INTERNATIONAL MONETARY FUND

The 'Fiscal Presource Curse':

Giant Discoveries and Debt Sustainability

Matteo Ruzzante and Nelson Sobrinho

WORKING PAPER

2022
JAN

IMF Working Paper
African Department

**The 'Fiscal Presource Curse': Giant Discoveries and Debt Sustainability
Prepared by Matteo Ruzzante and Nelson Sobrinho***

Authorized for distribution by Boileau Loko
January 2022

ABSTRACT: This paper investigates the dynamic impact of natural resource discoveries on government debt sustainability. We use a 'natural experiment' framework in which the timing of discoveries is treated as an exogenous source of within-country variation. We combine data on government debt, fiscal stress and debt distress episodes on a large panel of countries over 1970-2012, with a global repository of giant oil, gas, and mineral discoveries. We find strong and robust evidence of a 'fiscal presource curse', i.e., natural resources can jeopardize fiscal sustainability even before 'the first drop of oil is pumped'. Specifically, we find that giant discoveries, mostly of oil and gas, lead to permanently higher government debt and, eventually, debt distress episodes, specially in countries with weaker political institutions and governance. This evidence suggest that the curse can be mitigated and even prevented by pursuing prudent fiscal policies and borrowing strategies, strengthening fiscal governance, and implementing transparent and robust fiscal frameworks for resource management.

* **Ruzzante**: Northwestern University, 2211 Campus Dr, Evanston, IL 60208, United States. **Sobrinho**: International Monetary Fund, 700 19th Street NW, Washington, DC 20431, United States.

WORKING PAPERS

The 'Fiscal Presource Curse':
Giant Discoveries and Debt Sustainability

Prepared by Matteo Ruzzante and Nelson Sobrinho[1]

CONTENTS

LIST OF FIGURES

LIST OF TABLES

I INTRODUCTION

Natural resources, from fossil fuels to precious metals, have been recognized for several centuries to have a dark side or to be a curse.[1] Following seminal theories developed by Gelb (1988) and Auty (1993), the "natural resource curse" has become a well-known phenomenon in the economics literature and is now commonly cited even in the non-specialized press. Resource plenty has been associated with many undesirable outcomes, including lower economic growth, excessive macroeconomic volatility, higher domestic prices, weak political institutions, corruption and armed conflicts.[2] More recent evidence suggests that the resource curse can manifest itself even before extraction or production is rolled out. In particular, Cust and Mihalyi (2017) find that oil discoveries depress growth relative to counterfactual forecasts, before 'the first drop of oil is pumped', in countries with weak institutions. They call this phenomenon "presource curse".[3]

What about the impact of natural resources on a country's fiscal sphere and specifically on its debt sustainability?[4] Economic theory predicts that a small open economy would respond to a large resource discovery by initially increasing investment and consumption, running trade and current account deficits and borrowing abroad to pay for the investment and consumption boom. Once production comes on stream, savings and current account would turn positive and thus allow to pay off the accumulated debt (Arezki et al., 2017). In practice, however, investment and borrowing decisions can significantly deviate from these theoretical predictions due to expectations over future payoffs and distorted political incentives.

First, over-optimism about future growth following large discoveries might lead to over-borrowing by the government. Excessive optimism over development prospects may give rise to an economic boom in the short term, which is eventually followed by a recession later (Beaudry and Portier, 2004; Blanchard et al., 2013). Furthermore, over-optimism regarding future growth increases the likelihood of balance-of-payments, fiscal and debt crises (Beaudry and Willems, forthcoming). These problems may be fuelled by push factors such as easy access to international capital markets. In particular, investors' bullish sentiment about a country's outlook may facilitate over-borrowing, which, in turn, can lower economic growth and increase the incidence of fiscal crises (Al-Amine and Willems, 2020). Over-borrowing does not necessarily

---

[1]Adam Smith's *Wealth of Nations* and David Ricardo's *On the Principles of Political Economy and Taxation* contain some of the first contributions to the development of this idea. Ross (2018) discusses the intellectual roots of this literature in economics and political science.

[2]Frankel (2010), Van der Ploeg (2011) and Ross (2015) provide an overview of the theories and a survey of the empirical evidence on this subject.

[3]This expression was originally coined by the journalist Leigh Elston in the context of the 2010-2011 Mozambique discoveries of natural gas. Cust and Mihalyi (2017) expanded on this idea and found that, prior to resource windfalls, giant discoveries of oil or gas depress economic growth relative to counterfactual forecasts in countries with weak institutions. These authors use as counterfactuals the IMF's WEO medium-term growth projections at the time of discoveries and claim to control for the documented optimism bias embedded in such forecasts (e.g., IEO, 2014).

[4]Conceptually, public debt is defined as 'sustainable' if its initial level does not exceed the present value of the sum of all future primary balances. In practice, political economy considerations are also important because the fiscal balances that are required for sustainability must be politically feasible (IMF, 2021).

lead to debt distress.[5] This outcome is less likely when external borrowing is well allocated (e.g., invested productively and not wasted), public investment efficiency is sufficiently high, and institutions are capable of exerting discipline on politicians (Melina et al., 2016). Because these conditions set a high bar that few countries may be able to meet in practice, we expect post-discovery excessive borrowing to be a prevalent phenomenon in many contexts.

Second, policymakers' decisions might be distorted by impatience and time-inconsistency, even when growth expectations are correct on average. This is because politicians may want to buy electoral support in order to remain in power. For instance, Robinson et al. (2006) argue that countries are more likely to suffer from a resource curse when they lack strong institutions that prevent impatient politicians from over-extracting natural resources as a mean to remain in power (e.g., using patronage). This echoes earlier theoretical work by Tornell and Lane (1999), in which the absence of strong legal-political institutions enables powerful elites to excessively grab revenue windfalls ("voracity effect") that in turn leads to lower growth in equilibrium. Distorted policy decisions may interact with other factors and amplify the potential negative effects of resource discoveries. One of such factors is the formation of mass opinions or popular beliefs, which are often exposed to known biases (e.g., excessive discounting of the future) and can lead to policy deterioration in the aftermath of resource discoveries, including populism and conflict (Collier, 2017).

Anecdotal evidence suggests that distorted borrowing and political decisions in many developing countries may have paved the way to increased debt vulnerabilities and even debt crises following discoveries of giant deposits of fossil fuels or minerals. For instance, in the mid-2000s, Mozambique found large reserves of natural gas and borrowed large amounts against future revenues. Years later, the country experienced a debt crisis, with large hidden loans being exposed, and downgrading of its external debt risk rating to 'in debt distress' (IMF, 2020c).[6] Ghana's discovery of large oil reserves in the 2000s was also followed by significant borrowing from international capital markets and accumulation of sovereign debt. Indeed, "*between the discovery* [of oil] *in 2007 and the onset of extraction in 2011, the government responded to the pressure of exaggerated expectations by borrowing commercially on the international bond market, using the proceeds predominantly for consumption*" (Collier, 2017, p. 224), prompting the country to request IMF financial assistance in late 2014. Although Ghana has not experienced a debt crisis, its debt remains high and is assessed at 'high risk of distress' (IMF, 2020b). Other developing countries have also experienced excessive borrowing and/or growth disappointments in post-discovery years, including the recent case of Mongolia, although some others like Uganda have resisted the curse.[7]

---

[5]Sovereign default risk can still arise via other channels, for instance through the increased volatility of tradable income connected to the higher dependence on oil revenues (Esquivel, 2020). As an old saying goes, "*live by oil, die by oil*."

[6]"Mozambique gas projects raise risk of resource 'curse' " (*Reuters*, October 26, 2015). "Mozambique fell prey to the promise of fabulous wealth – now it can't pay nurses" (*The Guardian*, January 27, 2017). The Mozambican debt buildup was also driven by other relevant factors, including large depreciation of the Metical, natural disasters, and efforts to address security-related issues.

[7]Mongolia's large debt buildup and ensuing debt risks following the discovery of vast mineral resources in the 2000s was "mainly attributable to aggressive borrowing" (IMF, 2015, p. 2), which put debt on a unsustainable path and led to a large bailout program and debt exchange in 2017 (IMF, 2017b). While Uganda's public debt

This paper investigates the impact of natural resources on a country's fiscal sphere and most importantly on its debt sustainability in the short and medium term. Inspired by the country experiences mentioned above, our main hypothesis is that discoveries may lead to government over-borrowing, especially in the context of weak political institutions and governance, which would facilitate unwise borrowing decisions. This could eventually result in unsustainable debt levels and culminate in debt crises. We term this hypothesis "fiscal presource curse".

We use a global repository of 'giant' oil and gas discoveries, i.e., discoveries of oil and gas fields with at least 500 million barrels of recoverable oil equivalent reserves given the existing technology. We complement this data with information on 'giant' deposits of non-bulk minerals, i.e., deposits exceeding 1 million ounces of gold or 1 million metric tons of copper or equivalent, from a commercial dataset. For our main variable of interest, government debt, we compiled information from several data sources to maximize the number of observations in our estimation sample. Our debt panel data covers almost 50 years (1970-2017) and 171 countries, including advanced economies and most middle income- and low-income countries (MICs and LICs). We also rely on multiple data sources for constructing comprehensive measures of fiscal stress and debt distress episodes as well as political institutions and governance.

To estimate the impact of giant discoveries on government debt, we employ a dynamic panel distributed lag model. This framework allows to explore the dynamic relationship between discoveries and debt trajectory over different time horizons. We treat the timing of discovery events as an exogenous source of within-country variation to identify the causal effect of discoveries on government debt over time. To support our identification strategy, we show that lagged values of macroeconomic and political variables, including government debt itself, have negligible predictive power for discoveries, once we account for year and country fixed effects to control for global common factors and differences in time-invariant factors across countries.

Our findings confirm the existence of a fiscal presource curse. Debt-to-GDP ratios increase by about 1-2 percentage points of GDP per year in the first decade after a discovery. The impact is significant within a reasonable confidence range of 1-2 standard deviations around the average estimated effect and then gradually dies out in the second decade. This sizeable and persistent effect is mostly driven by oil and gas discoveries. The impact of mineral discoveries on debt dynamics is positive but its magnitude is imprecisely estimated. The average cumulative effect of discoveries on the debt-to-GDP ratio is large, amounting to about 15 percent of GDP in the first 10 years. This is in the order of magnitude of large debt buildups identified by the literature and would likely expose the affected countries to the risk of debt distress.[8] We also find that the impact of discoveries, especially of oil and gas fields, on debt sustainability is statistically and economically stronger in countries with weaker political institutions and governance. This suggests that the fiscal presource curse could be a manifestation of a deeper political curse that

---

has increased in recent years, it remains at moderate levels and the increase is partly explained by the COVID-19 pandemic. Uganda is also trying to learn lessons from the experiences of Mozambique and Ghana ("Uganda tries to dodge the 'presource curse' ", *The Economist*, April 4, 2019).

[8]Abbas et al. (2011) and IMF (2014) provide evidence that sovereign debt tends to be restructured when it is increasing too rapidly or is already too high.

encompasses the fiscal arena.[9]

Given that resource discoveries may lead to greater national wealth in the future, some debt accumulation in the aftermath of discoveries would be a rational policy response to such events. To test whether discoveries also lead to heightened risk of debt crises, we use a broad indicator of fiscal crisis from Medas et al. (2018) and a more specific measure of external debt distress mostly based on Catão and Milesi-Ferretti (2014) so to estimate the marginal impact of discoveries on a country's probability of fiscal stress and debt distress. We find significant effects in the first few years following a discovery, which suggests that discoveries not only lead to sizeable debt buildups relatively quickly but also to higher likelihood of debt crises.[10] Our findings are fairly robust to alternative measures of government debt and resource discoveries, sub-samples and country groupings, lag and regression model specifications.

This paper contributes to the natural resource curse literature in several ways. We improve upon empirical studies on the link between resource abundance and fiscal outcomes (El Anshasy and Katsaiti, 2013; Perez-Sebastian and Raveh, 2015; Bova et al., 2016; Bhattacharyya et al., 2017; von Haldenwang and Ivanyna, 2018; Masi et al., 2018) by: (1) focusing on the potential manifestation of the curse on public debt itself and (2) using discoveries instead of traditional measures of resource intensity such as commodity exports or resource rents. The link between natural resources (not necessarily resource discovery) and debt sustainability has been only studied through the lens of structural models. Mansoorian (1991) argues that discoveries can lead to over-borrowing if the extraction of the natural resource is capital intensive. More recently, Melina et al. (2016), using a dynamic general equilibrium model in which natural resource extraction can be financed by borrowing, find that risks to debt sustainability are higher when public investment is aggressively frontloaded, its efficiency is declining, and the realization of future resource revenues is below expectations. Our empirical findings discussed below are generally in line with these predictions.[11]

We follow a recent trend of the literature, which has largely overcome potential endogeneity issues between resource abundance and economic outcomes by using a framework where discoveries are treated as a 'natural experiment' or unanticipated 'news shock' (Tsui, 2010; Vicente, 2010; Cotet and Tsui, 2013; Lei and Michaels, 2014; Bhattacharyya et al., 2017). In particular, Cust and Mihalyi (2017) find that oil and gas discoveries cause significant declines in growth already in the short run, that is, prior to the materialization of private and public resource revenue windfalls. Analogously, Arezki et al. (2017) show that news about giant oil and gas discoveries trigger a significant 'anticipation effect'. Although an investment boom quickly

---

[9]A senior executive of an international oil company once noted: "*We don't like to call it the oil curse, we prefer 'governance curse'*" ("The paradox of plenty", *The Economist*, December 20, 2005).

[10]Part of the initial debt increase is predicted by economic theory as some borrowing is required to extract the resources. This paper is mostly concerned with excessive borrowing that could eventually lead to unsustainable debt.

[11]One related contribution is by Manzano and Rigobon (2001), who challenge the original resource curse hypothesis by claiming that the poor performance of resource-intensive economies is due to the fact that these countries took advantage of high commodity prices in the 1970's as implicit collateral for investment projects. This, in turn, left them with a debt-overhang problem and unsustainable balance of payments when commodity prices plummeted in the following decade.

follows a discovery, GDP growth takes several years to react, while employment remains persistently depressed. These authors do not investigate the implications of an investment boom financed by debt accumulation. We, therefore, complement this research, by providing novel evidence on the direct effect of the presource curse on government debt.

A third contribution of our paper is related to the 'political economy of the resource curse'. Following the seminal study by Sachs and Warner (1995), earlier work on the resource curse primarily focused on the negative correlation between resource abundance and economic growth, using some measure of resource intensity. The negative effects of resource abundance, most notably the 'Dutch Disease', were seen as having a purely economic root (e.g., Corden and Neary, 1982; van Wijnbergen, 1984; Krugman, 1987). Later studies suggested that political institutions are a key determinant of the resource curse (e.g., Mehlum et al., 2006; Robinson et al., 2006; Caselli and Cunningham, 2009; Cabrales and Hauk, 2010). The argument goes as follows: political institutions determine how political incentives are turned into policy decisions, hence strong political institutions would mitigate the perverse political incentives that resource abundance typically creates (e.g., patronage, corruption, fight for power, over-extraction). In the absence of such institutions, perverse incentives would dominate and the resource curse would arise. Our findings suggesting that the quality of political and fiscal institutions affect the manifestation of the curse through the government debt channel, align well with the views of this strand of the literature, and better connect it to fiscal issues.

The remainder of this paper is organized as follows. Section II describes the data and identifies some stylized facts. Section III presents our estimation and identification strategies. Section IV presents and discusses the results. Section V concludes.

II DATA

A DEFINITION AND SOURCES

Resource Discoveries. We combine data on oil, gas, and mineral discoveries and create a global dataset of 193 countries. The oil and gas data, compiled by Horn (2012) and freely available in the American Association of Petroleum Geologists (AAPG) datapages, refer to discoveries of oil and natural gas (including condensate equivalent) fields with at least 500 million barrels (79,000,000 m^3) of recoverable oil equivalent reserves in the period 1868-2012. This data builds on the initial effort by Halbouty et al. (1970) in tracking giant oil and gas fields trends, and reports information on date and location of the discovery, type of drilling (offshore vs. onshore), name of the company, ultimately recoverable size, and other variables.[12] These fields have been estimated to account for 40 to 60 percent of the world's petroleum reserves (Mann et al., 2007).

Data on mineral discoveries over roughly the same period are from *MinEx Consulting* (last update: February 2018) and include giant deposits of non-bulk minerals, exceeding 1 mil-

---

[12]Some of these variables will be used for robustness checks or heterogeneity analysis, but are subject to a higher degree of measurement error. See discussion in Subsection IV.D.

lion ounces of gold or 1 million metric tons of copper or equivalent.[13,14] The *MinEx*'s deposit dataset is based on information sourced from company public reports, i.e., annual reports, press releases, National Instrument (NI) 43-101 studies, technical and trade journals, such as Economic Geology, Northern Miner and Mining Journal, government files from geological surveys and direct communication with key people in the extractive industry. According to *MinEx*'s estimates, the database for gold and copper covers at least 99% of all giant-sized deposits in the world.[15]

Using this information, we construct a dummy variable, equal to 1 if there was at least one giant discovery in a given country in a given year, and 0 otherwise. For robustness, we define a discovery variable at the intensive margin, which counts the number of discovery episodes in the same year and has more variation with regard to mineral discoveries. We also use a measure of the net present value (NPV) of a discovery, as a percent of GDP, as in Arezki et al. (2017).[16] Summary statistics for these indicators as well as for the remaining variables described in this section or used in the paper can be found in online Appendix Table B1.

Government Debt.   Data on government debt, our main variable of interest, was prepared by the authors using information from several data sources. As described in detail in online Appendix A.I, the primary source of information is the comprehensive Global Debt Database (GDD) recently compiled by Mbaye et al. (2018), which accounts for over 80 percent of the observations in the sample. Our debt data panel covers five decades (1970-2017) and 171 countries, including almost all advanced economies, and most MICs and LICs. The main debt perimeter is the Central Government (about 70 percent of the observations), but information on broader perimeters such as the General Government and others is also available for a smaller number of countries.

In the robustness section, we also take into account government financial assets. We use a measure of 'net debt' (defined as 'gross debt minus liquid financial assets'), mostly from the IMF's World Economic Outlook (WEO) Database, complemented by information from Arbelaez and Sobrinho (2017). The underlying financial assets are typically held at the Central or General Government levels, and do not include international reserves at central banks. Unfortunately, the information on government financial assets is not comprehensive both across countries and across time. Despite our efforts compiling asset data from multiple sources, we obtained information for only one quarter of the country-years in our panel.

Fiscal Stress and Debt Distress Episodes.   Our baseline measure is a comprehensive indicator of distress that reflects situations of extreme fiscal duress (Medas et al., 2018). This measure

---

[13]Given that the collection of oil discovery data was halted in 2012, we have 5 additional years of coverage for mineral discoveries.

[14]This data excludes the so-called 'bulk' minerals such as coal, iron ore, bauxite, potash, and phosphate.

[15]The Horn (2012) dataset has been the main source of information on oil discoveries in most papers, using discovery events as exogenous shocks, since Lei and Michaels (2014). On the other hand, the mineral data has been employed by very few studies, starting with Bhattacharyya et al. (2017), yet it is supposed to have a more exhaustive coverage (almost complete for giant-sized deposits) than the oil data.

[16]We discuss the limitations of the latter approach, both in terms of measurement and identification, in Subsection IV.D. Also, note that this measure is only available for oilfields, but not for mineral deposits.

focuses on a broad concept of 'fiscal crises', defined as episodes in which large fiscal imbalances lead to the adoption of extreme measures, including external credit events (accumulation of external arrears); exceptionally large financial support from the IMF (above 100 percent of quota); implicit default on domestic public debt (proxied by large inflation or accumulation of domestic arrears); and loss of market access (proxied by inability to issue external debt and by spikes in sovereign bond spreads).

We also use an alternative indicator that focuses more narrowly on episodes of external debt crises. We closely follow the literature, including Catão and Milesi-Ferretti (2014) and IMF (2017c), and identify such episodes by using information on default on sovereign external debt. The main data sources are Catão and Milesi-Ferretti (2014) and the main credit ratings agencies. Despite its smaller country-year coverage compared to the baseline indicator, this alternative measure has the advantage of measuring distress that could be more directly associated with external over-borrowing. Given their underdeveloped domestic debt markets many MICs and LICs rely on external borrowing to finance their development needs.

Political Institutions and Governance. For the heterogeneity analysis in Subsection IV.C, we use four indicators of political institutional quality and governance: the Polity2 index from the Polity IV dataset (Marshall et al., 2017), the X-Polity index which only considers the components of the Polity2 associated with the executive branch (Vreeland, 2008), the 'control of corruption' indicator from Kaufmann et al. (2010), and a governance indicator compiled by the authors using multiple data sources (see below). These indicators are complementary, with the first two focusing on political regime characteristics, the third focusing on one relevant aspect of governance, i.e., corruption, and the last on overall governance. Broadly, governance is referred to as "framework for exercising authority" or the "rules of the game". For the purpose of this paper, we narrow the concept to the set of "*institutions, mechanisms, and practices through which governmental power is exercised in a country, including for the management of public resources and regulation of the economy*" (IMF, 2017d). This definition encompasses government policies and practices affecting public debt sustainability including natural resource management, public debt management, and borrowing decisions.

The Polity2 index varies from -10 (total autocracy) to 10 (total democracy). Its time and country coverage is very comprehensive and information is available for almost 90 percent of the country-years in our sample. As mentioned above, the X-Polity index is a subset of Polity2 and was used as an alternative indicator of political institutions. Because of the data limitations of the publicly available indicators on governance and corruption, we compiled a broader governance indicator, combining data from several sources, including from Kaufmann et al. (2010), International Country Risk Guide (ICRG), Cross-National Time-Series (CNTS) Data Archive, and Fraser Institute. Our indicator covers over 90 percent of the country-years in our panel, more than doubling the number of observations that we would obtain if we were to rely on single data sources. Further details are provided in online Appendix A.II.

B STYLIZED FACTS

The datasets on discoveries comprise over a thousand giant discoveries, 335 of oil, 284 of gas, and 458 of minerals. We observe discoveries in all years covered by the datasets. While mineral discoveries are somewhat evenly spread over time, oil and gas discoveries experienced a spike in the late 1960s to early 1970s and increased after mid-1990s (Figure 1).

Discoveries are observed across all regions, but understandably oil and gas discoveries have a higher incidence in the Persian Gulf, North Africa, Russia, and the North Sea. On the other hand, mineral discoveries are more evenly spread across the globe, with some prevalence in East Asia, Latin America, and Southern Africa. Nature has endowed some regions with both types of resources, as illustrated by East Asia and Latin America (Figure 2). Not surprisingly, the countries that experienced the largest numbers of giant discoveries are among the largest in terms of geographic area. The top five countries with giant oil and gas discoveries are Russia, Iran, United States, Saudi Arabia, and China, whereas the top five with giant mineral discoveries are the United States, Canada, Australia, South Africa, and Russia (online Appendix Figure B2a and B2b, respectively). Mineral discoveries are most prevalent for the precious metals gold and silver, as well as for copper (online Appendix Figure B3). Giant discoveries represent a salient shock for an economy, especially for smaller ones. According to computations by Arezki et al. (2017), the NPV of a median oil (or gas) discovery is equal to 9% of a country's GDP.

Individual country examples shed further light on the fiscal presource curse, including on the timing and size of the correlations between giant discoveries and public debt levels. For instance, in the decade after the discovery of giant reserves of natural gas, Mozambique experienced a large debt buildup (its public debt roughly tripled), culminating in economic stress and a debt crisis. Weak fiscal institutions, in particular the absence of a full-fledged framework for managing resource wealth and weak transparency and accountability, could be pointed as contributing drivers of Mozambique's difficulties.[17] On the other hand, strong political institutions and governance structures seem to have helped Botswana tame the curse. The country's large diamond revenues have boosted economic and human development, while its public debt remained relatively low. The case of Guyana is still unfolding. Following the discovery of large oil reserves in 2015, public debt still remains at moderate levels. The country is putting in place a framework to manage its resource wealth and has resisted excessive borrowing. But it is too early tell whether Guyana will become a success stories (see Online Appendix C).

---

[17] As mentioned before, this debt buildup was also driven by other factors. It should be also noted that Mozambique's debt risk rating reflects the triggering of one state guarantee on a relatively small debt (less than 1 percent of GDP), which is being negotiated with the creditor. Currently, the government of Mozambique is taking measures to address the debt problem and pave the way for a prudent management of natural resources in the future, including: prosecuting government officials involved in the hidden debt scandal; disputing the validity of the government guarantees to commercial creditors associated with the hidden loans; managing contingent liability risks associated with LNG projects; and reforming the public financial management law to strengthen budgeting, debt management and public procurement.

III MethodologY

To assess the impact of giant discoveries on government debt, we estimate the following dynamic panel distributed lag model,

$$Debt_{it} = A(L)\,Debt_{it} + B(L)\,Disc_{it} + \alpha_i + \delta_t + \gamma X'_{it} + \varepsilon_{it} \tag{1}$$

where $Debt_{it}$ is the public-debt-to-GDP ratio of country i at time t, $Disc_{it}$ is a dummy variable for a giant discovery event (either oil, gas or minerals). $A(L)$ and $B(L)$ are pth-order lag operators with $p \geq 1$. In line with Arezki et al. (2017), the baseline specification includes one lag of the dependent variable and 10 lags of the discovery dummies to control for serial correlation across discoveries.[18] We include country and year fixed effects as well as a country-specific linear trends.[19] X'_{it} is a vector of control variables, which are included in some of the estimations in the robustness section. ε_{it} is the error term. Standard errors are based on Driscoll and Kraay (1998) and robust to very general forms of spatial and temporal dependence.

This framework allows us to explore the dynamic relationship between discoveries and debt trajectory over different time horizons. In particular, the dynamic effect is estimated by computing the following impulse response function (IRF)

$$IRF(L) = \frac{B(L)}{1 - A(L)} \tag{2}$$

over a certain time horizon (e.g., 1 to 10 years). Because discoveries are arguably exogenous events that are likely to precede the underlying borrowing decisions, we consider discovery events as 'natural experiments' and argue that the estimated coefficients are not as vulnerable to the endogeneity problems that would arise in traditional panel regression models. After controlling for year and country fixed effects, which capture global common factors and differences in time-invariant factors across countries such as geographic location, the *timing* of discovery events represents an exogenous source of within-country variation through which we are able to identify the *causal effect* of discoveries over time.[20]

Second, we are interested in testing whether the evolution of a country's fiscal finances spills over to episodes of fiscal stress and debt distress. In order to do so, we rely on a different regression model given that such episodes are binary outcomes. In the spirit of Lei and Michaels

---

[18]Autocorrelation patterns in the discovery time series is arguably due to short-term learning-by-doing, which, in turn, is mostly related to geology. We are not able to fully account for learning in management of resources, but estimates with longer discovery lags (up to 20) reassures us this does not pose a major issue to our baseline estimation.

[19]This trend helps control for factors that are unrelated to discoveries (e.g., shocks in commodity prices and global interest rates) that also affected debt dynamics during the sample period (online Appendix Figure B5). In the robustness section below, we augment the regression model with country-specific quadratic trends. The estimated coefficients have about the same magnitude as in the baseline specification and are more precisely estimated.

[20]Nickell (1981) shows that estimates from dynamic individual-effects models are biased and inconsistent when T is small. For this reason, our estimation strategy exploits an extensive panel dataset both in terms of countries and time periods ($T = 42$ in the baseline sample). This helps reduce the Nickell bias, which is a positive function of $\frac{1}{T}$.

(2014), we estimate the following linear probability model,

$$crisis_{it+j} = \alpha_i + \delta_t + \beta_j \cdot Disc_{it} + \gamma_j \cdot pastDisc_{it} + \varepsilon_{it} \tag{3}$$

where $crisis_{it+j}$ is a dummy for fiscal stress or debt distress of country i at time $t + j$, $Disc_{it}$ is the discovery dummy at time t. We control for fixed effects and for the number of discoveries in the previous 10 years, $pastDisc_{it}$. As before, ε_{it} is the error term and standard errors are based on Driscoll and Kraay (1998). Our coefficient of interest is $\widehat{\beta_j}$, which we interpret as the marginal effect of a discovery on a country's probability of fiscal stress or debt distress after j years. Because such effect is likely to take some time to arise – sovereign debt would need to reach a level which would be considered to be unsustainable by policymakers or investors – in the next section we present estimates for $j \in \{1, 2, ..., 10\}$. The same assumptions about exogeneity of within-country variation in the timing of discoveries allow us to interpret these estimates as causal.

IV RESULTS

We now present and discuss our main findings. We start by presenting predictability tests to confirm that causation runs from discoveries to debt sustainability and not vice-versa. Second, we present the baseline estimates of the panel regressions for the dynamic effect of discoveries on government debt, fiscal stress and debt distress. We use information on all types of discoveries but also slice the data on into oil and gas discoveries and mineral discoveries. Next, we assess the role of political institutions and governance on the incidence and severity of the fiscal presource curse. Lastly, we submit the baseline findings to a battery of robustness checks.

A PREDICTABILITY TESTS

Past studies on natural resources have argued that discoveries are plausibly exogenous to economic and political circumstances (Arezki et al., 2017; Cust and Mihalyi, 2017; Harding et al., 2020). Even though a country's characteristics, such as geology, market orientation and institutions, may be associated with exploration efforts and effectiveness (Arezki et al., 2019; Cust and Harding, 2020), the *timing* of such a discovery is arguably hard to predict and has been viewed as an unanticipated news shock in the recent literature. In order to further validate our identifying assumption that giant discoveries are exogenous events, we perform a battery of predictability tests that are commonly used in the fiscal policy literature to address endogeneity concerns.

Granger Causality Test. It is possible that governments have privileged information about the likelihood of a future discovery and so increase borrowing to finance exploration as a response to anticipated discoveries. In turn, the accumulation of public debt to sustain exploration efforts may make discoveries more likely to occur because of better infrastructure to explore. Therefore, debt spikes would materialize before discoveries and the causality between discoveries and debt would be reversed. A similar reasoning would also apply to other indicators that

are commonly correlated with debt levels. If these variables predict discoveries, our estimated impulse responses would be biased and should not be interpreted as causal.

To address this concern, in the spirit of Cloyne (2013), we first estimate a panel version of the VAR Granger causality Wald test for debt levels and other macroeconomic or political variables. We estimate the following econometric model:

$$Disc_{it} = A(L)Disc_{it-1} + B(L)y_{it-1} + \alpha_i + \delta_t + \varepsilon_{it} \tag{4}$$

We consider one explanatory variable, y, at a time from the following list: government debt, population, real GDP per capita, real GDP growth, CPI inflation, current account balance, fiscal deficit, real exchange rate, the Polity2 index and our governance indicator. Standard errors are clustered at the country level. The panel VAR is fitted using generalized method of moments.

The goal of this test is testing to which extent discoveries are predictable on the basis of movements in the explanatory variables of interest. Table 1 presents the results when using one, two or three lags. The estimated coefficient is not statistically different from zero for most variables at conventional significance levels. Estimates are consistent across different lag specifications.In particular, we cannot reject the null hypothesis that government debt does not Granger cause discoveries (column 1), which suggests that countries do not tend to accumulate much debt during the exploration stage, i.e., prior to the actual discovery. This result is also in line with the anecdotal evidence from the country examples mentioned above.On the other hand, discoveries Granger cause debt accumulation at the 1 percent level.

Joint Significance. An alternative strategy, proposed by Mertens and Ravn (2012), is to estimate a binary response model with and without a set of lagged macroeconomic variables as regressors and then test whether the difference between both estimated likelihood functions is statistically significant. This goes beyond the Granger causality tests performed above by assessing the joint significance of the vector of observables. For our purpose, we estimate fixed effects logistic regressions and report the p-value from the likelihood ratio test that the coefficients of each lagged variable are equal to zero in Table 2.[21] In line with our identifying assumption, we cannot reject the null hypothesis of nonpredictability of discovery events.[22] On the other hand, after adding past discoveries to the regression model, the test turns significant at the 5 percent level. Past discoveries (of both oil and gas and minerals) seem to be the strongest predictor of future discoveries, that is, discoveries are serially correlated. This correlation could be driven by 'learning-by-doing', which has been shown to be a fundamental aspect of the extractive industry (Kellogg, 2011): past discoveries enhance geologic and technical knowledge as well as the efficiency of drilling activity, which in turn, makes future discoveries more likely to occur.

---

[21]This is analogous to running a linear probability model and performing an F-test on the vector of lagged variables. The latter estimates are consistent.

[22]Country and time fixed effects, also included in the regressions, are jointly significant at conventional significance levels.

B   BASELINE SPECIFICATION

Figure 3 shows the dynamic impulse responses of debt-to-GDP ratio to discoveries based on the baseline econometric model.[23] The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively, based on Driscoll-Kray standard errors and delta method, which allows to deal with nonlinear combinations of OLS-estimated parameters. Panel 3a shows the IRF pooling all types of discoveries, i.e., oil, gas, and minerals. The initial impact of discoveries on debt dynamics is relatively quickly and becomes sizeable and persistent over time. The panel shows that debt rises by about 1-2 percentage points of GDP per year in the 10 years immediately after a discovery. The impact gradually winds down in the second decade. This finding confirms our conjecture that it could take time for the impact of giant discoveries on debt levels to fully materialize. The estimated IRF implies that it could take up to a decade for the debt-to-GDP ratio to stabilize at a higher level.

Panel 3b shows that the bulk of the overall impact on debt in the first decade is mostly driven by oil and gas discoveries. This ranges between 1 and 3 percentage points of GDP anually in the first decade following a giant discovery of oil or gas. Panel 3c reveals that mineral discoveries tend to exert upward pressure on the debt trajectory but the estimates are imprecise and cannot be statistically distinguished from zero.[24] We do not have a conclusive explanation for why the fiscal presoure curse is stronger for oil and gas discoveries than for mineral discoveries. However, we conjecture that it could be related to at least three factors: heterogeneity of natural resources, ownership structure of extractive enterprises, and size of the expected revenue stream.

Mineral resources are seemingly more heterogeneous than oil and gas in terms of geography (Figure 2) and type (online Appendix Figure B3). In principle, these factors could favor a more decentralized control of resources, which could potentially mitigate policy distortions, including borrowing decisions, as well as misallocation of resources.

It also appears that the oil and gas industry is mostly run by the state or state-owned enterprises in MICs and LICs. These companies are typically more vulnerable to governance issues and political interference than private sector-firms. Even in oil-producing countries where international oil companies are also players, exploration of oil fields are often conducted by multinationals and their operations closely regulated by the state, either through a national oil company or a sectoral regulator or both. On the other hand, the mining sector seems to be have a larger incidence of private sector firms, including international mining companies (e.g., Albertin et al., 2021), which are subject to constant investors' scrutiny.[25] We found examples of emerging and developing countries where the mining sector is jointly controlled by the state and private enterprises (e.g., Botswana); or control was largely passed on to the private sector including through privatization (e.g., in the 1990s Brazil privatized its giant mining company

---

[23]The full set of fixed effects regression coefficients is in online Appendix Table D1.

[24]Note that the sum of the individual effects of each type of discovery is not necessarily equal to the combined effect including because oil/gas and mineral discoveries may overlap across time.

[25]Ross (2012) notes that the richest democracies of Europe, North America, Australia, and New Zealand control three-quarters of the stock of foreign direct investment in the world's mining sector.

Vale); or control is mostly exercised by the state but good governance practices are in place (e.g., Chile). It is more difficult to find many similar examples in the oil and gas sector.

As for the third factor, we think that the operations of the oil and gas sector tend to be relatively larger than those of the mining sector in most resource-rich countries. Hence, oil and gas discoveries would be expected to generate relatively larger revenue streams in the future, potentially leading to stronger incentives to "overborrow" today and riskier bets – the perceived large economic value would be worth fighting for. In short, size could be more like a curse than a blessing. Anecdotal evidence suggests that the national oil company in many oil-producing MICs and LICs is often the largest corporation and/or the most important source of exports proceeds and fiscal revenues in those countries.[26] Furthermore, the use of 'cash calls'–state's required cash contributions to joint ventures in charge of developing and operating oil and gas projects–seem to be more prevalent in the oil industry than in mining. In turn, this could introduce a debt accumulation bias when fiscal space is reduced and borrowing is the only way to finance paid state participation (Luca and Puyo, 2016).

To our knowledge, there is no consensus in the literature on whether or not oil could lead to more severe manifestations of the resource curse than mining. For instance, while Davis (1995) did not find evidence of a mineral resource curse, recent studies have shown that mineral riches favor the emergence of organized crime (Buonanno et al., 2015), increase local corruption (Knutsen et al., 2017), and fuel conflicts (Berman et al., 2017). On the other hand, one could argue that non-economic factors may facilitate the emergence of the curse in the case of oil and gas. For instance, Collier (2017) argues that biased mass opinions or popular beliefs can distort two aspects of resource ownership – spatial assignment of ownership between local and national claims and assignment of fiscal revenues between current consumption and future investment – and lead to populist policies, predatory behavior, and violence. All in all, the current literature seems to link mining more frequently to local issues and oil to countrywide distortions. Therefore, it appears that oil would be more often associated with macroeconomic distortions than mineral resources.

It has been pointed out that petroleum-related revenues have four distinctive qualities whose negative side effects are amplified in the presence of powerful state-oil companies: large scale, the specific nature of its source (i.e., a non-tax revenue that is less subject to citizen scrutiny), exposure to production and price volatility, and secrecy of underlying financial transactions: "*But the most important political factor about oil – and the reason it leads to so much trouble in so many developing countries – is that the revenue it bestows on governments are unusually large, do not come from taxes, fluctuate unpredictably, and can be easily hidden*" (Ross, 2012, p. 6).

While some of these features also apply to mining, they would seem more pervasive and easier

---

[26]E.g., *Sonatrach* in Algeria, *Sonangol* in Angola, *Petrobras* in Brazil, *Ecopetrol* in Colombia, *Pemex* in Mexico, *Gazprom* in Russia, *Aramco* in Saudi Arabia, and *PDVSA* in Venezuela. In December 2019, Aramco, the world's largest oil company, went public through an initial public offering ("Saudi Aramco raises USD25.6bn in world's biggest IPO", *Financial Times*, December 5, 2019) and, as a listed company, it adheres to Saudi Arabia's Capital Markets Authority regulations.

to manifest in the oil sector. Clearly, mining is also subject to commodity price volatility and its revenues may also assume a non-tax nature. However, it seems to be less prone to the perverse interaction with powerful state entities and undemocratic governments that are typically associated with the oil business, perhaps reflecting our above understanding that mineral resources are extracted mostly by private companies or joint ventures as opposed to mostly SOEs in the oil and gas industry. Success stories in MICs and LICs tend to be more associated with mining than with oil. For instance, Chuhan-Pole et al. (2017) do not find strong evidence that large-scale gold mining has led to economic decline at the national or local level in countries like Ghana, Mali, and Mauritania. Botswana, the diamond-rich country case discussed in this paper, has experienced one of the strongest economic performance in sub-Saharan Africa in recent decades (Limi, 2007).

As we mentioned before, in this paper we are mostly interested on the overall effect of discoveries on debt dynamics over the medium term and less on single-year effects (i.e., on the statistical significance of estimates for individual years). One reason is that debt sustainability assessment is inherently an inter-temporal concept, i.e., it requires information on the path of fiscal and economic variables over a certain horizon. Another reason is the long lag between discoveries (or the announcement of discoveries) and production. In the case of oil and gas, the average delay between discovery and production is about 4–7 years (Arezki et al., 2017). Absent the curse, standard economic theory would predict that following a discovery debt would initially rise and subsequently fall as production comes on stream (see discussion in Section I). Therefore, we test our null hypothesis over a certain time horizon and report the p-values on the cumulative impact of discoveries on debt levels.

Table 3 shows that the set of all discoveries lead to a sizeable cumulative effect on the debt-to-GDP ratio, to the tune 15 percent of GDP in the first 10 years, or almost 20 percent of GDP in the case of oil and gas discoveries. This pattern, both in terms of timing and magnitude, is comparable to the typical increase in government debt that has been identified in past episodes of large debt buildups (Abbas et al., 2011). The literature and careful documentation by international financial institutions (e.g., IMF, 2014) have shown convincing evidence that sovereign debt defaults and restructurings are more likely to occur when sovereign debt increases too rapidly (e.g., Argentina in early 2000s) and/or when it has reached high and unmanageable levels (e.g., Greece in early 2010s). Even when initial debt is not exceedingly large, for instance 40–50 percent of GDP as in the case of Mozambique (Online Appendix C), a sustained 20-percent of GDP increase could still bring government debt to unsafe levels.[27]

To test our hypothesis, i.e, whether discoveries lead to higher risk of fiscal stress or debt distress, we regress our debt crisis indicators on discoveries as stated in Equation 3. The findings lend support to our hypothesis. Figure 4a shows that discoveries have a significant impact (at the 5 percent level) on the probability of fiscal crisis around 2–4 years after a discovery. As in the

---

[27]The IMF-World Bank's debt sustainability framework for LICs (IMF, 2017a) sets 55 percent of GDP the level tolerable for a developing country with medium debt-carrying capacity, whereas the IMF's debt sustainability framework for market-access countries or MAC-DSA (IMF, 2013) used to consider 70 percent of GDP as a high-risk level for the typical emerging economy. A recent revision shifted the focus of the MAC-DSA from discrete single-variable thresholds to continuous metrics (IMF, 2021).

case of debt levels, the impact is mostly driven by oil and gas discoveries and lasts longer, up to 6–7 years following a discovery (Figure 4b). As mentioned in Section A, some of the episodes captured by the baseline indicator of fiscal stress are unrelated to debt crises; therefore, we turn our focus to external debt distress episodes, which are more specifically related to debt sustainability. We find that the impact of discoveries on this measure of debt distress is positive over a 10-year time horizon, but imprecisely estimated (Figure 5a). However, in line with the previous results, oil and gas discoveries significantly increase (at the 1 percent level) the probability of external debt distress after 3 to 8 years (Figure 5b).[28] In conclusion, oil and gas discoveries not only lead to sizeable government debt buildups but also increase the probability of a debt crisis as the buildup materializes.

Online Appendix Figure B4 shows that observed haircuts in debt restructurings tend to be positively correlated with the debt level prior to the debt exchange. Intuitively, the higher the debt level the larger the required haircut to cure the debt problem and restore debt sustainability in a durable way. However, requiring large haircuts from creditors also entails costs. Cruces and Trebesch (2013) show that larger haircuts are associated with persistently higher borrowing costs and longer exclusion from private capital markets in the post-restructuring period. Furthermore, Furceri and Zdzienicka (2012), among others, have shown that full-blown debt crises are typically messy events that involve large output costs. Against this background, our findings imply that the fiscal presource curse may also entail significantly large indirect economic costs.

C HETEROGENEITY

To what extent do institutions affect the intensity of the fiscal presource curse? Following the literature, we test whether the impact of discoveries on debt sustainability depends on a country's political institutions and governance. To this end, we split the sample into countries with "strong" institutions (i.e., country average index above the sample median) and countries with "weak" institutions (below the sample median). Because we take the sample average of each country's institutional quality, this analysis leaves out the time effects and focuses on cross-country variations. Moreover, our focus is on the impact of discoveries on government debt controlling for institutional quality/governance and not on the potential impact of discoveries on political institutions per se, or the marginal impact of governance/institutions on debt dynamics.[29]

Figure 6 shows that the fiscal presource curse is stronger in countries with weaker political institutions/governance. This differentiated impact is statistically and economically more significant especially for the two indicators of political institutions and during the first decade following a giant discovery of oil and gas. We also find some evidence that the impact of oil and gas discoveries on debt sustainability is not statistically significant in countries with better overall governance or lower incidence of corruption. This finding holds for countries with

---

[28]See full set of estimates in online Appendix Tables C2 and C3.

[29]Resource discoveries could spur rent-seeking and institutional erosion. This, in turn, might create a vicious cycle, also for fiscal outcomes, which we do not account for in our regression model.

stronger political institutions/governance, regardless the type of discovery, and for mineral discoveries, irrespective of the level of institutions/governance (online Appendix Figure E1 and E2).[30] Therefore, the fiscal presource curse seems to be a manifestation of a deeper political curse. These findings align with the branch of the literature that points to a close connection between political institutions and the resource curse (e.g., Mehlum et al., 2006, Robinson et al., 2006, Caselli and Cunningham, 2009). However, while this literature has focused on the resource curse in a broader sense, we specifically focus on the fiscal dimension, i.e., on the role of institutions in determining the severity of the curse on government debt sustainability.

Concrete country cases seem to further support our findings. Besides Botswana, our datasets on discoveries include a large number of mineral discoveries in Chile (world's largest copper producer) and a large number of oil and gas discoveries in Norway (one of the world's largest oil and gas producer). These two countries have not experienced any acute debt crisis that could be clearly linked to the fiscal presource curse. In the past decades the government gross debts of Chile and Norway Chile have remained at modest levels.[31] Recently, Chile's debt net of treasury (liquid) assets has increased as the country used its liquid assets to respond to the COVID-19 pandemic but is expected to continue at moderate levels (IMF, 2020a). Norway has positive net worth owing to its vast assets holdings–Norway's Government Pension Fund Global has assets under management that exceeds 1.3 trillion US dollars.[32] A few other cases, including in the Middle East, have managed to use their oil revenues to improve living standards, despite lacking strong institutions to check political power.

D   ROBUSTNESS

We now check the robustness of our baseline findings. We explore, inter alia, alternative measures of both government debt and resource discoveries, econometric specifications allowing for macroeconomic covariates, sensitivity to specific subsamples, and different regression model specifications.[33]

Alternative Measures of Government Debt.   We test the impact of discoveries on net debt, defined as gross debt minus government financial assets. The rationale for this test is that discoveries could be followed by accumulation of financial assets and these savings could eventually mitigate or even offset the increase in gross debt.[34] As online Appendix Figure G1 shows,

---

[30]To avoid overloading the figures on heterogeneity, they display the confidence intervals for the countries with weak institutions only. The error bands for the countries with strong institutions are not significantly different from zero, i.e., they consistently overlap with the zero line.

[31]Like other Latin American countries, Chile also experienced a debt crisis in the 1980s. However, different from many countries in the region which defaulted serially, Chile managed to cure its debt problem after implementing a final debt treatment in 1990.

[32]"Top 100 Largest Sovereign Wealth Fund Rankings by Total Assets" (*SWFI*).

[33]In this subsection, we present the dynamic effects of discoveries using IRFs up to 10 years. Cumulative effects and hypothesis testing over different time horizons are reported in online Appendix F.

[34]Recent empirical studies suggest that net debt may represent a better measure of government exposure to fiscal risks, especially in emerging economies (Hadzi-Vaskov and Ricci, 2016; Arbelaez and Sobrinho, 2017). Departing from this, IMF (2018) highlights the widespread benefits of examining both sides of the balance sheet in order to identify imbalances or mismatches and evaluate fiscal policies.

we dot not find strong evidence to support this conjecture. Similarly to gross debt, net debt increases following a discovery event, resulting in a cumulative effect of more than 20 percent of GDP in 10 years. This is explained by the fact that IRFs of financial assets in online Appendix Figure G2 are negative and small in magnitude and their cumulative response does not differ statistically from the post-discovery decade.[35] However, these results should not be taken as conclusive, given the low quality and coverage of the data on government financial assets.[36]

Alternative Measures of Discovery. Because some countries experienced more than one resource discovery in a year, the results using the dummy variable may hide a certain degree of heterogeneity. To check this conjecture, we estimate the dynamic model using a variable that counts the number of discovery episodes. As online Appendix Figure G3 shows, the estimated IRFs are not statistically different from zero. Hence, it is not the intensive margin (i.e., number of discoveries) that seems to matter the most for debt sustainability but rather whether or not a giant discovery has taken place.

Next, we replace the (oil and gas) discovery dummy with the measure of discovery used by Arezki et al. (2017). They define oil and gas discoveries in terms of their NPV as a percent of GDP, that is, the discounted sum of gross revenue derived from assuming a production profile from the fifth year after a discovery to the exhaustion year, and valued at the resource price prevailing at the time of the discovery. Online Appendix Figure G4a shows that IRFs are negative but very close to zero, i.e., the impact on debt is not economically relevant. We also have two concerns about this alternative measure of discoveries. First, it relies on seemingly endogenous variables such as country-specific risk-adjusted discount rates and GDP, whereas our discovery dummies do not mix endogenous variables with discovery events and are easier to interpret. Second, the ultimate recoverable reserves (URR) in the oil and gas data are subject to non-negligible measurement error.[37] We further test the sensitivity of these results to alternative measures of government debt, namely net debt and gross debt both from IMF's WEO. For both variables, the IRFs turn positive and statistically significant but their economic relevance remains modest (online Appendix Figures G4b and G4c). These results seem to suggest that the counter-intuitive finding above may be partly related to a possible sample selection in the unbalanced panel of debt data.

Alternative Controls. Our findings are robust to adding a number of macroeconomic controls on the right-hand side of the baseline regression model. In principle, there is no need to add controls in the regressions because discoveries are arguably random events, as we explained in Section III. However, we still do it to ascertain that the effect of discoveries on government debt is not spurious or driven by omitted variables. Adding controls would also improve the efficiency of the estimators as they contain information that helps explain the dynamics of gov-

---

[35]These results tallies with the findings of Ruzzante (2018), which suggest government assets to be less responsive than debt liabilities to exogenous shocks.

[36]Arbelaez and Sobrinho (2017) identify and discuss some of the pros and cons of publicly available data on government financial assets.

[37]Lei and Michaels (2014) point out that oilfields "*differ considerably in the identity of those who estimated the URR and in the way the URR was estimated. Moreover, the estimated URR of various oilfields was gradually updated, depending on the estimators and their methods*" (p. 142).

ernment debt, and are unlikely to be correlated with discoveries. We control for country size (log of population), level of development (log of real GDP per capita), price volatility (inflation) and quality of political institutions (polity2 index). All variables are included in the regression with one lag. Despite the smaller regression sample, which is constrained by the availability of data on some controls, online Appendix Figure G5a shows that the impact of the fiscal presoure curse on government debt is about the same size as the baseline, with the peak occurring around 8–11 years following a giant discovery. Interestingly, the IRFs for mineral discoveries are more precisely estimated than in the baseline model, with the maximum annual impact occurring around the same time as in the combined (oil/gas and minerals) sample and also statistically significant (online Appendix Figure G5c).

Alternative Samples.   We also test whether the impact is driven by resource intensity rather than by the discoveries themselves. To this end, we restrict the sample to only those countries that experienced at least one giant discovery since 1970, i.e., 74 percent of countries from the initial sample, 37 percent attributed to oil and gas, and 41 percent to minerals. Online Appendix Figure G6 presents the findings. Even with this smaller sample, we find that the magnitude of the impact is nearly the same as in the baseline estimation, although the IRFs seem to estimated more imprecisely. We conclude that the fiscal presoure curse is driven by discoveries themselves and not by the fact that countries are (or turn) resource rich.

Next we test whether our findings are robust to the sample period by splitting the regression sample into two different sub-periods: 1970–2000 and 1980–2010. Dropping the 2000s results in a more unbalanced panel, while dropping the 1970s results in a more balanced panel. The IRFs based on these alternative specifications, shown in online Appendix Figures G7 and G8, respectively, do not seem to uncover issues that would undermine the baseline findings. As illustrated in the first panel of these figures, the estimated impact on government debt has roughly the same order of magnitude as in the baseline but the timing of the annual peak differs across sub-samples. It is stronger at shorter horizons (up to 4 years after a discovery) in the 1970–2000 sample and at longer horizons (up to 10 years) in the 1980–2010 sample. Based on this set of tests, we believe the findings in this paper to have high external validity. A different research question is how the 'fiscal resource curse' will evolve in the aftermath of technological advances in hydrocarbon exploration and drilling, such as the recent surge in hydraulics fracturing or "fracking" in the United States.

Alternative Country Groupings.   Splitting the sample into advanced economies, emerging economies (mostly MICs), and developing countries (mostly LICs), we find that the impact of giant discoveries on debt dynamics is strongest in MICs (online Appendix Figures G13-G15). The estimated impact for advanced countries is not statistically significant, consistent with our priors – these countries tend to have the strongest political institutions and governance. However, we also found a muted impact in the sub-sample of LICs. At first, this could sound counterintuitive as most LICs tend to have weak institutions and governance. However, we think that these results can be explained by the fact that many giant discoveries in our sample occurred in countries during different stages of their development process, i.e., some emerging economies today would be considered LICs at the time of discoveries.

Other Specifications. We also test the robustness of our findings to different lag structure. We test longer lag specifications, for instance two lags for government debt and up to 20 lags for the discovery dummies. As online Appendix Figures G9, G10 and G11 show, the IRFs become less reliable as we increase the lag structure, in part because of data availability.

The secular increase in debt-to-GDP ratios starting in the 1970s (online Appendix Figure B5) could be a potential caveat to our identification strategy. To control better for this issue, we include a country-level quadratic trend in the baseline model. The magnitude of the impact under this alternative specification is comparable with that under the baseline and is estimated slightly more precisely (online Appendix Figure G12). We conclude that the our findings are largely unrelated to the secular trend in debt ratios.

To conclude, on the whole the evidence from the battery of tests seems to further reinforce our baseline findings. We believe it is safe to claim that we have found a statistically and economically meaningful evidence for the fiscal presoure curse. Our findings do not seem to be an artifact of the data or econometric specifications.

V CONCLUSION

In this paper we present an empirical analysis of the effect of giant oil, gas and mineral discoveries on government debt sustainability. We argue that within-country variation in the timing of discoveries is an exogenous source of variation that allows one to identify the causal effect of discoveries on debt dynamics. To test our hypothesis, we estimate a dynamic panel distributed lag model using a comprehensive panel of discoveries and data on government debt spanning four decades of observations. Our estimation exercise is akin to performing a 'natural experiment' that largely mitigates concerns about endogeneity problems that typically plague traditional panel data estimations.

We find that giant discoveries lead to large and persistent debt buildups, in the order of 15 percent of GDP during the first decade after the discoveries. This finding is largely robust and does not seem to be an artifact of the data or econometric specifications. Therefore, we think that we have found compelling evidence of a "fiscal presoure curse". The curse tends to be more prevalent in countries with weak political institutions and governance where perverse political incentives and/or over-optimism about future growth prospects may be associated with unwise borrowing decisions and misallocation of resources. We also find that the significant debt buildup is associated with an increased likelihood of fiscal stress and debt distress, thus shedding light on a possibly important indirect cause of sovereign debt crises in emerging and developing countries.

Policymakers and practitioners have raised concerns about rising debt levels in emerging and low-income countries since the 2008-09 global financial crisis (Essl et al., 2017; Nishio and Bredenkamp, 2018; Soyres et al., 2019). Cyclical factors such as negative commodity price shocks and loose fiscal policies are typically identified as the main culprits of large surges in government debt. In this paper we find that the fiscal presoure curse may be a key structural

driver of debt accumulation including in developing countries with weak political and fiscal institutions. Our estimates suggest that, quantitatively, the curse may be as important as the the cyclical drivers of debt accumulation and hence can pose a material threat to debt sustainability.

Understanding the fiscal channel of the resource curse is important for at least two reasons. First, because debt crises are associated with large economic and welfare costs (Furceri and Zdzienicka, 2012), and some of these costs tend to increase with the size of haircuts required to restore debt sustainability (Cruces and Trebesch, 2013). Second, it would provide stronger foundations to support the design and implementation of resilient fiscal frameworks and prudent borrowing strategies to counteract the curse (IMF, 2012; Poplawski-Ribeiro et al., 2012). Given the severity of the fiscal presprecure curse and its potentially large economic and welfare costs, we see scope for top-down and bottom-up policy interventions to mitigate the incidence and severity of the curse, as well as its perverse interaction with institutional weaknesses.

At a broader level, this intervention could aim, for instance, at improving the quality of institutions and strengthening overall governance, including by reducing corruption opportunities and implementing frameworks for preventing in-fighting over natural resources. More targeted interventions are also warranted and could focus on strengthening fiscal governance (e.g., enforcing good practices for budget execution, promoting transparency and accountability, and implementing rules-based resource management frameworks); reducing risks to debt sustainability (e.g., developing and implementing sound borrowing plans and medium-term debt management strategies); and adhering to international best practices for managing resource wealth (e.g., adopting the good practices for resource management under the Extractive Industries Transparency Initiative). Incentivizing multinationals operating in resource sectors to adhere to socially responsible corporate practices could also help reduce the risk of conflict (Berman et al., 2017). International financial institutions such as the IMF and the World Bank are already playing a critical role in mitigating the curse, including by providing policy advice and technical assistance targeted at resource management. However, the curse is unlikely to be tamed without domestic ownership of reforms.

Our investigation of the fiscal presprecure curse is of course not exhaustive. In particular, we did not investigate the relative importance of the two mechanisms we suggest in Section I – i.e., over-optimism about future growth, and distorted beliefs/policy decisions. This and other relevant questions remain for future research.

REFERENCES

ABBAS, A., N. BELHOCINE, A. EL-GANAINY, AND M. HORTON (2011): "Historical Patterns and Dynamics of Public Debt-Evidence from a New Database," *IMF Economic Review*, 59, 717–742.

AL-AMINE, R. AND T. WILLEMS (2020): "Investor Sentiment, Sovereign Debt Mispricing, and Economic Outcomes," IMF Working Paper No. 20/166.

ALBERTIN, G., B. YONTCHEVA, D. DEVLIN, H. DEVINE, M. GERARD, I. SULJAGIC,

V. THAKOOR, AND S. BEER (2021): "Tax Avoidance in Sub-Saharan Africa's Mining Sector," IMF Departmental Paper 2021/022.

ARBELAEZ, C. H. AND N. SOBRINHO (2017): "Government Financial Assets and Debt Sustainability," IMF Working Paper No. 17/173.

AREZKI, R., V. RAMEY, AND L. SHENG (2017): "News Shocks in Open Economies: Evidence from Giant Oil Discoveries," *The Quarterly Journal of Economics*, 132, 103–155.

AREZKI, R., F. VAN DER PLOEG, AND F. TOSCANI (2019): "The Shifting Natural Wealth of Nations: The Role of Market Orientation," *Journal of Development Economics*, 138, 228–245.

AUTY, R. M. (1993): *Sustaining Development in Mineral Economies: The Resource Curse Thesis*, Routledge.

BEAUDRY, P. AND F. PORTIER (2004): "An Exploration Into Pigou's Theory of Cycles," *Journal of Monetary Economics*, 51, 1183–1216.

BEAUDRY, P. AND T. WILLEMS (forthcoming): "On the Macroeconomic Consequences of Over-Optimism," *American Economic Journal: Macroeconomics*.

BERMAN, N., M. COUTTENIER, D. ROHNER, AND M. THOENIG (2017): "This Mine is Mine! How Minerals Fuel Conflicts in Africa," *American Economic Review*, 107, 1564–1610.

BHATTACHARYYA, S., L. CONRADIE, AND R. AREZKI (2017): "Resource Discovery and the Politics of Fiscal Decentralization," *Journal of Comparative Economics*, 45, 366–382.

BLANCHARD, O., J.-P. L'HUILLIER, AND G. LORENZONI (2013): "News, Noise, and Fluctuations: An Empirical Exploration," *American Economic Review*, 103, 3045–3070.

BOVA, E., P. MEDAS, AND T. PHOGOSYAN (2016): "Macroeconomic Stability in Resource-Rich Countries: The Role of Fiscal Policy," IMF Working Paper No. 16/36.

BUONANNO, P., R. DURANTE, G. PRAROLO, AND P. VANIN (2015): "Poor Institutions, Rich Mines: Resource Curse in the Origins of the Sicilian Mafia," *The Economic Journal*, 125, F175–F202.

CABRALES, A. AND E. HAUK (2010): "The Quality of Political Institutions and the Curse of Natural Resources," *The Economic Journal*, 121, 58–88.

CASELLI, F. AND T. CUNNINGHAM (2009): "Leader Behavior and the Natural Resource Curse," *Oxford Economic Papers*, 61, 628–650.

CATÃO, L. AND G. M. MILESI-FERRETTI (2014): "External Liabilities and Crises," *Journal of International Economics*, 94, 18–32.

CHUHAN-POLE, P., A. L. DABALEN, AND B. C. LAND (2017): *Mining in Africa: Are Local Communities Better Off?*, Africa Development Forum series. Washington, D.C.: World Bank.

CLOYNE, J. (2013): "Discretionary Tax Changes and the Macroeconomy: New Narrative Evidence from the United Kingdom," *American Economic Review*, 103, 1507–28.

COLLIER, P. (2017): "The Institutional and Psychological Foundations of Natural Resource Policies," *The Journal of Development Studies*, 53, 217–228.

CORDEN, M. AND P. NEARY (1982): "Booming Sector and De-Industrialization in a Small Open Economy," *The Economic Journal*, 92, 825–848.

COTET, A. M. AND K. K. TSUI (2013): "Oil and Conflict: What Does the Cross Country Evidence Really Show?" *American Economic Journal: Macroeconomics*, 5, 49–80.

CRUCES, J. AND C. TREBESCH (2013): "Sovereign Defaults: The Price of Haircuts," *American Economic Journal: Macroeconomics*, 5, 85–117.

CUST, J. AND T. HARDING (2020): "Institutions and the Location of Oil Exploration," *Journal of the European Economic Association*, 18, 1321–1350.

CUST, J. AND D. MIHALYI (2017): "Evidence for a Presource Curse?" World Bank Policy Research Working Paper No. 8140.

DAVIS, G. A. (1995): "Learning to Love the Dutch Disease: Evidence from the Mineral Economies," *World Development*, 23, 1765–1779.

DRISCOLL, J. AND A. KRAAY (1998): "Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data," *Review of Economics and Statistics*, 80, 549–560.

EL ANSHASY, A. AND M.-S. KATSAITI (2013): "Natural Resources and Fiscal Performance: Does Good Governance Matter?" *Journal of Macroeconomics*, 37, 285–298.

ESQUIVEL, C. (2020): "The Sovereign Default Risk of Giant Oil Discoveries," Rutgers University.

ESSL, S., S. K. CELIK, P. KIRBY, AND A. PROITE (2017): "Debt in Low-Income Countries: Evolution, Implications, and Remedies," World Bank Policy Research Working Paper No. 8140.

FRANKEL, J. (2010): "The Natural Resource Curse: A Survey," NBER Working Paper No. 15836.

FURCERI, D. AND A. ZDZIENICKA (2012): "How Costly Are Debt Crises?" *Journal of International Money and Finance*, 31, 726–742.

GELB, A. (1988): *Oil Windfalls: Blessing or Curse*, Oxford University Press.

GERLING, K., P. MEDAS, T. POGHOSYAN, J. FARAH-YACOUB, , AND Y. XU (2017): "Fiscal Crises," IMF Working Paper No. 17/86.

HADZI-VASKOV, M. AND M. L. A. RICCI (2016): "Does Gross or Net Debt Matter More for Emerging Market Spreads?" IMF Working Paper No. 16/246.

HALBOUTY, M. T., R. E. KING, H. D. KLEMME, R. H. DOTT SR, AND A. MEYERHOFF (1970): "World's Giant Oil and Gas Fields, Geologic Factors Affecting Their Formation, and Basin Classification," AAPG Special Volumes.

HARDING, T., R. STEFANSKI, AND G. TOEWS (2020): "Boom Goes the Price: Giant Resource Discoveries and Real Exchange Rate Appreciation," *The Economic Journal*, 130, 1715–1728.

HORN, M. (2012): "Giant Oil and Gas Fields of the World," Data retrieved from https://edx.netl.doe.gov/dataset/aapg-datapages-giant-oil-and-gas-fields-of-the-world.

IEO (2014): *IMF Forecasts: Process, Quality, and Country Perspectives*, independent Evaluation Office of the International Monetary Fund, Evaluation Report, Washington, D.C.

IMF (2012): "Macroeconomic Policy Frameworks for Resource-Rich Developing Countries," IMF Policy Paper.

——— (2013): "Staff Guidance Note for Public Debt Sustainability Analysis for Market-Access Countries," Washington, D.C.

——— (2014): "The Fund's Lending Framework and Sovereign Debt-Preliminary Considerations, Annex II," Washington, D.C.

——— (2015): "Mongolia: Staff Report for the 2015 Article IV Consultation," IMF Country Report No. 15/109.

——— (2017a): "Guidance Note on the Bank-Fund Debt Sustainability Framework for Low-Income Countries," Washington, D.C.

——— (2017b): "Mongolia: 2017 Article IV Consultation and Request for an Extended Arrangement under the Extended Fund Facility," IMF Country Report No. 17/140.

——— (2017c): "Review of the Debt Sustainability Framework in Low-Income Countries: Proposed Reforms, Annex III," Washington, D.C.

——— (2017d): "The Role of the Fund in Governance Issues: Review of the Guidance Note-Preliminary Considerations," Washington, D.C.

——— (2018): "Fiscal Monitor: Managing Public Wealth," Washington, D.C., October.

——— (2020a): "Chile: Request for an Arrangement Under the Flexible Credit Line," IMF Country Report No. 20/183.

——— (2020b): "Ghana: Request for Disbursements Under the Rapid Credit Facility," IMF Country Report No. 20/110.

——— (2020c): "Republic of Mozambique: Request for Disbursements Under the Rapid Credit Facility," Country Report No. 19/141.

——— (2021): "Review of the Debt Sustainability Framework for Market-Access Countries," IMF Policy Paper, January 2021.

KAUFMANN, D., A. KRAAY, AND M. MASTRUZZI (2010): "The Worldwide Governance Indicators: Methodology and Analytical Issues," World Bank Policy Research Working Paper No. 5430.

KELLOGG, R. (2011): "Learning by Drilling: Interfirm Learning and Relationship Persistence in the Texas Oilpatch," *The Quarterly Journal of Economics*, 126, 1961–2004.

KNUTSEN, C. H., A. KOTSADAM, E. H. OLSEN, AND T. WIG (2017): "Mining and Local Corruption in Africa," *American Journal of Political Science*, 61, 320–334.

KRUGMAN, P. (1987): "The Narrow Moving Band, the Dutch Disease, and the Competitive Consequences of Mrs. Thatcher," *Journal of Development Economics*, 27, 41–55.

LEI, Y.-H. AND G. MICHAELS (2014): "Do Giant Oilfield Discoveries Fuel Internal Armed Conflicts?" *Journal of Development Economics*, 110, 139–157.

LIMI, A. (2007): "Escaping from the Resource Curse: Evidence from Botswana and the Rest of the World," *IMF Staff Papers*, 54, 663–699.

LUCA, O. AND D. M. PUYO (2016): "Fiscal Analysis of Resource Industries (FARI) Methodology," IMF Technical Notes and Manual 16/01.

MANN, P., M. HORN, AND I. CROSS (2007): "Emerging Trends from 69 Giant Oil and Gas Fields Discovered from 2000–2006," Presentation at the 2007 Annual Meeting of the American Association of Petroleum Geologists in Long Beach, California. April 2, 2007.

MANSOORIAN, A. (1991): "Resource Discoveries and 'Excessive' External Borrowing," *The Economic Journal*, 101, 1497–1509.

MANZANO, O. AND R. RIGOBON (2001): "Resource Curse or Debt Overhang?" NBER Working Paper No. 8390.

MARSHALL, M., K. JAGGERS, AND T. GURR (2017): "Polity2 IV Project: Political Regime Characteristics and Transitions, 1800-2017, Dataset Users' Manual," Center for Systemic Peace.

MASI, T., A. SAVOIA, AND K. SEN (2018): "Is There a Fiscal Resource Curse? Resources Rent, Fiscal Capacity and Political Institutions," ESID Working Paper No. 96.

MBAYE, S., M. M. M. BADIA, AND K. CHAE (2018): "Global Debt Database: Methodology and Sources," IMF Working Paper No. 18/111.

MEDAS, P., T. POGHOSYAN, Y. XU, J. FARAH-YACOUB, AND K. GERLING (2018): "Fiscal Crises," *Journal of International Money and Finance*, 88, 191–207.

MEHLUM, H., K. MOENE, AND R. TORVIK (2006): "Institutions and the Resource Curse," *The Economic Journal*, 116, 1–20.

MELINA, G., S.-C. S. YANG, AND L.-F. ZANNA (2016): "Debt Sustainability, Public Investment, and Natural Resources in Developing Countries: The DIGNAR Model," *Economic Modelling*, 52, 630–649.

MERTENS, K. AND M. O. RAVN (2012): "Empirical Evidence on the Aggregate Effects of Anticipated and Unanticipated US Tax Policy Sshocks," *American Economic Journal: Economic Policy*, 4, 145–81.

NICKELL, S. (1981): "Biases in Dynamic Models with Fixed Effects," *Econometrica: Journal of the Econometric Society*, 1417–1426.

NISHIO, A. AND H. BREDENKAMP (2018): "Debt Vulnerabilities in Emerging and Low-Income Economies," World Bank-IMF joint document prepared for the the Joint Ministerial Committee of the Boards of Governors of the Bank Group and the Fund on the Transfer of Real Resources to Developing Countries, September 2018.

PEREZ-SEBASTIAN, F. AND O. RAVEH (2015): "The Natural Resource Curse and Fiscal Decentralization," *American Journal of Agricultural Economics*, 98, 212–230.

POPLAWSKI-RIBEIRO, M., M. M. VILLAFUERTE, M. T. BAUNSGAARD, AND C. J. RICHMOND (2012): "Fiscal Frameworks for Resource Rich Developing Countries," IMF Staff Discussion Note SDN/12/04.

ROBINSON, J., R. TORVIK, AND T. VERDIER (2006): "Political Foundations of the Resource Curse," *Journal of Development Economics*, 79, 447–468.

ROSS, M. L. (2012): *The Oil Curse: How Petroleum Wealth Shapes the Development of Nations*, Princeton University Press.

——— (2015): "What Have We Learned About the Resource Curse," *Annual Review of Political Science*, 18, 239–259.

——— (2018): "The Politics of the Resource Curse," in *The Oxford Handbook of the Politics of Development*, ed. by N. Van de Walle and C. Lancaster, Oxford University Press, 200–223.

RUZZANTE, M. (2018): "Financial Crises, Macroeconomic Shocks, and the Government Balance Sheet: A Panel Analysis," IMF Working Paper No. 18/93.

SACHS, J. AND A. WARNER (1995): "Natural Resource Abundance and Economic Growth," NBER Working Paper No. 5398.

SOYRES, C., A. PICCO, AND R. SAB (2019): "Debt Build-Up in Frontier Low-Income Developing Countries (LIDCs) Since 2012: Global or Country-Specific Factors and Way Forward?" IMF Working Paper No. 19/37.

TORNELL, A. AND P. R. LANE (1999): "The Voracity Effect," *American Economic Review*, 89, 22–46.

TSUI, K. K. (2010): "More Oil, Less Democracy: Evidence from Worldwide Crude Oil Discoveries," *The Economic Journal*, 121, 89–115.

VAN DER PLOEG, F. (2011): "Natural Resources: Curse or Blessing?" *Journal of Economic Literature*, 49, 366–420.

VAN WIJNBERGEN, S. (1984): "The 'Dutch Disease': A Disease After All?" *The Economic Journal*, 98, 41–55.

VICENTE, P. C. (2010): "Does Oil Corrupt? Evidence from a Natural Experiment in West Africa," *Journal of Development Economics*, 92, 28–38.

VON HALDENWANG, C. AND M. IVANYNA (2018): "Does the Political Resource Curse Affect Public Finance? The Vulnerability of Tax Revenue in Resource-Dependent Countries," *Journal of International Development*, 30, 323–344.

VREELAND, J. R. (2008): "The Effect of Political Regime on Civil War: Unpacking Anocracy," *Journal of Conflict Resolution*, 52, 401–425.

FIGURES

Figure 1: Temporal Distribution of Giant Discoveries
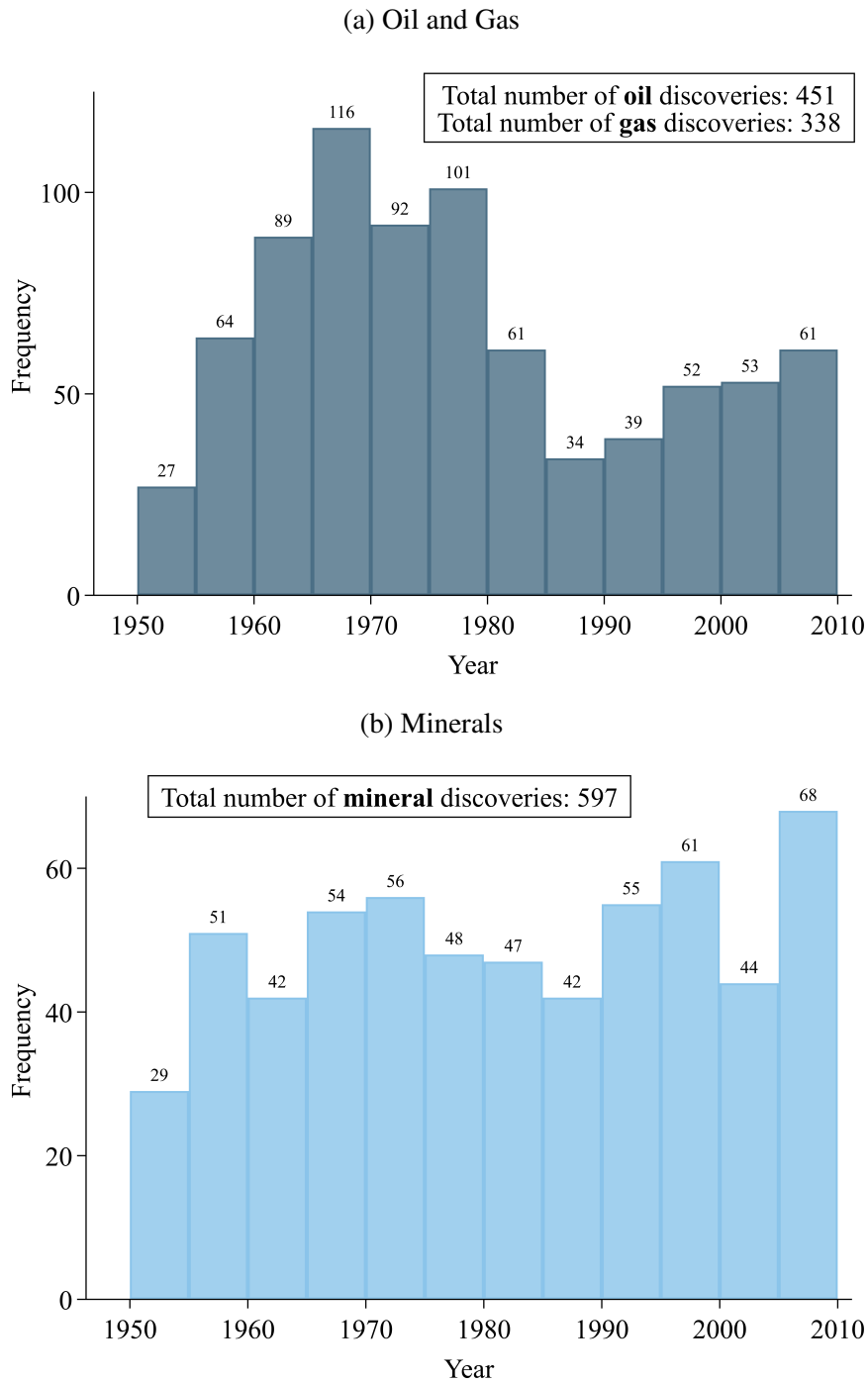
(a) Oil and Gas

(b) Minerals

Notes: These figures display the number of giant discoveries, as defined in Section II, in the period 1950-2010. Note that a country can experience more than one discovery event per year. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure 2: Geographical Distribution of Giant Discoveries
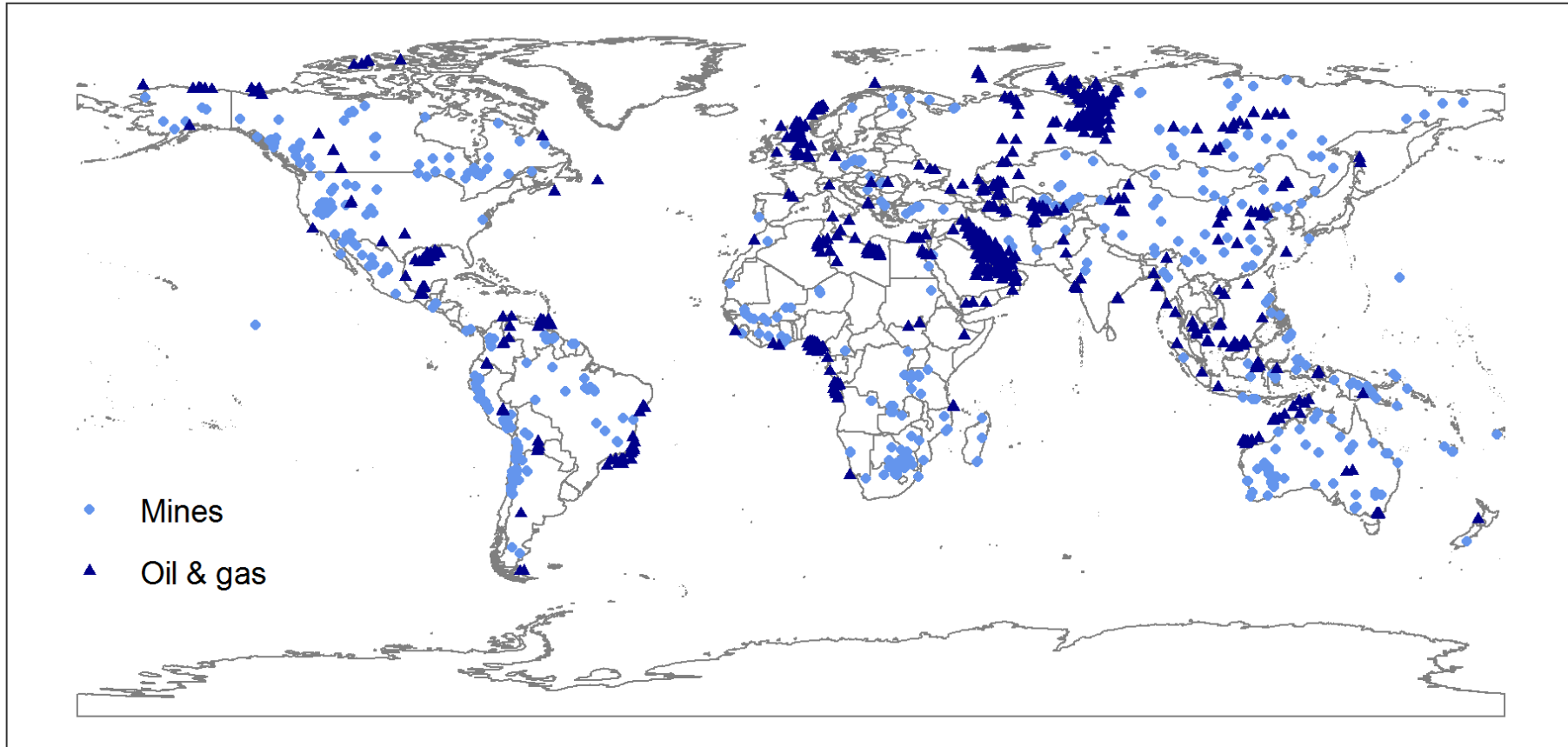
Notes: The map displays the location of all the giant oil and gas, and mineral discoveries, as defined in Section II, in the period 1950-2010. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update February 2018).

Figure 3: Impact of Giant Discoveries on Government Debt

(a) All Discoveries

(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and one lag of the dependent variable, and controls for a country specific linear time trend. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 (1970-2017 for mineral discoveries). Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure 4: Impact of Giant Discoveries on Probability of Fiscal Crises

(a) All Discoveries
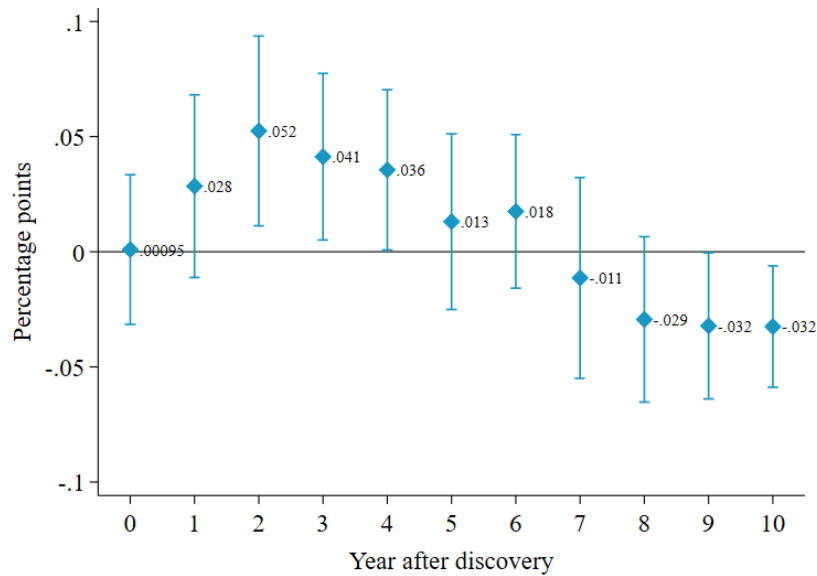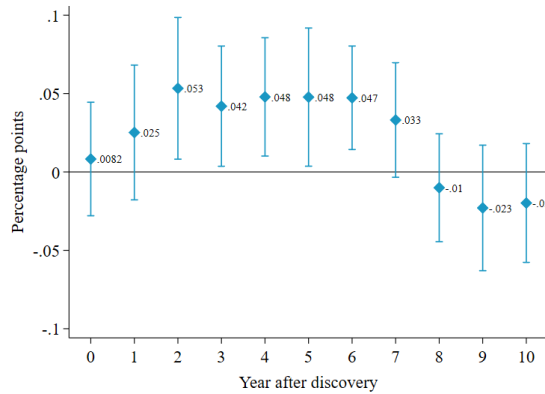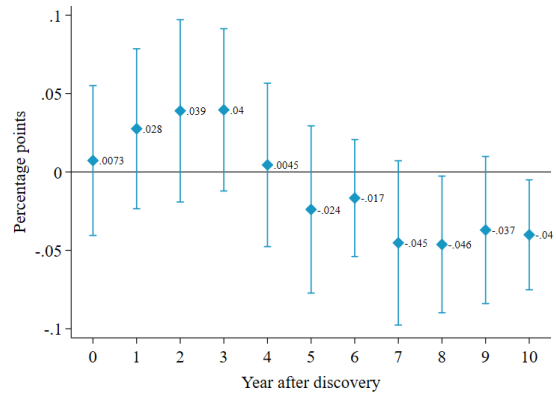
(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from a linear probability model with Driscoll-Kraay standard errors. Confidence interval are 95%. The sample includes an unbalanced panel of 188 countries on the period 1970-2012 (1970-2017 for mineral discoveries). 'Fiscal crises' are defined following Gerling et al. (2017). Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure 5: Impact of Giant Discoveries on Probability of External Debt Distress
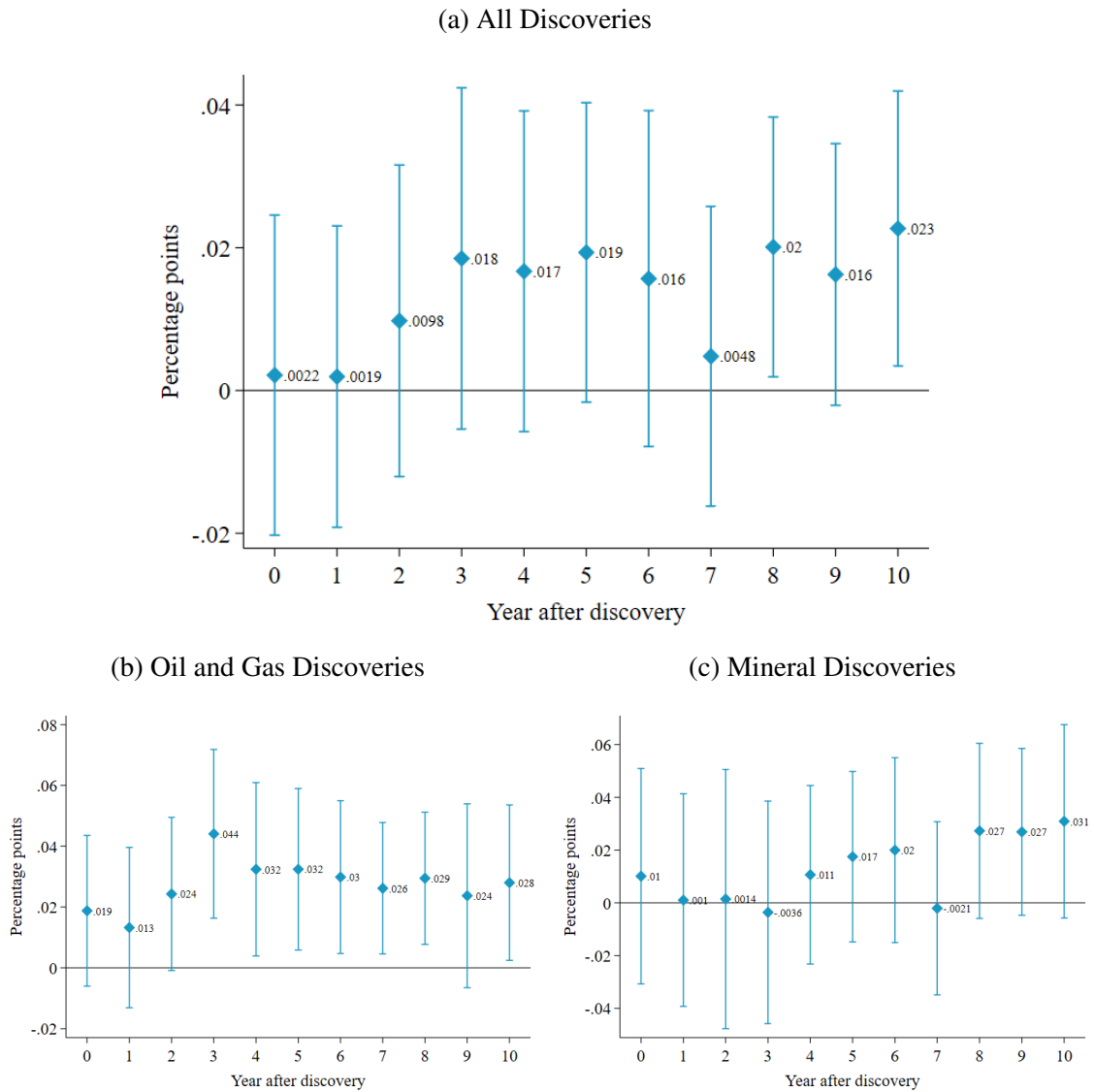
(a) All Discoveries

(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from a linear probability model with Driscoll-Kraay standard errors. Confidence interval are 95%. The sample includes an unbalanced panel of 188 countries on the period 1970-2012 (1970-2017 for mineral discoveries). Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure 6: Impact of Giant Discoveries on Government Debt – Heterogeneity by Quality of Political Institutions and Governance

(a) By Polity2 Index

(b) By X-Polity Index

(c) By Control of Corruption Indicator

(d) By Governance Indicator

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and one lag of the dependent variable, and controls for a country specific linear time trend. The light blue and dark blue shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters, for the sub-sample with institutions below the median. The intervals for countries above the median include the zero line and are omitted for the convenience of the reader. The sample includes an unbalanced panel of 169 countries on the period 1970-2012. Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018). The Polity2 index is from the Polity IV dataset, and the X-Polity only considers the components of the Polity2 Index associated with the executive branch. The 'control of corruption' indicator is from Kaufmann et al. (2010), and the governance indicator was compiled by the authors (see online Appendix A.II).

Table 1: Granger Causality Tests of Discovery Predictability

Regressors:	(1) Government debt (% of GDP)	(2) Log of population	(3) Log of real GDP per capita	(4) Real GDP growth	(5) CPI inflation	(6) Current account balance, 3-year average	(7) Fiscal deficit (% of GDP)	(8) Real exchange rate	(9) Polity2 index	(10) Governance indicator
1 lag										
Chi-square statistics	0.026	0.248	3.140	1.357	1.417	0.691	4.630	0.561	2.819	1.700
P-value	0.871	0.618	0.076	0.244	0.234	0.406	0.031	0.454	0.093	0.192
2 lags										
Chi-square statistics	0.043	1.155	4.063	5.917	1.824	2.599	4.765	0.582	2.937	3.027
P-value	0.979	0.561	0.131	0.052	0.402	0.273	0.092	0.446	0.230	0.220
3 lags										
Chi-square statistics	0.237	7.395	5.249	6.444	4.900	2.906	3.972	0.599	3.212	3.022
P-value	0.971	0.060	0.154	0.092	0.179	0.406	0.265	0.439	0.360	0.388

Notes: The dependent variable is a dummy for giant resource discovery events. The explanatory variables are included one at a time. We perform a panel vector autogregression (VAR) Granger causality Wald test based on a panel VAR including country and time fixed effects with standard errors clustered at the country level. The null hypothesis is that the coefficient(s) on the distributed lag(s) of each variable are (jointly) equal to zero, i.e., the explanatory variable does not Granger-cause the dependent variable. The sample frame considered is the same used for the baseline estimations, i.e., 1970-2012. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018). The economic and political explanatory variables are defined in Section II. See data sources in Table B1.

Table 2: Likelihood Ratio Tests of Discovery Predictability

Type of discovery:	All		Oil and gas		Mineral	
	(1)	(2)	(3)	(4)	(5)	(6)
Chi-square statistics	6.930	23.574	14.027	20.545	17.020	25.974
P-value	0.732	0.015	0.172	0.038	0.074	0.007
N. of observations	931	931	707	707	575	575
N. of countries	36	36	28	28	21	21
Country and year fixed effects	✓	✓	✓	✓	✓	✓
Previous discoveries in 10 years		✓		✓		✓

Notes: The dependent variable is a dummy for giant resource discovery events. The explanatory variables are: government debt (% of GDP), population (in log), real GDP per capita (in log), real GDP growth, CPI inflation, current account balance (3-year average), fiscal deficit (% of GDP), real exchange rate, Polity2 index and our governance indicator. The null hypothesis is that the coefficients on the first lag of each variable are jointly zero, based on panel logistic regressions with country and time fixed effects and standard errors clustered at the country level. The sample frame considered is the same used for the baseline estimations, i.e., 1970-2012. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018). The economic and political variables are defined in Section II. See data sources in Table B1.

Table 3: Cumulative Impact of Giant Discoveries on Government Debt

Type of discovery	(1) Time horizons	(2) Cumulative response	(3) Hypothesis test p-value
All discoveries	0-4	7.319	0.022
	5-10	7.752	0.073
	0-10	15.072	0.025
Oil and gas discoveries	0-4	7.916	0.069
	5-10	11.019	0.055
	0-10	18.935	0.033
Mineral discoveries	0-4	2.524	0.592
	5-10	2.203	0.755
	0-10	4.727	0.606

Notes: Cumulative responses are equal to $\sum_{h=i}^{N} b_h$ where b_h is the impulse response at horizon h, and i and N are the initial and final years, respectively, as shown in Column (1). P-values are computed using delta method, i.e., non-linear combinations of OLS-estimated parameters from Equation 2 (see Figure 3 for full set of IRFs). The null hypothesis tested is $H_0 : \sum_{h=i}^{N} b_h = 0$. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 (1970-2017 for mineral discoveries). Debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

ONLINE APPENDIX

A DATA SOURCES AND CONSTRUCTION

A.I GOVERNMENT DEBT

The government gross debt data used in the paper was compiled as follow. Our primary source is the IMF's Global Debt Database (GDD), available at Global Debt Database (*IMF*). This is an up to date and comprehensive repository that covers 190 countries over the period 1950-2018. The database was compiled by IMF staff using information from almost 100 different primary sources, complemented by information from scholars, and databases from multiple international institutions, including OECD and the IMF itself (Mbaye et al., 2018). We therefore take advantage of GDD's comprehensive coverage in terms of country, government perimeter, and time period. GDD accounts for about four fifths of all country-years in our sample. For each country, we chose the debt perimeter that covers the greatest number of years during the sample period. The Central Government is the main perimeter for most countries in the sample. However, data on broader perimeters such as General Government, Non-Financial Public Sector and Public Sector are also available for a few countries in our sample.

We combine GDD data with information from other sources, including WEO, the Historical Public Debt Database (A Historical Public Debt Database (*IMF*)), World Bank's International Debt Statistics (IDS), and data compiled by the authors from IMF country reports. A small number of observations were obtained by simple linear interpolation or backward extrapolation (e.g., for early 1970s). This helped obtain longer and continuous times series, without sacrificing consistency and integrity of the available raw data.

To remain in the final sample, a country must have continuous times series since at least early 1990s, which would catch most emerging economies (including many transition economies) and most low-income countries, which are our core sample of interest. Dropping the countries that did not meet this criterion, we are left with a final sample of 171 countries, comprising 31 advanced economies, 77 emerging market economies, and 63 low-income countries, as per the current WEO classification.

The government net debt data is defined as gross debt as compiled above minus government holdings of liquid financial assets, or liquidity is typically associated with holdings of cash and deposits or high-quality securities (see, for instance, Arbelaez and Sobrinho, 2017). The WEO is the main source for the net debt data. However, when WEO data are not available, the authors rely on information from OECD, Eurostat, and the IMF's Government Finance Statistics Yearbook, the same primary sources used by Arbelaez and Sobrinho. In most cases, the financial assets are typically held by the Central or the General Government. The data do not include international reserves held at central banks. Despite compiling asset data from multiple sources, the information available covers only one quarter of the country-years in our panel or 171 countries.

A.II   GOVERNANCE INDICATOR

We rely on multiple sources to construct a governance indicator with wider coverage of country-years compared to the existing indicators. Our starting point and core source is the Kaufmann et al. (2010)'s Worldwide Governance Indicators (WGI).[38] For these authors, governance includes (i) the process for selecting, monitoring, and replacing governments; (ii) the government's capacity to design and implement sound policies; and (iii) the respect for institutions that govern economic and social interactions. For the purpose of this paper, we select five of the six WGI: *Political Stability and Absence of Violence/Terrorism*, representing (i); *Government Effectiveness* and *Regulatory Quality* (ii); and *Rule of Law* and *Control of Corruption* (iii). Kaufmann et al. (2010) provide the definition and rationale of each of these sub-components.

While data on WGI covers all countries in our sample, it only goes as far back as 1996, and was not reported for the years 1997, 1999, and 2001. We use linear interpolation to obtain observations for these missing years. Therefore, in order to increase the number of observations in our panel data, we used the following strategy:

(i) We construct an aggregate WGI index by averaging out the five selected indicators above and normalizing the resulting indicator. This allowed to obtain a consistent governance indicator from 1996 to the end of the sample for almost all countries in our panel data.

(ii) For the missing years (1970-95), we rely on information from several data sources to construct individual components that are akin to the five WGI subcomponents.

Political Stability. For the country-years where ICRG's Political Risk Rating (PRR) is available, we aggregate two subcomponents of the PRR—*Government Stability* and *Internal Conflict* and use this aggregate indicator as a proxy for political stability. For the country-years where the PPR is not available (i.e., mostly prior 1984), we rely on the following two sets of indicators from the 2019 edition of the CNTS Data Archive: (a) *Number of Major Cabinet Changes*, *Number of Coups d'Etat*, *Riots*, and *Anti-Government Demonstrations*; and (b) *Major Government Crises*, *Revolutions*, *Assassinations*, *Terrorism/Guerrilla Warfare*, *Purges*, and *General Strikes*. By properly combining the indicators under (a) and under (b) we arrive at indicators that we think are akin to PRR's *Government Stability*, and *Internal Conflict*, respectively. We then aggregate the two subcomponents to arrive at a proxy for an aggregate indicator of political stability. CNTS data have been used in the literature as a proxy for political instability (e.g., by Aisen and Veiga, 2006).

Government Effectiveness. This is proxied by *Bureaucracy Quality*, another subcomponent of PRR.

Regulatory Quality. This is proxied either by PRR's *Investment Profile* subcomponent of PRR or *Regulation*, a component of the Economic Freedom of the World Index, compiled by Fraser Institute.[39] Both indicators measure factors affecting the risk of doing businesses,

---

[38]Worldwide Governance Indicators (*World Bank).*
[39]Economic Freedom Rankings (*Fraser Institute*).

such as (but not limited to) contract enforcement, expropriation risk, government constraints on factors of production, and licensing restrictions. In short, they capture government decisions and regulations affecting private sector development. Because data on the index of economic freedom and its component are available only for the years 1970, 1975, 1980, 1985, 1990, 1995, and 2000, we obtain the missing annual data using cubic spline. Aisen and Veiga (2006) used a somewhat similar approach, i.e., linear interpolation.

Rule of Law. This is proxied either by PRR's *Law and Order* or Economic Freedom of the World's *Legal System and Property Rights*. Both resonates the quality of the judicial system, law enforcement, and property rights.

Corruption. This is proxied either by PRR's *Corruption* or *Political Corruption Index* from the V-Dem Dataset.[40] Also see McMann et al. (2016).

To combine these different indicators meaningfully, they are properly normalized, and adjusted by the sample standard deviation for each country. While we acknowledge that there are caveats in our approach – most notably differences in the way the raw information is measured (e.g., WGI is a perception-based indicator, whereas some of the proxies used above are observables or have been estimated by the corresponding source) – we think that the added large number of observations outweigh those issues. Our approach allowed us to more than double the number of observations based on WGI data, covering over 90 percent of the country-years in our panel data. We also take comfort from the fact that, notwithstanding methodological differences, most of the proxies used above are strongly correlated with the WGI subcomponents.

[40]Varieties of Democracy (*V-Dem Institute*).

B DESCRIPTIVE STATISTICS

Table B1: Descriptive Statistics and Data Sources

	Mean	SD	Min	Max	N	Countries	Years	Main Sources
Outcome variables:								
Government debt	49.57	39.42	1.12	224.75	7695	169	47	Mbaye et al. (2018) IMF's World Economic Outlook (WEO), Historical Public Debt Database, World Bank's International Debt Statistics, IMF country reports
Government net debt	26.45	64.02	-344.21	222.46	1469	69	36	WEO, OECD, Eurostat, and IMF's Government Finance Statistics (IFS) Yearbook
Government gross debt	49.85	37.85	1.57	224.75	3525	110	36	WEO, OECD, Eurostat, and IFS Yearbook
Government financial assets	23.40	43.95	0	349.02	1292	67	36	WEO, OECD, Eurostat, and IFS Yearbook
Fiscal crises	0.24	0.43	0	1	8648	188	46	Gerling et al. (2017)
External debt defaults	0.03	0.18	0	1	7130	155	46	Catão and Milesi-Ferretti (2014) and Standard & Poor's
Main regressors:								
Discovery dummy	0.08	0.27	0	1	8299	193	43	Horn (2012) and *MinEx Consulting*
Oil and gas discovery dummy	0.04	0.20	0	1	8299	193	43	Horn (2012)
Mineral discovery dummy	0.04	0.20	0	1	9071	193	47	*MinEx Consulting*
Number of discoveries	0.11	0.44	0	5	9071	193	47	Horn (2012) and *MinEx Consulting*
Number of oil and gas discoveries	0.05	0.29	0	4	9071	193	47	Horn (2012)
Number of mineral discoveries	0.06	0.30	0	4	9071	193	47	*MinEx Consulting*
Net present value of oil and gas discoveries	3.04	82.24	0	6314.45	6969	184	43	Arezki et al. (2017)
Other independent variables:								
Polity2 index	2.86	7.06	-10	10	6901	165	47	Polity IV Project, Center for Systemic Peace
X-polity index	2.51	4.85	-6	7	6678	164	47	Vreeland (2008)
Control of corruption indicator	-0.21	0.69	-1.84	2.01	3650	186	20	Kaufmann et al. (2010)
Governance inficator	51.61	13.71	17.44	87.34	7627	169	47	Kaufmann et al. (2010), International Country Risk Guide, Cross-National Time-Series Data Archive, and Fraser Institute
Real GPD per capita, PPP (constant 2011 international USD)	74.27	220.12	0.45	1369.44	7126	169	45	Penn World Table, version 9 (PWT9), 2018
Population (in millions)	8578.38	13910.31	300.64	107778.64	3623	109	36	PWT9 and WEO
Real GDP growth	4.79	7.22	-15.14	147.67	6633	155	46	WEO, World Development Indicators (WDI) and United Nations (UN)
CPI inflation rate, annual average	10.39	37.32	-8.53	1061.21	6235	154	46	WEO, WDI and UN
Current account balance, % of GDP	0.20	10.85	-124.56	45.46	6214	154	46	WEO and WDI
Fiscal deficit, % of GDP	1.30	6.71	-43.30	17.88	5023	154	46	WEO, IMF Debt Sustanability Analyses, IFS, and Fund staff
Real exchange rate, index (2010=100)	97.07	25.44	40.28	300.37	6326	154	46	WEO, IFS and Fund staff

Notes: This table displays descriptive statistics, namely arithmetic mean, standard deviation (SD), maximum (max) and minimum (min) value, number of observations (N), number of countries and years, of the variables use throughout the paper. The sample period is 1970-2017. Each variable definition and data sources are described in Section II.

Figure B1: Temporal Distribution of Fiscal Stress and Debt Distress Episodes

(a) Fiscal Crises

(b) External Debt Distress
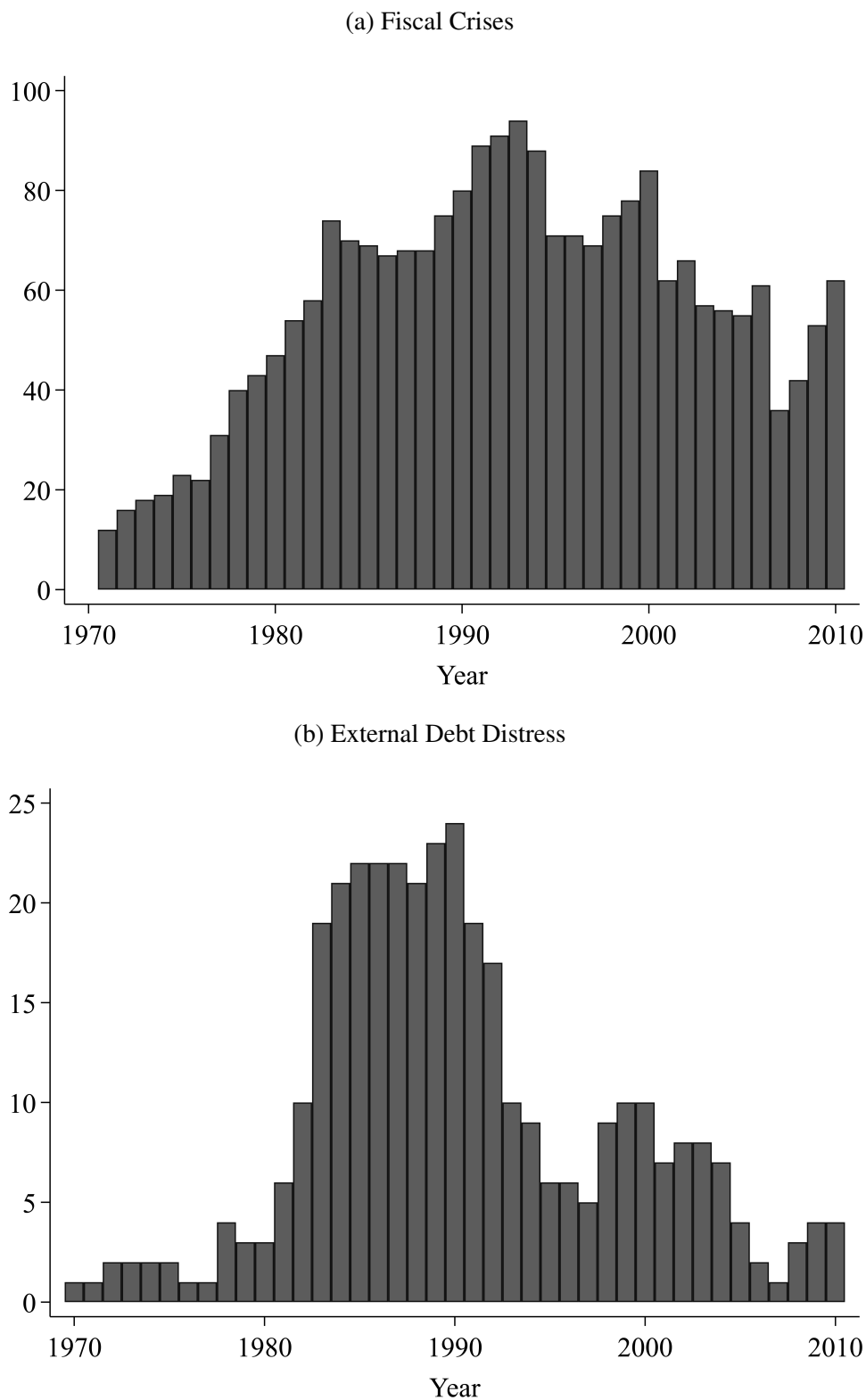
Notes: The bars display the number of fiscal stress and debt distress episodes per year. 'Fiscal crises' are defined following Gerling et al. (2017). 'External debt defaults' are defined following Catão and Milesi-Ferretti (2014).

Figure B2: Giant Discoveries By Country
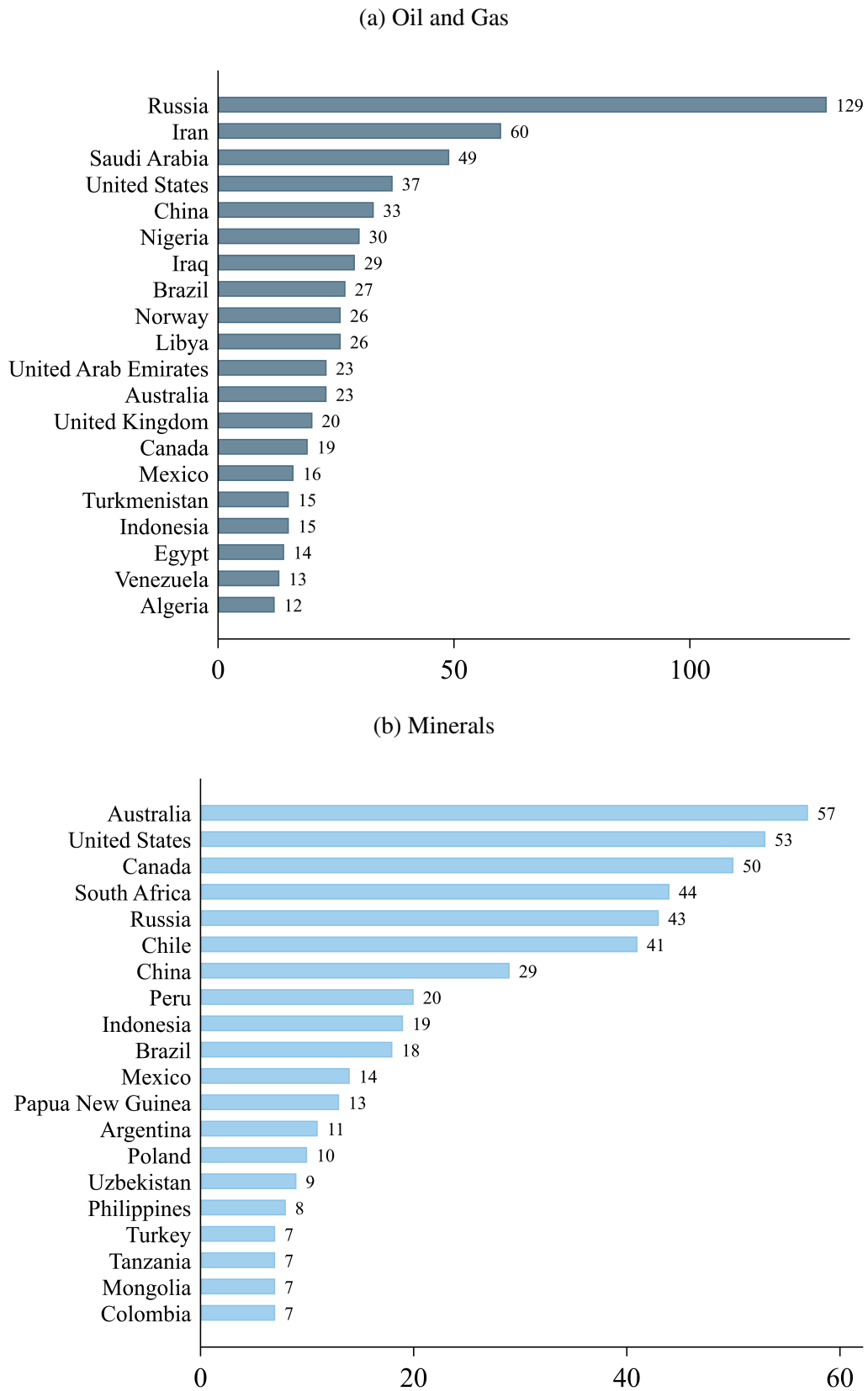
(a) Oil and Gas

(b) Minerals

Notes: These figures display the number of giant discoveries, as defined in Section II, for the 20 countries with most discoveries in the period 1950-2010. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure B3: Giant Discoveries by Type of Mineral
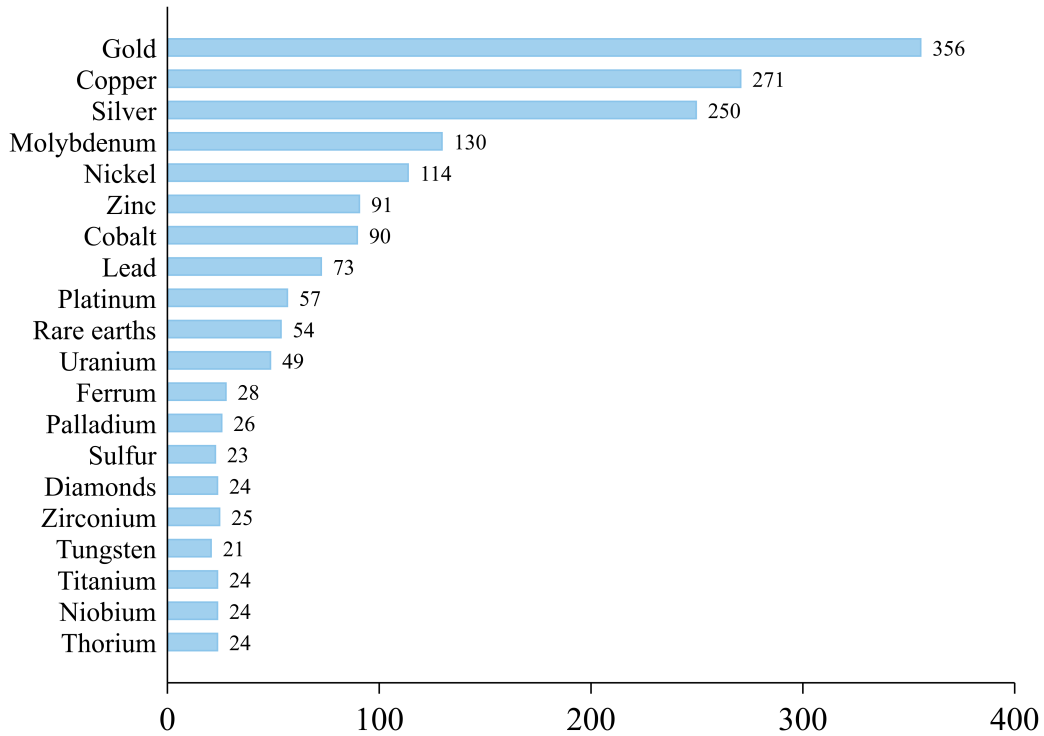
Notes: These figures display the number of giant mineral discoveries, as defined in Section II, for the 20 most common types of minerals in the period 1950-2010. Note that it is possible to have more than one discovery for a country in a certain year. Data are from *MinEx Consulting* (last update February 2018).

Figure B4: Public Debt and Haircuts in Restructurings
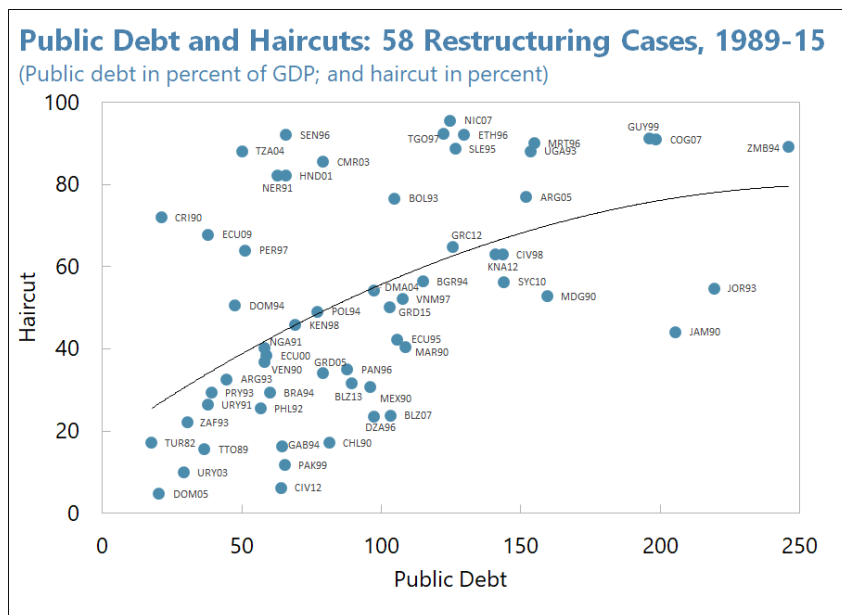
Notes: This figure shows the correlation between debt level three years prior restructuring and haircut in net present value terms. The trend line is a second-order polynomial fitted curve. The debt data are from IMF's GDD and authors' compilation, and the data on haircuts are from Cruces and Trebesch (2013).

Figure B5: Government Debt Patterns for the Baseline Sample, 1970-2015

(a) All Countries in the Sample

Baseline Sample, 154 Countries
(Percent of GDP)

(b) Oil Producing-Countries

28 Oil Producers
(Percent of GDP)

(c) Non-Oil Resource-Rich Countries
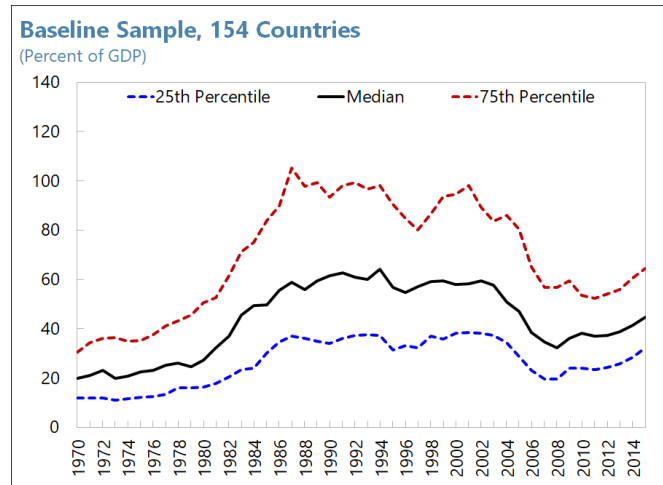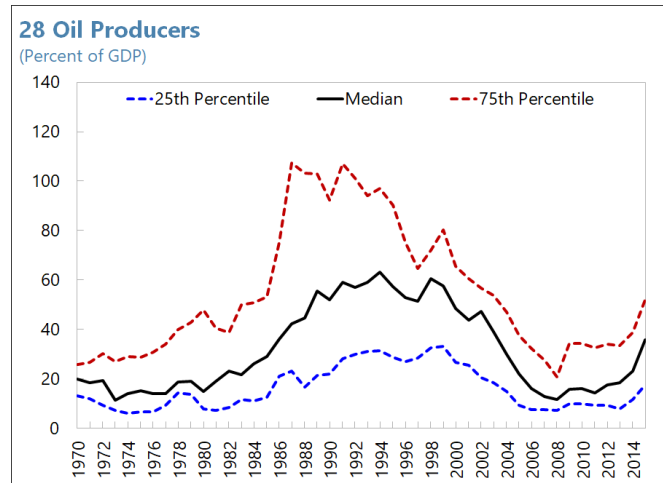
35 Nonoil Resource Rich Countries
(Percent of GDP)
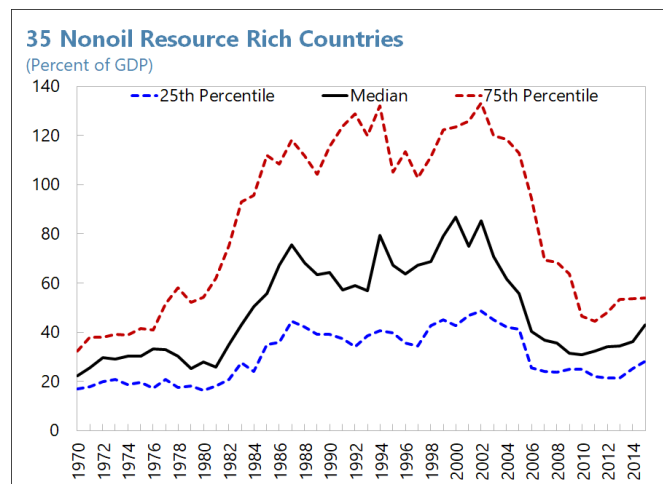
Notes: These figures show the evolution of the median government debt-to-GDP ratio in the baseline sample between 1970 and 2015, for different country groups. Dotted lines denote inter-quartile range. Data sources are shown in Table B1.

C   Public Debt Trajectory in Selected Examples

Figure C1: The "Fiscal Presource Curse" in Mozambique and Low-Income Countries

(a) Mozambique Debt Trajectory
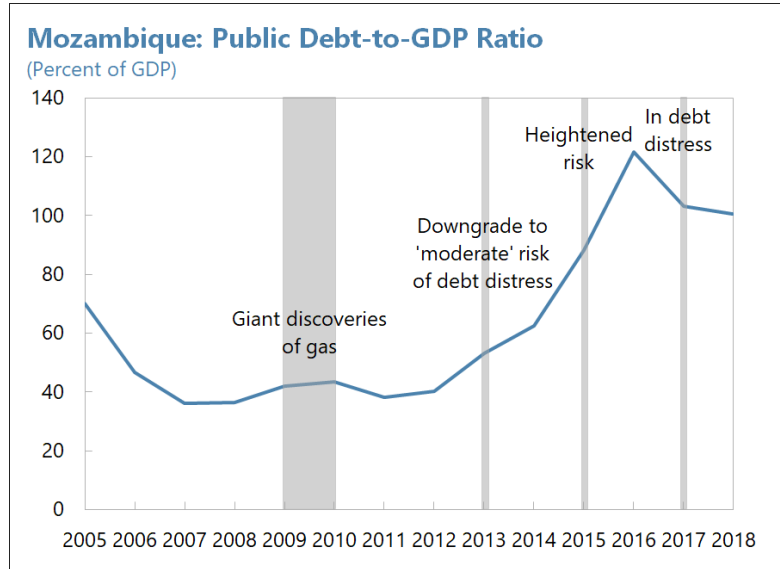
(b) Low-Income Countries (LICs) at High Risk of Debt Distress on in Distress
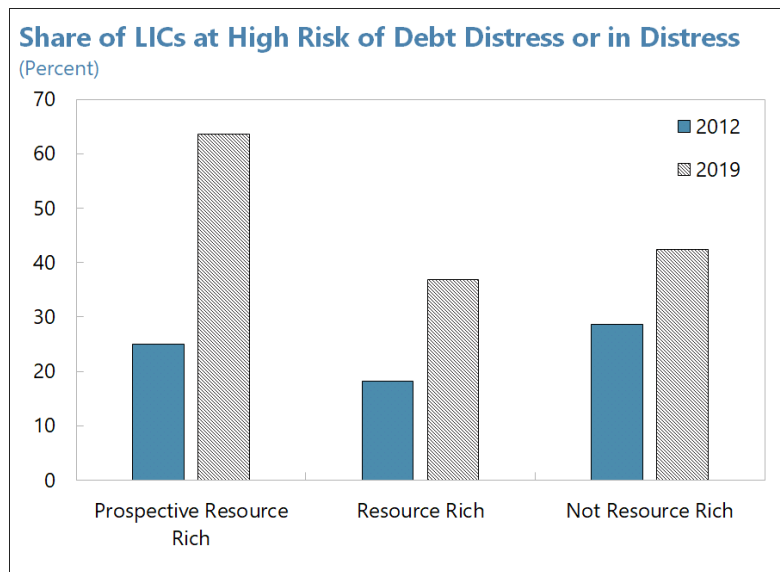
Notes: The top figure shows the evolution of Mozambique's public debt (blue line), prior and after giant gas discoveries (wide gray vertical bar), and debt distress events following discoveries (narrower gray vertical bars). The data sources are WEO, and IMF (2013, 2016, 2018). The bottom figure displays the change in debt-related risk ratings – as assessed by the IMF and the World Bank – between 2012 and 2019 for different groups of LICs. 'Prospective Resource Rich' are countries with identified reserves where production has not fully began or reached significant levels; 'Resource Rich' are countries where extraction is fully operational; and 'Not Resource Rich' are countries that are not abundant in natural resources. The data for this figure are from IMF (2012), List of LIC DSAs for PRGT-Eligible Countries (*IMF*, last access: 07/20/2019), and authors' calculations.

Figure C2: Absence of the "Fiscal Presource Curse" in Botswana
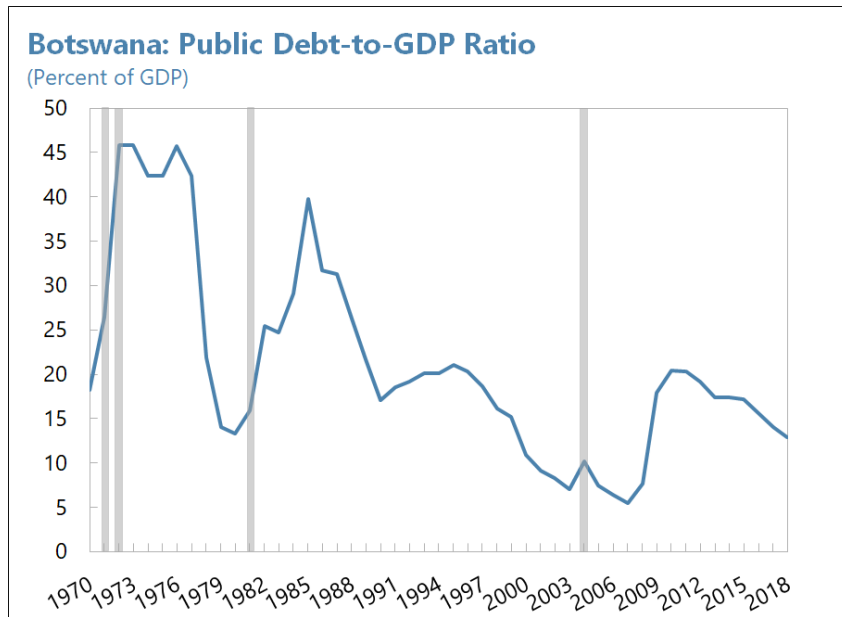
Notes: The figure shows the evolution of Botswana's public debt (blue line), prior and after giant diamond discoveries (gray vertical bars). The data sources for public debt are WEO, World Bank, Abbas et al. (2010), and authors' calculations. The data source for discoveries is *MinEx Consulting* (last update February 2018).

Figure C3: Curse or No Curse in Guyana?
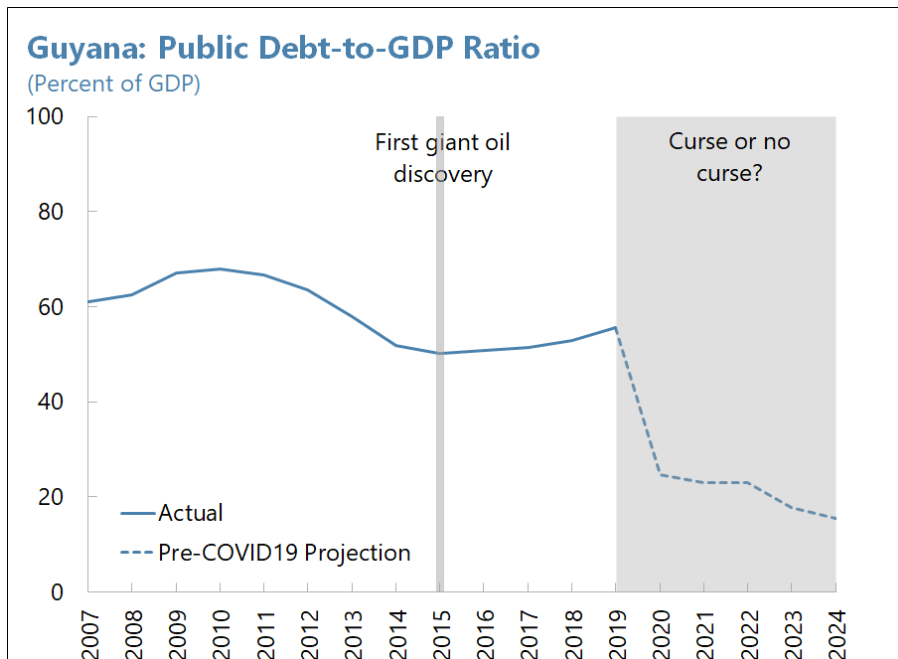
Notes: The figure shows the evolution of Guyana's public debt (blue line) prior and after giant oil discoveries (narrower gray bar). The data source for public debt is the IMF's WEO Database.

D COEFFICIENT ESTIMATES

Table D1: Dynamic Panel Distributed Lag Model Estimates

Type of discovery:	All discoveries			Oil and gas discoveries			Mineral gas discoveries		
Dataset:	GDD	WEO (Net)	WEO (Gross)	GDD	WEO (Net)	WEO (Gross) 2	GDD	WEO (Net)	WEO (Gross)
Variable:									
y_{t-1}	0.759***	0.655***	0.806***	0.759***	0.662***	0.806***	0.777***	0.729***	0.820***
	(0.101)	(0.053)	(0.027)	(0.101)	(0.052)	(0.027)	(0.090)	(0.056)	(0.026)
$Disc_t$	0.603	2.187*	1.540**	1.089	0.190	1.995**	-0.303	2.451**	0.277
	(0.574)	(1.092)	(0.562)	(0.936)	(1.291)	(0.956)	(0.702)	(1.138)	(0.728)
$Disc_{t-1}$	0.953	1.372**	1.462**	0.521	0.100	1.557	0.654	1.192	0.424
	(0.712)	(0.664)	(0.659)	(0.938)	(0.667)	(1.006)	(0.990)	(0.805)	(0.512)
$Disc_{t-2}$	0.600	0.247	0.904	0.487	-0.166	0.182	0.093	0.478	1.322
	(0.663)	(0.893)	(0.713)	(0.794)	(1.287)	(1.042)	(0.691)	(0.708)	(0.907)
$Disc_{t-3}$	0.635	-0.598	0.682	1.176	-2.722	0.826	0.476	1.282	0.155
	(0.651)	(1.426)	(0.528)	(0.898)	(2.151)	(0.740)	(0.531)	(1.030)	(0.636)
$Disc_{t-4}$	0.285	1.798*	0.574	-0.118	1.916	0.462	0.569	0.632	1.029*
	(0.545)	(1.023)	(0.478)	(0.673)	(1.644)	(0.640)	(0.615)	(0.529)	(0.537)
$Disc_{t-5}$	-0.141	0.674	0.528	-0.351	0.203	0.221	0.173	0.522	0.681
	(0.570)	(0.626)	(0.593)	(0.650)	(0.975)	(0.623)	(0.777)	(0.590)	(0.862)
$Disc_{t-6}$	0.194	0.653	0.278	1.675***	-0.712	0.674	-0.833	0.858	0.433
	(0.538)	(0.621)	(0.757)	(0.536)	(0.830)	(0.879)	(0.921)	(0.794)	(1.144)
$Disc_{t-7}$	0.024	0.350	-0.112	0.180	0.357	0.397	-0.254	0.696	-0.267
	(0.623)	(0.819)	(0.444)	(0.497)	(1.048)	(0.696)	(0.701)	(0.843)	(0.748)
$Disc_{t-8}$	0.691	1.057	0.050	0.994	0.271	-0.104	-0.021	0.845	0.586
	(0.587)	(0.763)	(0.664)	(0.842)	(0.886)	(0.502)	(0.540)	(0.700)	(0.877)
$Disc_{t-9}$	0.706	0.148	0.181	0.078	-1.613	-0.855	0.662	1.435	0.985
	(0.816)	(1.334)	(0.772)	(0.969)	(1.176)	(0.819)	(0.648)	(0.993)	(0.875)
$Disc_{t-10}$	0.285	0.497	0.237	-0.165	0.056	-1.025*	0.635	0.538	1.326*
	(0.620)	(0.900)	(0.417)	(0.640)	(1.364)	(0.537)	(0.671)	(0.727)	(0.653)
Number of observations	6850	1196	3088	6850	1196	3088	7526	1400	3415
Number of countries	169	68	110	169	68	110	169	69	110
Within R-squared	0.675	0.912	0.853	0.675	0.912	0.853	0.693	0.919	0.864

Notes: *Significant at 10%. **Significant at 5%. ***Significant at 1%. All regressions are OLS with country and year fixed effects. Driscoll-Kray standard errors in parentheses. *y* indicates the dependent variable, i.e., debt-to-GDP ratio from the dataset specified in the column header, and *Disc* the discovery event dummy. Alternative government debt datasets are described in online Appendix A.I. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

50

Table C2: Linear Probability Model Estimates – Fiscal Crises

	t+1		t+2		t+3		t+4		t+5		t+6		t+7		t+8		t+9		t+10	
All discoveries																				
Discovery event	0.028	0.028	0.050**	0.052**	0.038**	0.041**	0.031*	0.036**	0.008	0.013	0.012	0.018	-0.018	-0.011	-0.035**	-0.029	-0.039**	-0.032**	-0.038***	-0.032**
	(0.020)	(0.020)	(0.021)	(0.020)	(0.018)	(0.018)	(0.018)	(0.017)	(0.020)	(0.019)	(0.017)	(0.017)	(0.022)	(0.022)	(0.017)	(0.018)	(0.015)	(0.016)	(0.014)	(0.013)
Number of discoveries in the previous 10 years		-0.003		-0.010		-0.013**		-0.019***		-0.020***		-0.021***		-0.021***		-0.019***		-0.019***		-0.018***
		(0.007)		(0.007)		(0.007)		(0.007)		(0.006)		(0.004)		(0.004)		(0.004)		(0.004)		(0.004)
Number of observations	8272	8272	8460	8460	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648
Number of countries	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188
Within R-squared	0.097	0.097	0.097	0.097	0.098	0.099	0.098	0.100	0.098	0.100	0.098	0.100	0.098	0.100	0.098	0.100	0.098	0.100	0.098	0.100
Oil and gas discoveries																				
Discovery event	0.028	0.025	0.054**	0.053**	0.041*	0.042**	0.045**	0.048**	0.043*	0.048**	0.041**	0.047***	0.026	0.033*	-0.016	-0.010	-0.029	-0.023	-0.025	-0.020
	(0.022)	(0.021)	(0.023)	(0.022)	(0.021)	(0.019)	(0.021)	(0.019)	(0.024)	(0.022)	(0.018)	(0.016)	(0.020)	(0.018)	(0.017)	(0.017)	(0.020)	(0.020)	(0.019)	(0.019)
Number of discoveries in the previous 10 years		0.007		0.001		-0.001		-0.006		-0.010		-0.012*		-0.015**		-0.013*		-0.012**		-0.012**
		(0.007)		(0.007)		(0.007)		(0.007)		(0.007)		(0.007)		(0.006)		(0.006)		(0.006)		(0.006)
Number of observations	8272	8272	8460	8460	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648
Number of countries	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188
Within R-squared	0.097	0.097	0.097	0.097	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.099	0.098	0.099	0.098	0.098	0.098	0.098	0.098	0.098
Mineral discoveries																				
Discovery event	0.028	0.028	0.039	0.039	0.038	0.040	0.003	0.004	-0.026	-0.024	-0.018	-0.017	-0.047*	-0.045*	-0.048**	-0.046**	-0.039*	-0.037	-0.042**	-0.040**
	(0.025)	(0.025)	(0.029)	(0.029)	(0.026)	(0.026)	(0.027)	(0.026)	(0.027)	(0.026)	(0.019)	(0.019)	(0.026)	(0.026)	(0.021)	(0.022)	(0.022)	(0.023)	(0.017)	(0.017)
Number of discoveries in the previous 10 years		-0.016*		-0.023***		-0.029***		-0.034***		-0.034***		-0.033***		-0.032***		-0.030***		-0.029***		-0.026***
		(0.009)		(0.008)		(0.007)		(0.007)		(0.007)		(0.006)		(0.006)		(0.007)		(0.007)		(0.008)
Number of observations	8648	8532	8648	8590	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648	8648
Number of countries	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188	188
Within R-squared	0.098	0.099	0.098	0.099	0.098	0.100	0.098	0.100	0.098	0.100	0.098	0.100	0.098	0.100	0.098	0.100	0.098	0.100	0.098	0.099

Notes: *Significant at 10%. **Significant at 5%. ***Significant at 1%. All regressions are OLS with country and year fixed effects. Driscoll-Kray standard errors in parentheses. The column headers indicate the time span at which the coefficient is estimated. 'Fiscal crises' are defined following Gerling et al. (2017). Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Table C3: Linear Probability Model Estimates – External Debt Distress

|	t+1		t+2		t+3		t+4		t+5		t+6		t+7		t+8		t+9		t+10	
All discoveries																				
Discovery event	0.004	0.002	0.012	0.010	0.021*	0.018	0.019*	0.017	0.021**	0.019*	0.017	0.016	0.006	0.005	0.021**	0.020**	0.017*	0.016*	0.023**	0.023**
	(0.011)	(0.010)	(0.011)	(0.011)	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)	(0.010)	(0.012)	(0.012)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Number of discoveries in the previous 10 years		0.012***		0.012***		0.010***		0.008***		0.007***		0.005***		0.005***		0.004*		0.003		0.001
		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.003)		(0.003)
Number of observations	6820	6820	6975	6975	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130
Number of countries	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155
Within R-squared	0.063	0.065	0.063	0.066	0.064	0.066	0.064	0.066	0.064	0.065	0.064	0.065	0.064	0.064	0.064	0.065	0.064	0.064	0.064	0.064
Oil and gas discoveries																				
Discovery event	0.020	0.013	0.032**	0.024*	0.051***	0.044***	0.038***	0.032**	0.038***	0.032**	0.034***	0.030**	0.030***	0.026**	0.032***	0.029***	0.026*	0.024	0.029**	0.028**
	(0.014)	(0.013)	(0.013)	(0.012)	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.010)	(0.011)	(0.010)	(0.011)	(0.015)	(0.015)	(0.012)	(0.013)
Number of discoveries in the previous 10 years		0.018***		0.017***		0.014***		0.012***		0.010***		0.008**		0.007*		0.006		0.004		0.003
		(0.002)		(0.002)		(0.002)		(0.003)		(0.004)		(0.004)		(0.004)		(0.004)		(0.004)		(0.004)
Number of observations	6820	6820	6975	6975	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130
Number of countries	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155
Within R-squared	0.063	0.068	0.064	0.069	0.066	0.069	0.065	0.067	0.065	0.067	0.065	0.066	0.064	0.065	0.064	0.065	0.064	0.064	0.064	0.064
Mineral discoveries																				
Discovery event	0.003	0.001	0.003	0.001	-0.002	-0.004	0.012	0.011	0.019	0.017	0.021	0.020	-0.000	-0.002	0.029*	0.027	0.028*	0.027*	0.032*	0.031*
	(0.021)	(0.020)	(0.025)	(0.024)	(0.022)	(0.021)	(0.017)	(0.017)	(0.016)	(0.016)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)	(0.017)	(0.018)
Number of discoveries in the previous 10 years		0.014**		0.015***		0.017***		0.016***		0.016***		0.014***		0.014***		0.012**		0.010*		0.008
		(0.006)		(0.004)		(0.004)		(0.003)		(0.003)		(0.003)		(0.004)		(0.005)		(0.006)		(0.007)
Number of observations	7130	7042	7130	7086	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130	7130
Number of countries	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155	155
Within R-squared	0.064	0.066	0.064	0.066	0.064	0.066	0.064	0.066	0.064	0.066	0.064	0.066	0.064	0.066	0.064	0.066	0.064	0.065	0.064	0.065

Notes: *Significant at 10%. **Significant at 5%. ***Significant at 1%. All regressions are OLS with country and year fixed effects. Driscoll-Kray standard errors in parentheses. The column headers indicate the time span at which the coefficient is estimated. External debt distress episodes are defined following Catão and Milesi-Ferretti (2014). Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).
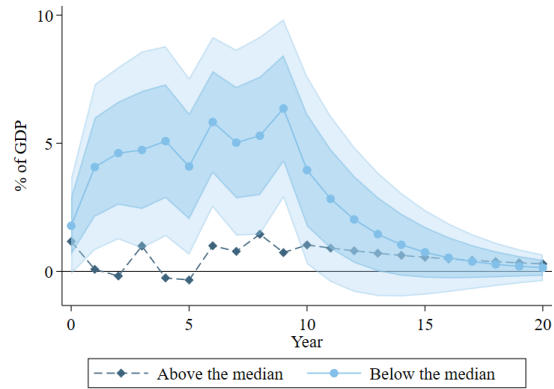
E HETEROGENEITY

Figure E1: Impact of Giant Discoveries on Government Debt – Heterogeneity by Quality of Political Institutions and Type of Discovery
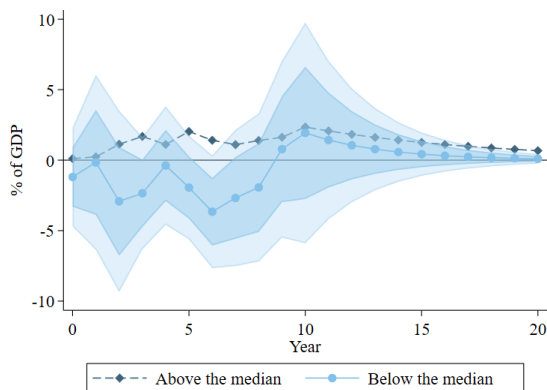
Oil and Gas Discoveries

(a) By Polity2 Index
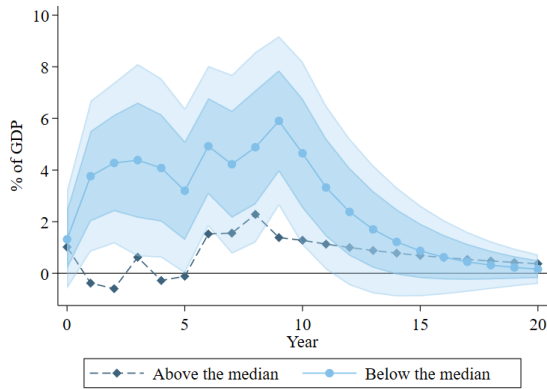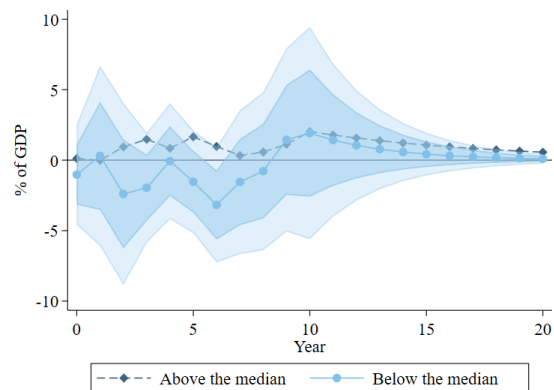
(b) By X-Polity Index

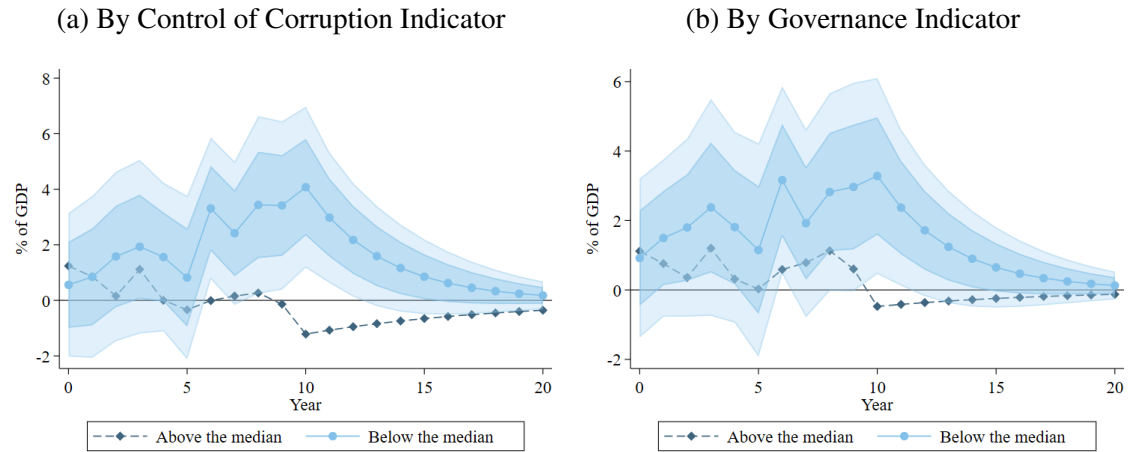## *Mineral Discoveries*

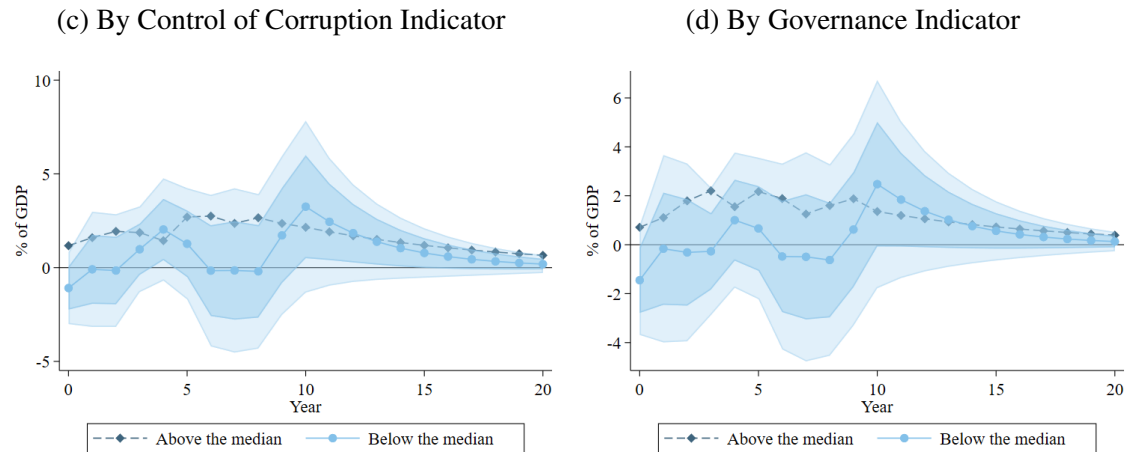(c) By Polity2 Index

(d) By X-Polity Index

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and one lag of the dependent variable, and controls for a country specific linear time trend. The light blue and dark blue shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters, for the sub-sample with institutions below the median. The intervals for countries above the median include the zero line and are omitted for the convenience of the reader. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 for oil and gas discoveries and 1970-2017 for mineral discoveries. Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018). The Polity2 index is from the Polity IV dataset, and the X-Polity only considers the components of the Polity2 Index associated with the executive branch.

Figure E2: Impact of Giant Discoveries on Government Debt – Heterogeneity by Governance and Type of Discovery

Oil and Gas Discoveries

(a) By Control of Corruption Indicator   (b) By Governance Indicator

Mineral Discoveries

(c) By Control of Corruption Indicator   (d) By Governance Indicator

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and one lag of the dependent variable, and controls for a country specific linear time trend. The light blue and dark blue shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters, for the sub-sample with institutions below the median. The intervals for countries above the median include the zero line and are omitted for the convenience of the reader. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 for oil and gas discoveries and 1970-2017 for mineral discoveries. Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018). The 'control of corruption' indicator is from Kaufmann et al. (2010), and the governance indicator was compiled by the authors (see online Appendix A.II).

F CUMULATIVE RESPONSES

Table F1: Cumulative Impact of Giant Discoveries on Government Debt – Alternative Debt Measures

Debt data:	Type of discovery	(1) Time horizons	(2) Cumulative response	(3) Hypothesis test p-value
Net debt	*All discoveries*	0-4	10.140	0.122
		5-10	11.254	0.092
		0-10	21.394	0.087
	Oil and gas discoveries	0-4	-2.228	0.762
		5-10	-2.303	0.804
		0-10	-4.531	0.760
	Mineral discoveries	0-4	14.276	0.077
		5-10	17.747	0.143
		0-10	32.023	0.099
Gross debt	*All discoveries*	0-4	13.613	0.001
		5-10	12.679	0.004
		0-10	26.291	<0.001
	Oil and gas discoveries	0-4	13.834	0.003
		5-10	10.253	0.142
		0-10	24.087	0.012
	Mineral discoveries	0-4	6.863	0.271
		5-10	15.515	0.163
		0-10	22.377	0.158
Financial assets	*All discoveries*	0-4	-6.022	0.109
		5-10	-2.735	0.474
		0-10	-8.757	0.221
	Oil and gas discoveries	0-4	-8.624	0.050
		5-10	-2.031	0.699
		0-10	-10.655	0.173
	Mineral discoveries	0-4	-2.946	0.284
		5-10	-3.973	0.282
		0-10	-6.919	0.256

Notes: Cumulative responses are equal to $\sum_{h=i}^{N} b_h$ where b_h is the impulse response at horizon h, and i and N are the initial and final years, respectively, as shown in Column (1). P-values are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters from Equation 2 (see Figures G1 and G2 for full set of IRFs). The null hypothesis tested is $H_0 : \sum_{h=i}^{N} b_h = 0$. Alternative data compilation and samples are described in detail in Section II. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 (1970-2017 for mineral discoveries). Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Table F2: Cumulative Impact of Giant Discoveries on Government Debt – Alternative Discovery Measures

Discovery variable:	Type of discovery	(1) Time horizons	(2) Cumulative response	(3) Hypothesis test p-value
Intensive margin	*All discoveries*	0-4	1.302	0.455
		5-10	1.518	0.442
		0-10	2.820	0.346
	Oil and gas discoveries	0-4	2.910	0.267
		5-10	4.753	0.112
		0-10	7.663	0.090
	Mineral discoveries	0-4	-1.136	0.737
		5-10	-4.126	0.247
		0-10	-5.262	0.323
	Outcome variable:			
Net present value	Government Debt (GDD)	0-4	-0.046	0.384
		5-10	-0.251	0.002
		0-10	-0.297	0.013
	Gross Debt (WEO)	0-4	0.404	0.040
		5-10	0.311	0.156
		0-10	0.715	0.056
	Net Debt (WEO)	0-4	0.364	0.104
		5-10	0.928	<0.001
		0-10	1.291	0.005

Notes: Cumulative responses are equal to $\sum_{h=i}^{N} b_h$ where b_h is the impulse response at horizon h, and i and N are the initial and final years, respectively, as shown in Column (1). P-values are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters from Equation 2 (see Figures G3 and G4 for full set of IRFs). The null hypothesis tested is $H_0 : \sum_{h=i}^{N} b_h = 0$. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 (1970-2017 for mineral discoveries). Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Table F3: Cumulative Impact of Giant Discoveries on Government Debt – Alternative Samples

Lag specification:	Type of discovery	(1) Time horizons	(2) Cumulative response	(3) Hypothesis test p-value
Subsample of countries	*All discoveries*	0-4	6.436	0.044
		5-10	7.537	0.144
		0-10	13.973	0.079
	Oil and gas discoveries	0-4	9.192	0.038
		5-10	13.460	0.103
		0-10	22.652	0.060
	Mineral discoveries	0-4	3.513	0.417
		5-10	2.701	0.749
		0-10	6.213	0.554
Advanced countries	*All discoveries*	0-4	2.635	0.497
		5-10	13.663	0.159
		0-10	16.297	0.216
	Oil and gas discoveries	0-4	-3.879	0.298
		5-10	9.267	0.315
		0-10	5.388	0.666
	Mineral discoveries	0-4	3.540	0.337
		5-10	-1.597	0.854
		0-10	1.943	0.868
Emerging economies	*All discoveries*	0-4	8.741	0.048
		5-10	23.258	0.018
		0-10	31.999	0.008
	Oil and gas discoveries	0-4	5.902	0.315
		5-10	18.855	0.070
		0-10	24.758	0.108
	Mineral discoveries	0-4	4.888	0.304
		5-10	18.845	0.063
		0-10	23.734	0.051
1980-2010 time period	*All discoveries*	0-4	2.068	0.851
		5-10	1.615	0.888
		0-10	3.684	0.852
	Oil and gas discoveries	0-4	2.939	0.881
		5-10	17.322	0.583
		0-10	20.261	0.674
	Mineral discoveries	0-4	-8.847	0.513
		5-10	-20.641	0.036
		0-10	-29.488	0.099
1970-2000 time period	*All discoveries*	0-4	9.312	0.034
		5-10	5.619	0.240
		0-10	14.932	0.066
	Oil and gas discoveries	0-4	11.145	0.059
		5-10	-0.114	0.981
		0-10	11.031	0.229
	Mineral discoveries	0-4	5.005	0.477
		5-10	14.770	0.071
		0-10	19.775	0.148
	All discoveries	0-4	8.258	0.018
		5-10	11.579	0.018
		0-10	19.837	0.011
	Oil and gas discoveries	0-4	8.635	0.076
		5-10	16.978	0.034
		0-10	25.613	0.028
	Mineral discoveries	0-4	4.554	0.415
		5-10	3.606	0.729
		0-10	8.160	0.545

Notes: Cumulative responses are equal to $\sum_{h=i}^{N} b_h$ where b_h is the impulse response at horizon h, and i and N are the initial and final years, respectively, as shown in Column (1). P-values are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters from Equation 2, where p indicates the lags of government debt variable and q the lags of the discovery dummy (see Figures G6, G13, G14, G7, and G8 for full set of IRFs). The null hypothesis tested is $H_0 : \sum_{h=i}^{N} b_h = 0$. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 (1970-2017 for mineral discoveries). Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Table F4: Cumulative Impact of Giant Discoveries on Government Debt – Alternative Lag Specifications

Lag specification:	Type of discovery	(1) Time horizons	(2) Cumulative response	(3) Hypothesis test p-value
p=2; q=10	*All discoveries*	0-4	8.076	0.015
		5-10	9.785	0.044
		0-10	17.860	0.021
	Oil and gas discoveries	0-4	9.363	0.039
		5-10	14.090	0.036
		0-10	23.453	0.023
	Mineral discoveries	0-4	3.199	0.485
		5-10	2.552	0.745
		0-10	5.751	0.569
p=1; q=15	*All discoveries*	0-4	6.787	0.049
		5-10	6.146	0.216
		0-10	12.933	0.093
	Oil and gas discoveries	0-4	9.373	0.028
		5-10	11.819	0.067
		0-10	21.193	0.024
	Mineral discoveries	0-4	0.687	0.871
		5-10	-2.784	0.702
		0-10	-2.097	0.804
p=1; q=20	*All discoveries*	0-4	4.371	0.172
		5-10	0.939	0.866
		0-10	5.310	0.509
	Oil and gas discoveries	0-4	6.992	0.058
		5-10	7.742	0.306
		0-10	14.734	0.148
	Mineral discoveries	0-4	0.180	0.966
		5-10	-4.613	0.587
		0-10	-4.434	0.653

Notes: Cumulative responses are equal to $\sum_{h=i}^{N} b_h$ where b_h is the impulse response at horizon h, and i and N are the initial and final years, respectively, as shown in Column (1). P-values are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters from Equation 2, where p indicates the lags of government debt variable and q the lags of the discovery dummy (see Figures G9, G10 and G11 for full set of IRFs). The null hypothesis tested is $H_0 : \sum_{h=i}^{N} b_h = 0$. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 (1970-2017 for mineral discoveries). Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Table F5: Cumulative Impact of Giant Discoveries on Government Debt – Alternative Regression Specifications

		(1)	(2)	(3)
Model specification:	Type of discovery	Time horizons	Cumulative response	Hypothesis test p-value
Quadratic time trend	*All discoveries*	0-4	8.662	0.004
		5-10	8.523	0.013
		0-10	17.185	0.004
	Oil and gas discoveries	0-4	6.643	0.063
		5-10	6.875	0.109
		0-10	13.518	0.047
	Mineral discoveries	0-4	10.263	0.032
		5-10	10.882	0.131
		0-10	21.145	0.039
Controlling for debt defaults	*All discoveries*	0-4	8.173	0.012
		5-10	11.587	0.014
		0-10	19.760	0.006
	Oil and gas discoveries	0-4	7.878	0.085
		5-10	17.556	0.012
		0-10	25.434	0.012
	Mineral discoveries	0-4	4.281	0.455
		5-10	1.836	0.838
		0-10	6.117	0.618
Including other controls	*All discoveries*	0-4	8.456	0.106
		5-10	14.967	0.031
		0-10	23.424	0.026
	Oil and gas discoveries	0-4	7.194	0.199
		5-10	14.733	0.062
		0-10	21.927	0.062
	Mineral discoveries	0-4	6.806	0.298
		5-10	12.083	0.075
		0-10	18.889	0.057

Notes: Cumulative responses are equal to $\sum_{h=i}^{N} b_h$ where b_h is the impulse response at horizon h, and i and N are the initial and final years, respectively, as shown in Column (1). P-values are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters from Equation 2 (see Figures G12, G5, and G6 for full set of IRFs). The null hypothesis tested is $H_0 : \sum_{h=i}^{N} b_h = 0$. Controls are geographic location (regional dummies), country size (logged population), level of development (logged real GDP per capita), real GDP growth and inflation rates, current account balance (3-year average) and fiscal deficit as a percentage of GDP, real exchange rate index, openness (export + imports by GDP), armed conflict episodes and quality of political institutions (political risk ratings and polity2 index). All these variables are taken at the time of discoveries. 'Discover' countries are defined as countries with at least one discovery, either oil and gas or mineral, since 1970. The 'time trend' is a country-specific linear trend. All robustness checks are described in detail in Subsection IV.D. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 (1970-2017 for mineral discoveries). Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).
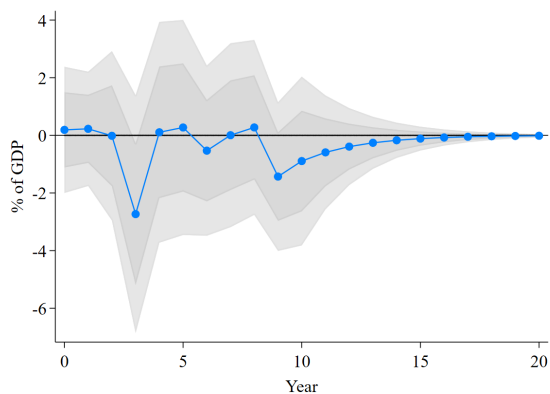
G ROBUSTNESS

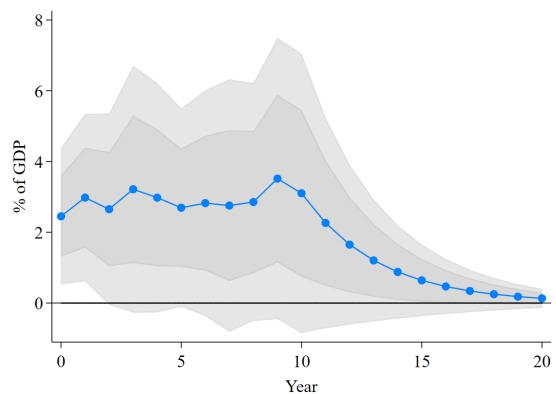## Figure G1: Impact of Giant Discoveries on Government Net Debt

(a) All Discoveries
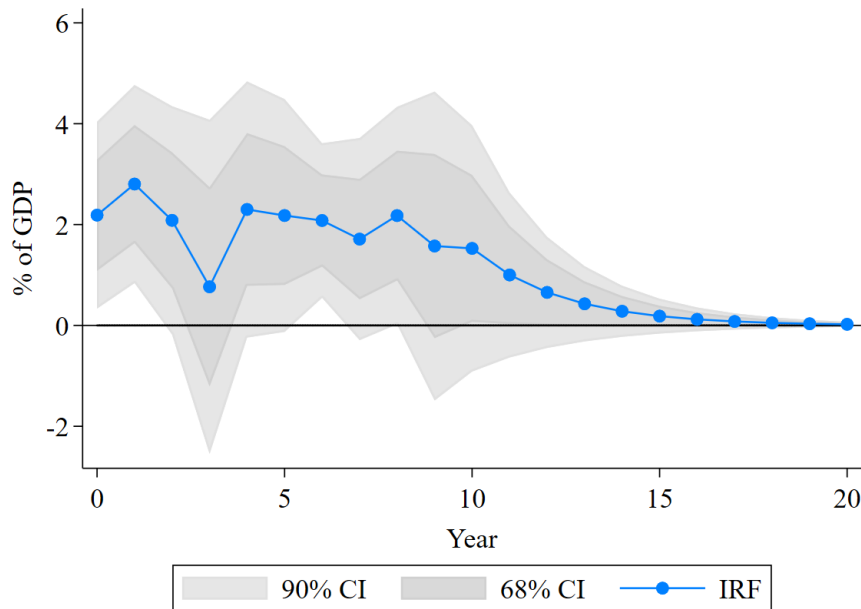
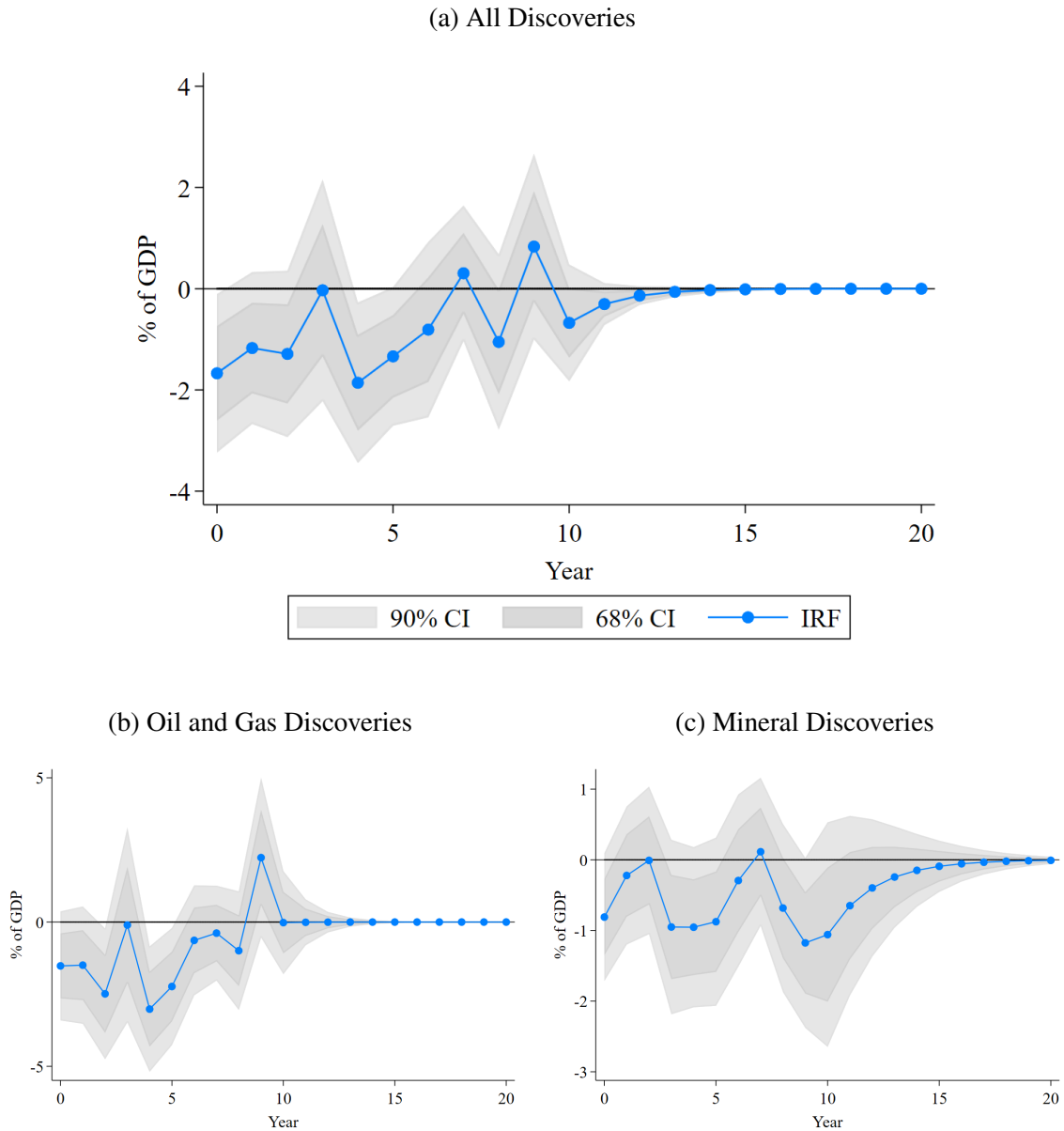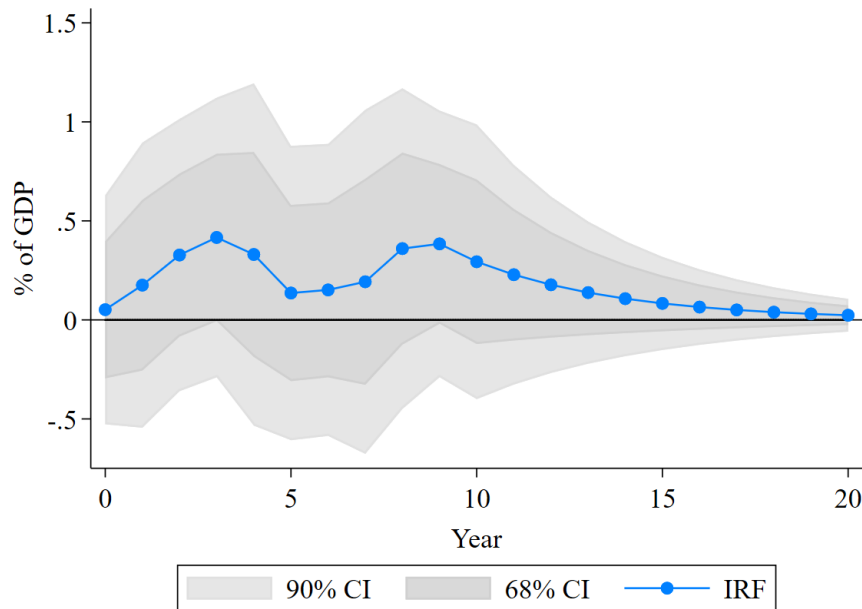### (b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and one lag of the dependent variable. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The sample includes an unbalanced panel of 68 countries on the period 1980-2010. Net debt data are from the IMF's World Economic Outlook and Arbelaez and Sobrinho (2017). Alternative government debt datasets are described in online Appendix A.I. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

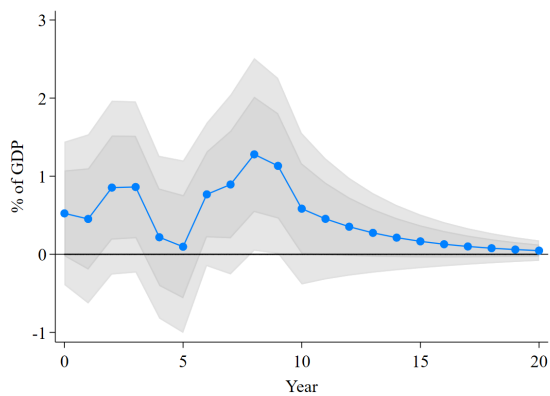Figure G2: Impact of Giant Discoveries on Government Financial Assets

(a) All Discoveries

(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and one lag of the dependent variable. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The sample includes an unbalanced panel of 68 countries on the period 1980-2010. Financial assets data are from the IMF's World Economic Outlook and Arbelaez and Sobrinho (2017). Alternative government debt datasets are described in online Appendix A.I. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure G3: Impact of Giant Discoveries on Government Debt at the Intensive Margin
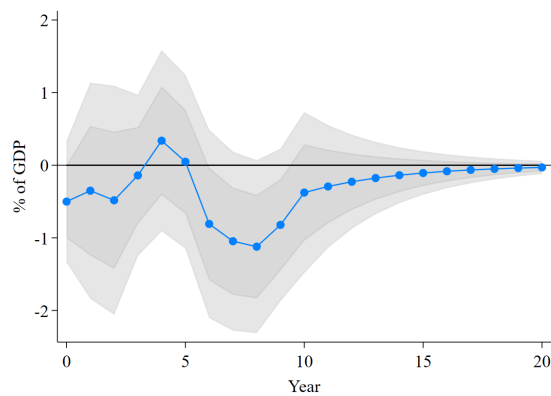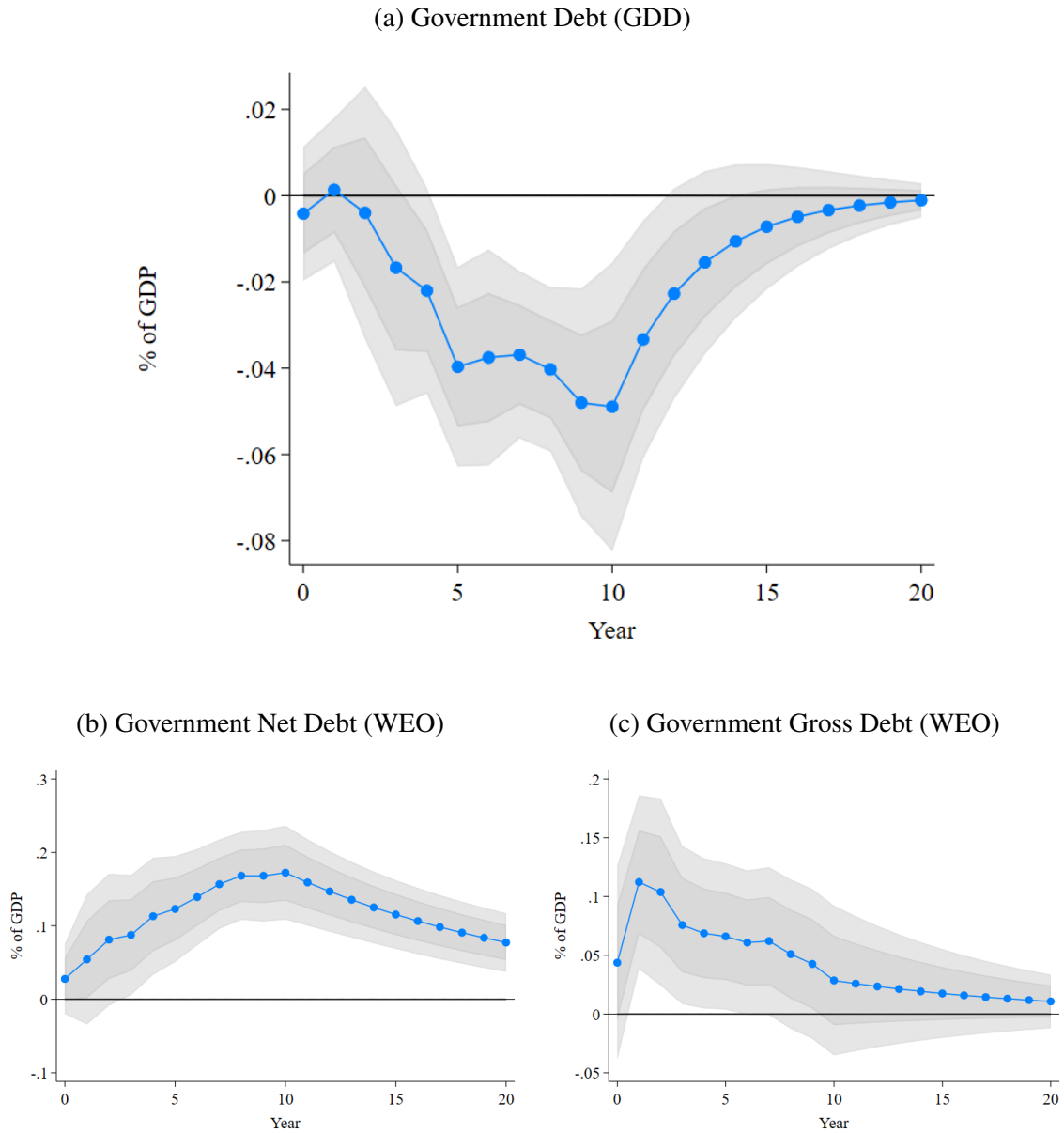
(a) All Discoveries

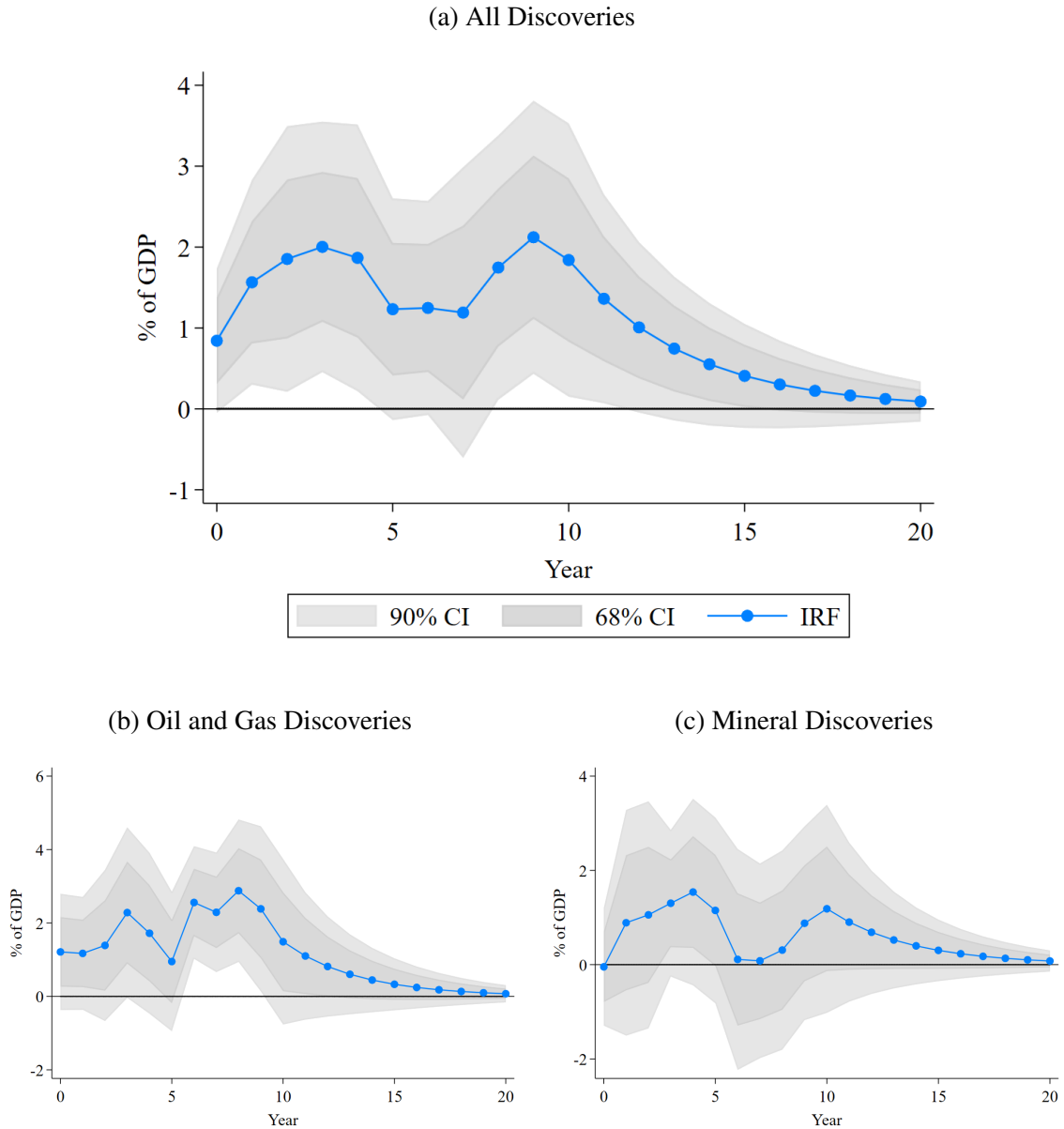(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery indicator variables, defined as the number of discovery in a country-year, instead of as a dummy, and one lag of the dependent variable. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 (1970-2017 for mineral discoveries). Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure G4: Impact of Giant Oil and Gas Discoveries' Net Present Value on Government Debt

(a) Government Debt (GDD)

(b) Government Net Debt (WEO)

(c) Government Gross Debt (WEO)

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery indicator variables, defined as the number of discovery in a country-year, instead of as a dummy, and one lag of the dependent variable. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Net and gross debt data are from the IMF's World Economic Outlook and Arbelaez and Sobrinho (2017). Alternative government debt datasets are described in online Appendix A.I. Oil and gas discovery data are from Horn (2012). The outcome variable is defined in terms of net present value of giant discoveries as a percent of GDP, that is, the discounted sum of gross revenue derived from assuming a production profile from the fifth year after a discovery to the exhaustion year, and valued at the resource price prevailing at the time of the discovery (data from Arezki et al., 2017).

Figure G5: Impact of Giant Discoveries on Government Debt – Controlling for Covariates

(a) All Discoveries

(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and one lag of the dependent variable, and controls for country size, level of development, price inflation, and quality of political institutions (all lagged). The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 (1970-2017 for mineral discoveries). Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure G6: Impact of Giant Discoveries on Government Debt – Subsample of Discoverers
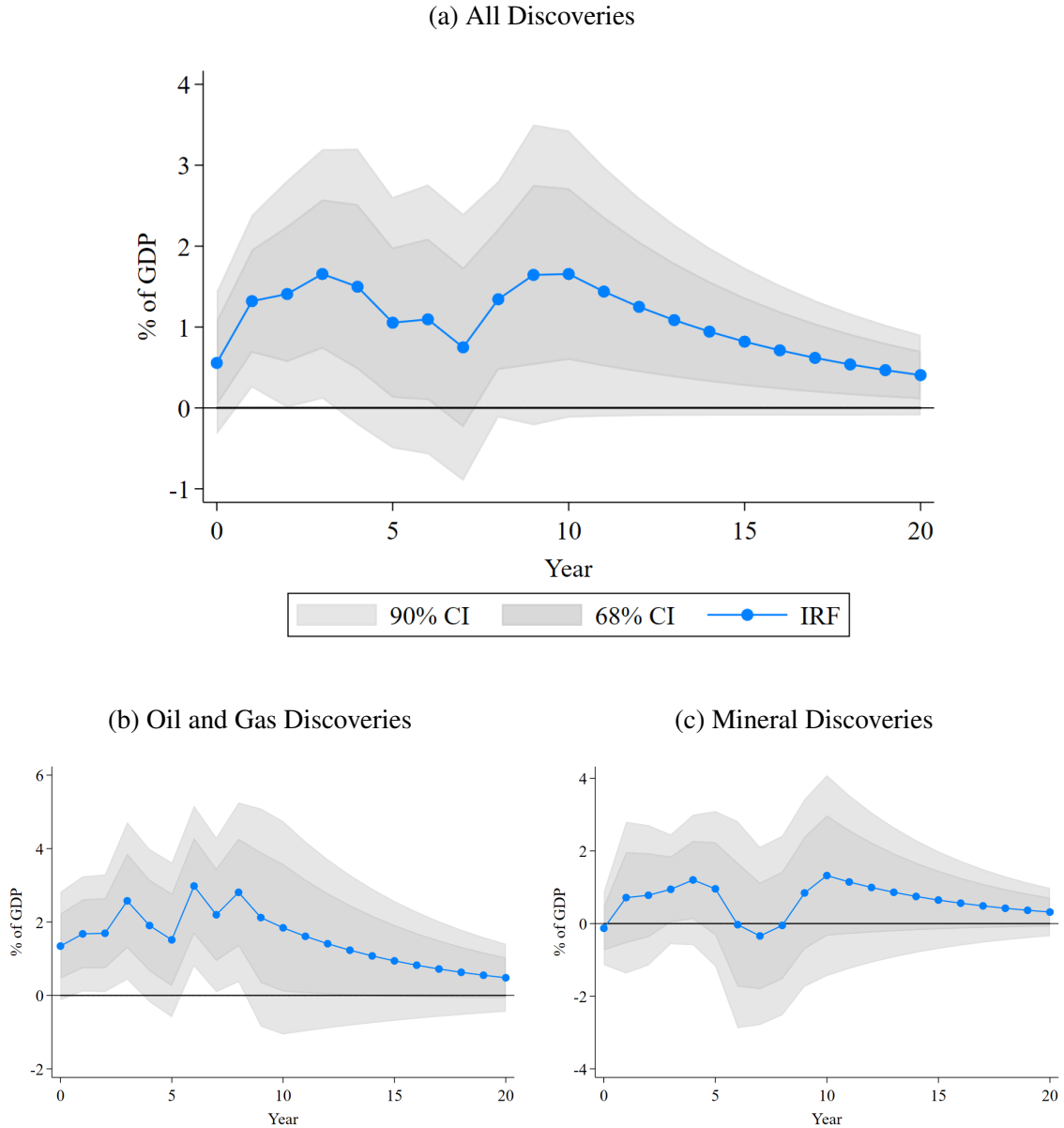
(a) All Discoveries

(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and one lag of the dependent variable. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The baseline sample is restricted to countries with at least one discovery. Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure G7: Impact of Giant Discoveries on Government Debt between 1970 and 2000
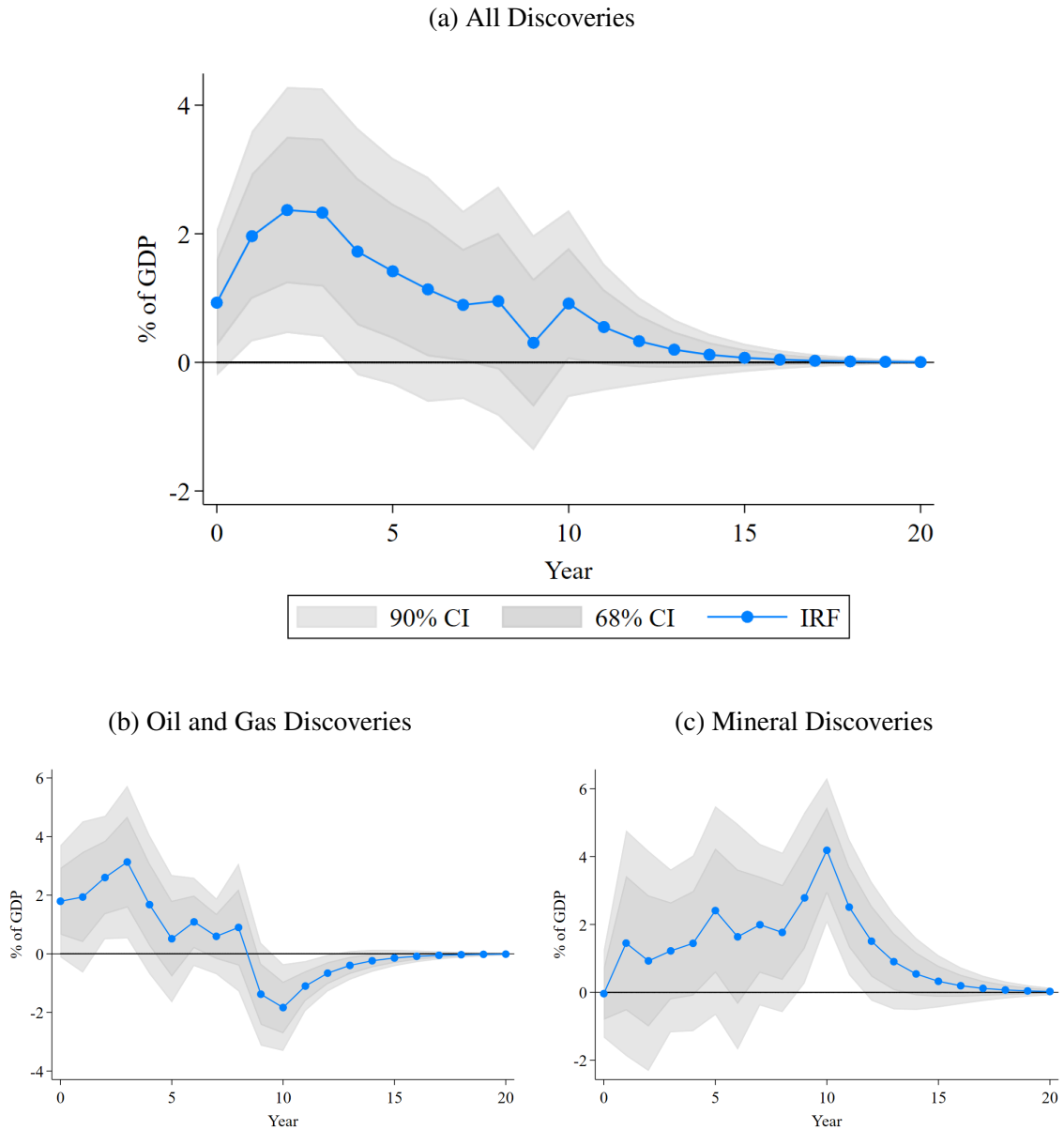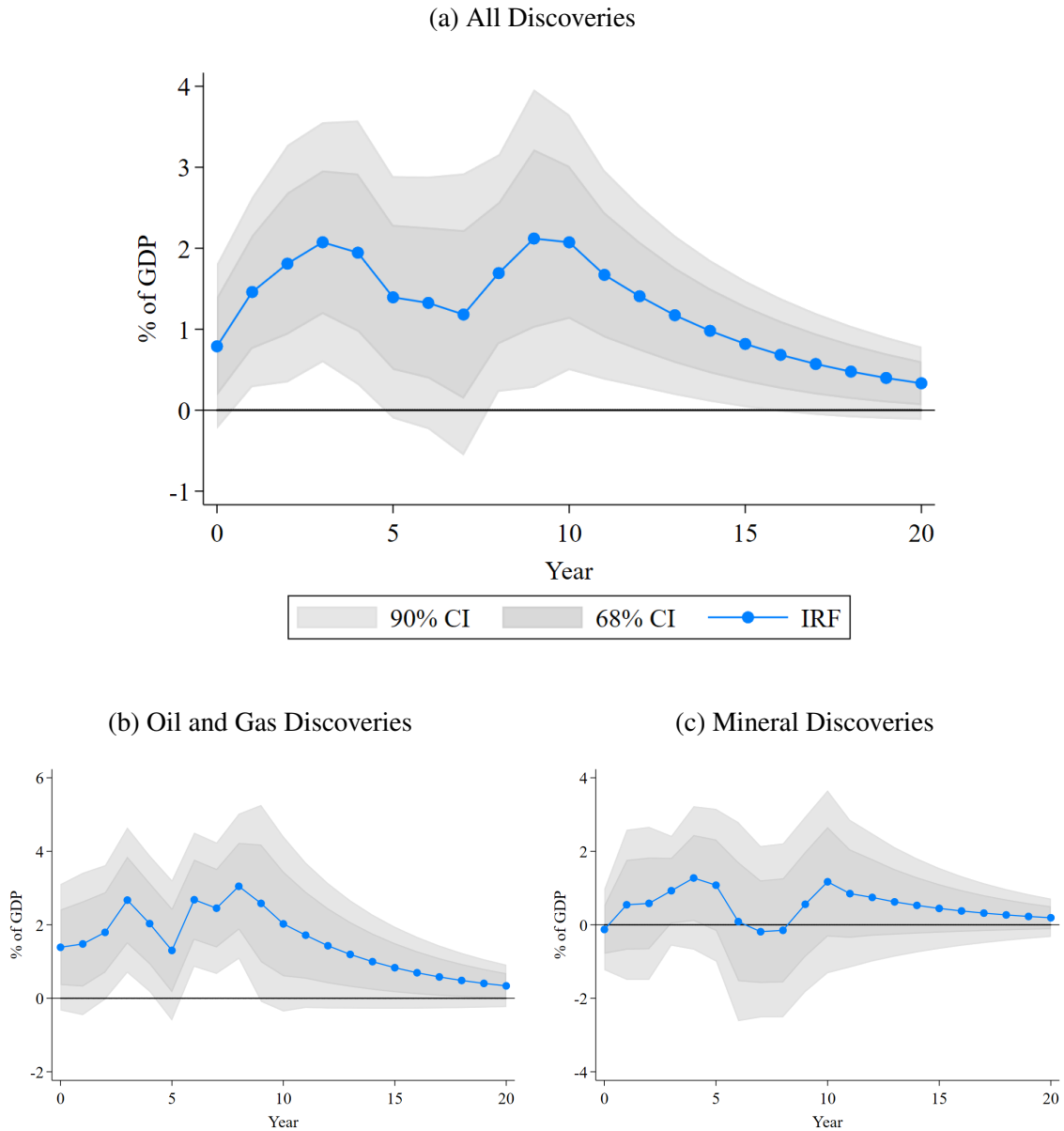
(a) All Discoveries

(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and one lag of the dependent variable. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The sample includes an unbalanced panel of 169 countries on the period 1970-2000. Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure G8: Impact of Giant Discoveries on Government Debt between 1980 and 2010
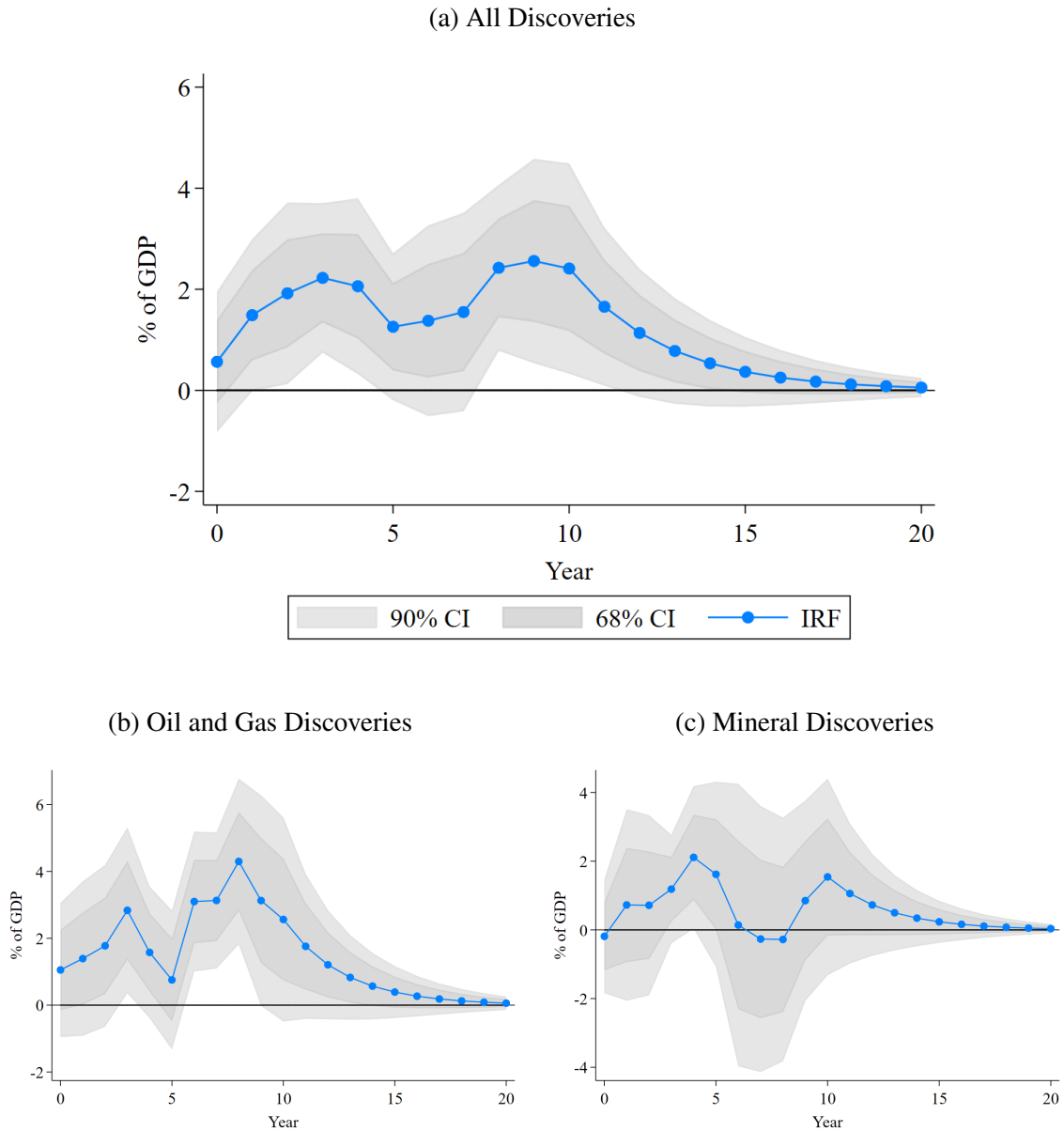
(a) All Discoveries

(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and one lag of the dependent variable. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The sample includes an unbalanced panel of 169 countries on the period 1980-2010. Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure G9: Impact of Giant Discoveries on Government Debt – Lags: $p = 2, q = 10$

(a) All Discoveries

(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and 2 lag of the dependent variable. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 (1970-2017 for mineral discoveries). Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure G10: Impact of Giant Discoveries on Government Debt – Lags: $p = 1$, $q = 15$
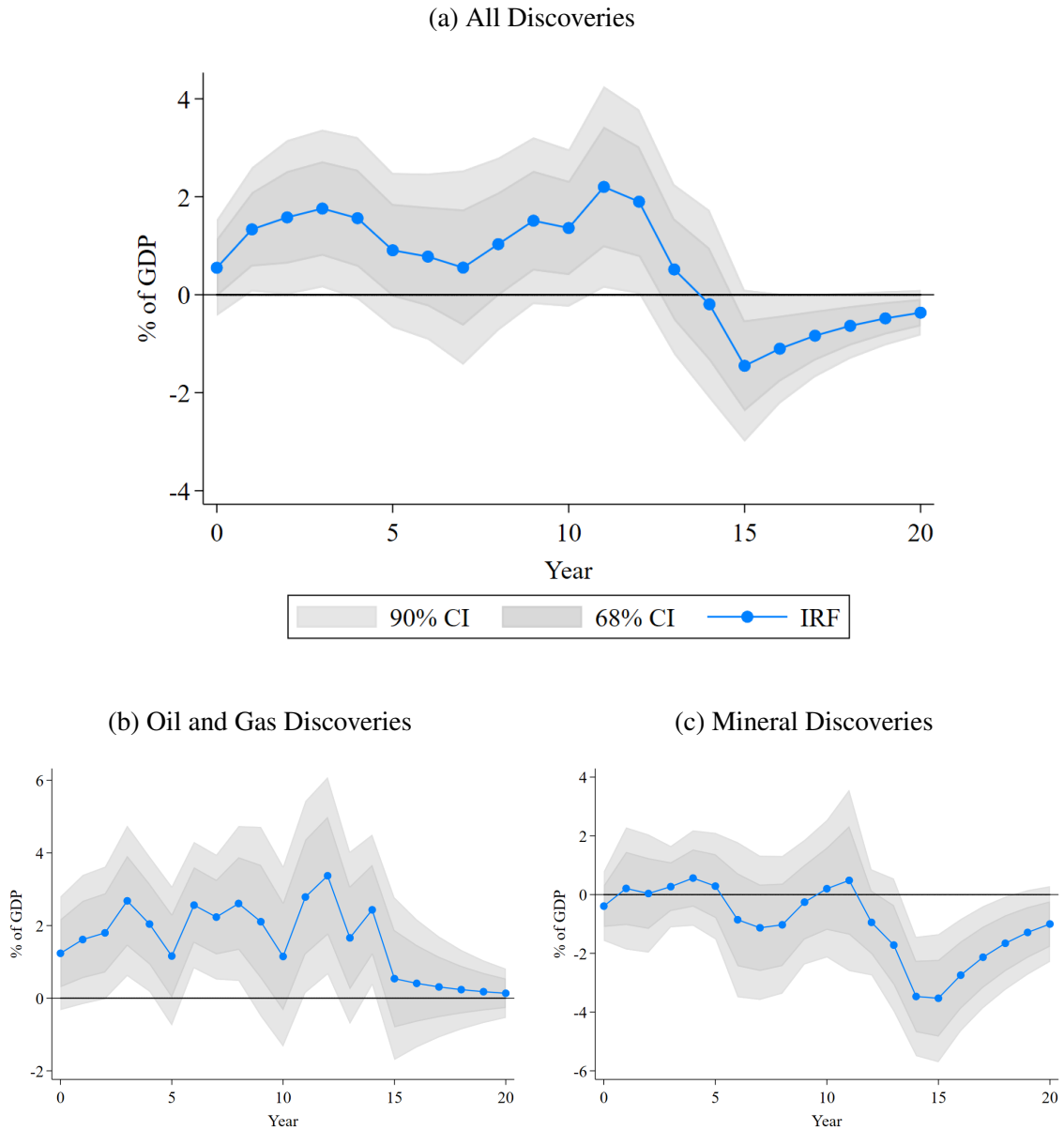
(a) All Discoveries

(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 15 lags of discovery dummies and one lag of the dependent variable. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 (1970-2017 for mineral discoveries). Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure G11: Impact of Giant Discoveries on Government Debt – Lags: $p = 1, q = 20$
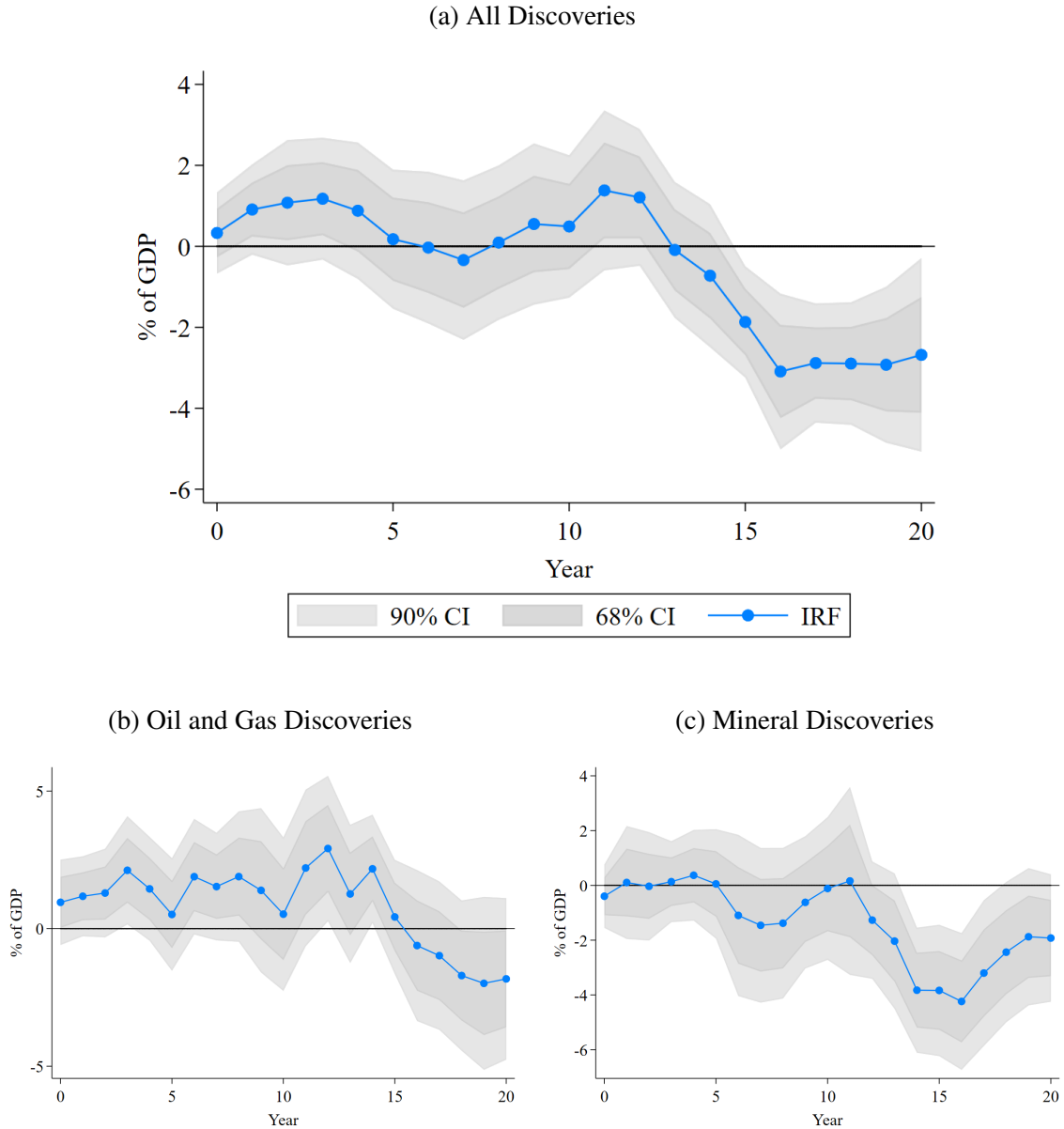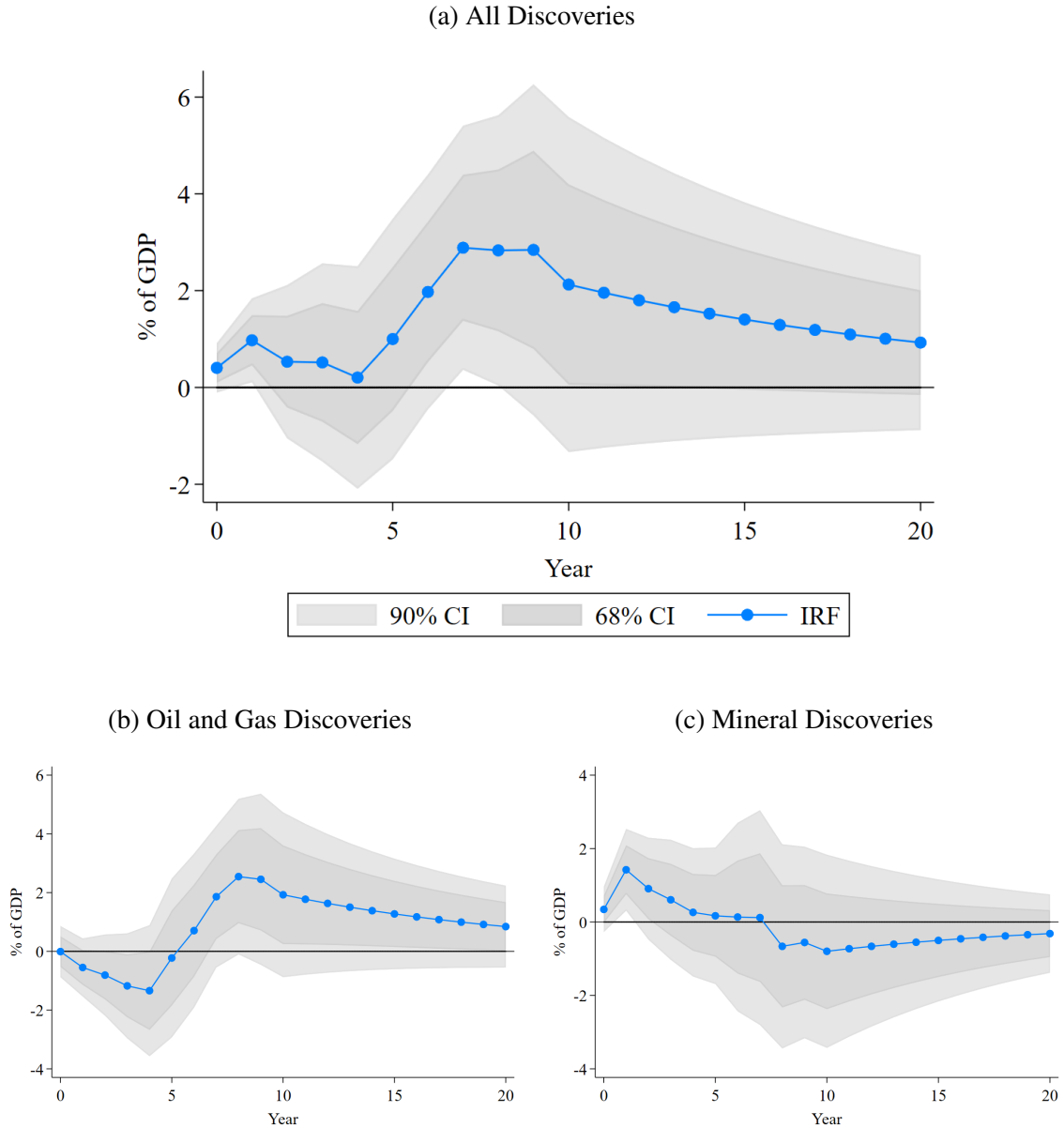
(a) All Discoveries

(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 20 lags of discovery dummies and one lag of the dependent variable. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 (1970-2017 for mineral discoveries). Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure G12: Impact of Giant Discoveries on Government Debt – With Quadratic Trend
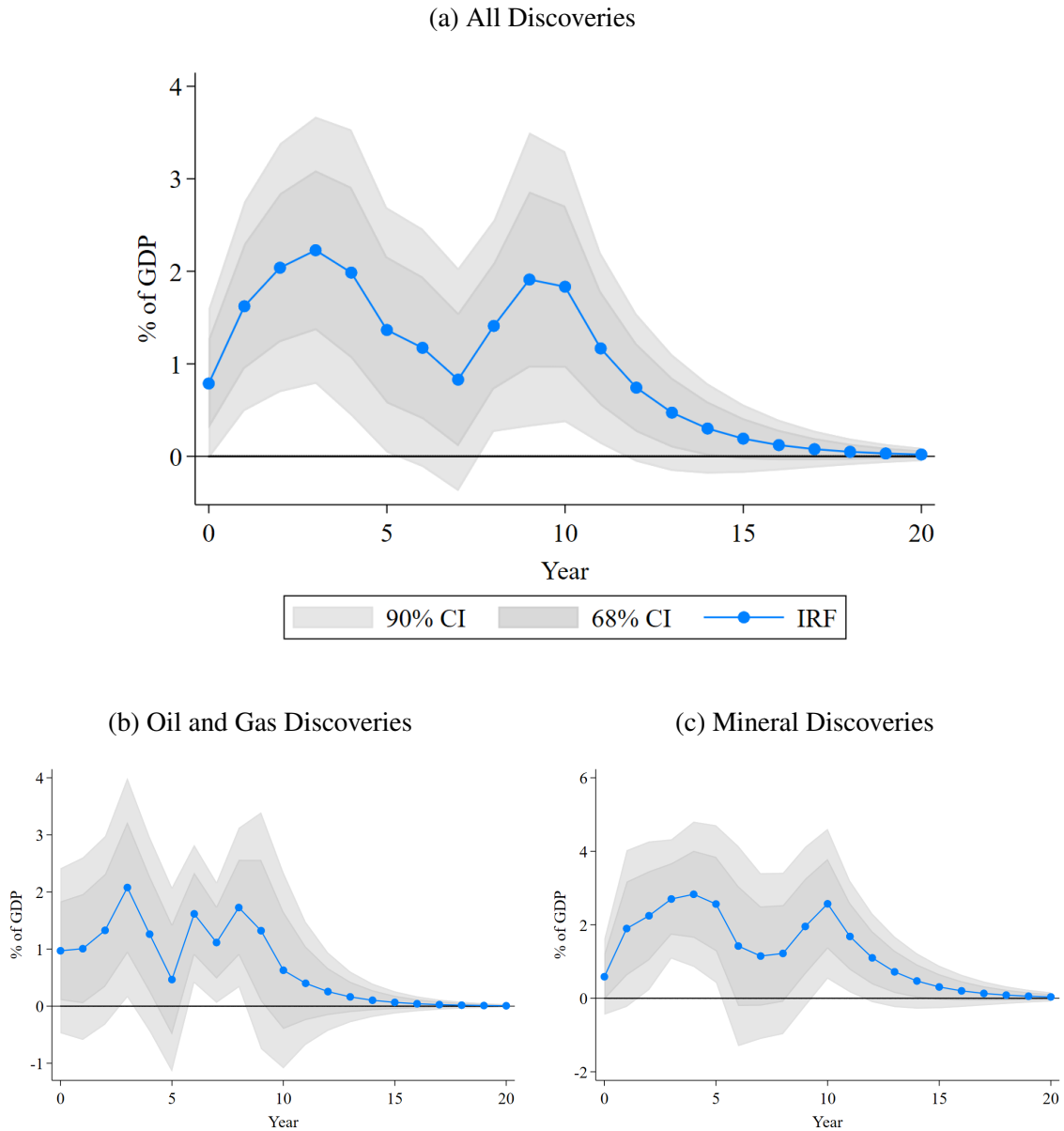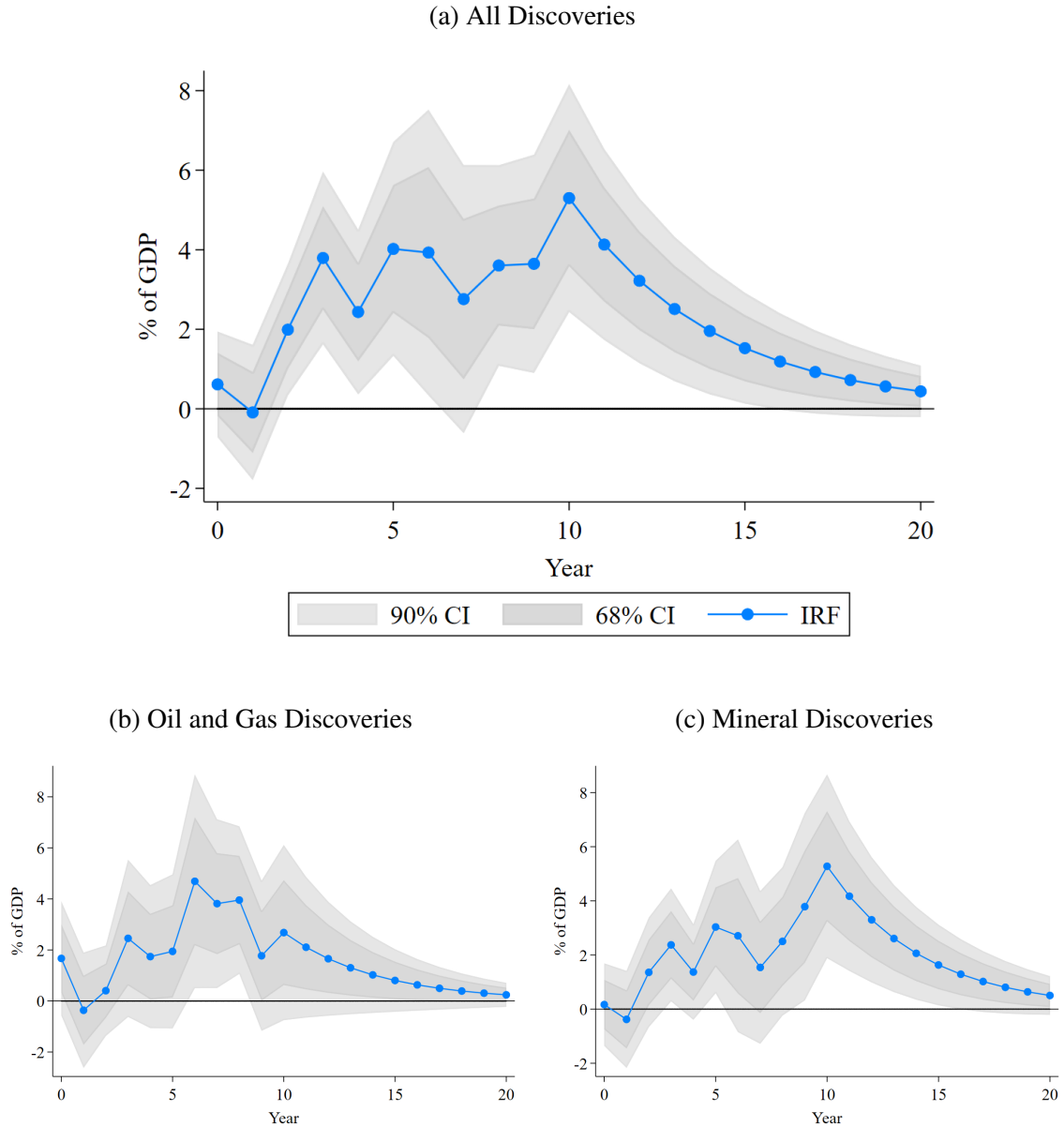
(a) All Discoveries

(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and one lag of the dependent variable, and controls for a country specific quadratic time trend. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The sample includes an unbalanced panel of 169 countries on the period 1970-2012 (1970-2017 for mineral discoveries). Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure G13: Impact of Giant Discoveries on Government Debt in Advanced Economies

(a) All Discoveries

(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and one lag of the dependent variable. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The baseline sample is restricted to advanced economies. Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure G14: Impact of Giant Discoveries on Government Debt in Emerging Economies

(a) All Discoveries

(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and one lag of the dependent variable. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The baseline sample is restricted to emerging economies. Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

Figure G15: Impact of Giant Discoveries on Government Debt in Developing Economies
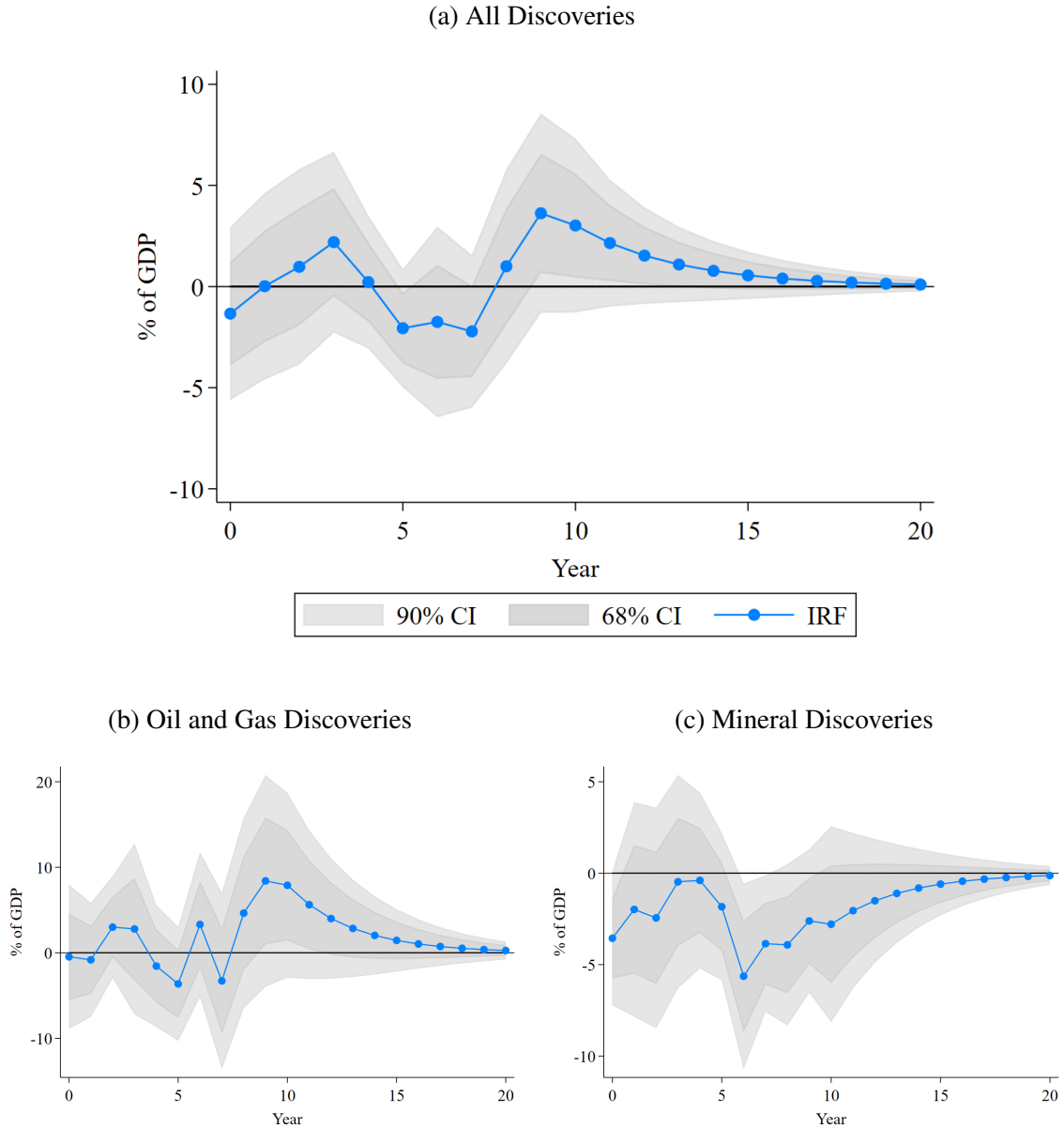
(a) All Discoveries

(b) Oil and Gas Discoveries

(c) Mineral Discoveries

Notes: Estimates from fixed effects regressions with Driscoll-Kraay standard errors. The dynamic model includes 10 lags of discovery dummies and one lag of the dependent variable. The light gray and dark gray shaded areas are the 90 percent and 68 percent confidence intervals, respectively. These are computed using delta method, i.e., nonlinear combinations of OLS-estimated parameters. The baseline sample is restricted to developing economies. Government debt data are from the IMF's Global Debt Database (Mbaye et al., 2018) and authors' compilation. Oil and gas discovery data are from Horn (2012), and mineral discovery data are from *MinEx Consulting* (last update: February 2018).

ONLINE APPENDIX REFERENCES

ABBAS, A., N. BELHOCINE, A. ELGANAINY, AND M. HORTON (2010): "A Historical Public Debt Database," IMF Working Paper No. 10/245.

AISEN, A. AND F. J. VEIGA (2006): "Does Political Instability Lead to Higher Inflation? A Panel Data Analysis," *Journal of Money, Credit and Banking*, 38, 1379–1389.

ARBELAEZ, C. H. AND N. SOBRINHO (2017): "Government Financial Assets and Debt Sustainability," IMF Working Paper No. 17/173.

AREZKI, R., V. RAMEY, AND L. SHENG (2017): "News Shocks in Open Economies: Evidence from Giant Oil Discoveries," *The Quarterly Journal of Economics*, 132, 103–155.

CATÃO, L. AND G. M. MILESI-FERRETTI (2014): "External Liabilities and Crises," *Journal of International Economics*, 94, 18–32.

CRUCES, J. AND C. TREBESCH (2013): "Sovereign Defaults: The Price of Haircuts," *American Economic Journal: Macroeconomics*, 5, 85–117.

GERLING, K., P. MEDAS, T. POGHOSYAN, J. FARAH-YACOUB, , AND Y. XU (2017): "Fiscal Crises," IMF Working Paper No. 17/86.

HORN, M. (2012): "Giant Oil and Gas Fields of the World," Data retrieved from https://edx.netl.doe.gov/dataset/aapg-datapages-giant-oil-and-gas-fields-of-the-world.

IMF (2012): "Macroeconomic Policy Frameworks for Resource-Rich Developing Countries," IMF Policy Paper.

——— (2013): "Republic of Mozambique: Staff Report for the 2013 Article IV Consultation," IMF Country Report No. 13/200.

——— (2016): "Republic of Mozambique: Staff Report for the 2015 Article IV Consultation," Country Report No. 16/9.

——— (2018): "Republic of Mozambique: Staff Report for the 2017 Article IV Consultation," Country Report No. 18/65.

KAUFMANN, D., A. KRAAY, AND M. MASTRUZZI (2010): "The Worldwide Governance Indicators: Methodology and Analytical Issues," World Bank Policy Research Working Paper No. 5430.

MBAYE, S., M. M. M. BADIA, AND K. CHAE (2018): "Global Debt Database: Methodology and Sources," IMF Working Paper No. 18/111.

MCMANN, K., D. PEMSTEIN, B. SEIM, J. TEORELL, AND S. I. LINDBERG (2016): "Strategies of Validation: Assessing the Varieties of Democracy Corruption Data," The Varieties of Democracy Institute Working Paper No. 2016:23.

VREELAND, J. R. (2008): "The Effect of Political Regime on Civil War: Unpacking Anocracy," *Journal of Conflict Resolution*, 52, 401–425.

PUBLICATIONS

The 'Fiscal Presource Curse': Giant Discoveries and Debt Sustainability