
LMP	2.362**	1.117	0.631	6.442	4.886	1.586	1.699*	0.969	0.454
DEP	2.018**	0.917	0.693	8.364	5.922	2.646	0.358	0.943	0.123
ISTC	-0.115	0.905	-0.039	3.762	3.655	1.185	1.238*	0.735	0.423
LAB	2.386***	0.813	0.400	1.901	4.198	0.294	0.331	0.878	0.055
HC	-0.363	0.946	-0.102	11.297**	5.693	2.929	-1.452*	0.880	-0.409
RND	0.449	1.145	0.060	5.765	4.253	0.704	0.687	0.778	0.091

Note: The first column indicates each specific channel interacting with a fiscal policy countercyclicality measure when estimating equation (1). T-statistics based on clustered standard errors at the industry-country level are reported in parenthesis. *, **, *** denote significance at 10, 5, and 1 percent, respectively. EFD (external financial dependence), FIX (asset fixity), SPEC (input specificity), LMP (investment lumpiness), DEP (depreciation), ISTC (Investment-specific technical change), LAB (labor intensity), HC (skilled labor intensity), RND (R&D intensity). Differential effects are computed for an industry whose characteristics would increase from the 25th percentile to the 75th percentile of the distribution when fiscal policy countercyclicality would increase from the 25th to the 75th percentile.

Table 9. The effect of countercyclical fiscal policy on industry growth: Recessions vs. expansions

	Value-added growth (N=22,655)					
	Recession			Expansion		
Channel	Coef	S.E	Differential effects (%)	Coef	S.E	Differential effects (%)
EFD	7.841**	3.557	1.990	0.145	1.802	0.037
FIX	-7.488***	2.448	-2.457	-3.018**	1.418	-0.990
SPEC	2.304	2.781	0.545	2.043	1.446	0.484
LMP	8.870***	3.124	2.370	1.674	1.915	0.447
DEP	3.417	3.627	1.174	1.863	1.399	0.640
ISTC	3.120	2.295	1.067	-0.001	1.378	0.000
LAB	-1.805	2.173	-0.303	4.321***	1.414	0.724
HC	2.619	3.289	0.737	-3.887**	1.367	-1.094
RND	7.315**	3.026	0.970	-1.316	1.620	-0.175

Note: The first column indicates each specific channel interacting with a fiscal policy countercyclicality measure when estimating equation (5). T-statistics based on clustered standard errors at the industry-country level are reported in parenthesis. *, **, *** denote significance at 10, 5, and 1 percent, respectively. EFD (external financial dependence), FIX (asset fixity), SPEC (input specificity), LMP (investment lumpiness), DEP (depreciation), ISTC (Investment-specific technical change), LAB (labor intensity), HC (skilled labor intensity), RND (R&D intensity). Differential effects are computed for an industry whose characteristics would increase from the 25th percentile to the 75th percentile of the distribution when fiscal policy countercyclicality would increase from the 25th to the 75th percentile.

Table 10. The effect of countercyclical fiscal policy on industry growth: Horserace

	Baseline (N=22,655)			Advanced economies (N=12,465)			Developing economies (N=10,184)		
Channel	Coef	S.E	Differential effects (%)	Coef	S.E	Differential effects (%)	Coef	S.E	Differential effects (%)
EFD	1.908	2.248	0.484	3.651**	1.671	0.682	1.206	3.533	0.337
FIX	-5.037**	2.213	-1.653	-4.014**	1.709	-0.969	-7.260**	3.340	-2.625
SPEC	0.694	1.326	0.164	-0.494	0.849	-0.086	1.473	2.142	0.384
LMP	-2.459	3.554	-0.657	-3.335	2.305	-0.656	-2.155	5.360	-0.634
LAB	1.050	1.300	0.176	1.932**	0.906	0.238	0.332	2.377	0.061

Note: Estimates are based on equation (1) by including EFD, FIX, SPEC, LMP, and LAB channels altogether. T-statistics based on clustered standard errors at the industry-country level are reported in parenthesis. *, **, *** denote significance at 10, 5, and 1 percent, respectively. EFD (external financial dependence), FIX (asset fixity), SPEC (input specificity), LMP (investment lumpiness), LAB (labor intensity. Differential effects are computed for an industry whose characteristics would increase from the 25th percentile to the 75th percentile of the distribution when fiscal policy countercyclicality would increase from the 25th to the 75th percentile.

Appendix A. Simple theoretical models

We layout simple theoretical frameworks drawn from the existing literature (Aghion et al., 2014; Samaniego and Sun, 2016) to formulate the main hypotheses of the paper. The first model describes how countercyclical fiscal policy can enhance growth by stabilizing future economic conditions, especially for credit-constrained firms. The second model illustrates the growth-enhancing effect of countercyclical fiscal policy when firms are subject to the cost of waiting. This model also implies the growth-dampening effect of countercyclical fiscal policy when firms are flexible in their investment or production decision.

Credit constraint channel. Formally, consider a two-period model in which a risk-neutral entrepreneur owns a firm. Firm-level productivity $A_{i,t}$ in period t is given by a product of aggregate level productivity a_t and firm-specific level of the human capital (or knowledge) $H_{i,t}$. Each entrepreneur is endowed with the same initial wealth $W_t = wH_t$ ($H_{i,t} = H_t$ for all i). An entrepreneur allocates her wealth between short-term physical investment $K_t = kH_t$ and long-term productivity-enhancing investment $Z_t = zH_t$ in period t, so that $w = k + z$.

There are two types of shock: an aggregate productivity shock a_t and an idiosyncratic liquidity shock $C_{i,t}$. Following Bloom (2009), we assume that aggregate productivity evolves as an augmented geometric random walk, and uncertainty shocks are modeled as time variations in the standard deviation of the driving process.

$$a_{t+1} = a_t(1 + \sigma_t \varepsilon_{t+1}),\ \sigma_t \in \{\sigma_L, \sigma_H\} \text{ and } \varepsilon_t \sim N(0,1),$$

where σ_t is the standard deviation of an aggregate productivity shock and ε_t is an independent and identically distributed (*i.i.d.*) normal shock. Before making its investment decisions, a firm observes the current state of aggregate productivity ($a_t = a$).

Once investment decisions of the entrepreneurs are made, two types of shock (an aggregate productivity shock and an idiosyncratic liquidity shock) occur at the beginning of the period $t + 1$. The short-term investment yields profits $\pi_{t+1} = a_{t+1}k^{\alpha}H_t$, where $0 < \alpha < 1$, while the long-term investment yields profits $v_{t+1}H_t$ at the end of the period $t + 1$ with probability λz if the firm survives an idiosyncratic liquidity shock $C_{i,t+1} = c_{i,t+1}H_t$, $c_{i,t} \sim_{i.i.d.} unif(0,1)$ at the beginning of the period $t + 1$. Under risk neutrality and *i.i.d.* shocks, the timing convention implies that firms are identical ex-ante. Thus, we focus on the symmetric equilibrium in which all firms choose identical k and z. The model is highly stylized under the following assumptions, given that our objective is to derive the simplest possible theoretical prediction on how an increase in aggregate uncertainty affects sectoral productivity growth via financial constraints.

Assumption 1.

The long-term investment is sufficiently productive: $v_{t+1} > \frac{a\alpha}{\lambda} w^{\alpha-1}$.

Assumption 2.

There are two types of firms in this economy. Whereas a fraction of $1-\mu$ *(unconstrained) firms can borrow up to the net present value of their profit, a fraction of* μ *(constrained) firms needs to refinance their project using their cash flow only*. $0 < \mu < 1$.

Constrained firms survive the liquidity shock if their realized short-term profit is greater than their liquidity cost. Thus, the probability that a constrained firm survives the liquidity shock is $f_{t+1} = Pr(a_{t+1}k^{\alpha} \geq c) = min\{a_{t+1}k^{\alpha}, 1\}$ under the uniform distribution of a liquidity shock. A unit mass of total firms in the economy implies that a fraction f_{t+1} of constrained firms will survive the liquidity shock.

Proposition 1.

Unconstrained firms always invest a positive amount of their human capital in the long-term investment, $z_{nc} > 0$ *and their investment is larger than that of constrained firms:* $z_{nc} > z_c$.

Proof.

First, an unconstrained firm maximizes its end of $t+1$ consumption by choosing k and z after observing $a_t = a$:

$$max_{k,z} E_t[a_{t+1}k^{\alpha}H_t + \lambda z v_{t+1} H_t | a_t = a] \tag{A.1}$$

subject to $k + z = w$.

One can rewrite (A.1) as

$$max_z (a(w-z)^{\alpha} + \lambda z v_{t+1}) H_t \tag{A.2}$$

Maximization of (A.2) leads to

$$z_{nc} = w - \left(\frac{\lambda}{\alpha a} v_{t+1}\right)^{\frac{1}{1-\alpha}}.$$

Lemma 1.

A mean preserving spread of aggregate productivity distribution decreases z_c, but does not affect z_{nc}.

Proof.

Proposition 1 shows that only z_c is a function of σ_t and $\frac{\partial z_c}{\partial \sigma_t} < 0$.

We can decompose firm growth into:

$$ln\, A_{i,t+1} - ln\, A_{i,t} = ln\, a_{t+1} - ln\, a_t + ln\, H_{i,t+1} - ln\, H_{i,t}. \tag{A.3}$$

Under the random walk assumption on the aggregate productivity process, the expected firm growth rate depends on the fraction of projects that survive the liquidity shocks:

$$g_{t+1} = E\left[\ln A_{i,t+1} - \ln A_{i,t}\right] = \lambda((1-\mu)z_{nc} + \mu z_c \min(a_{t+1}(w - z_c)^{\alpha}, 1)). \tag{A.4}$$

Lemma 2.

A decline in productivity volatility due to countercyclical fiscal policy enhances the expected firm growth: $\frac{\partial g_{t+1}}{\partial \sigma_t} < 0$.

Proof.

Lemma 1 *and the assumption of* $0 < \mu < 1$ *complete Lemma 2.*

Lemma 3.

Countercyclical fiscal policy increases the expected firm growth more the higher the fraction of constrained firms: $\frac{\partial}{\partial \mu}\left(\frac{\partial g_{t+1}}{\partial \sigma_t}\right) < 0$.

Proof.

Lemma 1 *and Lemma* 2 *complete Lemma* 3*.*

Lemma 4.

The differential effect of countercyclical fiscal policy is larger when realized productivity is lower: $\frac{\partial}{\partial a_{t+1}}\left(\frac{\partial}{\partial \mu}\left(\frac{\partial g_{t+1}}{\partial \sigma_t}\right)\right) < 0$.

Proof.

$\frac{\partial f_{t+1}}{\partial a_{t+1}} < 0$ *from Proposition 1.*

Lemma 2 implies that an increase in fiscal policy countercyclicality has a positive effect on firm growth at aggregate-level. Lemma 3 further suggests that an increase in fiscal policy countercyclicality enhances productivity growth more in industries that are financially constrained, which is our main hypothesis. Finally, Lemma 4 implies that financial constraints bind more in a bad state. Thus, the interaction between an increase in fiscal policy countercyclicality and credit constraints on firm growth rate is larger in recessions than expansions. We empirically test these theoretical predictions by exploiting cross-industry variation in μ that is proxied by various industry-specific characteristics, such as external financial dependence and asset fixity and cross-country and time variation in σ_t that is captured by fiscal policy countercyclicality.

Real options and convexity channel. Consider a simple three-period model $(t = 0, 1, 2)$. Suppose that a firm holds a project in period 0 that yields a known profit of V_0. The firm discounts future with factor $0 < \beta \leq 1$. In period $t > 0$, this project yields $V_0(1-\delta)^t$, where δ captures a broad notion of depreciation of the given project. One can interpret it as the physical depreciation of capital stock or economic depreciation captured by technological obsolescence and specific input usage.

In period 1, the firm can invest in a new project with an unknown profit of $V_1 = V_0 + \mu + \varepsilon$, where $\mu > 0$, $\varepsilon \in \{-\sigma, \sigma\}$, and $\sigma > \mu$. The positive value of μ implies that the new project delivers higher returns *ex-ante*, while the presence of term ε indicates that the new project is subject to uncertainty. $\sigma > \mu$ assumes that the new project is *ex-post* more profitable than the old project only in the good state. For simplicity, each state realizes with probability 1/2, so an increase in σ captures the mean-preserving spread in underlying shocks as in the credit constraint model.

The firm can switch to the new project, but only by abandoning the old project, in which case its old capital invested in the old project becomes worthless. The shock ε will be realized in period 2, so the firm can make an informed decision if it waits until period 2. Now, the firm needs to consider the trade-off between the cost of waiting and the benefit from obtaining more information. For simplicity, we further assume that the new project does not depreciate.[19]

More formally, the firm's expected profit function can be written as:

$$V_0 + \max\{V^{switch},\, V^{wait}\},$$

$$V^{switch} = \beta(V_0 + \mu) + \beta^2(V_0 + \mu)$$

$$V^{wait} = \beta(1-\delta)V_0 + \frac{\beta^2}{2}(1-\delta)^2 V_0 + \frac{\beta^2}{2}(V_0 + \mu + \sigma) \tag{A.5}$$

where V^{switch} denotes the expected profit of switching to the new project in period 1, while V^{wait} denotes the expected profit of waiting in period 1 and adopt the new project in period 2 only if the good state realizes. This asymmetry between the states limits the downside risk, thereby creating the option value of waiting. In other words, an increase in uncertainty captured by σ increases the value of waiting, while not affecting the value of switching: $\frac{\partial V^{switch}}{\partial \sigma} = 0$ and $\frac{\partial V^{waiting}}{\partial \sigma} > 0$. The firm will wait for the resolution of uncertainty if and only if $V^{switch} < V^{wait}$. In the absence of the cost of waiting (i.e., investment or production decisions are fully flexible), the expected profit always increases in σ, which is the intuition behind the convexity channel. Thus, industries with a more flexible input of production grow slower under the countercyclical fiscal policy, as they are no longer able to enjoy the large upside risk.

Under the presence of the cost of waiting ($\delta > 0$), a firm must weigh the cost of waiting against its benefit. It is straightforward to see that the firm is inclined to take an early switching decision with an increase in δ. This means that this firm would sometimes adopt the wrong project that it would have been optimal to let it pass if the firm were to wait, thus having lower growth on average. Countercyclical fiscal policy can enhance the growth of industries that are subject to a higher cost of waiting by limiting this downside risk. While this model is highly stylized, it describes a common problem faced by firms and provides intuition on how fiscal

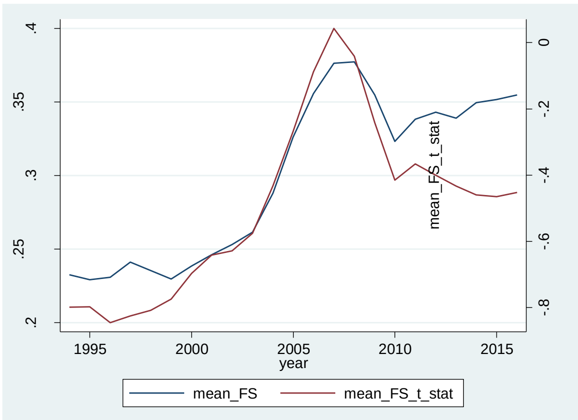
[19] This is not a critical assumption. The theoretical prediction still holds unless the depreciation rate of the new project is sufficiently higher than that of the old project.

policy countercyclicality could have different growth implications depending on the underlying industry technological characteristics.

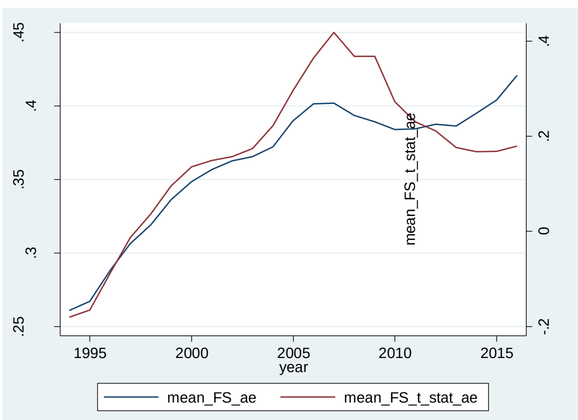
Appendix B. Additional figures and tables

Figure B.1. The average fiscal policy countercyclicality coefficients and the associated t-statistics

a) All countries, N=55



b) Advanced economies, N=21



c) Developing economies, N= 34

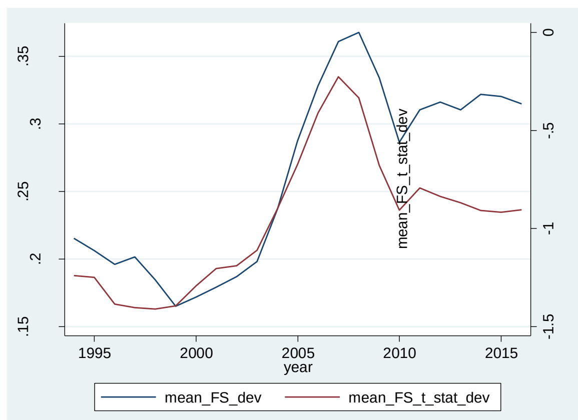


Table B.1. Industry classification: INDSTAT2 vs. INDSTAT3

	INDSTAT2		INDSTAT3
ISIC	**Industry**	ISIC	Industry
15	**Food products and beverages**	311	Food
16	**Tobacco products**	313	Beverages
17	**Textiles**	314	Tobacco
18	**Wearing apparel; dressing and dyeing of fur**	321	Textiles
19	**Tanning and dressing of leather**	322	Apparel
20	**Wood and of products of wood and cork, except furniture**	323	Leather
21	**Paper and paper products**	324	Footwear
22	**Publishing, printing, and reproduction of recorded media**	331	Wood products
23	**Coke, refined petroleum products and nuclear fuel**	332	Furniture, except metal
24	**Chemicals and chemical products**	341	Paper and products
25	**Rubber and plastics products**	342	Printing and publishing
26	**Other non-metallic mineral products**	351	Industrial chemicals
27	**Basic metals**	352	Other chemicals
28	**Fabricated metal products, except machinery and equipment**	353	Petroleum refineries
29	**Machinery and equipment n.e.c.**	354	Misc. pet. And coal products
30	**Office, accounting, and computing machinery**	355	Rubber products
31	**Electrical machinery and apparatus n.e.c.**	356	Plastic products
32	**Radio, television and communication equipment and apparatus**	361	Pottery, china, earthenware
33	**Medical, precision and optical instruments, watches and clocks**	362	Glass and products
34	**Motor vehicles, trailers, and semi-trailers**	369	Other nonmetallic mineral products
35	**Other transport equipment**	371	Iron and steel
36	**Furniture; manufacturing n.e.c.**	372	Nonferrous metals
		381	Fabricated metal products
		382	Machinery, except electrical
		383	Machinery, electric
		384	Transport equipment
		385	Prof. and sci. equip.
		390	Other manufactured products

Table B.2. Country coverage

Advanced economies			Developing economies		
Country	Number of observations	Maximum coverage	Country	Number of observations	Maximum coverage
Australia	378	1988-2013	Algeria	56	1990-1996
Austria	545	1988-2014	Bahrain	25	2001-2005
Belgium	623	1980-2014	Bangladesh	318	1980-2011
Canada	733	1979-2014	Bolivia	405	1981-2010
Denmark	700	1979-2014	Chile	306	1990-2013
Finland	722	1979-2014	China	493	1982-2007
France	699	1980-2014	Colombia	602	1982-2012
Greece	669	1976-2013	Costa Rica	244	1990-2003
Hong Kong	460	1984-2014	El Salvador	104	1993-1998
Iceland	237	1980-1996	Ethiopia	420	1990-2014
Italy	577	1988-2014	Gabon	56	1991-1995
Japan	797	1970-2010	Ghana	178	1980-2003
Netherlands	651	1981-2014	Honduras	107	1990-1995
New Zealand	187	1985-2012	India	550	1988-2014
Norway	723	1978-2014	Iran	554	1990-2014
Portugal	580	1986-2014	Jamaica	63	1990-1996
Singapore	532	1990-2014	Jordan	554	1985-2013
Spain	722	1980-2014	Kenya	315	1982-2013
Sweden	711	1980-2014	Kuwait	430	1990-2013
Switzerland	316	1986-2013	Lebanon	39	1998-2007
U.K.	716	1978-2013	Madagascar	172	1980-2006
			Malaysia	429	1990-2012
			Mexico	348	1990-2013
			Mongolia	345	1990-2011
			Morocco	458	1990-2013
			Oman	437	1993-2014
			Paraguay	55	2001-2010
			Philippines	389	1989-2012
			Qatar	330	1990-2013
			Romania	469	1990-2013
			Sri Lanka	369	1990-2012
			Swaziland	155	1980-2011
			Trinidad and Tobago	236	1988-2003
			Venezuela	188	1988-1998

Table B.3. Alternative treatment of standard errors

Channel	Coef	S.E (baseline)	S.E (clustered at country-time)	S.E (HAC-robust)	S.E (Driscoll-Kraay)
EFD	2.373	1.427	1.595	1.413	1.149
FIX	-4.534	1.163	1.301	1.209	1.565
SPEC	2.1276	1.144	1.280	1.137	1.445
LMP	3.861	1.529	1.627	1.472	1.533
DEP	2.376	1.464	1.404	1.438	1.012
ISTC	1.022	1.206	1.283	1.151	0.989
LAB	2.417	1.114	1.253	1.214	1.374
HC	-1.715	1.383	1.297	1.410	1.071
RND	1.136	1.496	1.667	1.419	0.957

Note: The first column indicates each specific channel interacting with a fiscal policy countercyclicality measure when estimating equation (1). T-statistics based on alternative standard errors are reported in parenthesis. EFD (external financial dependence), FIX (asset fixity), SPEC (relationship-specific investment), LMP (investment lumpiness), DEP (depreciation), SPEC (input specificity), LAB (labor intensity), HC (skilled labor intensity), RND (R&D intensity). Differential effects are computed for an industry whose characteristics would increase from the 25th percentile to the 75th percentile of the distribution when fiscal policy countercyclicality would increase from the 25th to the 75th percentile.