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Do IMF Programs Stimulate Private Sector Investment?

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Abstract: This paper investigates the dynamic aggregate response of firm investments to the approval of an IMF arrangement. Using a local projection methodology, we find that distinguishing between General Resource Account (GRA) and Poverty Reduction and Growth Trust (PRGT) financing matters for the path of investment. Following a GRA arrangement, investments start to increase after two years, while the effect is quite limited after a PRGT. Adopting a stacked difference-in-differences estimator and exploiting firm-level characteristics, we find that firms having a domestic ownership, relying more on external finance, or which are more subject to uncertainty, invest more following a GRA agreement.

Keywords: IMF, Firm investment, Local Projection, Financial Frictions, Difference-in-Differences

JEL Classification: E22, F33, O19

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1 Introduction

Economic headwinds, from the pandemic, to supply crises, to geopolitical tensions faced by countries have reinvigorated the role of the International Monetary Fund (IMF). Fund 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. 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 future prospects during periods of heightened risks.[1]

At the macro level, the effects of IMF programs have been investigated focusing on two main channels. One strand of literature considers 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). More recently, the signaling argument is typically used to explain a catalytic finance effect, namely the propensity of private capital to flow into the country following the approval of an IMF program (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).

This paper links IMF participation to firm investment decisions, which are contingent also on future macroeconomic and policy prospects. While previous work documents the relationship between the IMF and firm performance in the short term (Bomprezzi and Marchesi 2023), this paper, using detailed balance sheet data, provides evidence on the interplay between the IMF and the firm's decision to invest, which represents a medium to long-term effect.[2]

IMF programs may have a positive investment effect through different channels. They may provide the recipient governments with additional money to spend, as well as reducing uncertainty about future economic policies and improving expectations of domestic and foreign investors by serving as a seal of approval. Beyond specific financial or legal factors, economic policy uncertainty is

[1] In the presence of policy uncertainty and hence lack 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).

[2] Bomprezzi and Marchesi (2023) find that IMF intervention has a positive impact on firms' sales growth and that firm performance improves through the alleviation of the financing constraint. 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; Chauvet and Ehrhart 2018; Dreher and Lohman 2015; Dreher et al. 2021; Marchesi et al. 2021).

an important determinant of investment decisions. Providing additional resources represents a necessary but not sufficient condition to boost investments, if expectations on the country's future prospects are not affected.

This paper focuses on tangible fixed asset investments, which tend to be non-reversible. Hence firms would favor precautionary delays in long-term decisions until future expectations improve. We propose a signaling mechanism under which firms, when undertaking these investment decisions, are sensitive to the expected economic environment. Under this hypothesis, the reduction of uncertainty that accompanies IMF programs ultimately triggers the firms' decision to increase tangible investments, even if no real macroeconomic effects have had time to materialize.

The literature on determinants of firm investment dynamics emphasizes the role of firm and sector-specific factors such as size, profitability, asset tangibility, and industry leverage (Myers 1984; Myers and Majluf 1984; Titman and Wessels 1988; Harris and Raviv 1991; Booth et al. 2001; Baker and Wurgler 2002; Lemmon et al. 2008; Graham et al. 2015). Another strand of literature focuses on 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). Furthermore a growing strand of literature 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; Bloom 2009; Panousi and Papanikolaou 2012; Alfaro, Bloom, and Lin 2021). In particular, Alfaro et al. (2021) provide two different proxies of firm uncertainty at the micro level: realized stock return volatility and implied volatility.

We consider the difference between Poverty Reduction and Growth Trust (PRGT) and General Resource Account (GRA) IMF arrangements. This distinction is relevant, as IMF programs are not "one size fits all". Under GRA financing, a member's balance of payment needs should be resolved by the end of the program period and no follow-up arrangement would be anticipated. 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. We first estimate the dynamic aggregate response of firm investments following the approval of an IMF program, financed either through GRA or PRGT, through a local projection methodology. We find that following the approval of a GRA, investments start to increase after two years, while after the beginning of a PRGT there is a mild effect that vanishes after two years.

While the main advantage of the local projection is to give a broad picture of the evolution of investments over time, it comes at the cost of assessing more in detail the role of firm-level indicators. For this reason, we adopt a stacked difference-in-differences approach to exploit firm-level information. We focus on three main firm characteristics: firm external financial dependence (Rajan and Zingales 1998), the role of sectoral uncertainty (Alfaro et al. 2021) and whether the firm operates within the country. These represent the various channels through which the IMF "seal of approval" may play a role in determining investments. Specifically, a reduction in the recipient country's level of uncertainty improves future economic prospects, and for this reason influences the decision of lenders to finance firm investments as well as of firms to invest, especially for those firms relying more on external finance or more exposed to firm-level uncertainty. Moreover, firms with domestic ownership are also more constrained by the future prospects of their own country when making an investment plan, while foreign owned firms gain a sort of natural hedge by being part of a foreign group and hence less sensitive to what happens in a country. Our results show that firms relying more on external finance, more subject to uncertainty, or having domestic ownership invest relatively more following a program approval.

This paper contributes to the literature on IMF effectiveness, and in particular to the strand of macro-micro work studying 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 ones more willing to invest.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 shows the results obtained using a local projection methodology, while section 4 presents the results of a stacked difference-indifferences estimator. Section 5 contains some robustness analysis. The final section 6 concludes.

2 Data

2.1 Identifying IMF Programs

We focus on the pre COVID-19 period, drawing data on 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 other specific country circumstances. Unlike previous work, we distinguish between

GRA and PRGT.[3] 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 distinction between GRA and PRGT lending facilities because the policy ramifications differ between the two. Under GRA, policy measures must be taken within the program period and the macroeconomic adjustment be completed by the time repurchases (or repayment) to the IMF begin.[4] Balance of payment needs should also 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.[5] 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 one if a country approved an IMF program during the year but no later than October. Otherwise, the subsequent year is coded as the program approval year.[6] As such, we account only for announcement effects which occur sufficiently early in the calendar year as to determine investments. Our sample contains only countries that with an IMF program over the sample years. This setup helps to mitigate problems of endogeneity, whereby estimates of the effects of an IMF program 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 two types of arrangements considered (GRA and PRGT). GRA make up the bulk of programs over the full sample, while PRGT programs represent a smaller share, generally not surpassing 5

[3] Lending instruments under the GRA include the Stand-By Arrangement (SBA) for short-term or potential balance of payments problems, the Extended Fund Facility (EFF) for medium-term support to address protracted balance of payments problems, 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. For 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.

[4] Amounts drawn under a SBA are repaid over $3\frac{1}{4}$–5 years, whereas credit provided under an EFF are to be repaid over $4\frac{1}{2}$–10 years in 12 equal semiannual installments.

[5] Repayments under the ECF carries a grace period of $5\frac{1}{2}$ years and a final maturity of 10 years, whereas the SCF has a grace period of four years and a final maturity of 8 years.

[6] We follow the IMF Independent Evaluation Office (IEO, 2021) strategy for coding program start years.

per year. On average, 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.

[Figure 1 about here]

2.2 Firm Tangible Fixed Asset Investment and Balance Sheet Data

We retrieve balance sheet data from the Orbis database provided by Bureau Van Dijk. To assess the influence of expectations on firm investment decisions, it is important to focus on tangible investments because of their non-reversible 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 scale tangible fixed assets by total assets as a preferred investment measure. As opposed to other more generic categories (financial or intangible), this allows us to capture how firms react to changes or potential changes in the macroeconomic environment.

The Orbis database provides balance sheet data for 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. Leverage 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. Debt maturity is 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). Sales growth captures growth opportunities for the firm. Finally, we control for cash flows scaled by total assets as is standard in the literature. Table A1, in Appendix A, presents variable descriptions and sources, while Table A2 provides the full summary statistics.

Finally, Orbis provides information on firm ownership, incorporation dates, and sectors of operation. From these we construct sector-year fixed effects to account for time-varying, sector specific heterogeneity.[7] There are several data issues with Orbis however that deserve discussion. Most significantly, firm coverage varies by region and by country (see Table A5, in Appendix A). For

[7] Table A4, in Appendix A, reports the average tangible investment by NACE main sector for each year across all firms.

countries where the filing of financial information is mandatory for all, the Orbis sample is more comprehensive (Kalemli-Özcan et al. 2015). 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 has typically more limited data in these countries compared with firms from other parts of the world, particularly with respect to Western Europe and the Americas. Figure 2 gives a graphical representation of countries having had an IMF program, showing a clear concentration in Africa. The size of the dots indicates the number of unique firms for which we have balance sheet data in the country. The Orbis coverage of this data in Africa is provided for half of the MONA sample. Nonetheless, there is strong overlap between Orbis and MONA coverage in Eastern Europe, Latin America, and Central Asia.

[Figure 2 about here]

We follow the procedure outlined by Kalemli-Özcan et al. (2015) in order to mitigate remaining data quality issues related to Orbis 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 and drop financial firms, government sector firms, and other firms which operate primarily in service activities.[8] We avoid double counting by considering only consolidated financial statements when available and clean the data by removing cases of erroneously reported balance sheet items, such as negative costs. Finally, all balance sheet variables are winsorized 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.[9] In the next section we explain our identification strategy and baseline model.

3 Event study approach

We are 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

[8] 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.

[9] Some descriptive statistics are presented in Figure A1, in Appendix A, where we categorize firms by age according to their age. As would be expected investments for younger firms generally grow faster than for other firms.

have become a popular because of their flexibility and simplicity.[10] 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.

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.[11] Therefore we accept the endogeneity of entering an IMF program and attempt to explicitly model for it. If the probability is modeled correctly, we can re-balance the sample as if random. In a second stage we use as the outcome variable the cumulative change in the ratio of tangible fixed assets to total assets. The final estimator gives an average treatment effect known 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.[12]

Table 1 presents the local projection baseline results, with the impulse response functions plotted in Figure 3. The ATE is computed at each time t+h for programs approved at time t. We find that the effect of GRA programs is increasing over time, peaking at four years after program approval. On average, tangible assets 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 weak temporary effect. In the first year after program approval, tangibles accumulate marginally, with a value around one percentage point above the reference level, with no significant effects afterwards.

The positive effect of GRA approval suggests that in GRA countries an IMF intervention is enough to trigger an increase in investments. On the other hand, in PRGT-eligible countries multiple confounders inhibit firm investments. The positive effect of a Fund program is not enough to offset the drag on private sector investments due to poorer access to credit, lower quality of

[10] 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.

[11] Dealing with the endogeneity of IMF programs is an issue that is tackled in several different ways in the literature (e.g., Barro and Lee 2005; Gehring and Lang 2020; Lang 2021). Crucially for our empirical strategy, this IV is suitable for the identification into an IMF program but not into program type (GRA vs. PRGT).

[12] 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).

institutions, and fewer cash generating opportunities that are associated with the markets in which these firms likely operate. The differential effects of the type of IMF financing on investments can also be explained by the nature of these programs. Under PRGT, it is likely that repeated IMF engagement, which our treatment does not capture, would provide firms with the kind of confidence boost needed to match GRA effects. Finally, PRGT arrangements target mostly social programs and safety nets, therefore dimensions that wouldn't impact firms' decisions to invest. In the next section, we focus on GRA agreements and present the results using a stacked difference-in-differences estimator.

[Table 1 and Figure 3 about here]

4 Stacked difference-in-differences

While our baseline result provides estimates of dynamic effects of an IMF program, it does not allow us to evaluate how firm-specific heterogeneity influences the outcome. In this section, we take a more granular approach to capture the differential effects of a GRA program approval. Specifically, using a difference-in-differences (DiD) approach, we consider a firms' external financial dependence, level of uncertainty, and whether it operates within the recipient country.

Our sample consists of countries that have an IMF program at different points in time and switch in and out of treatment.[13] The analysis presented in the previous section has therefore the flavor of a staggered difference-in-differences. As recent developments in the applied econometrics literature suggest (Goodman-Bacon 2021, De Chaisemartin and D'Haltfoeuille 2020, Callaway and Sant'Anna 2021, Borusyak and Jaravel 2021), two-way fixed effects estimates may produce inconsistent estimates in this setting. One of the reasons is that countries treated at the beginning of the sample may enter in the control group for countries that experience a crisis toward the end of the sample. To address this potential concern, we carry out an alternative estimation strategy based on a "stacked difference-in-differences" similar in spirit to Cenzig et al. (2019) and Deshpande and Li (2019). The objective of the procedure is to ensure that every country experiencing an IMF program (treated) is compared only to clean controls, i.e., countries that did not experience a program.

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-

[13] Figure A2, in Appendix A, plots the treatment status by country and program type for each year in the sample, showing the dynamic nature of treatment is evident in our sample.

sectional group (country). A treatment window is defined, such that only observations with treatment outside a k-years are considered as controls. As a result, all observations within a sub-experiment will have the same program adoption year, and a clean control group without confounding effects from other program adoptions. These sub-experiments are then stacked to create a dataset which consists of n independent panel event studies.

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 firm characteristics (FC). 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):

$$\begin{aligned} Tan/TA_{i,j,k,t} =& \alpha + \beta Z_{i,j,k,t-1} + \delta X_{j,t-1} + \sum_{j=-k\alpha}^{kb} \gamma_j \left[FC_{i/i,t} * 1(YSE_t = j) \right] \\ & + \sigma FC_{i/i,t} + \sum_{j=-k\alpha}^{kb} \rho_j + 1(YSE_t = j) + \mu_{j/i} + \tau_{k,t} + +\varepsilon_{i,j,k,t} \end{aligned} \tag{1}$$

Our parameter of interest is γ_i, representing the interaction between the indicator for the jth year before/after the program approval and the firm characteristics.

We start by considering the importance of firm financial frictions, which is the typical obstacls to a firm investment. We rely on the seminal work by Rajan and Zingales (1998) (henceforth RZ) on external financial dependence. The underlying idea is that the adoption of an IMF program should disproportionately help firms which are more dependent on external financing. In particular, 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.[14] We then merge these industry values reported as NACE sectors with our Orbis data.[15]

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

[15]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.

We then turn to our second measure of firm heterogeneity, which is a proxy for firm-level uncertainty. Alfaro, et al. (2021) 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. We employ the first of these indicators as our preferred measure of firm-level uncertainty.[16] The data spans from 1992 to 2019 and provides the year-by-year two 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 constructing a measure of uncertainty that is not firm varying. This measure should then be interpreted as an industry-specific characteristic, which is comparable across countries, à la RZ.[17]

Finally, 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. Using Orbis historical vintages, we take ownership data for firms beginning in 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 classify a firm as having a foreign vs. a domestic owner each year. However, simply comparing domestically owned versus foreign-owned firms could be misleading, as foreign firms are likely to be larger and more successful, for example when part of a multinational corporate group. Furthermore, their ownership changes occur quite frequently, and are likely driven by economic expansions or recessions. Yet, we want to identify a set of firms, which are tied to the country and whose activity is strongly contingent on the domestic country's economic performance. To that end, we take as treatment firms which do not switch ownership in the immediate years before and after program approval, labeling them as "never-leavers."

Table 2 presents the results of the DiD specification. Panel A of Table 2 presents the results when considering external financial dependence, the results in panel B consider firm's uncertainty, while those reported in panel C reports the dynamic stacked DiD estimates for "never-leavers". In all panels, the first two columns, which indicate the two years leading up to the program approval, show no evidence of an anticipation effect. As shown in panel A, we find that tangible assets grow disproportionately more relative to the base year for firms operating in sectors that are characterized by a high degree of external financial dependence. The effect is persistent over time.

[16] 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.

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

For example, for the industry which is at the bottom 5th percentile of external financial dependence (publishing and printing), the expected effect after one 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.

As shown in panel B, there is evidence that after the adoption of an IMF program firm investments increase in those sectors with higher volatility. Specifically, three years after the program adoption, greater sector-wide volatility leads to a 3-percentage point increase in tangible assets. Finally, the results presented in panel C, show that firms which remain exposed to the Fund program throughout the treatment period increase their tangible assets by around one percentage point as opposed to firms that change in ownership.

[Table 2 about here]

In conclusion, we find that firm characteristics are important to assess the effect of an IMF program. Consistently with our initial hypothesis, we find that firms relying more on external finance, more subject to sectoral uncertainty, or more tied to the domestic economy, all increase their investments after the adoption of an IMF program. The next section presents some robustness analysis and alternative specifications.

5 Robustness

This section provides a series of robustness tests. We start by testing pre-treatment trends. Then, 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 selecting into a program type, namely 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 occurring at t+h. As shown in Table C1, in Appendix C, we find no evidence of systematic anticipation effects.

As is well documented in the literature on the IMF, program interruption is common and compliance with Fund conditionality can be low (see among others, Dreher 2003, Dreher 2006 and, Reinsberg et al. 2022a, 2022b). Since the main assumption in this paper is that entry into a program signals a reduction in policy uncertainty, we test if program interruption interferes with this mechanism. Based on the number of reviews, a program can be either classified as completed or off-track. We take as treatment, rather than the adoption year of a program, the final program year, whether this is the originally scheduled end of the program or the effective end if the program went off-track. Table C2, in Appendix C, presents the results using this alternative treatment for the AIPW estimator. Consistently with Table 1, we find different long-term effects for GRA and PRGT. In the case of GRA, we find that the effects are positive and significant regardless of whether the program goes off track or not. In the case of PRGT, we find that investments drop following the end of a program and this drop persists if the program goes off-track. Furthermore, we run our baseline estimates dropping programs classified as off-track, finding that the results are robust to this change.

An important issue to address is the sensitivity of results to the composition of the sample. While it is unlikely that a given country is driving the results, issues of sample dependence could arise from the firm sample within countries. We start by considering whether the results might be affected by specific country groups. We systematically drop countries belonging to the different IMF regional departments. Table C3 shows that the baseline results are robust to these sensitivity checks only considering GRA arrangements, except when dropping Europe.[18] On the other hand, 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 in these regions. Additionally, we reduce our sample by dropping firms for which we do not have balance sheet data on investments for the full 5-year horizon. Given differences in cross-country coverage in Orbis, our local projection estimates could be driven by firms subject to differing reporting standards or covering more years. As Table C4, in Appendix C, shows, we find that the results are consistent with the baseline estimates.

Lastly, we consider an alternative specification. In particular, we estimate the response of firm investments to Fund program approval considering firm age as a proxy for financial frictions, as indicated by the literature (Gertler 1988; Hadlock and Pierce 2010; Cloyne et al. 2018; Bahaj et al. 2019).[19] Especially in developing countries, firm age has been shown to be an appropriate proxy, where given less developed financial markets, younger firms are more leveraged, less liquid, and smaller in size.[20] More specifically, we split the sample into firms which are above vs. below

[18] Since, because our sample includes the European debt crises, it is unsurprising that removing this event attenuates the effect that the Fund may have on investments.

[19] 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.

[20] 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.

the median age of firms. 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 the baseline results, for both PRGT and GRA programs, younger, more financially constrained firms benefit more from an IMF arrangement. In the case of GRA, there is also a positive but much smaller effect for mature firms, while in the case of PRGT programs we find no such effects.

6 Conclusions

This paper provides new evidence on the role of IMF programs in stimulating firm investments. Using detailed firm-level data on tangible fixed assets, we estimate the dynamic response of firm investments to the approval of an IMF program. 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. Moreover, leveraging a DiD methodology, we document the presence of three potential channels through the reduction of policy uncertainty associated with an IMF program conditionality may affect firm investment choices. Specifically, focusing on GRA agreements, we examine the degree of firms' external financial dependence, firms' sectoral uncertainty, and the degree to which a firm is tied to the local economy. We find evidence that private investments are higher for firms relying more on external finance, or those which are exposed to greater uncertainty or for domestic firms.

To sum up, to the best of our knowledge, this is the first paper documenting the effects of IMF participation on firms' tangible assets The presence of a private investment transmission channel helps improving our understanding of what factors influencing the effectiveness of IMF programs. Future research could focus on alternative mechanisms behind our results, in particular through specific conditionality, and of the implications for public investments.

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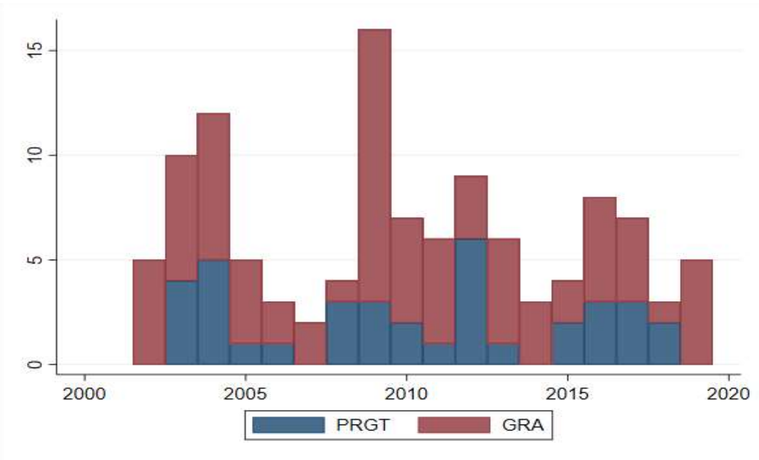
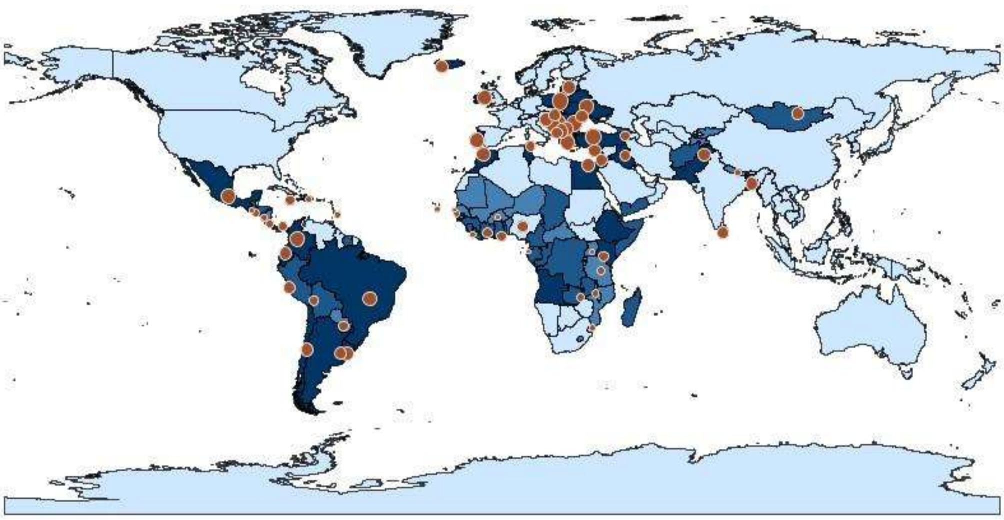
Figures and Tables

Figure 1: Distribution of IMF Programs per Year



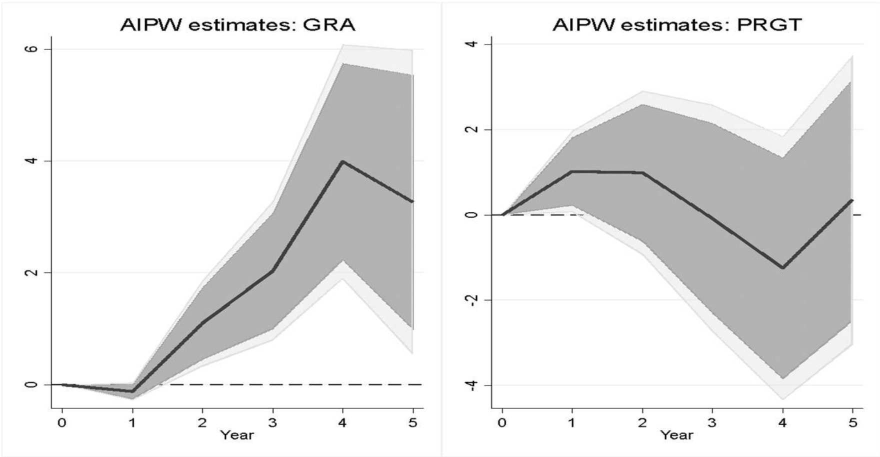
Notes: Number of unique IMF programs signed per year, by program type. Blue bars are for the PRGT category, red bars are for the GRA category.

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.

Figure 3: 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.

Table 1: Program Signing and Firm Investment Response, AIPW

			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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Firm Frictions and Dynamic Stacked DiD Estimates

Years since treatment	**-2**	**-1**	**1**	**2**	**3**	**4**	**5**
Panel A: External Financial Dependence							
IMF participation	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
Panel B: Realized Volatility							
IMF participation	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
Panel C: Ownership switches							
IMF participation	0.341	0.509	1.341**	1.332**	1.091*	1.075*	0.086
	(0.41)	(0.68)	(2.41)	(2.38)	(1.83)	(1.73)	(0.35)
N	66,845	66,845	66,845	66,845	66,845	66,845	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. Panel C considers the interaction between a dummy identifying "never-leavers" and a dummy equal to 1 for the year *t* before/after the program approval All specifications include full controls and sector-year fixed effects. Panel A uses country fixed effects, Panel B and C use firm fixed effects. IMF participation refer to GRA agreements. Standard errors clustered at the country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendices

Appendix A: Sample and Descriptive Statistics

Appendix B: Augmented Inverse Propensity Score Weighted

Appendix C: Alternative Specification

Appendix A: Sample and Descriptive Statistics

Table A1: 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 A2: 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 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

Year	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

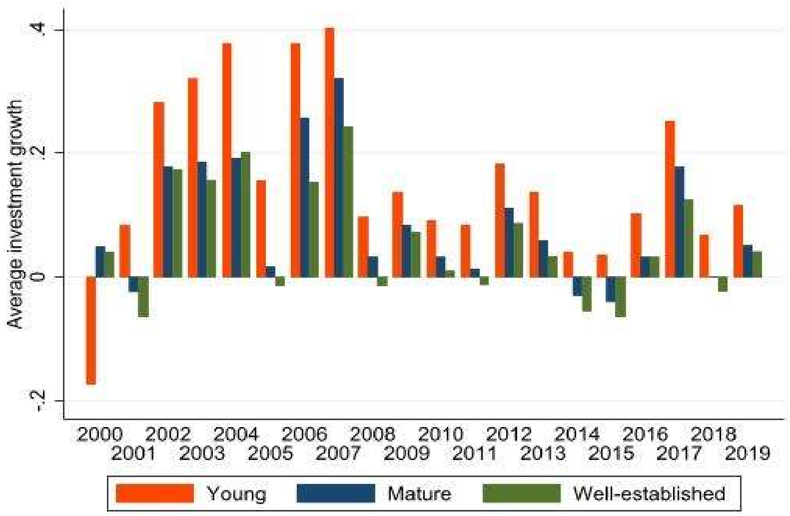
Notes: Number of observations and unique firms available per country of Orbis tangible fixed asset investment data.

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

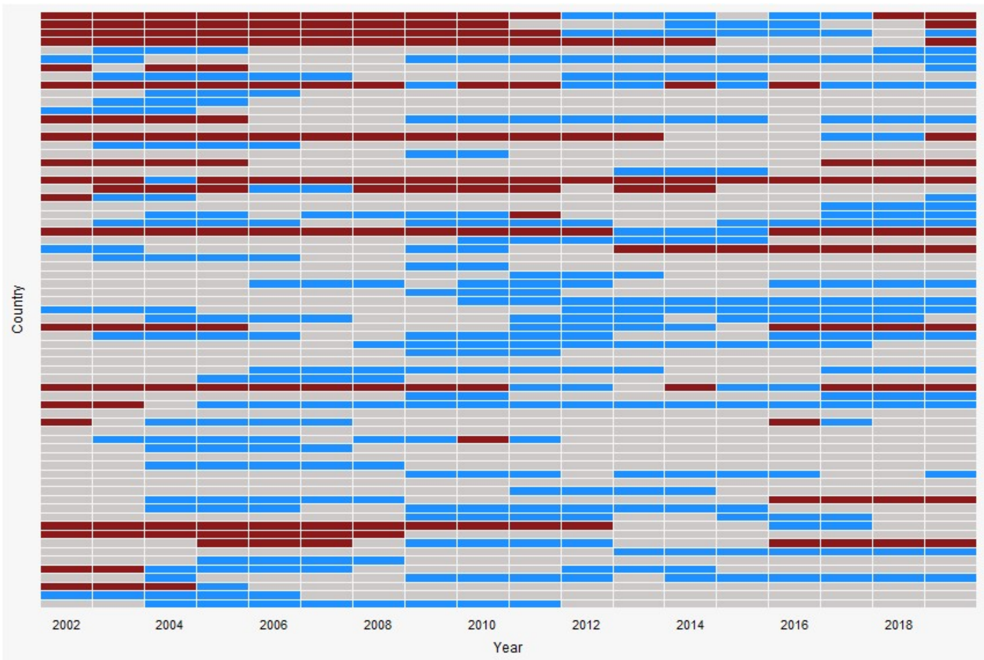
Notes: Eppinger and Neugabauer (2022) EFD indices computed from Compustat according to RZ (1998) methodology.

Figure A1: 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.

Figure A3: 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.

Appendix B: Augmented Inverse Propensity Score Weighted

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:

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

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.[1] 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 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.[2] For

[1] 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.

[2] See for example Przeworski and Vreeland (2000) and Dreher and Vaubel (2004).

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.[3]

$D_{j,t}$ 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 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:

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

Where $\Delta y_{i,j,k,t+h}$ are the estimated conditional forecasts for the local projections (Equation *2*), and $D_{j,t}$ 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.[4]

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

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

[4] 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.

compute and can be estimated using ordinary least squares (OLS). In evaluating the properties of local projections, Montiel Olea and Plagborg-Møller (2021) and Plagborg-Møller and Wolf (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 5), we test the sensitivity of results by restricting estimates to groups of firms with data over a full forecast and lag horizon.

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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.

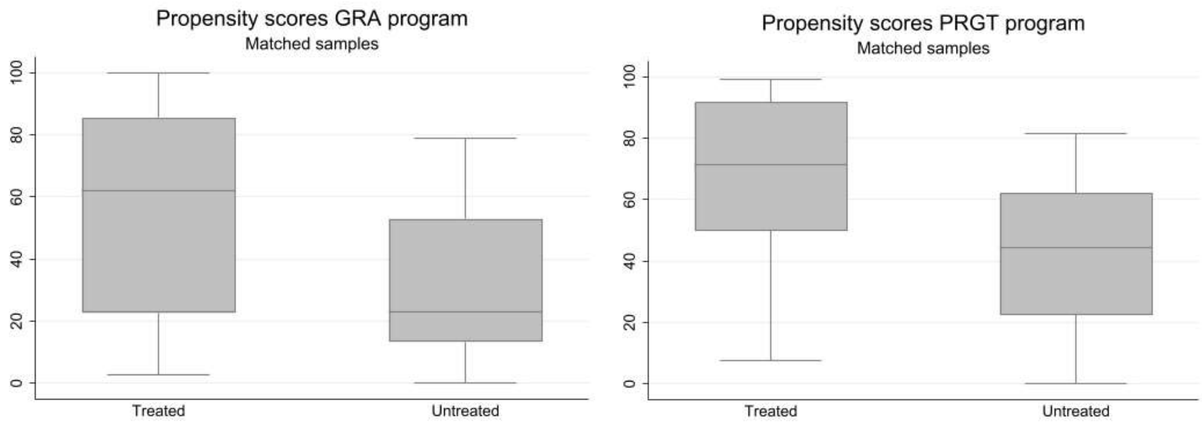
Table B2: AIPW Estimates, Second Stage

	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.

Appendix C: Alternative Specifications

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 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

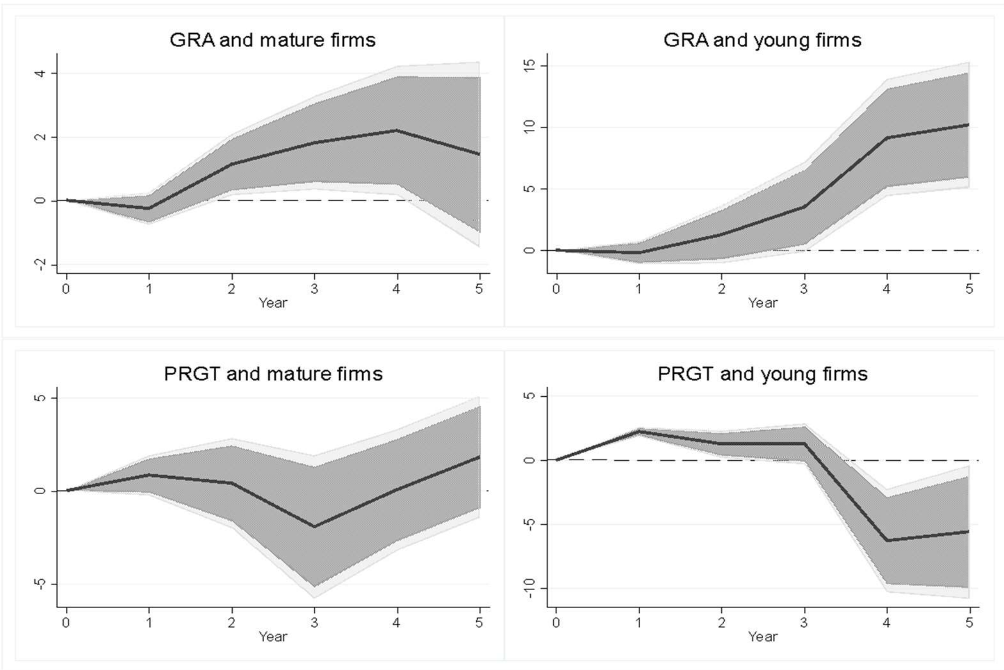
Notes: AIPW average treatment effects for each time horizon h=1,2,3,4,5 when region *m* is dropped. Regions correspond to IMF Regional Department groups. Standard errors clustered at the country-sector level, T-statistics in parenthesis. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table C4: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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.