Do IMF Programs Stimulate Private Sector Investment?

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ABSTRACT: This paper provides new evidence on the role of IMF programs in stimulating private sector investments. In the first part of the paper, we use detailed firm-level data on tangible fixed asset investments and a local projection methodology to estimate the dynamic response of firm investments to the approval of an IMF arrangement. We find that distinguishing between General Resource Account (GRA) and Poverty Reduction and Growth Trust (PRGT) financing matters for the path of firm investment and its growth. Following the approval of a GRA arrangement, investments start to increase after two years (peaking after four years), while after the beginning of a PRGT there is a mild effect that vanishes after two years. In the second part of the paper, we adopt a difference-in-differences approach to exploit firm-level characteristics. We focus on three main characteristics: external financial dependence (Rajan and Zingales 1998), sectoral uncertainty (Alfaro, Bloom and Lin 2021), and whether the firm operates within the country. We find that firms that rely more on external finance, or are more subject to uncertainty, invest more following a program approval, indicating that financial frictions become less binding. Finally, using ownership data, we find that private investments are stimulated more for firms having domestic ownership. The presence of a private investment transmission channel could help improve our understanding of what factors can influence the effectiveness of IMF programs.

[1] The views expressed in this paper are those of the author(s) and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

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1. Introduction

The economic headwinds over the past several years, from the pandemic, to supply crises, to geopolitical tensions faced by countries have reinvigorated the role of multilateral lenders such as the International Monetary Fund (IMF) in international finance. IMF resources have been tapped over the past decade to deal with systemic debt crises in advanced economies such as in the Euro area, as well as reviving its role among developing and fragile economies.[2] Traditionally, financial support by the IMF aims to create breathing room for countries hit by crises as they implement adjustment policies to restore macroeconomic stability and growth. While policies depend on country circumstances, the set of corrective actions provide a seal of approval that appropriate policies are adopted, helping mitigate crises and boosting market confidence during periods of heightened risks. In the absence of economic stability, misallocation of resources leads to lower aggregate productivity and investments, which are leading explanations for economic disparities across countries (Hsieh and Klenow, 2009).

In this paper, we aim to show in the first place how the IMF influences private sector investments, and then we document through which channels these investments are affected. The goal of the IMF in spurring the private sector as the engine of economic growth is well understood. While previous work documents the relationship between the IMF and firm performance in the short term (Bomprezzi and Marchesi 2021), this paper, using more detailed information on firm characteristics, provides evidence on the interplay between the IMF and firm fixed asset investments.[3]

At the macro level, the effects of IMF programs have been extensively investigated focusing on two main channels. The “seal of good faith”, or signaling, argument is typically used to explain a catalytic finance effect, whereby foreign capital or creditors return to the country (Corsetti et al. 2006; Marchesi 2003; Morris and Shin 2006). Another strand of the literature has instead looked at the liquidity effects of IMF credit injections, which can reduce the probability of self-fulfilling runs arising from illiquidity problems (Boockmann and Dreher 2003; Dreher 2006; Dreher and Vaubel 2004; Zettelmeyer 2000). On the other hand, in our analysis we consider whether the signaling effect of an IMF program operates within the confines of the country itself. Consistent with acting as a seal of good faith to outside investors, an IMF program can also be viewed positively by domestic investors (i.e., firms in the private sector). By strengthening policy frameworks and institutions and pushing for the adoption of concrete and credible policy actions, IMF programs can therefore be viewed as triggering a policy uncertainty reduction mechanism. Domestically, these would induce the private sector to undertake positive net present value capital investments.

An increasing amount of research focuses on the impact of uncertainty on firms (among others see Abel 1983; Bernanke 1983; Bloom et al. 2007; Gilchrist et al. 2014; Gulen and Ion 2015; Handley and Limao 2015; Huihua et al. 2020; Julio and Yook 2014; Kang et al. 2014). While few early studies contend that uncertainty may in some cases stimulate firm investments (Bar-Ilan and Strange 1996; Abel 1983), more recent research predicts that uncertainty would instead inhibit their investment (Gulen and Ion 2016 and Rao et al. 2017). This paper leverages balance sheet data to evaluate whether the approval of an IMF program, by reducing policy uncertainty, may

[2] For example, the IMF has introduced a set of measures aimed to help developing economies tackling both liquidity (e.g., the Short-term Liquidity Line, or SLL) and solvency problems caused by the pandemic (e.g., the Catastrophe Containment and Relief Trust, or CCRT). Most importantly, the new issuance of $650 billions of new IMF special drawing rights (SDRs) should boost emerging economies’ balance sheets. At the same time, the IMF, together with the World Bank, urged G20 countries to establish the DSSI, a form of debt relief that eases financing constraints by deferring debt service repayments.

[3] In 2010 The Economist Schumpeter columnist wrote on the private sector investment response to an IMF SBA arrangement in Jamaica that had recently been approved, reporting how Jamaican business owners were optimistic and expanding in light of the new program (The Economist, May 14th 2010. “Island Stories”)

enhance firm investments. More specifically, since tangible fixed asset investments tend to be non-reversible, firms favor precautionary delays in long-term decisions until policy uncertainty subsides. By focusing on firm investment dynamics following the approval of an IMF program, we aim to assess the reaction of the private sector to a reduction of policy uncertainty. Documenting an uncertainty channel can help improve our understanding of the effectiveness of IMF programs.

Using detailed firm-level data on tangible fixed asset investments, we consider the difference between Poverty Reduction and Growth Trust (PRGT) and General Resource Account (GRA) arrangements. This distinction is important because they address two different types of policy uncertainty. Under GRA financing, the member's balance of payment needs should be resolved by the end of the program period and no follow-up arrangement would in principle be expected. In contrast, financing under the PRGT is tied to achieving or making progress towards a stable and sustainable macroeconomic position consistent with strong and durable poverty reduction and growth, without necessarily expecting a resolution of the balance of payments problem during the program period. We start by estimating the dynamic response of firm investments following the approval of an IMF program through a local projection methodology. As the main advantage of the local projections is to give a broad picture of the evolution of investments over time, it comes at the cost of assessing in detail the role of firm-level indicators. For this reason, in the second part of the paper, we adopt a difference-in-differences approach to exploit firm-level characteristics. We focus on three main characteristics: external financial dependence (Rajan and Zingales 1998), sectoral uncertainty (Alfaro, Bloom, and Lin 2021), and whether the firm operates within the country.

We find that following the approval of a GRA investments start to increase after 2 years and peak after 4 years, while after the beginning of a PRGT there is a mild effect that vanishes after 2 years. In the second part of the analysis, we find that firms that rely more on external finance or are more subject to uncertainty invest more following a program approval, indicating that financial frictions become less binding. Finally, using ownership data, we find that private investments are stimulated more for firms having domestic ownership. The presence of a private investment transmission channel improves our understanding of what factors influence the effectiveness of IMF programs. This paper contributes to the literature on IMF effectiveness, and in particular to the strand of macro-micro work which leverages firm data to study the channels through which IMF programs influence local economic activity. Given the importance of private sector activity to the success of an IMF program, the evaluation of different lending facilities and their outcomes has practical relevance for program stakeholders. To the best of our knowledge, this is the first paper that investigates whether different types of IMF programs, as well as improving a country's creditworthiness for external investors, may also make "internal" investors more willing to invest in their own country by reducing the impact of uncertainty.

The remainder of the paper is organized as follows. Section 2 provides a review of the main literature on both the effects of IMF financing and firm investment under policy uncertainty. Section 3 presents our data, while Section 4 illustrates the methodology and identification strategy. Section 5 presents our main empirical results and Section 6 summarizes robustness tests. Section 7 concludes.

2. Literature Review

2.1 Effects of IMF Programs

Traditionally the literature on IMF effectiveness focuses on broad country-level outcomes (Przeworkski and Vreeland 2000; Barro and Lee 2005; Easterly 2005; Dreher 2006; Marchesi and Sirtori 2011; Bas and Stone 2014). Among these studies, more recent ones have focused on the specific objectives of IMF policy conditions

in pursuing macroeconomic stability. For example, some argue monetary stability, debt management, and the containment of external arrears as key goals of IMF programs (Kentikelenis, Stubbs, and King 2016). Also, IMF programs have been associated with reduced inflation and monetary growth, lower risk of currency crises and banking crises, and improved market performance of banks (Dreher and Walter 2010; Papi et al. 2015; Steinwand and Stone 2008).[4] In sum, the evidence suggests some positive adjustment effects regarding financial, fiscal, and monetary positions, though the benefits have generally fallen short of expectations, especially in terms of GDP growth and debt reduction (IMF 2018; IEO 2021).

The success of IMF programs, however, largely hinges on its catalytic effect, namely the propensity of private capital to flow into the country following the approval of an IMF program. The signaling role of an IMF-supported adjustment program and its catalytic effects have both been extensively analyzed in the literature with mixed findings (e.g., Chapman et al. 2015; Corsetti et al. 2006; Gehring and Lang 2020; Krahnke 2020; Marchesi and Thomas 1999; Marchesi 2003; Mody and Saravia 2006; Morris and Shin 2006; Zwart 2007). While conditionality can reassure international investors that adequate policies are being implemented to resolve the balance of payments needs (Tirole 2002), the preferred creditor status of the IMF could make foreign investors fear penalization in case of a debt restructuring (Mody and Saravia 2003).

This paper belongs more generally to the growing body of literature focusing on the effects of official intervention at the subnational level. Recent studies have re-investigated economic outcomes following official capital flows at a more disaggregated level with respect to broad macroeconomic aggregates (Bluhm et al. 2020; Bomprezzi and Marchesi 2021; Chauvet and Ehrhart 2018; Dreher and Lohman 2015; Dreher et al. 2021; Marchesi et al. 2021).[5] The paper which most closely relates to ours is Bomprezzi and Marchesi (2021), who evaluate the effects of IMF programs on firm-level outcomes by considering two dimensions: participation in a program and scope of conditionality. They find that IMF intervention has a positive impact on firms' sales growth and that firm performance improves through the alleviation of the financing constraint.

More broadly, a growing literature is investigating the effects of official capital flows on domestic firms. Broner et al. (2021) find that sovereign debt inflows encourage banks to expand domestic credit, therefore benefitting domestic firms, especially those that are financially constrained.[6] To the extent that the signaling role and the catalytic effect of an IMF program work to reassure financial markets, sovereign risk of the recipient country can also be reduced. Some papers explain how an increase in sovereign risk may propagate to firms (Mendoza and Yue, 2012; Hébert and Schreger, 2017; Andrade and Chhaochharia, 2018).

2.2 Firm Investment Under Uncertainty

The literature on determinants of investment dynamics emphasizes the role of firm and sector-specific factors such as size, profitability, asset tangibility, and industry median leverage (Myers, 1984; Myers and Majluf, 1984; Titman and Wessels, 1988; Harris and Raviv, 1991; Booth and et al. 2001; Baker and Wurgler, 2002; Lemmon

[4] In addition, moral hazard incentives by borrowing countries expecting a bail-out could also be a concern (Dreher 2006).

[5] Dreher and Lohman (2015) were among the first to apply a macro-micro approach to evaluate the effectiveness of official capital flows. Using night-time light intensity, evaluate the effects of World Bank aid on development. Similarly, Marchesi et al. (2021) use survey data confront Chinese and World Bank project aid effects on firm sales. Bluhm et al. (2020) explore the equality inducing effects of Chinse infrastructure investments. Chauvet and Ehrhart (2018) use survey data to evaluate the effects of multilateral and bilateral aid flows on firm sales, finding a positive effect which manifest through the alleviation of an infrastructural constraint as well as a financing constraint.

[6] In general, the international macroeconomics literature on the effects of capital flows on the real economy is vast, especially for foreign direct investment, banks, and equity portfolio flows (Broner et al. 2020; Schnabl 2012; Baskaya et al. 2017).

et al. 2008; Frank and Goyal, 2009; Gungoraydinoglu and Öztekin, 2011; Graham et al. 2015; De Angelo and Roll, 2015; Öztekin, 2015). On the other hand, another strand of literature instead emphasizes the role of country-specific macroeconomic and institutional factors in determining firm outcomes (Borio, 1990; Rajan and Zingales, 1998; Kayo and Kimura, 2011; Cevik and Miryugin, 2018), as well the role of political instability (Herrala and Turk-Ariss, 2016).

Recent work underlines the importance in distinguishing between different sources of uncertainty as determinants of firm investments. For example, Baum et al. (2010) distinguish between own uncertainty (based on a firm's stock returns), market uncertainty (derived from the returns on a stock index), and a measure of covariance between the two. They find that an increase in market uncertainty inhibits investments, while finding that the effects of firm-level uncertainty are contingent on other firm specific factors such as cash flow. Similarly, Kang et al. (2014) find that economic policy (i.e., macro) uncertainty depresses firms' investment decisions, and the effect is greater for firms with higher firm-level uncertainty (proxied by stock price volatility). Finally, recent methodological advances focus on providing improved proxies of uncertainty. For example, Jurado et al. (2015) provide econometric estimates of aggregate uncertainty, showing that popular uncertainty proxies overestimate the number of quantitatively important uncertainty episodes. Baker et al. (2013) deviate from traditional proxies by constructing a three-part index containing news-based, future tax provisions, and economic forecast components. Gulen and Ion (2016) use this index to show that the news-based component is the most relevant in explaining the negative relationship between aggregate uncertainty and capital investments and highlighting how the magnitude of the effect varies by the degree of investment irreversibility.

More closely related to our paper is the growing strand of literature that considers the adverse impact of uncertainty on firm investment. A common strategy is to proxy exposure to uncertainty through the volatility of returns of stock prices (Leahy and Whited 1996; Bloom et al. 2007; Baum et al. 2010; Bloom 2009; Panousi and Papanikolaou 2012). For example, Bloom et al. (2007) present a model in which uncertainty reduces firms' irreversible long-term investments in response to shocks to sales, arguing that firms become more cautious during times of heightened stock price volatility. Using data on U.S. firms over 1970–2005, Panousi and Papanikolaou (2012) show that firm-level idiosyncratic risk (or the volatility of stock price returns that is not explained by market or industry returns) associates negatively with corporate investment. In particular, and directly relevant for our paper, Alfaro, Bloom, and Lin (2021) construct a firm-level dataset of uncertainty measures as well as firm-level instruments to address endogeneity concerns. They provide two different proxies of uncertainty at the micro level: (i) realized stock return volatility of daily returns from the Center for Research in Security Prices (CRSP) and (ii) implied volatility, as constructed from a mix of put and call-at-the-money options. As will be shown in later sections, we employ the first of these indicators as our preferred measure of firm-level uncertainty.

In summary, this paper contributes to the empirical literature on IMF effectiveness by exploring the effect of IMF programs on private sector investments. It proposes a *domestic* signaling effect, under which economic agents (firms) when undertaking non-reversible long-term investment decisions are sensitive to the current and expected macroeconomic environment. Under this hypothesis, the reduction of domestic policy uncertainty that accompanies IMF programs induces firms to increase tangible investments. The paper also contributes to the empirical literature on economic uncertainty by incorporating micro-level indicators in the context of international capital flows.

3. Data

3.1 Identifying IMF Programs

We focus on the pre COVID-19 period, drawing data on IMF programs from the IMF's Monitoring of Fund Arrangements (MONA) database between 2002 and 2019. We consider the main lending instruments in the IMF's toolkit, which are tailored to different types of balance of payments needs as well as the specific circumstances of the diverse membership. However, unlike previous work that we are familiar with, we focus separately on financing through the GRA and the PRGT.[7] Whereas GRA financial support is available to all member countries on non-concessional terms, the IMF also provides concessional financing through the PRGT to cater to the diversity and needs of low-income countries.

We make the explicit distinction between GRA and PRGT lending facilities because the policy ramifications of financing differ between the two. Financing under the GRA requires that policy measures be taken within the program period and the macroeconomic adjustment be completed by the time repurchases (or repayment) to the IMF begin.[8] Under GRA financing, the member's balance of payment needs should be resolved by the end of the program period and no follow-up arrangement would in principle be expected. In contrast, financing under the PRGT is tied to achieving, or making progress towards, a stable and sustainable macroeconomic position consistent with poverty reduction and growth.[9] The distinction between GRA and PRGT is important because it implies that, unlike for the GRA, repeated programs financed under the PRGT can be expected for sustained engagement to deliver progress towards macroeconomic stability. For expositional simplicity, from here on we label lending facilities under GRA financing as "GRA programs" and likewise PRGT financed lending facilities as "PRGT programs".

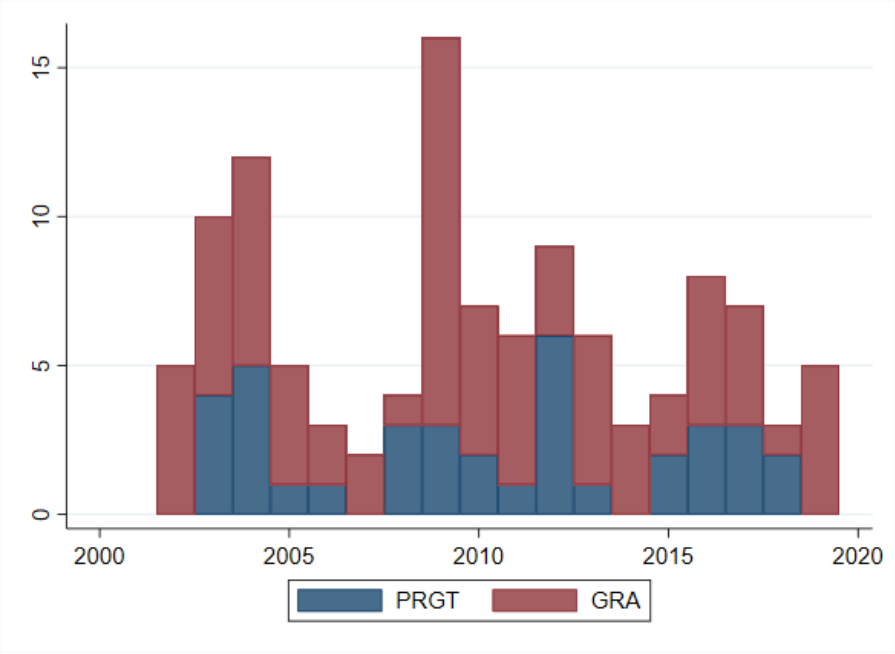
Our treatment variable of interest is an indicator that takes the value 1 if a country, as reported in MONA, approved an IMF program during the year but no later than October.[10] Otherwise, the subsequent year is coded as the program approval year. [11] This coding allows us to explicitly account for program effects that would not manifest in a certain year if the program was effectively adopted later in the year. Our sample contains only countries that have had an IMF arrangement over the sample years. This setup helps to mitigate problems of endogeneity, whereby estimates of the effects of an IMF arrangement approval on investment dynamics could be biased by selection into the sample. Secondly, with a sample of treated countries, the focus can shift to the heterogeneity among arrangements.

Figure 1 plots the number of unique programs recorded per year in the MONA database for the 2 types of arrangements considered (GRA and PRGT). GRA arrangements make up the bulk of programs over the full sample, while PRGT arrangements represent a smaller share, generally not surpassing 5 per year. On average,

[7] Lending instruments under the GRA include the Extended Fund Facility (EFF) for medium-term support to address protracted balance of payments problems, the Stand-By Arrangement (SBA) for short-term or potential balance of payments problems and, for members with already strong policies, and the Flexible Credit Line (FCL) and the Precautionary and Liquidity Line (PLL) to help prevent or mitigate crises and boost market confidence during periods of heightened risks. As for the concessional PRGT, two lending facilities are considered; (i) the Extended Credit Facility (ECF) for sustained medium- to long-term engagement in case of protracted balance of payments problems and (ii) the Standby Credit Facility (SCF) to address short-term balance of payments and adjustment needs caused by domestic or external shocks, or policy slippages.
[8] Amounts drawn under an EFF are to be repaid over 4½–10 years in 12 equal semiannual installments, whereas credit provided under an SBA are repaid over 3¼–5 years.
[9] Repayments under the ECF carries a grace period of 5½ years and a final maturity of 10 years, whereas the SCF has a grace period of 4 years and a final maturity of 8 years.
[10] In the case of blended resources (neither GRA nor PRGT), we code them as PRGT programs.
[11] We follow the IMF Independent Evaluation Office (IEO, 2021) strategy for coding program start years.

the overall number of programs per year increased in the latter half of our sample. The following sub-section introduces the various firm-level data, including both investments and other balance sheet measures.

Figure 1. Distribution of IMF Programs per Year



Notes: Number of unique IMF programs signed per year, by program type. Blue bars are for the PRGT category, red bars are for the GRA category.

3.2 Firm Tangible Fixed Asset Investment and Balance Sheet Data

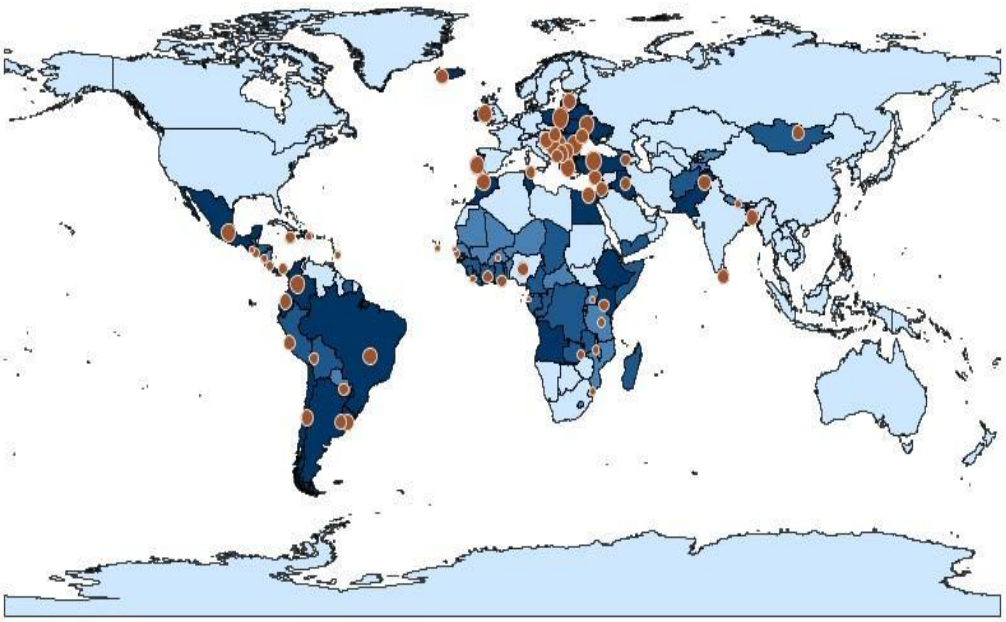
We retrieve detailed firm-level balance sheet data from the Orbis database provided by Bureau Van Dijk. To assess the influence of uncertainty on firm investment decisions, it is important to focus on tangible investments because of their non-reversible and long-term nature. Generically, tangible investment refers to investments in physical assets (e.g., property, plants, and equipment) acquired by a firm for long-term use and which have tangible value. We take the ratio of tangible fixed assets to total assets to compute investments. Considering these investment types, as opposed to other more generic investment categories (financial or intangible), allows us to capture how firms react to changes or potential changes in the macroeconomic environment.

The Orbis database allows us to use other balance sheet data as firm-level controls. We follow the specification of Kalemli-Özcan et al. (2022) in identifying our main Orbis firm-level controls. These include a set of balance sheet variables and ratios that are standard in the corporate finance literature as determinants on firm investment. First, we use the log of total assets to proxy for firm size. We also use leverage, which is measured as the ratio of total debt to total assets, where total debt is in turn the sum of all long-term debt, loans, credits, and other current liabilities. Then, we take debt maturity as proxied by the ratio of long-term debt to total debt in order to capture the rollover risk of firms. Companies with a longer debt maturity structure are more “locked-in” in their investment paths and have lower rollover risk, namely they are less likely to rollover their debt in the short-term to finance new investments. To capture the drag that past debt has on current finances, we include the ratio of interest expense to earnings before taxes (EBIT). We capture growth opportunities at the firm level using sales growth. Finally, we control for cash flows scaled by total assets as is standard in the literature. Table A1 in Appendix A provides the full summary statistics of our variables.

Furthermore, the Orbis database also provides information on firm ownership, incorporation dates, geographic areas, and sectors of operation. From these we construct sector-year fixed effects to account for time-varying, sector specific heterogeneity. Table A4 in Appendix A reports the average tangible investment by NACE main sector for each year across all firms.

There are several data issues with the Orbis database that deserve attention. First and foremost, firm coverage of Orbis varies by region and by country (see Table A5 in Appendix A). Orbis collects data from a range of sources, including publicly available national company registries. The principal reason for the variation in firm coverage by country is the difference in legal standards for companies when it comes to financial documents. For countries where the filing of financial information is mandatory for all, the Orbis sample is more comprehensive (Kalemli-Özcan et al. 2015).[12] By nature of funding needs, countries in the sample that have had an IMF program are for the most part middle and lower income, and highly concentrated in Africa, Latin America, the Caribbean, Eastern Europe, and Southeast or Central Asia. Orbis, just like other data service providers with this type of information, has typically more limited firm financial data in these countries compared with firms from other parts of the world, particularly with respect to Western Europe and the Americas. The data is particularly scant for Africa, where more than 90 percent of companies have no financial information in the Orbis database. Figure 2 gives a graphical representation of countries having had an IMF program, showing a clear concentration in the African continent. The size of the bubbles indicates the number of unique firms for which we have detailed balance sheet data in the country. The Orbis coverage of firm-level data in African countries is provided for half of the MONA sample from Africa. Nonetheless, there is strong overlap between Orbis and MONA coverage in Eastern Europe, Latin America, and Central Asia.

Figure 2. IMF Programs and Firms



Notes: The figure plots average SDR access (MONA) over sample years and number of unique firms in Orbis sample for a given country. Light blue indicates no programs between 2002 and 2020, darker color indicates greater average access, larger bubbles indicate larger panel of firms.

[12] For example, most private U.S companies are not required to disclose financial information to the public after incorporation.

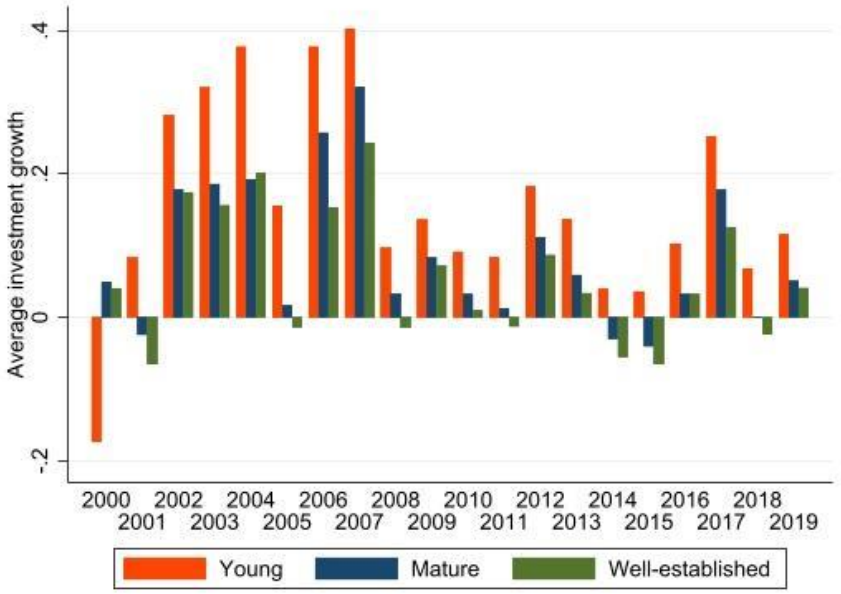
As with any data provider of balance sheet data, there are issues of missing or unreliable data that need to be acknowledged. As Kalemli-Özcan et al. (2015) show, utilizing a single vintage (i.e., a single download with time series data) leads to inconsistent coverage by Orbis. Furthermore, industry classifications may be misleading because over time firms move in and out of industries through expanding operations or statistical offices change definitions. Instead, we follow the procedure outlined by the Kalemli-Özcan et al. (2015) and rely on historical Orbis data, downloading year-specific vintages and then matching firms over time with Orbis' unique firm identifiers. This produces firm samples which are more nationally representative and mitigates the need to re-weigh the data.

We adopt some simple data cleaning to our sample and our main variables. First, we drop financial firms, government sector firms, and other firms which operate primarily in service activities.[13] Then we avoid double counting by considering only consolidated financial statements when available, otherwise unconsolidated. We clean the data by removing cases of erroneously reported balance sheet items, such as negative costs. Finally, as per Kalemli-Ozcan et al. (2022), all balance sheet variables are winsorized or trimmed so that their kurtosis falls to a value around 10.

Our final firm sample is an unbalanced panel of 43,949 firms for 69 countries from 2000 to 2019. Some descriptive statistics are presented in Figure 3, where we categorize firms by age according to their year of establishment as either young (less than 15 years old), mature (established between 15 and 34 years), or well-established (more than 35 years old). The plot shows the average investment growth by firm age for each year in the sample. As would be expected investments for younger firms generally grow faster than for other firms. There is also yearly variation across groups, with drops in the middle of the sample likely due to a series of global shocks like the Great Financial Crises, adverse commodity price shocks, and "taper tantrums", all which threw developing countries into turmoil. In the next section we explain our identification strategy and baseline model.

[13] We drop firms with a main NACE Rev. 2 category of Financial, Public administration and defense, Real estate activities, Administrative and support services, Human health and social work, Other service activities, Activities of the household, and Extraterritorial. We drop these sectors either because they follow different accounting standards or have core activities which do not require tangible assets.

Figure 3. Average Investment by Firm Age



Notes: Average firm investment growth by firm age. Young firms are between 0 and 14 years old, mature between 15 and 34, well-established are 35 and above. Investment growth is measured as the average per firm-age-category across countries and sectors each year.

4. Methodology and Identification Strategy

4.1 Augmented Inverse Propensity Weighted Estimator

We hypothesize that entry into a program signals a reduction in policy uncertainty, inducing firms to undertake non-reversible investments even if no real macroeconomic effects have had time to materialize yet. We are therefore interested in the dynamic response of firm investments to the approval of an IMF program. As a baseline method, we estimate impulse response functions using local projections (LP), which have become a popular alternative to VAR models because of their flexibility and simplicity. As described by Jordà (2005), local projections can be estimated by simple regression models and are in general more robust to misspecification errors than other related methods.

We not only aim to track the evolution of firm investment dynamics over time following the approval of an IMF program, but also estimate the average treatment effect (ATE) of such programs on investments. Calculating the unbiased effect of a Fund program on investments would require comparing two contrasting scenarios: one where we can measure the change in investment for a firm following a program approval, and another where we measure the change in investment when no such event has occurred, ceteris paribus. If the decision to enter an IMF program were fully exogenous, we would simply compare average investment across the two groups.

However, the decision to enter a program is endogenous to several observable and non-observable factors that contemporaneously determine firm investment. Dealing with the endogeneity of IMF programs is an issue that is tackled in several different ways in the literature. Initial papers focused on instrumental (IV) strategies that relied on political determinants (e.g., Barro and Lee 2005). As the exclusion restrictions for political variable IVs have

been challenged (Dreher et al., 2013; Dreher et al., 2018), another type of IVs popularized by Lang (2021) and Gehring and Lang (2020) have become a preferred strategy.[14] However, crucially for our empirical strategy, this IV is suitable for the identification into an IMF program but not into program type, as we wish to explore the differential effects of IMF programs looking at GRA and PRGT separately.

To account for the endogeneity of an IMF program approval, we exploit a methodology developed by Jordà and Taylor (2016) that uses a propensity-score based method, combined with local projections (Jordà, 2005) to find the ATE of an IMF program on the firm tangible fixed assets investment rate. With this method, we accept the endogeneity of entering an IMF program and attempt to explicitly model for it. If the probability of entering a program is modeled correctly, we can re-balance the sample as if the decisions were taken at random. Then, in a second stage we use as the potential outcome variable the cumulative change in the ratio of tangible fixed assets to total assets. The final estimator gives an average treatment effect which is referred to as the Adjusted Inverse Propensity Weighted (AIPW) estimator (Jordà and Taylor, 2016). The AIPW estimator incorporates the flexibility of local projections with a method for reducing endogeneity bias. The two-stage method described above is doubly robust, in that the estimator will be unbiased if either of the two stages is correctly specified. The underlying idea is that the predictor set in the first stage, and then the control set in the second stage, should be expansive enough to capture as much of the variation in program approval as possible.[15]

In our first stage we model the probability of being under a specific program type by estimating a propensity score for each observation in our sample. Our dependent variable is the dummy variable identifying IMF program years as indicated in the MONA dataset. The propensity score for being under a program is predicted by the multinomial logit model:

$$P_{(i,t,p)} = \lambda\left(\beta, Z_{(t-1,i)}\right) \qquad (1)$$

Where λ is the multinomial logistic distribution function and Z is a vector of country-specific controls including macro and political variables as well as macro-region fixed effects.[16] We estimate then the probabilities of either a) having no program, b) having a GRA program, c) having a PRGT program. In the model, the base values are the non-program years, and we estimate the propensity scores for each outcome. This allows us to capture the heterogeneity of program type as well as the types of country typically associated to one of the two.

This first stage specification follows Dreher et al. (2009) and includes a dummy if a country was under a program in the past, a measure of autocracy, the country's investment to GDP ratio, the log of real GDP per capita measured in PPP, total debt service, the budget balance, ratio of reserves to imports, real GDP growth, changes in reserves, the current account balance to GDP, and two measures of political quality including a dummy for election years and the log of checks-and-balances. Table A2 in the Appendix describes the predictor variables in detail.

The estimated $P(i,t,p)$ is then the predicted probability of being under program type *p,* for country *i* at time *t* given our set of predictor variables. From this, the second stage re-balances to create a synthetic sample where

[14] This shift-share IV exploits the differential effects of a country's past participation in an IMF program given the IMF's budget constraint to predict current participation in another program.

[15] With this approach, we do not need to rely on exclusion restrictions. Even if all our variables were endogenous, if there is no unexplained deviation from the conditional forecasted change in ratings, the ATE will be unbiased (Jordà and Taylor 2016).

[16] Since our outcome is based on program type, as opposed to considering all programs together, including country fixed effects would produce collinearity with the outcome in certain groups that only had one type of program. For this reason we use macro-region fixed effects.

the decision to be under an IMF arrangement is as good as random. Using our logit estimates, we can estimate the extent of the non-randomness in our sample. Specifically, a highly endogenous event would be predictable based on observables and have a high $P(i,t,p)$, while a control would have a low $P(i,t,p)$. We assign the weights $\frac{1}{P(i,t,p)}$ to the treatment group and $\frac{1}{(1-P(i,t,p))}$ to the control group. The average treatment effect, given the re-balanced sample, will then be the difference of the average weighted potential outcomes of the two groups across our sample.

Table B1 in Appendix B reports the estimated coefficients for the first stage. The results are in line with the literature. There is strong evidence of path dependency, where countries that have participated in programs in the past are more likely to enter a new program. GDP per capita and GDP growth are both negatively associated with the likelihood of being under a PRGT arrangement, as more well-off countries typically have less of a need for these programs. The positive coefficient on GDP per capita when treatment is GRA is justified by the fact that among our sample of always-taker IMF countries, the richer ones are eligible for GRA arrangements only. An increase in reserves is also negatively correlated with IMF arrangements, indicating the importance of reserves in staving off balance of payment crises which can lead to an IMF program. It may be surprising that variables such as current account to GDP are not significant in some cases, given the Fund's mandate to help countries in a balance of payment crises, but this result is in line with previous work (Conway, 1994). Finally, we find some evidence of the role of political variables in our sample. The literature speaks to different reasons as to why these variables might influence the probability of being under a program.[17] For example, combative elections might make the stigma of a program unappealing for incumbent politicians, which reflects the negative sign on our legislative election dummy.

The outcome variable, which is modeled in the second stage, is the cumulative change in the firm tangible fixed assets scaled by total assets, which captures investment throughout the years. Our baseline model models the outcome variable as measured with a local projection (Jordà 2005) according to the following baseline specification:

$$\Delta y_{i,j,k,t+h} = \alpha + \beta Z_{i,j,k,t-1} + \delta X_{j,t-1} + \gamma D_{j,t} + \mu_i + \tau_{k,t} + \varepsilon_{i,j,k,t} \quad h = 1,2 \ldots .5 \qquad (2)$$

Where $\Delta y_{i,j,k,t+h}$ is thus the conditional forecast of the dependent variable from time *t* to *t+h*, where *h* denotes the forecast time horizon of up to five years. The outcome is measured for firm *i*, in country *j*, and sector *k*. $Z_{i,j,k,t-1}$ is a vector of firm control variables as described in Section 3, and also contains the lagged difference in investment $\Delta y_{i,j,k,t,t-1}$ to account for serial correlation. $X_{j,t-1}$ is a vector of country-level controls and lagged treatment variables. These country-level variables fall into three broad categories of economic, financial, and political factors. We consider both the growth rate of real GDP and the log of real GDP per capita, which capture growth opportunities for the firm. We proxy for the size of the banking sector and financial development using the log of claims by depository institutions on the private sector. The real interest rate captures both the representative lending rate offered in the economy as well as inflation risk to investments. Finally, we use the International Country Risk Guide (2021) index of political risk to control for the broad perception of investment risk within the country.[18]

$D_{j,t}$ is our country-level treatment variable, which is equal to one for the year when the country enters an IMF program as described in Section 3.1. We also control for the remaining program years. Finally, we include firm

[17] See for example Przeworski and Vreeland (2000), Dreher and Vaubel (2004), and Sturm (2005).

[18] See Table A2 in Appendix A for a list, description, and sources of all variables).

fixed effects μ_i and sector-year time-varying heterogeneity $\tau_{k,t}$. This way, we account for both global factors determining investment dynamics as well as industry-specific unobservable characteristics tied to investment choices. Standard errors are clustered at the country level. $\varepsilon_{i,j,k,t}$ is the error term. Regression equation *(2)* is run for each point in horizon *h* on the rebalanced sample to obtain the desired average treatment effect, ATE:

$$ATE_h = \frac{1}{n}\sum_{i}^{I} \sum_{t}^{T} \left\{ \left[\frac{(\Delta y_{i,j,k,t+h})(D_{i,t})}{P_{i,t,p}} - \frac{(\Delta y_{i,j,k,t+h})(1 - D_{i,t})}{1 - P_{i,t,p}} \right] - \frac{D_{i,t} - P_{i,t,p}}{P_{i,t,p}(1 - P_{i,t,p})} \left[(1 - P_{i,t,p}) m_1^h (Z_{i,t-1}, X_{i,j,k,t-1}) + (P_{i,t,p}) m_0^h (Z_{i,t-1}, X_{i,j,k,t-1}) \right] \right\} \quad (3)$$

Where $\Delta y_{i,j,k,t+h}$ are the estimated conditional forecasts for the local projections (Equation *2*), and $D_{i,t}$ is the dummy variable to indicate treatment, in our case program approval. $P_{i,t,p}$ are the estimated propensity scores from Equation *1*. The first part of Equation *3* is a standard inverse propensity-score weighted ATE. Intuitively, this is like a group-means comparison between countries that have signed a program and those that have not, with the additional step that we correct for allocation bias of the treatment by modeling it in Equation *1*, reducing it to a unidimensional element which is the estimated propensity score, and inverting to achieve a random distribution. The second part is an adjustment term consisting of the weighted average of the two independent regression estimates. The purpose of the adjustment term is to stabilize the estimator as the propensity scores get close to the extremes (0 or 1) and therefore alleviates the need to truncate weights.[19]

In conclusion, the use of local projections for our estimation strategy is motivated by several factors. First, local projections are free of structural constraints that would otherwise be imposed on a parallel VAR model, thereby allowing for the response of investments to an IMF program approval to vary non-linearly over the forecast horizon, making them useful for computing dynamic effects. Local projections are also easier to compute and can be estimated using ordinary least squares (OLS). In evaluating the properties of local projections, Plagborg-Møller and Wolf (2021) and Montiel Olea and Plagborg-Møller (2021) argue for the use of lag-augmented local projections as a requirement for robustness. However, local projections are not without drawbacks. Since the estimation does not impose any direct link between impulse responses at times h and $h+1$, estimates can sometimes display erratic behavior (Ramey and Zubairy, 2014). Furthermore, as the horizon increases, observations are lost on both sides, which can lead to loss of efficiency. Therefore, local projections are optimal for short to medium term projections, and the efficiency of the estimator is a function of forecast horizon over the total size of the time dimension T. Because we forecast the impulse response of investments up to a max of 5 years over a 20-year period, our choice of method remains safe. In the robustness tests (Section 6), we test the sensitivity of results by restricting estimates to groups of firms with data over a full forecast and lag horizon.

4.2 Stacked difference-in-differences

While our baseline AIPW estimator provides estimates of dynamic effects of an IMF program, it does not allow us to evaluate how firm-specific heterogeneity influences the outcome. In the second part, we take a more granular approach to capture the differential effects of firm characteristics, specifically firm financial constraints, on investments using a difference-in-differences (DiD) style approach. Traditionally the generalized (two-way fixed effects) DiD was the workhorse method in panel setups such as ours, the recent explosion in DiD

[19]Jordà and Taylor (2016) show that their AIPW estimator has properties such that extreme values of the propensity scores are offset by the adjustment term, in contrast to a standard IPW estimator.

methodologies provides a new set of tools to deal with the many limitations of the original methods. New estimators from de Chaisemartin and d'Haultfoeuille (2021), Callaway et al. (2021), and Goodman-Bacon (2021) have recently been developed to account for issues such as multiple time periods of treatment, staggered adoption, or treatment switching. In our case, all such issues are relevant. Our sample consists of countries that can have an IMF program at different points in time and crucially switch in and out of treatment continuously. To understand the extent of this issue, Figure A2 in Appendix A plots the treatment status by country and program type for each year in the sample. Each row represents a country, while each column represents a year. The coloring of each point in this matrix is then a representation of the treatment status. Grey blocks are years with no treatment (i.e., no IMF program), red blocks correspond to years where a country was under a GRA program, and blue blocks are for PRGT program-years. As such, the dynamic nature of treatment is evident in our sample, motivating the use of a more robust methodology.

Given the structure of our data, we rely on a recent causal inference methodology popularized by Cengiz et al. (2019) and Deshpande and Li (2019), the stacked DiD method. The procedure is an event-study based approach to analyze the effects of multiple events (such as multiple IMF programs) in a way that eliminates the typically problematic comparisons between treated and control groups that occur in a generalized DiD. In brief, the method consists in splitting the data into *n* sub-experiments, where each sub-experiment represents a unique calendar year where treatment (program approval) occurred for any cross-sectional group (country). A treatment window is then defined, such that only observations with a subsequent treatment at least *k* years ahead are considered as controls. As a result, all observations within one sub-experiment will have a program adoption year which is the same, and the control group consists of observations sufficiently far into the future so as not to be confounded by other program adoptions. These sub-experiments are then stacked on top of each other to create a dataset which consists of *n* independent panel event studies identified between each other by a sub-experiment id.

For evaluating the role of financial frictions, we first rely on the seminal work by Rajan and Zingales (1998) (henceforth RZ) on external financial dependence. The underlying idea is that the role of financial markets is to reduce problems of moral hazard and adverse selection, thereby reducing the costs of the firm in raising funds. Financial development, or any structural shock to the financial system of a country, should disproportionately help firms which are more dependent on external financing. In our context, we consider our main treatment as such a shock. Program approval reduces policy uncertainty with positive spillover effects on the financial system. Then the response of investment will be contingent on a firm’s reliance on external finance.

The RZ index is a sector-specific, time-invariant measure of the share of investment that is not financed by internal cash flow in the median listed U.S firm over the 1980s. The guiding assumption to this approach is that the U.S capital market is a good proxy for a frictionless market, and credit demand is driven by industry-specific technological fundamentals. In a cross-country framework such as ours, the second assumption is that these industry fundamentals are constant across countries. While a small literature compares the original index with a few country-specific measures (Eppinger and Neugabauer, 2022), the RZ index has been widely used and shown to be consistent across countries (Cetorelli and Gambera, 2001; Beck and Levine, 2002; Fisman and Love, 2003, 2007; Kroszner et al., 2007; Pagano and Pica, 2012). Furthermore, the use of country-specific indices computed on our data would have an additional drawback specific to our research setting. The index is constructed using firm cash flows. Previous work by Bomprezzi and Marchesi (2021) have shown that IMF programs have a strong quantitative effect on sales and therefore on cash flows of firms, making such an index endogenous.

For these reasons, we use the indices computed by Eppinger and Neugabauer (2022) following the RZ methodology. From Compustat, the authors define the index of external financial dependence for U.S firms over the years 1990-2005. Being closer in time to our sample, it is a better proxy of technological demands of an

industry. External financial dependence is then defined as capital expenditures minus cash flow from operations for each firm, then divided by the sum of capital expenditure over the period, and finally using the median value by industry as a measure.[20] We then merge these industry values reported as NACE sectors with our Orbis data. Table A6 in Appendix A reports the values of the EFD indices. As in RZ, the indices are only computed for a set of firms in manufacturing-oriented industries.

Given the setup, we fit a DiD to the stacked data. The model contains the same country and firm controls as in our baseline specifications, fixed effects, and sector-year fixed effects to account for time-varying heterogeneity. A further advantage of a stacked DiD setup is the ability to compute dynamic effects. As in our baseline local projection specifications, we are interested in the time-varying effects of the adoption of an IMF program conditional on the degree of dependence on external finance. We specify a model, as shown in Equation 7, where we identify the two years before and the five years after program approval (with year 0 as the reference year) with a set of indicator variables YSE (years since event):

$$Tan/TA_{i,j,k,t} = \alpha + \beta Z_{i,j,k,t-1} + \delta X_{j,t-1} + \sum_{j=-ka}^{kb} \gamma_j \left(FIRMINDEX_{i/i,t} * 1(YSE_t = j) \right) + \sigma FIRMINDEX_{i/i,t} + \sum_{j=-ka}^{kb} \rho_j * 1(YSE_t = j) + \mu_{j/i} + \tau_{k,t} + \varepsilon_{i,j,k,t} \quad (7)$$

Our parameter of interest is γ_j, representing the interaction between the indicator for the j^{th} year before/after the program approval and external financial dependence.

5. Empirical Findings

5.1 Local Projections Baseline Results

Table 1 presents the local projection baseline results, with the impulse response functions plotted in Figure 4. Each panel in Figure 4 shows the ATE at time *t+h* for programs approved at time *t* separately for GRA and PRGT financing. We find that the effect of GRA programs is increasing over time, peaking at four years after program approval. On average, investments grow over four years by a cumulative amount of almost four percentage points with respect to the approval year. For PRGT programs on the other hand, we find only a very weak temporary effect. In the first year after program approval, tangibles accumulate marginally, with a value around one percentage point above the reference level, but afterwards there is no evidence of increased investments.

The positive effect of GRA approval suggests that in GRA countries an IMF intervention is enough to trigger the willingness to invest by firms. On the other hand, in PRGT-eligible countries there are likely many factors other than policy uncertainty inhibiting firm investments. The positive signaling effects of a Fund program are not enough to offset the drag on private sector investment due to poorer access to credit, lower quality of institutions, and fewer cash generating opportunities that are associated with the markets in which these firms operate. The differential effects of the type of IMF financing on investment can also be explained by the nature of these arrangements. Under PRGT, repeated arrangements are the norm, and it could likely be that repeated IMF engagements would instead provide firms with the kind of confidence boost needed to match GRA effects, since macroeconomic stability would be safeguarded over an extended period.

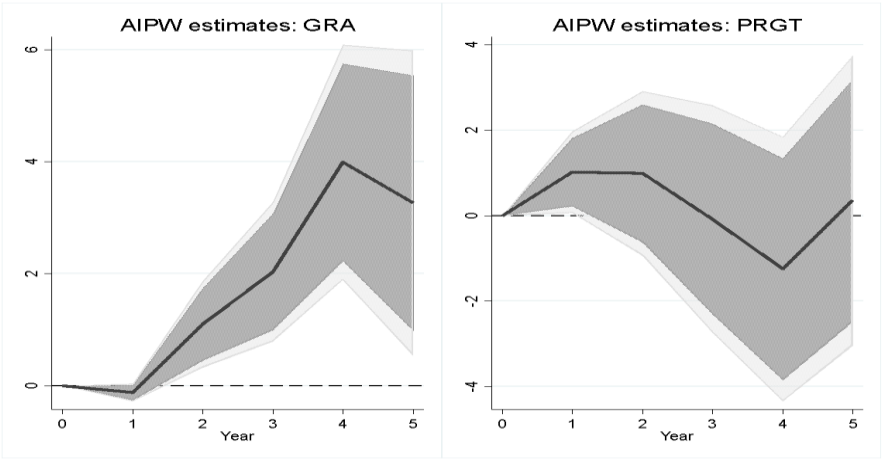
[20] See Eppinger and Neugabauer (2021) Appendix A for a detailed methodology on the construction of the index.

Table 1. Program Signing and Firm Investment Response, AIPW Estimates

			GRA		
	1	2	3	4	5
AIPW	-0.123	1.096*	2.036**	3.986**	3.260*
	(-1.48)	(2.78)	(3.21)	(3.72)	(2.34)
N	21643	19002	16516	14337	12608
			PRGT		
	1	2	3	4	5
AIPW	1.019*	0.989	-0.079	-1.254	0.359
	(2.09)	(1.00)	(-0.06)	(-0.79)	(0.21)
N	21643	19002	16516	14337	12608

Notes: Average treatment effect of a Fund program approval estimators for each h-step ahead forecast on the cumulative change in firm tangibles/TA, with h=1,2,3,4,5. Standard errors clustered at the country level, T-statistics in parenthesis. * p < 0.1, ** p < 0.05, *** p < 0.01.

Figure 4. Program Approval and Firm Investment Response, AIPW Estimates



Notes: Panel A shows AIPW average treatment effects for each h-step ahead cumulative change in tangible fixed asset investment rate with respect to base year ($y_{t+h} - y_t$) following the signing of the respective IMF program (GRA or PRGT). Shaded areas show 90 and 95% confidence intervals, standard errors clustered at the country level.

5.2 Financial Frictions and Uncertainty: A Stacked Difference-in-Differences Approach

Table 2 presents our results. First, we find no evidence of an anticipation effect or of pre-treatment trends. When considering external financial dependence (Panel A in Table 2), in the case of GRA programs, we find that tangible investments grow disproportionately more relative to the base year for firms operating in sectors that are characterized by a high degree of external financial dependence, at every point in time after the program approval up to 5 years. For example, for the industry which is at the bottom 5th percentile of external financial dependence (publishing and printing), the expected effect after 1 year is small and negative, at around -0.17 percentage

points. For the firms in the industry at the top 95th percentile (communication equipment) the effect is 0.5 percentage points. For PRGT programs the size of the effect is smaller, but we do find that, contrary to our aggregate results, in the long run there is a strong and significant effect, indicating that more financially constrained firms in PRGT-eligible countries do benefit from IMF arrangements.

We then turn to an alternative measure of firm heterogeneity, in order to directly measure the effects of micro-level uncertainty on investments in the context of an IMF program. We adopt the measure constructed by Alfaro, Bloom, and Lin (2021), the annualized stock return volatility. This is constructed as the annualized 12-month standard deviation of daily CRSP returns of a sample of U.S firms. Furthermore, the authors provide firm level measures of 12-month compounded stock returns and Tobin's Q as additional controls to tease out first-moment effects. Their data spans from 1992 to 2019 and provides the year-by-year 2 digit SIC industry codes. We therefore aggregate these measures by taking the median sector-year value and match them with our firm data also at the sector-year level. By matching U.S data with our sample at the sector level we are also constructing a measure of uncertainty that is not firm varying. These measurements should be interpreted as an industry-specific characteristic which are comparable across countries, *à la* Rajan and Zingales (1998).[21]

Panel B in Table 2 presents these results. As before, for GRA programs, there is evidence that firm investments increase as sector-wide volatility, and therefore uncertainty, increases. Greater volatility of yearly returns under a GRA program is associated with a 3-percentage point increase in investments after three years relative to the base year. On the other hand, under PRGT programs there is no consistent long-term effect.[22] We take this as evidence of our initial hypothesis that the institutional and macro-financial environment of PRGT eligible countries is a strong deterrent to firm investments, and a single program is insufficient to reverse investor tendencies.

[21] We also aggregate at the sector level because uncertainty is an industry-specific process that is driven by elements such as supply chain networks and product-specific demand elasticities.

[22] We also consider an alternative uncertainty indicator from Alfaro, Bloom, and Lin (2021), which is the 365-day implied volatility build from a mix of put and call-at-the-money option. We find results which mirror these results but are statistically weaker.

Table 2. Firm Frictions and Dynamic Stacked DiD Estimates

Years since treatment	**-2**	**-1**	**1**	**2**	**3**	**4**	**5**
			Panel A: External Financial Dependence				
GRA program	0.186	0.275	0.427*	0.501**	0.543**	0.591**	0.630**
	(0.87)	(1.41)	(2.08)	(2.73)	(2.98)	(3.19)	(3.29)
N	34,416	34,416	34,416	34,416	34,416	34,416	34,416
PRGT program	0.087	-0.104	0.081	0.168*	0.164	0.189*	0.310**
	(0.84)	(-1.14)	(1.48)	(2.26)	(1.50)	(1.81)	(2.43)
N	75,835	75,835	75,835	75,835	75,835	75,835	75,835
			Panel B: Realized Volatility				
GRA programs	1.756	1.548	1.571	1.744*	1.835	1.961*	2.334*
	(1.37)	(1.53)	(1.55)	(1.71)	(1.63)	(1.75)	(1.89)
N	77,554	77,554	77,554	77,554	77,554	77,554	77,554
PRGT programs	0.153	0.189*	-0.121	0.260	0.194*	0.150	0.086
	(1.38)	(2.10)	(-0.95)	(0.97)	(1.84)	(1.29)	(0.35)
N	181,005	181,005	181,005	181,005	181,005	181,005	181,005

Notes: Year-specific DiD effect of a treatment *d* on tangibles/TA in a stacked event study setup. Panel A considers the interaction between the degree of external finance dependence and a dummy equal to 1 for the year *t* before/after the program approval. Panel B considers as the interacting term the measure of realized volatility. All specifications include full controls and sector-year fixed effects. Panel A uses country fixed effects, Panel B uses firm fixed effects. Standard errors clustered at the country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Domestic Ownership of Firms

In the previous sections, we considered measures of financial frictions and quantitative estimates of uncertainty as channels through which this effect can influence private sector investments. In this section, we try to capture the extent to which a domestic firm could be differentially exposed to policy uncertainty within a country as opposed to a foreign owned firm by considering changes in its ownership structure.

From Orbis historical vintages, we can download ownership data for the firms beginning from 2007. We retrieve information on the global ultimate owner (GUO) and the global ultimate consolidated owner where it exists. These are the ultimate owners, net of all intermediate ownership connections, with at least 50% of direct or indirect ownership in the firm. We can extract information on the owner country, and therefore classify a firm as having a foreign or domestic owner each year, identifying foreign ownership as the case where the country of operation of the firm is different from the country of the GUO.

Simply comparing domestically owned versus foreign-owned firms could be misleading. Foreign-owned firms are likely to be by nature larger and more successful because they are part of a multinational corporate group. Furthermore, their ownership changes occur quite frequently, and often they are cross-border and likely driven by economic expansions or recessions. We want to identify a set of firms which are tied to the country more than a counterpart firm. Firms which remain "committed" to the country and are therefore more sensitive to the reduction in uncertainty brought on by an IMF program. In contrast, firms that do switch to foreign ownership become less sensitive to what is happening in the country, because they gain a sort of natural hedge by being part of a foreign group. To that end, we consider firms which do not switch ownership in the immediate years before and after program approval, labeling them as "never-leavers."

We report the dynamic stacked DiD estimates for "never-leavers" in Table 3. The change in investments for these firms that remain exposed to the Fund programs throughout the treatment period is positive with respect to firms with changes in ownership. This effect is here again stronger for GRA countries. The magnitude of the effect is around 1 percentage point, while for PRGT countries it is only around 0.3 percentage points increase.

Table 3. Ownership Switches and Dynamic Stacked DiD Estimates

Years since treatment	**-2**	**-1**	**1**	**2**	**3**	**4**	**5**
GRA program	0.341	0.509	1.341**	1.332**	1.091*	1.075*	1.110*
	(0.41)	(0.68)	(2.41)	(2.38)	(1.83)	(1.73)	(1.76)
N	66,845	66,845	66,845	66,845	66,845	66,845	66,845
PRGT program	0.087	-0.104	0.081	0.168*	0.164	0.189*	0.310**
	(0.84)	(-1.14)	(1.48)	(2.26)	(1.50)	(1.81)	(2.43)
N	75,835	75,835	75,835	75,835	75,835	75,835	75,835

Notes: Year-specific DiD effect of a treatment *d* on tangibles/TA in a stacked event study setup. Results show the interaction between a dummy identifying "never-leavers" and a dummy equal to 1 for the year *t* before/after the program approval. Specifications include full controls and firm and sector-year fixed effects. Standard errors clustered at the country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6. Robustness and Alternative Specifications

This section provides a series of robustness tests to our baseline analysis. We start by testing pre-treatment trends. Second, we test for compliance with an IMF program and for the persistence of the effects. Finally, we run a series of tests on sample dependence.

Our identification strategy captures primarily the systemic differences between countries that select into a program type, GRA or PRGT. We want to rule out the possibility that investments were already growing before program approval, for example due to an anticipation effect. As sensitivity check, we then estimate a simple fixed effects model, regressing investment at time *t,* on dummies for a program approval that will occur at *t+h*. Table C1 in Appendix C shows the results. Each estimate represents the response of investments at time *t* to a program signing occurring *h* years ahead. For both GRA and PRGT programs, we find no evidence of systematic anticipation effects.

We also want to test how compliance with an IMF program may affect firm investment choices. Based on the number of reviews, a program can be either classified as completed or off-track. When at most the first review phase has successfully been concluded, a program is considered off-track. We test for persistence by considering the final program years as treatment in the second stage estimation in our AIPW estimator. Table C2 in Appendix C presents these findings. Consistent with previous results, we find different long-term effects for GRA and PRGT. In the case of GRA, we document the presence of effects which are positive and significant regardless of whether the program went off track or not. For PRGT, we find that investments drop in the first years after the end of a program and these negative effects persist if the program goes off-track. As a further test for the importance of compliance in influencing firms' decisions to invest, we run our baseline estimates dropping programs that are classified as off-track.[23] The results are also robust to this change, as we find no significant differences in the investment dynamics relative to the baseline model.

Tables C3 and C4 in Appendix C instead show a series of tests checking whether the results are driven by sample dependence. We start by reducing our sample to only those firms for which we have balance sheet data on investments for the full 5-year horizon. With differences in cross-country coverage in Orbis, it could be that our local projection estimates are driven by firms subject to rigorous reporting standards or covering more years. We can test for this by considering only spells of observations equal to or greater than our maximum forecast horizon. The findings are consistent with our baseline estimates. Then, we consider the case where results might be affected by different country groups. We systematically drop, one at a time, countries belonging to the different IMF regional departments. The results in Table C4 show that our GRA results are robust to these sensitivity checks. For example, when Sub-Saharan Africa is removed, we still find a positive and significant effect on investments, and furthermore the results are consistent when dropping alternative regions, except in the case of Europe. We explain this result in two ways. First, because our sample includes the European Debt Crises, it is unsurprising that removing this event attenuates the effect that the Fund has on investments, given the large role it had in Europe during this period. Secondly, our sample shrinks considerably, making the results harder to interpret. In the case of PRGT, the results are weaker when dropping regions like Sub-Saharan Africa or Middle East and Central Asia, since PRGT-programs are more common there.

Finally, we consider an alternative specification to document whether the heterogenous response of firm investments to Fund program approval is attributable not just to the program type, but also to the exposed firm

[23] A related dimension would be the degree of implementation of conditions (Reinsberg et al. 2022a, 2022b)

type. As mentioned above, we expect that firms react differentially to an IMF program based on their degree of financial frictions. As indicated by the literature (Gertler 1988; Hadlock and Pierce 2010; Cloyne et al. 2018; Bahaj et al. 2019), we use firm age as a proxy for these financial frictions.[24] Firm age has been shown to be an appropriate proxy, especially in developing countries, where given less developed financial markets, younger firms are more leveraged, less liquid, and smaller in size.[25] To this end, we adapt our baseline specification presented in Equation 2 following the flexible local projection methods of Jordà and Taylor (2016). More specifically, we split the sample into firms which are above vs. below the median age of firms in the sample. The rest of the specification follows the baseline model. Figure C1 in Appendix C shows the AIPW average treatment effect for the two groups. Consistently with our baseline results, for both PRGT and GRA programs, younger, more financially constrained firms benefit more from an IMF arrangement. In the case of GRA programs, five years after program approval, there is on average a positive 10 percentage point cumulative change in tangibles above the reference year value for younger firms, which is a sizeable effect. On the other hand, we find a significant albeit short-lived effect on investments for younger firms under a PRGT program. Instead, there is also a positive but much smaller effect for mature firms under GRA programs, while under PRGT programs we find no such effects.

7. Conclusion

This paper provides new evidence on the role of IMF programs in stimulating private sector investments. Using detailed firm-level data on tangible fixed investments, we estimate the dynamic response of firm investments to the approval of an IMF arrangement. We find that distinguishing between GRA and PRGT financing matters for the path of investments, and that GRA programs seem to induce a stronger investor reaction. Leveraging a novel DiD methodology, we document the presence of two financial channels: the degree of firms' external financial dependence and firms' sectoral uncertainty. Only in the case of GRA programs, we find evidence that investments are higher for firms relying more on external finance, or those which are exposed to greater uncertainty. Finally, using ownership data, we find that private investments are stimulated more for domestic firms.

The presence of a private investment transmission channel could help improve our understanding of what factors could influence the effectiveness of IMF programs. More generally, the results speak to the role of official cross-border lending, which as documented by Horn et al. (2020), has historically been larger than commonly thought. To the best of our knowledge, this is the first paper that investigates whether IMF programs, as well as improving a country's creditworthiness for external investors, may also make "internal" ones more willing to invest in their own country.

[24] There is an obvious disadvantage to using direct measures of financial frictions such as size, leverage, or liquidity because they respond endogenously to shocks, such as the approval of IMF arrangements, making it difficult to interpret ex-post effects as driven by ex-ante heterogeneity.

[25] It can also be argued that age is not fully exogeneous because of a survivorship bias or changes in ownership–younger firms tend to be more likely to go bust because of those same characteristics just defined or, when they do survive, they are more likely to be absorbed by older, larger firms in M&A operations.

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Appendix

A. Sample and Descriptive Statistics

Table A1. Summary Statistics

	Observations	Mean	Sd	Max	Min
Dependent					
Tangibles over total assets	277,572	31.08	27.25	100	0
Country controls					
Real PC GDP growth	277, 818	3.25	4.28	81.79	-29
Log real PC GDP	277, 780	9.91	0.51	11.37	6.63
Log claims by depository institutions	263, 772	12.90	2.18	20.12	6.11
Real lending rate	147, 993	5.44	9.05	93.92	-25.7
Political Risk Rating	264, 879	67.22	10.18	92.50	31
Firm controls					
Log Total Assets	277, 816	15.89	1.94	35.73	.693
Long-term to total debt	231, 150	39.26	40.02	100.00	0
Leverage	277, 816	19.53	21.91	100.00	0
Interest expense to EBIT	169, 973	27.47	437.62	10000.00	0
Cash flow to TA	192, 994	8.09	11.15	60.96	-28.2
Sales growth	169, 952	14.29	54.29	582.72	-92

Notes: Summary statistics run on winsorized sample.

Table A2. Variable Descriptions and Sources

Variable	Definition	Sources
Dependent variables (first and second stage)		
GRA	First stage (logit) dependent. Dummy = 1 if country signs GRA program within the first 9 months of the year.	Monitoring of Fund Arrangements (MONA)
PRGT	First stage (logit) dependent. Dummy = 1 if country signs PRGT program within the first 9 months of the year.	Monitoring of Fund Arrangements (MONA)
Investment	Second stage (local projections) outcome. Annual percentage change of tangible fixed assets investment growth	BvD Orbis (2021)
Predictors and controls in both first stage (logit) and second stage (firm-level local projections)		
Real GDP growth	GDP in constant prices, annual percent change	World Economic Outlook (October 2021)
Log real GDPPC	Log of GDP per capita in 2017 PPP dollars	World Economic Outlook (October 2021)
Predictors in first stage (logit) only		
Past program	Dummy = 1 for program years when country has been in a program in the past	MONA; Authors' calculations
Autocracy	Institutionalized autocracy index capturing constraints on executive and competitiveness of electoral process. Higher values indicate stronger autocratic regime	Polity 5 - CSP/INSCR
GFCF to GDP	Gross fixed capital formation to GDP	World Economic Outlook (October 2021)
Total debt service to GNI	Total debt service as percent of GNI	Word Development Indicators (2021)
Budget surplus	General govt. revenues – general govt. expenditures as percent of GDP	Word Development Indicators (2021); Authors' calculations
Total reserves/imports	Total international reserves in months of imports	Word Development Indicators (2021)
Inflation	Annual percentage change in consumer price inflation	World Economic Outlook (October 2021)
Change in reserves	Change in international reserves	World Development Indicators (2021); Authors' calculations
Current account/GDP	Current account balance to GDP	World Economic Outlook (October 2021)
Legislative election	Dummy = 1 if country had legislative election in previous year	Database of Political Institutions (2020)
Log legislative checks	Checks on the executive branch	Database of Political Institutions (2020)
Predictors in second stage (firm-level local projections) only		
Log claims	Log of claims by depository institutions on private sector	International Financial Statistics (2021)
Real interest rate	Representative interest rates offered by banks to resident customers adjusted for inflation	Word Development Indicators (2021)
Political risk rating	Index of political risk based on government stability, socioeconomic conditions, religious or ethnic tensions, and investment profile of country. Higher values indicate lower risk	International Country Risk guide (2021)
Program years	Dummy =1 if country under a program in a given year (excluding year of signing)	MONA
Log total assets	Log of total assets	BvD Orbis (2021)
Debt maturity	Ratio of long-term debt to total debt	BvD Orbis (2021)
Leverage	Total debt to total assets	BvD Orbis (2021)
Interest/EBIT	Interest payments over EBIT (earnings before interest and taxes)	BvD Orbis (2021)
Cash flows/TA	Cash flows scaled by total assets	BvD Orbis (2021)
Sales growth	Annual percentage change in sales	BvD Orbis (2021)

Table A3. Program Completion Status

	Final review status				
Program Type	Completed	Off track	Ongoing	Partially completed	Total
PRGT	23	6		8	37
GRA	23	10	4	42	79
Others	29	2	4	4	39
Total	75	18	8	54	155

Notes: Tabulation of programs and their final review status as of 2020. For each program type, indicates the number of programs that were completed, offtrack, partially completed, or ongoing, as well as total number of unique programs. Offtrack is defined as programs that failed to complete more than two reviews, partially entails the completion of more than two but less than the total number of expected final reviews (IMF 2018 Review of Conditionality, 2019). Others refers to precautionary and non-disbursing programs which are not considered in the sample.

Table A4. Yearly Average Firm Investment by Primary NACE Sector

	Agriculture, forestry, fishing	Mining and quarrying	Manufacturing	Electricity, gas, steam	Water supply, waste management	Construction	Wholesale and retail trade – repair	Transport and storage	Accommodation and food services	ICT	Professional, scientific, technical activities	Education	Arts
2000	-0.370	-0.127	-0.137	0.114	-0.106	-0.156	-0.079	-0.133	-0.062	0.097	0.007	-0.019	-0.094
2001	-0.241	-0.027	0.009	0.135	0.050	-0.001	0.141	0.077	-0.012	0.101	-0.032	0.105	0.208
2002	0.196	0.215	0.188	0.184	0.209	0.265	0.331	0.264	0.250	0.254	0.274	0.330	0.499
2003	0.200	0.192	0.215	0.458	0.228	0.282	0.376	0.286	0.239	0.287	0.238	0.373	0.415
2004	0.257	0.203	0.265	0.254	0.345	0.337	0.419	0.306	0.250	0.366	0.286	0.488	0.301
2005	0.046	0.162	0.073	0.204	0.076	0.111	0.167	0.088	0.022	0.126	0.083	0.047	0.219
2006	0.285	0.360	0.260	0.489	0.304	0.361	0.373	0.318	0.265	0.366	0.291	0.412	0.385
2007	0.293	0.398	0.308	0.167	0.349	0.429	0.412	0.362	0.271	0.365	0.385	0.431	0.420
2008	0.033	0.210	0.013	0.030	0.090	0.113	0.092	0.079	0.068	0.065	0.053	0.087	0.110
2009	0.110	0.232	0.088	0.398	0.117	0.142	0.133	0.078	0.072	0.124	0.039	0.087	0.109
2010	0.068	0.209	0.044	0.207	0.022	0.034	0.091	0.028	-0.013	0.084	0.043	0.102	0.016
2011	0.054	0.208	0.013	0.109	0.055	0.047	0.072	0.067	0.010	0.057	0.013	-0.004	0.037
2012	0.132	0.316	0.135	0.254	0.124	0.101	0.167	0.108	0.047	0.150	0.114	0.069	0.138
2013	0.089	0.102	0.074	0.281	0.103	0.090	0.105	0.079	0.052	0.105	0.061	0.012	0.090
2014	-0.005	0.005	-0.004	0.020	-0.067	-0.028	0.021	-0.007	-0.045	0.000	-0.063	-0.122	-0.026
2015	-0.072	0.005	-0.018	-0.060	-0.040	-0.017	0.005	-0.011	-0.058	0.001	-0.067	-0.140	-0.006
2016	0.137	0.055	0.041	0.094	0.009	0.069	0.070	0.051	0.007	0.078	0.032	0.262	0.122
2017	0.207	0.080	0.188	0.293	0.172	0.205	0.208	0.151	0.166	0.237	0.194	0.168	0.232
2018	0.002	-0.006	-0.003	0.073	-0.021	0.010	0.031	0.038	-0.006	0.029	0.019	0.150	0.102
2019	0.038	0.043	0.042	0.284	0.023	0.049	0.091	0.061	0.029	0.124	0.066	0.014	0.093

Notes: Table shows the year-sector firm average for investment for the full set of countries. Sectors are the NACE Rev. 2 main sections, excluding Financial, Public administration and defense, Real estate activities, Administrative and support services, Human health and social work, Other service activities, Activities of the household, and Extraterritorial sections.

Table A5. Panel Summary

2-digit country ISO	Num. Obs.	Unique firms	2-digit country ISO	Num. Obs.	Unique firms
AF	6	1	JO	1,078	90
AL	240	81	KE	390	33
AM	72	24	KN	10	1
AO	4	1	LK	1,062	143
AR	982	149	LR	34	4
BA	9,391	806	LV	5,028	530
BB	29	5	MA	3,672	727
BD	1,550	191	MD	2,251	272
BF	8	3	MK	3,449	526
BG	10,056	1,084	ML	5	1
BO	143	25	MN	1,263	180
BR	6,336	949	MW	46	6
CD	1	1	MX	6,508	1,837
CI	138	21	MZ	23	4
CL	2,200	227	NG	1,161	104
CM	5	1	NI	32	6
CO	16,831	1,801	NP	48	7
CR	47	9	PA	150	21
CV	26	3	PE	683	128
CY	1,401	263	PK	1,385	313
DM	1	1	PL	100,859	9,919
DO	16	5	PT	40,587	3,198
EC	644	142	PY	215	37
EG	2,612	449	RO	45,738	3,614
GA	23	2	RS	23,605	1,783
GH	229	25	RW	7	1
GM	5	3	SN	18	2
GR	17,522	1,501	SV	24	6
GT	35	3	TN	349	40
HR	9,022	762	TR	44,411	7,944
HU	971	171	TZ	57	7
IE	12,024	1,364	UA	11,779	1,761
IQ	509	49	UG	21	2
IS	2,276	241	UY	1,079	296
JM	231	35	ZM	72	8

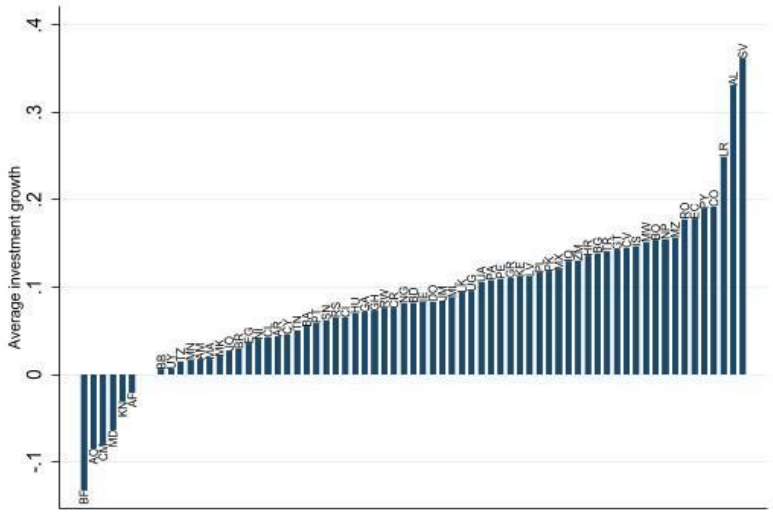
Notes: Number of observations and unique firms available per country of Orbis tangible fixed asset investment data.

Table A6. EFD by Sector

NACE Rev 1.1	Sector	EFD
16	Tobacco	-3.4462
19	Leather and footwear	-1.3422
361	Furniture	-0.5680
22	Publishing and printing	-0.4268
28	Fabricated metal products	-0.3272
35	Other transport equipment	-0.3057
150	Food (excl. beverages)	-0.1454
21	Pulp, paper and paper products	-0.1343
23	Coke and refined petroleum products	-0.1114
26	Non-metallic mineral products	-0.0884
20	Wood products, except furniture	-0.0627
17	Textiles	-0.0427
240	Chemicals (excl. pharamaceuticals)	0.0047
34	Motor vehicles	0.0759
27	Basic metals	0.0870
18	Wearing apparel and fur	0.1021
25	Rubber and plastic products	0.1205
29	Machinery and equipment	0.1255
31	Electrical machinery and apparatus	0.3269
360	Other manufacturing (excl. furniture)	0.3719
159	Beverages	0.3992
30	Office machinery and computers	0.6565
33	Medical/ precision/ optical instruments	1.0336
32	Radio/ TV/ communication equipment	1.1559
244	Pharmaceuticals	8.6029

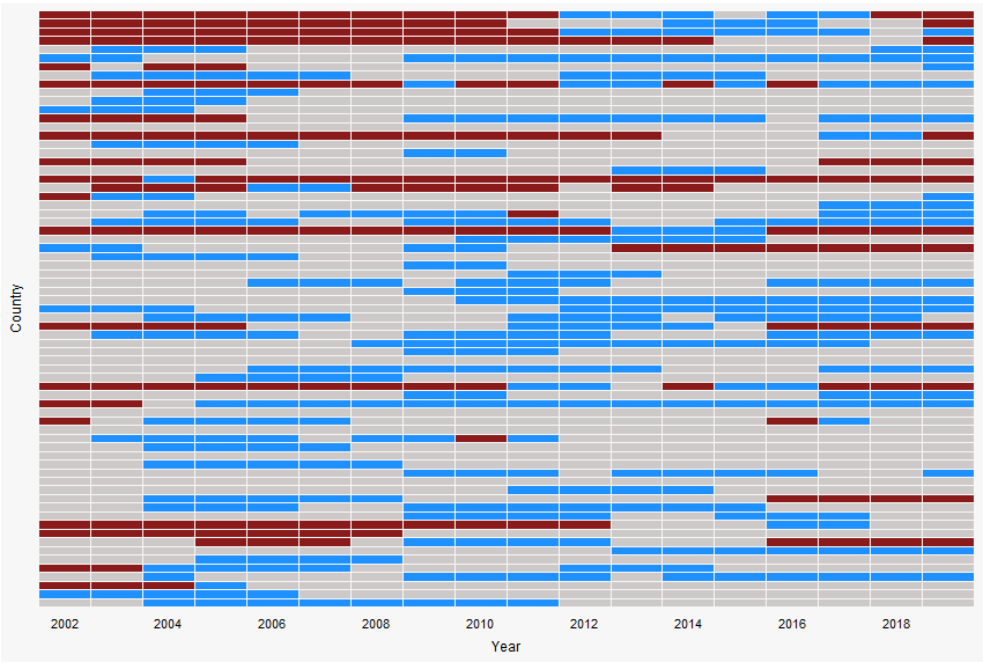
Notes: Eppinger and Neugabauer (2022) EFD indices computed from Compustat according to RZ (1998) methodology.

Figure A1. Investment Growth by Country



Notes: Average firm tangible fixed asset investment by country across sample years, considering all firms and sectors. Ranked by investment.

Figure A2. Treatment Status, by Program Type



Notes: Treatment status by year for countries in sample. Shaded bars indicate a country is under a given program for a specific year; red for GRA, blue for PRGT. Grey bars indicate no program, while white bars indicate missing years for the dependent variable (tangible fixed assets investments) due to Orbis missing data. Effective treatment status of observations therefore defined by years for which there exists Orbis data for at least one firm for a given country.

B. Additional Tables and Augmented Inverse Propensity Score Weighted

Table B1. AIPW First Stages

	GRA	PRGT
Past program	2.195***	2.053***
	(8.041)	(7.343)
Log real GDPPC	0.575*	-0.813*
	(1.831)	(-1.841)
Autocracy	0.119	-0.154
	(0.814)	(-1.122)
GFCF/GDP	-0.097***	0.025
	(-3.431)	(0.867)
Total debt service to GNI	0.027	-0.145**
	(1.469)	(-2.460)
Budget surplus	-0.040	0.138***
	(-0.629)	(3.844)
Total reserves/imports	-0.112*	-0.175*
	(-1.773)	(-1.750)
Real GDP growth	-0.042	-0.097***
	(-0.802)	(-3.309)
Inflation (consumer price)	0.009	0.014
	(0.699)	(0.672)
Change in reserves	-0.006**	-0.000
	(-2.294)	(-0.001)
Current account/GDP	0.088**	-0.023
	(2.166)	(-0.872)
Legislative election	-0.387	-0.990
	(-1.379)	(-1.457)
Log(legislative checks)	-0.092	0.030
	(-0.143)	(0.055)
Observations	806	806

Notes: The model uses predictors listed in Table A2 in the first stage and region dummies as fixed effect. T- statistics in parenthesis, standard errors clustered at the country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

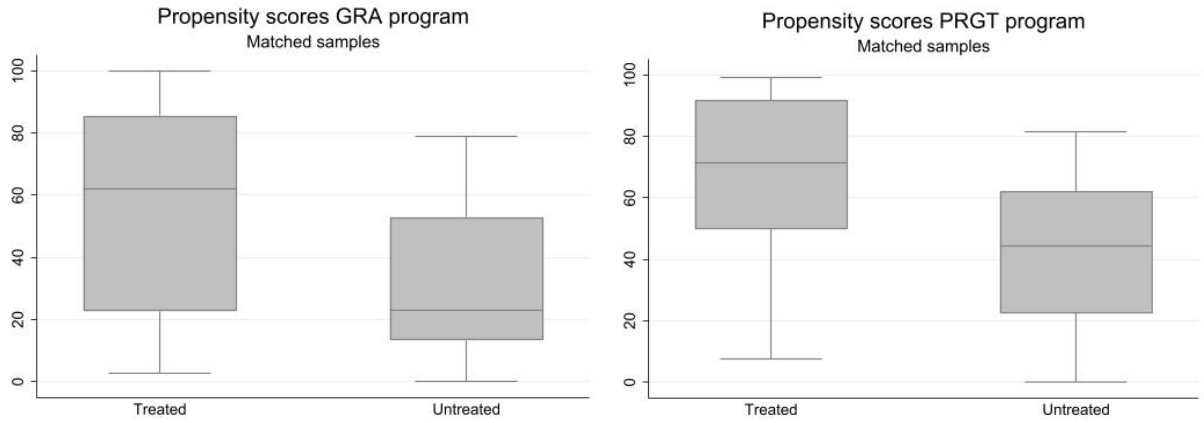
Table B2. AIPW Estimates, Second Stage

	GRA				
	(1)	(2)	(3)	(4)	(5)
GRA dummy	0.122*	0.119	0.147*	0.115*	0.102**
	(2.91)	(1.98)	(3.01)	(2.27)	(3.58)
Lagged investments	-0.024*	-0.028*	-0.012	-0.016	-0.005
	(-2.35)	(-2.90)	(-1.12)	(-1.39)	(-0.62)
GRA years	0.122**	0.121*	0.093**	-0.022	-0.006
	(3.52)	(2.84)	(3.25)	(-0.59)	(-0.10)
Log (total assets)	-0.037*	-0.042	0.021	0.083**	0.121**
	(-2.54)	(-1.36)	(0.82)	(3.11)	(3.60)
Long term debt/total	0.001	0.022	0.011	0.012	0.035
	(0.05)	(0.94)	(0.31)	(0.29)	(0.50)
Leverage	0.068**	0.077	0.073*	0.171**	0.163***
	(3.31)	(1.53)	(2.72)	(3.50)	(11.01)
Interest coverage	0.002	0.002**	0.001	0.002	0.004
	(0.74)	(3.80)	(0.18)	(1.67)	(1.85)
Cash flows/TA	-0.048	-0.089	-0.121*	-0.124*	-0.089
	(-0.70)	(-1.33)	(-2.42)	(-2.57)	(-1.44)
Sales growth	-0.045**	-0.074***	-0.057***	-0.077**	-0.105***
	(-4.25)	(-5.03)	(-4.97)	(-3.67)	(-4.65)
Real GDP growth	0.001	-0.001	0.001	0.005	-0.002
	(0.17)	(-1.39)	(0.02)	(1.05)	(-0.29)
Real GDPPC	0.528**	0.139	0.388	0.475	1.015
	(3.08)	(0.97)	(1.08)	(0.94)	(2.11)
Bank claims	-0.079***	0.009	0.131	0.049	-0.004
	(-4.73)	(0.14)	(1.72)	(0.40)	(-0.04)
Real interest rate	0.004	-0.001	0.003	0.005	0.009
	(1.41)	(-0.07)	(1.22)	(1.45)	(1.80)
Political risk rating	-0.008*	-0.001	0.001	0.013	0.009
	(-2.56)	(-0.10)	(0.16)	(1.07)	(0.74)
R-squared	0.425	0.454	0.468	0.562	0.598
N	21817	18560	15900	13685	11899

	PRGT				
	(1)	(2)	(3)	(4)	(5)
PRGT dummy	0.123	0.112	0.026	-0.061	0.021
	(2.10)	(1.61)	(0.36)	(-0.61)	(0.19)
Lagged investments	-0.012	-0.025**	-0.015	-0.009	-0.004
	(-1.54)	(-3.07)	(-1.79)	(-1.06)	(-0.80)
PRGT years	0.037	-0.071	-0.098	-0.087	-0.015
	(1.56)	(-1.63)	(-1.71)	(-0.93)	(-0.17)
Log (total assets)	-0.017	-0.011	0.056**	0.085***	0.137***
	(-2.08)	(-0.46)	(3.82)	(4.47)	(5.17)
Long term debt/total	0.012	0.023	0.006	0.014	0.009
	(0.64)	(1.57)	(0.30)	(0.41)	(0.17)
Leverage	-0.018	0.004	0.044	0.091*	0.098**
	(-0.52)	(0.07)	(0.91)	(2.61)	(3.77)
Interest coverage	0.001	0.001	-0.001	0.001	0.003
	(0.46)	(0.31)	(-0.46)	(0.55)	(1.46)
Cash flows/TA	-0.055	-0.191***	-0.211**	-0.228*	-0.159*
	(-1.01)	(-7.23)	(-3.16)	(-2.82)	(-2.86)
Sales growth	-0.041**	-0.054***	-0.059**	-0.073***	-0.093**
	(-4.13)	(-4.47)	(-3.72)	(-4.73)	(-4.17)
Real GDP growth	-0.002	-0.002	-0.003	-0.002	-0.007
	(-1.34)	(-0.61)	(-0.49)	(-0.62)	(-1.88)
Real GDPPC	0.079	0.054	0.179	0.488	0.667
	(0.61)	(0.27)	(0.44)	(0.89)	(1.24)
Bank claims	-0.009	0.087	0.077	0.041	0.011
	(-0.36)	(1.21)	(0.92)	(0.42)	(0.11)
Real interest rate	0.002	0.002	0.004	0.001	0.004
	(0.69)	(0.72)	(1.53)	(0.74)	(0.89)
Political risk rating	-0.001	-0.004	0.001	0.004	0.005
	(-0.00)	(-0.57)	(0.17)	(0.45)	(0.68)
R-squared	0.127	0.196	0.228	0.266	0.295
N	21817	18560	15900	13685	11899

Notes: Control coefficient estimates for second stage regression in AIPW estimates, baseline model. Standard errors clustered at the country-sector level, T-statistics in parenthesis. * p < 0.1, ** p < 0.05, *** p < 0.01.

Figure B1. Balance Tests for Propensity Scores



Notes: Plots show the estimated propensity scores for different outcome levels in the first stage multinomial logit model, where untreated is the base value “no program” and treated is either GRA or PRGT.

C. Alternative Specification

Table C1. Anticipation Effects

Years to program	-5	-4	-3	-2	-1
			GRA		
Effect on investment growth	0.03	0.01*	-0.03***	0.01	0.01
	(1.56)	(1.75)	(-2.99)	(1.17)	(1.02)
N	27,585	27,585	27,585	27,585	27,585
			PRGT		
Effect on investment growth	0.01	0.02	-0.02	-0.03***	0.04
	(1.00)	(0.91)	(-0.67)	(-2.85)	(1.17)
N	27,585	27,585	27,585	27,585	27,585

Notes: Change in firm tangibles/TA investment rate in the *h* years leading up to program approval, with h=1,2,3,4,5. Model is a fixed effects regression with baseline controls, firm and sector-year fixed effects. Standard errors clustered at the country level, T-statistics in parenthesis. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table C2. End-of-Program Effects by Completion Status

			GRA		
	(1)	(2)	(3)	(4)	(5)
Completed programs	-0.23***	0.56	1.77**	3.46***	2.57*
	(-3.32)	(1.06)	(2.46)	(3.16)	(1.85)
N	21,643	19,002	16,516	14,337	12,608
Offtrack programs	0.27	1.15**	2.01***	3.91***	3.16**
	(1.18)	(2.49)	(3.32)	(4.03)	(2.78)
N	21,643	19,002	16,516	14,337	12,608
			PRGT		
	(1)	(2)	(3)	(4)	(5)
Completed programs	-1.05*	-0.99	-1.65	-0.27	2.72
	(-1.81)	(-0.91)	(-1.14)	(-0.17)	(1.62)
N	21,643	19,002	16,516	14,337	12,608
Offtrack programs	-2.58***	-1.17	-4.21**	-2.04	-0.76
	(-3.88)	(-1.07)	(-2.74)	(-1.27)	(-0.44)
N	21,643	19,002	16,516	14,337	12,608

Notes: AIPW average treatment effect of a program end, by completion status, for each time horizon h=1,2,3,4,5. Standard errors clustered at the country level, T-statistics in parenthesis. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table C3. AIPW Robustness Tests

			GRA		
	(1)	(2)	(3)	(4)	(5)
Spell length	-0.131	1.094**	2.175**	4.173**	3.144*
	(-1.69)	(2.99)	(3.35)	(3.81)	(2.27)
N	21642	18941	16448	14281	12551
No offtrack	-0.113	1.073*	2.151**	4.075**	3.718*
	(-1.40)	(2.18)	(3.18)	(3.94)	(2.86)
N	21643	19002	16516	14337	12608
			PRGT		
	(1)	(2)	(3)	(4)	(5)
Spell length	1.072*	1.002	-0.296	-1.450	0.198
	(2.30)	(1.01)	(-0.21)	(-0.86)	(0.12)
N	21642	18941	16448	14281	12551
No offtrack	0.824	0.637	1.220	0.349	2.548
	(1.62)	(0.63)	(0.90)	(0.23)	(1.50)
N	21643	19002	16516	14337	12608

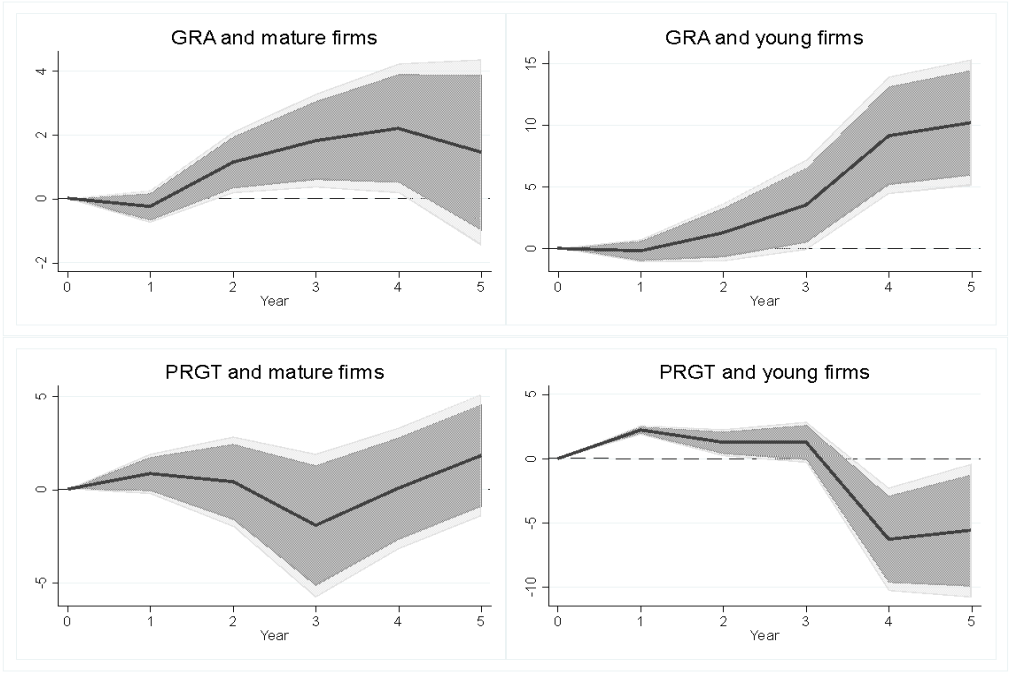
Notes: AIPW estimators for each time horizon h=1,2,3,4,5 under different conditions. Spell length restricts the sample to firms with a series of yearly observations spanning at least 5 years to cover the full projection horizon. No offtrack drops programs from the treatment dummy that were classified as off track. No advanced drops countries from the 2010 European Union sovereign debt crisis that required IMF intervention. Standard errors clustered at the country-sector level, T-statistics in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C4. AIPW Dropping Regions

			GRA		
	(1)	(2)	(3)	(4)	(5)
Asia Pacific	-0.09	1.24**	2.20***	4.44***	3.63**
	(-0.96)	(2.78)	(3.10)	(3.67)	(2.65)
N	20839	18284	15938	13908	12305
Europe	-0.02	0.29	-1.88	-5.13**	0.05
	(-0.06)	(0.19)	(-0.99)	(-2.98)	(0.02)
N	2228	1836	1483	1211	982
Mid. East & Cent. Asia	-0.04	1.21**	2.30***	4.61***	3.93**
	(-0.53)	(2.46)	(3.31)	(3.76)	(2.43)
N	21072	18579	16187	14054	12360
SSA	-0.13	0.99***	1.81***	4.10***	3.25**
	(-0.92)	(3.03)	(3.03)	(3.56)	(2.24)
N	21450	18840	16375	14213	12502
West. Hemisphere	-0.23***	1.46***	2.45***	3.61***	2.57**
	(-4.42)	(3.62)	(3.89)	(4.44)	(2.30)
N	20943	18438	16059	13933	12252
			PRGT		
	(1)	(2)	(3)	(4)	(5)
Asia Pacific	3.17***	2.48*	2.94	-2.30	1.58
	(5.74)	(1.76)	(1.73)	(-1.13)	(0.97)
N	20839	18284	15938	13908	12305
Europe	0.98*	-2.91	-4.60*	-4.91**	-13.27*
	(1.88)	(-1.74)	(-2.05)	(-2.25)	(-2.09)
N	2228	1836	1483	1211	982
Mid. East & Cent. Asia	0.72	0.61	-0.45	-1.55	0.51
	(1.42)	(0.60)	(-0.31)	(-0.88)	(0.26)
N	21072	18579	16187	14054	12360
SSA	-0.01	0.17	-0.97	-0.91	0.01
	(-0.03)	(0.19)	(-0.81)	(-0.52)	(0.01)
N	21450	18840	16375	14213	12502
West. Hemisphere	1.10**	0.95	-0.36	-0.97	0.34
	(2.52)	(0.90)	(-0.24)	(-0.70)	(0.21)
N	20943	18438	16059	13933	12252

Notes: AIPW average treatment effects for each time horizon h=1,2,3,4,5 when region *m* is dropped. Regions correspond to IMF Regional Department groups. Standard errors clustered at the country-sector level, T-statistics in parenthesis. * p < 0.1, ** p < 0.05, *** p < 0.01.

Figure C1. AIPW and Firm Age



Notes: AIPW average treatment effects of program signing on firm tangible fixed assets investment rate for groups of firms based on age. Firms are divided into two groups: mature firms are those with above-median age, young firms below-median age. Areas indicate 90 and 95% confidence intervals, standard errors are clustered at the country-level