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Short-Run and Long-Run News: Evidence from Giant Commodity Discoveries

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Abstract

The bulk of the news shocks literature focuses on shocks materializing after four or five quarters, with limited evidence on news about longer-run events. We build a new dataset of discovery and production start dates for a wide range of giant commodity discoveries worldwide from 1960 to 2012. Standard open economy models match the empirical responses of short-run news but fail in the case of long-run news. Incorporating financial frictions in the form of collateral constraints is crucial for capturing the dynamics implied by long-run news. We also provide direct evidence on the role of these frictions.

Topics: Business fluctuations and cycles; International topics
JEL codes: E23, F3, F4, Q33

Résumé

La plupart des études sur les chocs informationnels traitent des chocs qui produisent des effets après quatre ou cinq trimestres. Il existe peu de données probantes sur l'effet d'informations qui concernent des événements à plus long terme. Nous élaborons un nouvel ensemble de données comprenant les dates de découverte et d'entrée en production d'un large éventail de gisements géants de matières premières trouvés à travers le monde entre 1960 et 2012. Les modèles courants d'économie ouverte réussissent à reproduire les effets observés des chocs informationnels portant sur des découvertes dont l'horizon est à court terme, mais n'y parviennent pas dans le cas des découvertes rattachées à un horizon plus long. Pour bien saisir les dynamiques liées à un tel horizon de long terme, il est primordial d'introduire des frictions financières sous la forme de contraintes sur les garanties. Nous présentons également des données probantes directes sur le rôle de ces frictions.

Sujets : Cycles et fluctuations économiques ; Questions internationales
Codes JEL : E23, F3, F4, Q33

1 Introduction

The seminal work of Beaudry and Portier (2004, 2006) sparked a renewed interest in the idea that news about the future can generate important macroeconomic fluctuations. Our understanding of news shocks is, to a large extent, based on studies that focus empirically on short-run news. This paper brings new insights by analyzing the effects of giant commodity discoveries, which typically materialize over the longer run.

The bulk of the news shocks literature analyzes the effect of shocks that materialize after four or five quarters, with limited evidence on news about longer-run events. Arezki et al. (2017) (henceforth ARS) take an important step in the identification of these shocks by using giant oil and gas discoveries as a measure of news about higher future output. By their nature, giant discoveries are major surprises, accompanied by a lead time of several years before production begins. This makes them an attractive set of macroeconomic events to identify news shocks. We extend ARS analysis by building a dataset of giant discoveries for a wide range of commodities, notably minerals. Importantly, we collect information on both discovery and production dates, which were not available in ARS. This enables us to calculate the time interval between discovery and the start of production, defining the horizon of the news shock.

We start by documenting significant heterogeneity in lead times to production across commodities. In particular, the median lead time for mineral discoveries is about 11 years, which is roughly twice the median lead time for oil discoveries. Oil extraction is faster due to lower upfront development requirements, while mining projects face longer lead times to production due to complex geological, regulatory, and infrastructure challenges. We exploit this heterogeneity to analyze the role of the horizon in the transmission of news shocks.

Using a dynamic panel distributed lag model, we estimate the macroeconomic impact of oil and mineral discovery news shocks for a sample of up to 180 countries over 1960–2012. In response to both types of discoveries, we observe sizable anticipation effects, with a sharp drop of the current account along with a rise in investment and output, *before* production begins. However, the timing of the anticipation effects strongly differs between the two types of discovery news. We find that the macroeconomic effects of mineral discovery news are delayed, with little to no action 4 years into the discovery. This contrasts with the responses to oil discovery news, which exhibit significant fluctuations in the years immediately following the discovery.

We perform several robustness checks and extensions. Our results hold if we keep only countries that experience both types of discoveries, or if we remove discoveries with very long or very short lead times to production. We also examine alternative splits by type of commodity, leveraging heterogeneity in lead times within each category. Our results also remain robust to alternative measures of giant commodity discoveries, different dynamic specifications, and the use of methodologies such as local projections. To further explore the role of the news horizon, we use an instrumental variable approach to predict the lead time to production and then split our sample of giant discoveries based on the predicted lead time, regardless of commodity type. We find that long-run discovery news results in delayed macroeconomic effects, a pattern similar to that observed with mineral discovery news. Overall, our empirical findings highlight the crucial role of the horizon of the news shock.

Our analysis reveals that the standard small open economy model in ARS fails to rationalize the empirical patterns observed in response to long-run news shocks. Specifically, the model exhibits two key shortcomings. First, when a news shock occurs, the country borrows internationally to finance investment in the commodity sector, leading to an immediate drop in the current account.

Second, the model suggests an abrupt reallocation of capital from the rest of the economy to the commodity sector, which causes an initial decline in overall investment.

To address these limitations, we enhance the standard model along two key dimensions. First, we incorporate a *collateral constraint* based on the framework of Mendoza (2002, 2010), where borrowing is limited by the value of collateral. This collateral value depends on the capital stock in the commodity sector and a proportionality factor reflecting the pledgeability of assets. Such resource-backed loans are particularly common in commodity-rich countries, where natural resources serve as collateral for long-term loans from international creditors (Mihalyi et al., 2020; Wang et al., 2023). Second, to mitigate the excessive reallocation of capital between sectors, we introduce *investment irreversibility* in the non-commodity sector, following the work of Pindyck (1991) and Abel and Eberly (1999). The presence of these frictions fundamentally alters the timing of macroeconomic adjustments. In our model, the inability to immediately borrow from abroad or to reallocate capital to the commodity sector forces households to reduce consumption (relative to the counterfactual of no collateral constraint). This allows them to self-finance early capital accumulation and invest in the commodity sector.

Hence, in the case of *long-run news*, it is optimal to postpone the increase in consumption, leading to a more gradual investment response. This results in a delayed but sharper increase in capital accumulation once borrowing constraints begin to ease. This dynamic interaction between collateral constraint, irreversible investment, and the timing of production explains the observed delay in current account responses to long-run news, improving the model's ability to match empirical evidence while maintaining consistency with short-run news dynamics.

Finally, we provide evidence supporting the proposed mechanism. First, we investigate how the macroeconomic impact of commodity discoveries varies across countries with different levels of financial openness. While responses to oil discoveries are similar across both groups, responses to mineral discoveries are delayed only in financially closed countries, suggesting the presence of borrowing constraints. Finally, we examine the impact of commodity discoveries on international capital flows. We find that oil discoveries lead to an immediate increase in foreign direct investment, while mineral discoveries generate a delayed response, which further points to the importance of financial frictions in the transmission of news shocks.

Overview of the literature. This paper contributes to the literature on the macroeconomic effects of news shocks, which has been revived since the seminal works by Beaudry and Portier (2004, 2006) (see, e.g., Jaimovich and Rebelo (2009), Barsky and Sims (2011), Schmitt-Grohe and Uribe (2012), Blanchard et al. (2013), Chahrour and Jurado (2018)). While previous research focuses on short-run news shocks, our study expands on this by examining long-horizon news shocks. Building on the work by ARS, we create a new dataset of giant commodity discoveries, with information on discovery and production start dates, for oil and a wide range of minerals. We document significant heterogeneity in the lead time to production. This allows us to shed light on the effects of long-run news shocks, addressing a significant gap in both theoretical and empirical literature.

Second, this paper contributes to the literature on business cycle fluctuations in open economies. We build on a rich literature which argues that world shocks, such as changes in commodity prices, terms of trade, and interest rates, are major drivers of business cycles in developed and emerging small open economies (see, e.g., Mendoza (1995), Neumeyer and Perri (2005), Fernández et al. (2017), Zeev et al. (2017), Drechsel and Tenreyro (2018), Di Pace, Federico and Juvenal, Luciana and Petrella, Ivan (2024)). While a line of research claims that business cycles in emerging countries are well explained by the canonical small open economy real business cycle model (see, e.g., Schmitt-Grohe and Uribe (2003), Aguiar and Gopinath (2007), Jaimovich and Rebelo (2008)), another strand emphasizes the importance of introducing financial frictions to capture key features of these economies (see, e.g., Uribe and Yue (2006), Garcia-Cicco et al. (2010), Mendoza (2010)). Our analysis of the effects of giant commodity discoveries allows us to contribute to this debate and provide novel insights into the propagation of these shocks. We find that the horizon of news shocks matters and helps to distinguish between the two types of models. Specifically, we show that models with a collateral constraint à la Mendoza (2010) offer a robust framework for understanding business cycles in open economies, not just during crises but also in response to news shocks.

Lastly, this paper adds to the few recent studies which analyze the role of financial frictions in the propagation of news shocks. In a closed-economy setting, Görtz and Tsoukalas (2017) and Görtz et al. (2022) show that the presence of credit supply frictions provide a key amplification mechanism to assign significant empirical relevance to TFP news shocks. Kamber et al. (2017) introduce a working capital constraint in a standard small open economy model to replicate business cycle co-movements in response to news shocks.

Outline. The paper is organized as follows. Section 2 explains the construction of the dataset on giant commodity discoveries and presents summary statistics. Section 3 outlines the econometric specification and presents our empirical results on the dynamic impact of giant commodity discovery news shocks. Section 4 describes the model and how financial frictions affect the propagation of news shocks. Section 5 provides evidence highlighting the presence of financial frictions. Section 6 concludes.

2 Data

A giant "discovery" is an event in which a major deposit of a commodity, whether mineral or oil, is discovered in a given country, in a given year (all our data is annual). Giant discoveries are rare but highly significant events. They represent less than 2% of all mineral discoveries and under 1% of all oil fields, yet they account for 33% of global mineral reserves (Schodde, 2014) and 65% of global oil reserves (Robelius, 2007), respectively. These discoveries are defined based on reserve size.[1] For example, a giant oil field must contain over 500 million barrels, equivalent to the annual oil production of Algeria—a major oil producer and OPEC member. Similarly, a giant gold mine contains at least 200 tons of gold, exceeding the annual gold production of the United States, one of the world's top five gold producers, while a giant copper mine holds at least 4 million tons of copper, which corresponds to the annual output of Chile, the world's largest copper producer.

As argued by ARS, commodity discoveries have two additional features, beyond their size, that make them particularly suited for identifying news shocks. First, they are plausibly exogenous events due to the uncertainty surrounding commodity exploration. The exploration effort, measured by the number of wildcats drilled, is not a reliable predictor of giant oil field discoveries (Tsui, 2011). Our analysis further shows that the size of a country is a major determinant of the probability of a giant discovery, while the level of development has no significant influence. Second, it typically takes several years for production to begin after a giant commodity discovery happens. This lead time can be used to proxy the time horizon of the news shock.

[1] Giant discoveries are defined according to the criteria established by Tkachev et al. (2019) for minerals and Horn (2014) for oil. See Appendix A for details on how definitions vary across commodities.

To estimate the macroeconomic responses to giant commodity discoveries, we combine data from several sources to construct: (i) a dataset on reserves of giant commodity discoveries worldwide, (ii) a newly constructed dataset of both discovery and production dates for these giant discoveries, which allows us to calculate the lead time or horizon of the news shocks, (iii) a dataset of commodity prices, and (iv) a dataset of macroeconomic variables for a large number of countries. In this section, we describe each dataset in turn and present summary statistics. Appendix A provides more details on the commodity discoveries data.

2.1 Giant Commodity Discoveries and Other Macroeconomic Data

Commodity Reserves. The starting point is the database of large and super-large mineral deposits (LSLDs) worldwide, created and continually updated by the State Geological Museum of the Russian Academy of Sciences (Rundquist et al., 2006). Nearly all the information is available online through the "World's Largest Mineral Deposits" WEB-GIS application on the "Metallogeny" Geoportal (Tkachev et al., 2019). This dataset provides detailed information on deposits size and location. To the best of our knowledge, the LSLDs dataset has not been previously used in the economics literature. We complement our mineral discovery dataset with the 2015 version of Horn dataset (Horn, 2014), which contains information on the reserves and location of giant-sized oil and gas fields.

For brevity, unless stated otherwise, throughout the paper we refer to oil and gas as simply "oil". Our final dataset includes information on the estimated total reserves for over a thousand giant discoveries for the period 1960–2012 across the following types of commodities:

- base metals: bauxite, copper, iron ore, lead, nickel, tin, zinc, cobalt;
- precious metals: gold, silver, platinum-group elements (PGE);
- specialty metals: manganese, lithium, chromium, molybdenum, niobium, titanium, tungsten, vanadium;
- mineral sands: zirconium, rare earth elements;
- non-metallic minerals: potash, phosphorus, coal, fluorite, boron;
- diamonds;
- uranium;
- oil and gas.

Discovery and Production Start Dates. A distinctive feature of our final dataset—beyond the inclusion of a broad set of commodities—is high-quality information on production start dates. This allows us to calculate the lead time from discovery to production, which defines the horizon of the news shock. As our results will show, the horizon is crucial for understanding the news effect of these giant discoveries. Descriptive statistics of these lead times to production are presented in the next subsection.

For mineral discoveries, the LSLDs dataset lacks information on discovery and production dates. To address this, we compiled our own dataset on these dates, drawing from a range of sources, including proprietary data. The primary source is a proprietary dataset generously provided by Richard Schodde, Managing Director of MinEx Consulting. This dataset is further supplemented with information from Global Energy Monitor (Global Energy Monitor, 2024), Porter GeoConsultancy (portergeo.com.au), Mindat, The Diggings, the International Atomic

Energy Agency, Mining Technology (mining-technology.com), Rio Tinto, and De Beers, among others.

For oil discoveries, the Horn dataset provides information on discovery dates but lacks production start dates, as noted in ARS (p. 120). To fill this gap, we identified the production start dates for each discovery in the Horn dataset by consulting various alternative sources. These include the Uppsala University Giant Oil Field Database (Höök et al., 2009; Robelius, 2007), the Petroleum Dataset from the Peace Research Institute Oslo (PRIO) (Lujala et al., 2007), Global Energy Monitor (Global Energy Monitor, 2024), the International Atomic Energy Agency, and The Diggings, among others.[2]

After this effort, we managed to obtain the production dates for nearly half of the oil discoveries and two-thirds of the mineral discoveries in our sample.

Commodity Prices. To determine the economic value of the discoveries, we rely on commodity price data. Our primary sources for this data are the U.S. Geological Survey and the World Bank Commodity Price Data, which cover giant commodities starting from 1960. Uranium price data is obtained from TradeTech (`www.uranium.info`).

Macroeconomic Data. Our main macroeconomic data source is similar to ARS, namely the IMF World Economic Outlook. Our macro dataset contains information on GDP, investment, consumption, the current account, the saving rate, and the employment rate for 181 countries. Our baseline estimation is based on the 1980–2012 time span at the yearly frequency.[3] All national accounts data are provided in real local currency units. For GDP, we also use a series in real USD in order to compute the value of the discovery (in USD) as a percentage of GDP. We also note that the dataset contains some extreme values, such as a drop in the current account in Kuwait from 20% of GDP in 1990 to -224% in 1991 (due to the Gulf War.) We have checked that the results are not driven by these rare instances. Finally, to investigate the role of financial frictions in the impact of commodity discoveries, we also use panel data on capital flows from Alfaro et al. (2014), which is normalized by the annual nominal GDP in USD.

2.2 Descriptive Statistics

Table 1 contains a first set of descriptive statistics for all commodities in our merged dataset (minerals and oil). It lists the total number of discoveries across commodities, along with their value, which is calculated by multiplying reserves (in physical quantities) by the prices at the time of discovery, expressed in billions of 1998 US dollars.

Our sample includes a total of 220 mineral discoveries, with more than one-third of these being base metal discoveries. The second and third most common types of mineral deposits are precious metals and uranium. The sample also contains 421 oil discoveries and 388 gas discoveries. As we will discuss below, many of these oil and gas discoveries occur in the same country and year. Although there are fewer mineral discoveries than oil discoveries in the data, their economic significance is similar. The average value of a mineral deposit is USD 51 billion, while the average

[2]For the Petroleum Dataset, we used the PETRODATA V1.2 update.

[3]Similar to ARS, due to data limitations, we cannot start earlier. Before 1970, the macroeconomic data is mostly available for advanced economies. Even though our estimation starts in 1980, we use the information on discoveries pre-1980 in the ADL model below. We also point out that the World Economic Outlook misses some of the series for some countries even after 1980—the most complete series being GDP—and therefore these are automatically dropped from the regression.

values of oil and gas deposits are USD 50 billion and USD 83 billion, respectively. Additionally, there is substantial heterogeneity in deposit values.

Diamond and precious metal discoveries have the lowest mean values, whereas base metal discoveries, particularly copper, stand out with the highest averages.

Table 1: Giant Discoveries Merged Data Set: Type, Number, and Value (bln 1998 USD), 1960–2012

	Obs.	Mean	Median	Std. Dev.	Min	Max
Minerals	**220**	**51**	**13**	**119**	**13**	**958**
Base Metals	85	83	37	152	.58	958
Precious Metals	65	12	9	11	1.7	62
Specialty Metals	8	121	23	269	6.9	785
Mineral Sands	14	29	21	29	.16	85
Non-Metallic Minerals	13	137	92	138	3.3	438
Diamonds	10	4.9	4	3.8	.13	10
Uranium	25	12	7	17	1.1	82
Oil & Gas	**792**	**58**	**21**	**204**	**2.8**	**4,997**
Oil	417	50	20	100	2.8	1,141
Gas	375	67	21	278	2.8	4,997

Figure 1 shows the geographical distribution of discoveries. These discoveries happened in 96 countries between 1960 and 2012. 26 countries in the sample have experienced only one discovery.

It is interesting to note that discoveries are well spread out around the globe. There are more oil discoveries in our data; consequently, a country is more likely to experience an oil discovery than a mineral discovery. Moreover, large countries have—naturally—a higher probability of multiple discoveries of both oil and minerals. On the contrary, small countries often have no discovery.

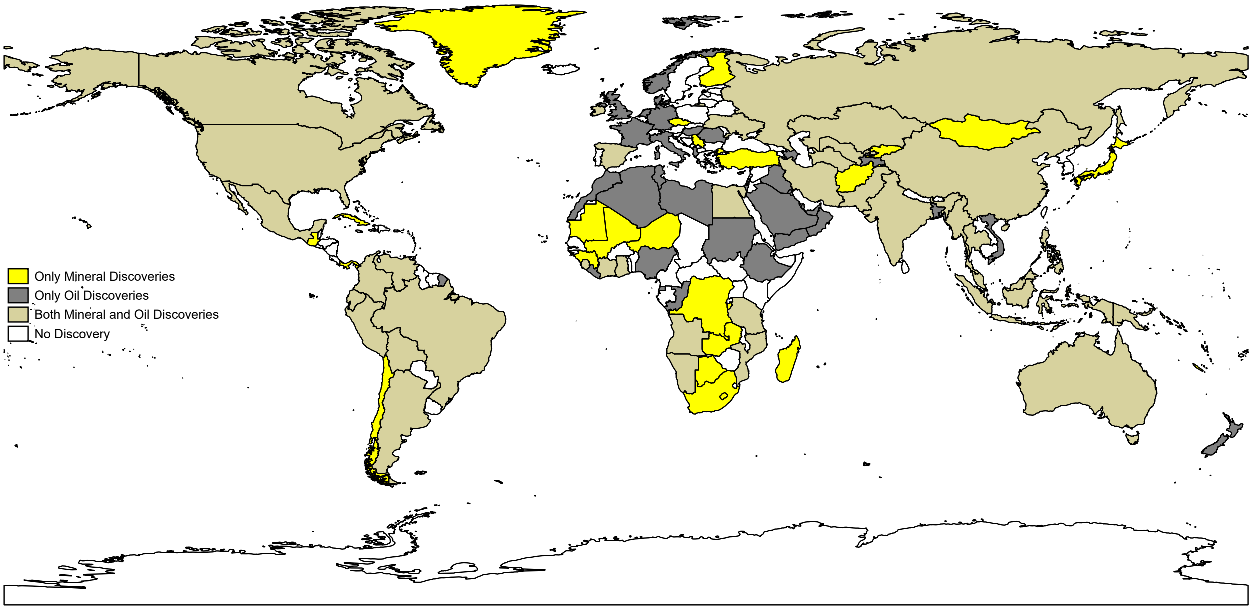
Commodity discoveries require significant lead time of several years or even decades before production begins. These lead times in developing resource fields and mines stem from a complex mix of technical, regulatory, environmental, safety, economic, and geopolitical challenges, despite continuous efforts to push projects forward.[4] Overcoming these obstacles often necessitates collaborative efforts, involving cooperation among governments, private companies, and international organizations. Figure 2 shows histograms of these lead times to production for minerals (left) and oil (right) discoveries.[5] We note that minerals exhibit significantly longer lead times to production, with a median of 11 years, compared to 6 years for oil discoveries.[6] Oil extraction is faster due to lower upfront development requirements, while mining projects face longer lead times to production due to complex geological, regulatory, and infrastructure challenges. Mineral deposits are often more challenging to locate and extract, requiring deeper exploration and more specialized extraction techniques. Mineral mining requires extensive infrastructure, including roads, tunnels, and processing plants, with many deposits

[4] In Appendix A.3, we provide further details on the discoveries that experienced lead times to production of over 40 years.

[5] Ideally, we would want to have access to the ex-ante (expected) lead time once a discovery is made. This data, however, is not available. The implicit assumption in our statistical analysis below is that agents form a rational expectation on the lead time conditional on the information of the type of discovery (essentially the type of commodity).

[6] ARS assume that the typical lead time for oil discoveries is 4 to 6 years. We confirm this assumption in our sample, with a median lead time of 6 years for this type of discoveries.

Figure 1: Geographical Distribution of Giant Mineral and Oil Discoveries, 1960–2012



needing significant excavation and waste management, which can take several years to develop, particularly in remote locations. In addition, mining projects often face more intense regulatory and environmental scrutiny.

Moreover, we observe substantial heterogeneity in lead times across discoveries for each type of commodity, ranging from 0 years to several decades, resulting in a long right tail in the empirical distributions. However, the distribution of lead times for mineral discoveries is relatively uniform, while the distribution for oil discoveries is more concentrated around the median. Notably, for approximately 5% of oil discoveries, production began in the same year as the discovery.

A key distinction between the mineral discovery data and the oil data used by ARS lies in these lead times to production, which define the horizon of the news shocks.

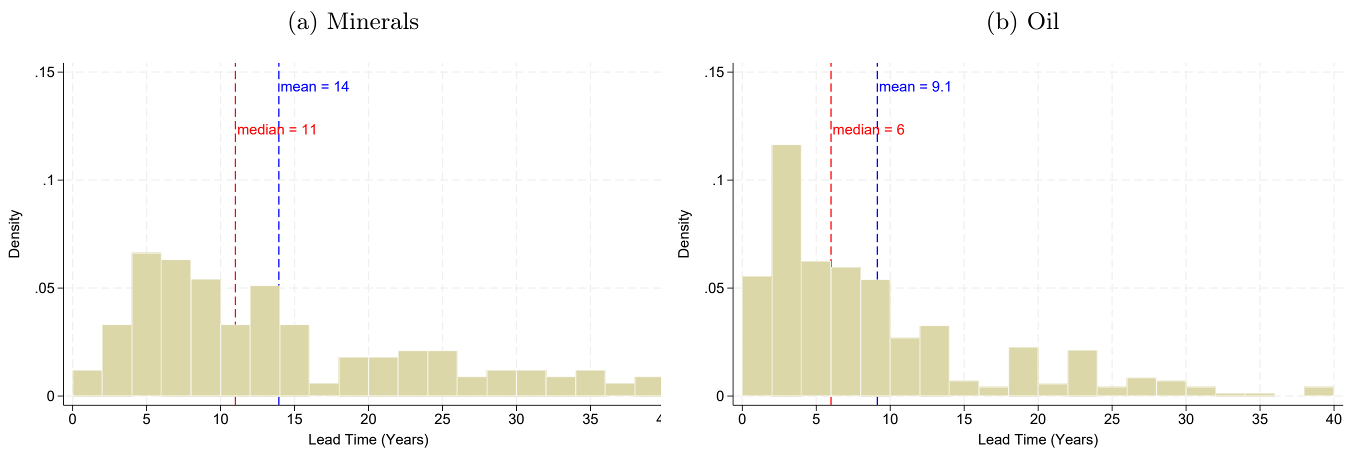
Table 2 shows some descriptive statistics of the lead times to production. Notably, there is considerable variability within each commodity type. Specifically, gas discoveries tend to have longer lead times compared to oil, with an average lead time of 11 years versus 8 years for oil. Gas discoveries typically take longer to reach production than oil due to the complex infrastructure required for transportation and processing, especially in offshore or remote locations. As final markets are typically distant, gas discoveries require simultaneous investments in drilling and transport infrastructure. Among minerals, our data shows that precious metals experience the shortest lead times, averaging around 9 years, while uranium and base metals discoveries have the longest lead times, averaging 19 and 17 years, respectively. Gold deposits tend to be either high-grade underground mines that require less infrastructure or near-surface deposits that involve less complex and quicker exploration, studies, and construction. On the other hand, longer lead times for base metals such as copper reflect more intensive exploration of deeper deposits and greater infrastructure to bring into production and transport the ore to export markets.[7]

[7]For example, the proximity of Chile's copper mines to the sea has facilitated the profitable shipment of concentrates, while copper mines in central Africa have had to depend on local smelting and refining to minimize the volume of material transported to ports (Crowson, 2011).

In addition, uranium discoveries face heavy environmental and safety requirements due to the radioactive nature of the commodity.

We will exploit this remarkable heterogeneity in lead times between oil and minerals, but also within each commodity type, to analyze the role of the horizon in the transmission of news shocks.

Figure 2: Histograms: Lead Time (in years) from Discovery to Production Start



Notes: For presentation purposes, in these histograms we do not include discoveries with lead time greater than 40 years (there are 6 oil discoveries and 6 mineral discoveries with lead time greater than 40 years).

Table 2: Giant Discoveries Merged Dataset: Lead Time (in years) from Discovery to Production Start 1960–2012

	Obs.	Mean	Median	Std. Dev.	Min	Max
Minerals	**147**	**14**	**11**	**11**	**0**	**58**
Base Metals	51	17	13	12	1	58
Precious Metals	52	8.9	6	7.4	0	36
Specialty Metals	4	16	10	15	6	38
Mineral Sands	5	11	8	7.7	4	23
Non-Metallic Minerals	5	16	9	17	4	45
Diamonds	9	13	10	10	4	32
Uranium	21	19	16	11	5	39
Oil & Gas	**358**	**9.1**	**6**	**9.4**	**0**	**55**
Oil	223	8	5	8.2	0	42
Gas	135	11	7	11	0	55

3 Macroeconomic Effects of Giant Commodity Discoveries

In this section, we describe the econometric specification and present our baseline empirical results for the dynamic impact of giant commodity discovery news shocks on relevant macroeconomic variables. We document that macroeconomic responses to commodity discovery news shocks are delayed, with little or no action 4 years into the discovery. A news effect appears only 2 or 3 years before production starts. After splitting by commodity type, we find that this result is driven by mineral discovery news shocks, characterized by significantly longer lead times to production than oil discovery news shocks.

3.1 Empirical Model

We follow ARS and use an autoregressive distributed lag (ADL) regression model to estimate the response of key macroeconomic variables to a giant commodity discovery. Specifically, we estimate the following linear regression:

$$y_{it} = ay_{i,t-1} + B(L)MV_{it} + \alpha_i + \mu_t + \varepsilon_{it} \tag{1}$$

where y_{it} is the value of a dependent macroeconomic variable in country i at time t. Given our focus on the open economy dimension, our analysis centers on the following three dependent macroeconomic variables: the ratio of investment over GDP, the ratio of CA over GDP and log GDP.

MV_{it} is the monetary value of the commodity deposit discovered in country i in year t (fully described below) normalized by GDP. α_i denotes country fixed effects, which control for unobserved time-invariant country-specific characteristics (like geographic features), and μ_t denotes time fixed effects, which control for global trends or events (like commodity price shocks, global economic downturns, etc.) that might affect all countries in a given year. ε_{it} is a homoscedastic disturbance. $B(L)$ is a pth order lag polynomial, with $p \geq 0$. Impulse responses are derived from the ADL model's coefficients by recursively combining the direct effects of discovery shocks, captured by the coefficients of $B(L)$, with the dynamic feedback effects from the dependent variable's lag, governed by the a coefficient.

Next, to compare the dynamic effects of mineral and oil news shocks, we extend this regression model as follows:

$$y_{it} = ay_{i,t-1} + B(L)MV^O_{it} + C(L)MV^M_{it} + \alpha_i + \mu_t + \varepsilon_{it} \tag{2}$$

where $C(L)$ is a qth order polynomial, with $q \geq 0$. This specification accommodates separate analysis of the effects of each type of discovery by allowing distinct coefficients for all independent variables.[8] For Equation (1), we pick p=15, which is roughly twice the median lead time between discovery and production dates in the sample. Similarly, for Equation (2), we pick p=10 and q=20. Following ARS, we do not include controls (beyond country and time fixed effects) to compute our baseline estimates. In regressions using log levels of variables (rather than percent of GDP) and employment rate, we also include (country-specific) linear trends. Under the assumption—introduced by ARS—that giant discoveries are exogenous, these regressions can be estimated by OLS. Standard errors are computed applying the Driscoll and Kraay (1998) correction.

To measure the size of a commodity discovery, we construct its monetary value (MV) as percent of GDP. This measure differs from the net present value used in ARS, as it abstracts from the

[8] This specification assumes identical autoregressive coefficients (and other control variables) for both types of discoveries. However, when we estimate the regressions separately for each discovery type, the results remain consistent.

production profile. This simplification allows us to accommodate very different types of minerals, which largely differ in their production profiles and timing.[9] Specifically, we use the following formula for MV_{it}:

$$MV_{it} = \frac{100}{GDP_{it}} \times \sum_{\{\text{discovery } j\}} \left[\frac{Res_{jit} \times p_{jit}}{(1 + r_{it})^{LT_{jit}}} \right]$$

where LT_{jit} is the observed lead time from the year of discovery to the start of production, Res_{jit} the estimated reserves (quantity), and p_{jt} the price of the commodity of discovery j in country i at time t.[10]

Due to data limitations, we do not observe the lead time for all discoveries (see Section 2.1 for more details), in which case we use the average of our sample.

The summation is over discoveries, because it is possible—and actually observed in our data—that two or more discoveries happen in a given country in the same year.[11] GDP_{it} is the output of country i at time t, and r_{it} is the country-specific risk-adjusted rate used for discounting. In countries with high political risk, the development of commodity fields can become extremely difficult, if not entirely unfeasible. Consequently, discoveries in such regions must be discounted more heavily compared to those in lower-risk countries, to compensate for political and economic risk. The adjusted discount rate is calculated by adding a country-specific risk premium, based on a NYU report compiled by Damodaran (2019), to a risk-free rate based on the prevailing rate in the United States.

3.2 Pooled Oil and Mineral Discoveries

We start the analysis by examining the aggregate effects of all giant commodity discoveries—both oil and mineral—in our sample. Figure 3 displays the estimated impulse responses of the current account-GDP ratio, the investment-GDP ratio and GDP to a commodity discovery news shock. In this pooled sample, the median lead time between the discovery date and the start of production is 7 years, indicated by a vertical red dashed line on the plots. The 68% and 90% confidence bands are shown in all cases.

As regards the current account, we observe a long initial period with a small or nil reaction, followed by a sharp decline after 5 years and sequential reversal. It reaches a trough 6 years after the discovery, i.e., 1 year before the median start of production. Then, the response of the current account turns positive and reaches a peak about 10 years after the discovery, before gradually returning to normal. The response of investment reflects the response of the current account. Investment starts to rise significantly after 4 years and reaches a peak 6 years after the discovery, with no reaction during the first 3 years. The response of investment quickly returns to normal after the start of production. Regarding GDP, there is a strong positive impact a few years after the discovery, which peaks after 7 years, followed by a slow return to normal.

Quantitatively, the estimates indicate that GDP peaks at 0.015 in year 8, meaning that the median discovery—which is of size 8% of GDP—raises GDP by 8% × 0.015 = 0.12%. The total

[9] ARS embed in the net present value the notion of a discounted production profile for oil fields. This is difficult to do in our case given the large heterogeneity of minerals and, likely, respective extraction technologies.

[10] Results are similar if we use the average lead time by commodity type instead of the observed lead time for each discovery.

[11] The summation takes into account that different minerals may be discovered in the same field. Note that MV_{it} is expressed as a percentage of GDP and differs from the value of discovery in dollars ($Res_{jit} \times p_{jit}$) prior to aggregation across discoveries, as reported in Table 1. The descriptive statistics for MV_{it}, both for the pooled sample and for oil and mineral discoveries separately, can be found in Appendix A.2 (see Table 7).

cumulated effect of this discovery is the integral below the impulse response and is equal to 0.188. This means that the median discovery leads to a total increase of GDP of $8\% \times 0.188 = 1.5\%$. Similarly, investment peaks at 0.06% of GDP, with a cumulative increase that represents about 0.26% of GDP. The current account falls by 0.08% of GDP and later peaks at 0.07% of GDP.

Similar to ARS, we find evidence of anticipation effects in response to these discovery news shocks, as current account, investment, and GDP react before the median start of production. A standard news effect appears to kick in: this effect generates a procyclical response of investment and GDP. At that moment, the economy borrows from abroad, generating a fall in the current account. When production starts, the response of the current account turns positive, as output rises and investment starts to decline. However, the timing of the anticipation effects strongly differs from ARS. In contrast to ARS, there is relatively little or no impact, in any of the variables, 4 years into the discovery. In addition, we observe significant fluctuations in both the current account and investment up to 15 years after the discovery, although the estimates for investment are imprecise. In contrast, in ARS the effects begin to fade after 10 years.

This raises the question of what accounts for these differences. Why are the responses of macroeconomic variables to a commodity discovery more delayed, with fluctuations persisting even after 10 years, compared to the responses to an oil discovery as observed in ARS? One obvious explanation is that our sample includes not only oil discoveries, but also mineral discoveries. As discussed in Section 2, the lead time before production start of new mines is significantly longer than that for new oil fields, notably due to geological, regulatory, and infrastructure challenges.

To investigate this hypothesis, we next split our sample of giant discoveries by commodity type in order to compare the dynamic responses to an oil discovery and to a mineral discovery.

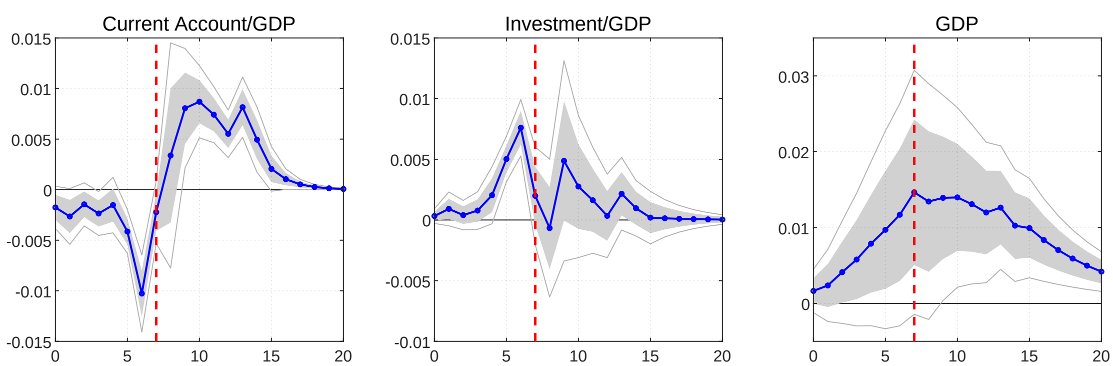


Figure 3: Impulse responses to commodity discoveries

Notes: These graphs show the estimated impulse responses of aggregate variables to a commodity news shock. The vertical red dashed line indicates the median lead time between the discovery date and the start of production date (7 years). 90% and 68% confidence intervals are shown in all cases.

3.3 Split by Commodity: Oil vs. Mineral Discoveries

We now compare the dynamic effects of mineral and oil discovery news shocks. To do this, we split our sample of commodity discoveries into two categories, oil and minerals, and we estimate Equation (2). Figure 4 shows the impulse responses of the current account-GDP ratio, the investment-GDP ratio, and GDP to an oil discovery news shock (first row) and to a mineral discovery news shock (second row), along with 90% and 68% confidence bands. Further evidence for savings, consumption, and employment is reported in Appendix C. The median lead time before the start of production is 6 years in the sample of oil discoveries and 11 years in the sample of mineral discoveries, indicated by the vertical red dashed lines on the plots.

The responses to an oil discovery news shock are qualitatively similar to the responses reported by ARS (p. 128-9) and indicate significant anticipation effects.[12] The current account sharply declines from period zero as investment begins to rise 1 year after the discovery. It reaches a trough when investment peaks, 5 years after the discovery, 1 year before production starts. Following the start of production, 6 years after the discovery, the current account turns positive as investment declines and stabilizes by year 7. GDP begins to rise significantly 5 years after the discovery, peaking in year 8. These results suggest that a country discovering oil initially borrows from abroad to finance investment, then repays the borrowed funds as returns from these investments materialize and production starts.

In contrast, after a mineral discovery, there is no response in the current account or investment for the first 4 years. However, we still observe anticipation effects, as investment rises significantly *before* production begins, from 5 to 9 years after the discovery. GDP gradually increases, peaking after 11 years. The current account drops significantly 6 years after the discovery, coinciding with the first peak in investment. This delay contrasts with the immediate news effects we observe after oil discoveries and suggests that the time horizon matters to understand the impact of news shocks. Investment reaches a second peak a few years before the median start of production and remains elevated even after GDP peaks, between years 12 and 14. This is reflected in a second drop in the current account around the same time, followed by its reversal in year 19.

Turning to the magnitude of the impulse responses, the estimates indicate that investment peaks at 0.018 following an oil discovery and at 0.014 after a mineral discovery. This implies that the median oil discovery, which represents 9% of GDP, raises investment by 0.16% of GDP, while the median mineral discovery, at 2% of GDP, raises investment by 0.03% of GDP. The total cumulative effect of a commodity discovery on investment, represented by the integral of the impulse response, is 0.044 for oil discoveries and 0.079 for mineral discoveries. Thus, the median oil discovery leads to a total investment increase of 0.40% of GDP (0.044% $\times$ 9), while the median mineral discovery leads to a total increase of 0.16% of GDP. These effects are substantial, given that the median investment-GDP ratio is approximately 21%. In terms of GDP, the median oil discovery results in a peak increase of 0.18% and a total cumulative change of 1.08%, while the median mineral discovery leads to a peak increase of 0.09% and a total change of 0.80%.

Overall, the qualitative shape and the magnitude of the responses of investment and the current account are similar for both types of discoveries, with two important distinctions. First, the responses after mineral discoveries are clearly delayed by at least 4 years compared to those after oil discoveries. Second, the effects are more spread out across a larger number of periods. As discussed in Section 2, the first difference likely reflects the fact that mineral discoveries have, on average, lead times that are nearly twice as long as those for oil discoveries; the second difference may arise from the more uniform distribution of lead times for mineral discoveries, while the distribution of lead times for oil discoveries is more concentrated around the median.[13] The

[12]While the responses to an oil discovery are qualitatively similar to those in the ARS results, there may be minor quantitative differences. These discrepancies arise from differences in how the size of the discoveries is measured. Additionally, we use an updated version of the Horn dataset, which includes some revisions. Nevertheless, the median size of an oil discovery remains the same as in ARS, at 9% of GDP.

[13]The initial reversal in the current account following a mineral discovery is likely muted due to the more evenly distributed lead times associated with these discoveries, resulting in a mix of discoveries occurring with different lead times before production starts. Note that the estimates of responses to mineral discoveries are more imprecise, particularly for the GDP response. This is also likely due to the more uniform distribution of lead times associated

importance of this heterogeneity in the lead time between discovery and production has been overlooked by the literature, as it lacked detailed information on these lead times.

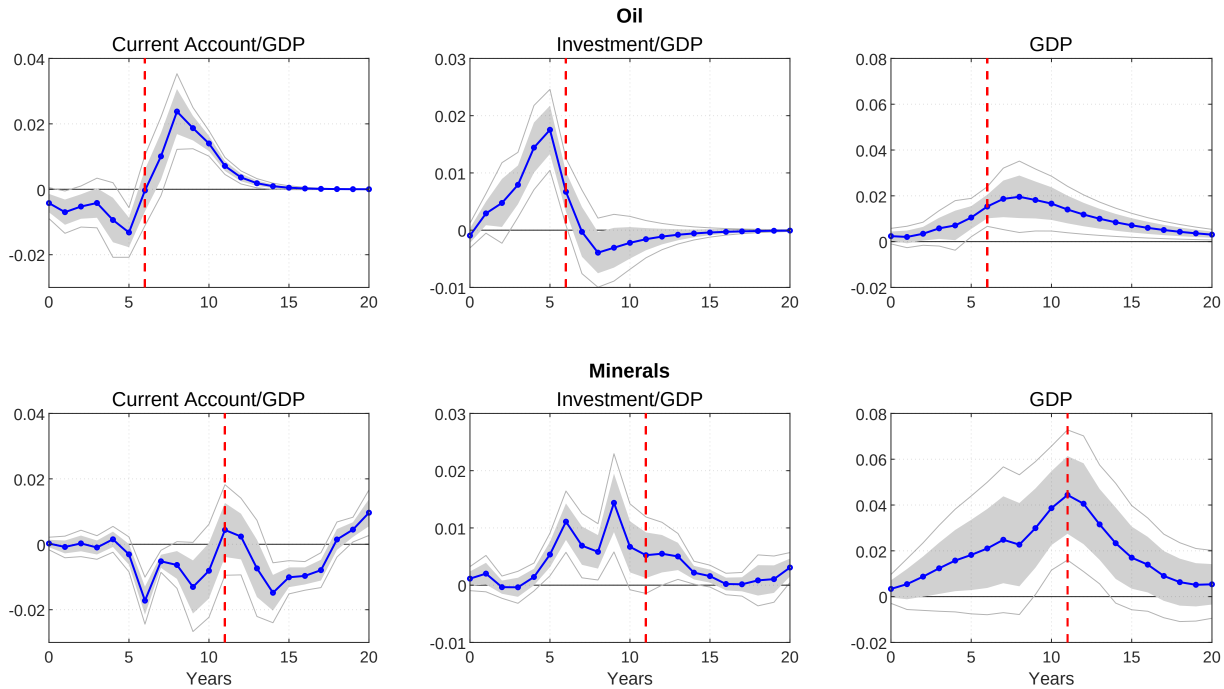


Figure 4: Impulse responses to oil (first row) and mineral (second row) discoveries

Notes: These graphs show the estimated impulse responses of aggregate variables to an oil news shock (first row) and to a mineral news shock (second row). The vertical red dashed line indicates the median lead time between the discovery date and the start of production date for each type of commodity (6 years for oil discoveries, 11 years for mineral discoveries). 90% and 68% confidence intervals are shown in all cases.

To further assess the general patterns of the responses, we perform hypothesis tests on the cumulative effects over the first 5 years and the subsequent 5 years to determine whether these effects are significantly different from zero after oil and mineral discoveries. Table 3 presents the results of these hypothesis tests. For the current account-GDP ratio, the results show that, after an oil discovery, the response is significantly negative during the first 5 years and significantly positive during the next 5 years. In contrast, after a mineral discovery, the response is not significantly different from zero in the first 5 years but becomes significantly negative in the subsequent 5 years. Regarding the investment-GDP ratio, the response to an oil discovery shock is significantly positive in the first 5 years, whereas the response to a mineral discovery shock is not significantly different from zero. However, the investment response to a mineral discovery turns significantly positive in the following 5 years, while the response to an oil discovery is no longer different from zero. For GDP, the response is significantly positive after an oil discovery during the first 5 years and subsequent 5 years, while it is not different from zero during the first 5 years after a mineral discovery. In sum, these tests confirm that the responses after a mineral discovery are significantly delayed, with negligible impact during the first 5 years. This contrasts with the responses after an oil discovery, which exhibit significant fluctuations in the first 5 years, before production begins.

with these discoveries.

Table 3: Hypothesis tests on responses to an oil and a mineral news shock

Variable	Hypothesis test	P-Value	
		Oil	Minerals
Current account	$H_0 : \sum_0^5 \mathrm{irf}_h = 0$	0.00	0.80
	$H_0 : \sum_0^5 \mathrm{irf}_h \geqslant 0$	0.00	0.40
	$H_0 : \sum_6^{11} \mathrm{irf}_h = 0$	0.01	0.11
	$H_0 : \sum_6^{11} \mathrm{irf}_h \geqslant 0$	1.00	0.06
	$H_0 : \sum_6^{11} \mathrm{irf}_h \leqslant 0$	0.00	0.94
Investment	$H_0 : \sum_0^5 \mathrm{irf}_h = 0$	0.00	0.22
	$H_0 : \sum_0^5 \mathrm{irf}_h \leqslant 0$	0.00	0.11
	$H_0 : \sum_6^{11} \mathrm{irf}_h = 0$	0.80	0.01
	$H_0 : \sum_6^{11} \mathrm{irf}_h \leqslant 0$	0.60	0.01
GDP	$H_0 : \sum_0^5 \mathrm{irf}_h = 0$	0.02	0.28
	$H_0 : \sum_0^5 \mathrm{irf}_h \leqslant 0$	0.01	0.14
	$H_0 : \sum_6^{11} \mathrm{irf}_h = 0$	0.02	0.08
	$H_0 : \sum_6^{11} \mathrm{irf}_h \leqslant 0$	0.01	0.04

Notes: irf_h denotes the estimated impulse response at horizon h. p-values are obtained from the delta method.

It is tempting to interpret the different timing of macroeconomic responses to the type of discovery as being driven by the lead time between discovery and production. However, for this interpretation to be causal, it is crucial to ensure that macroeconomic factors do not affect the likelihood of discovering one type of commodity over another. To check this, we perform multinomial logistic regressions of the type of discovery (oil, mineral, both, or none) on key long-term growth determinants, using cross-country data from Sala-i-Martin, Xavier and Doppelhofer, Gernot and Miller, Ronald I (2004). Specifically, we regress the discovery type on variables identified by Sala-i-Martin, Xavier and Doppelhofer, Gernot and Miller, Ronald I (2004) as significantly related to growth, including geographic factors (land area, East Asian, Latin American, and African dummies), demographic factors (life expectancy, overall and coastal population density, and the fraction of the population under 15), and economic growth factors (real GDP per capita, relative price of investment, primary school enrollment, and number of years the economy has been open). The demographic and economic explanatory variables are measured in 1960, the start of our sample period, which helps mitigate concerns about reverse causality.

The results, reported in Appendix C (see Table 10), indicate that country size, measured by total land area, is the strongest predictor of a commodity discovery (either oil, minerals, or both). Larger countries are significantly more likely to experience giant commodity discoveries.

Additionally, East Asian countries show a higher likelihood of experiencing both types of discoveries. Most demographic factors are not significant, except for population density, where countries with lower population densities are more likely to experience both types of commodity discoveries. This likely reflects the association between larger land area and a greater probability of commodity discoveries. Notably, economic factors such as GDP per capita, relative investment price, primary school enrollment, and years of openness do not appear to significantly influence the likelihood of a commodity discovery. Therefore, while we do not formally rule out reverse causality, it seems reasonable to interpret the differences in responses to giant mineral and oil discoveries as causal. As robustness checks, we examine other splits by commodity type in Section 3.5, as well as by short and long lead time in the next subsection.

3.4 Split by Lead Time: Short vs. Long

Previous results show that the macroeconomic effects of mineral discoveries are delayed, with negligible impact during the first 5 years, while oil discoveries trigger short-run anticipation effects. A major difference between oil and mineral discoveries is the lead time before production, which is significantly longer for mineral discoveries, notably due to geological, technological, and regulatory challenges, as discussed in Section 2.2. To further explore the role of the lead time, we next split our sample of giant discoveries based on the time lag between the discovery date and the start of production, irrespective of the commodity type.

A potential issue with this split is that the lead time might be influenced by economic conditions. To investigate this, we first regress the lead time on key long-term growth determinants, using cross-country data from Sala-i-Martin, Xavier and Doppelhofer, Gernot and Miller, Ronald I (2004), as in the multinomial logistic regressions in Section 3.3. The estimates from these regressions, reported in Appendix C (see Table 11), show that some demographic factors have a significant impact, with shorter lead times in countries with coastal population density and with higher fraction of population under 15. The most significant determinants appear to be the type of commodity, with significantly lower lead times for oil and gas discoveries, and whether the discovery is offshore, which are characterized by longer lead times. However, the geographic variables related to the continent or the land area of the countries where the discoveries occur are not statistically significant. Importantly, none of the economic variables are statistically significant. This confirms that economic conditions do not appear to play a major role in explaining the lead time between discovery and production start.

Next, to overcome endogeneity concerns, we use an instrumental variable approach to predict the lead time to production for all discoveries in our sample. As an instrument, we use the distance between the location of the discovery and the nearest major city.[14] The identifying assumption is that the proximity of the commodity field to a large urban center affects the timing of production through its impact on infrastructure development and access to resources, but is not related to macroeconomic conditions at the time of discovery.

To compute this distance, we use the latitude and longitude coordinates of the commodity fields for all discoveries in our giant mineral discoveries dataset. The information on the location of major cities worldwide (defined as cities with more than one million inhabitants) is collected from the World Cities Database available at Simplemaps.com. Using our sample of discoveries with observed lead times, we regress the observed lead time on the distance to the nearest big city,

[14] We also used as an instrument the minimum distance between the discovery location and the nearest port or city. The results are qualitatively similar.

as well as commodity dummies, an offshore dummy, and the interaction between these dummies and the distance, controlling for regional and time fixed effects. The regression estimates are provided in Appendix D.8. They show that the distance to the nearest major city and the type of commodity discovered explain a substantial portion of the lead time to production, with an adjusted R-squared of 0.19. The estimates indicate that greater distance to the nearest major city is associated with longer lead times, with statistical significance at the 5% level. As expected, minerals are associated with longer lead times to production compared to oil discoveries, further supporting our earlier analysis based on the split by commodity type. The lead time to production increases more for offshore and gas discoveries as the distance to the nearest big city grows, while it decreases more for precious metals. These results are consistent with our analysis in Section 2.2.

We then split our sample into two groups based on the predicted lead time: short-run discoveries (predicted lead time below the median) and long-run discoveries (predicted lead time above the median). The estimated impulse responses to short- and long-run discoveries are displayed in Figure 5. They reveal strikingly similar patterns to the responses observed in the baseline split by commodity type. Short-run discoveries yield almost immediate anticipation effects, while long-run discoveries have delayed macroeconomic effects, with negligible impact during the first 5 years. These results highlight the crucial role of the horizon of the news shock.

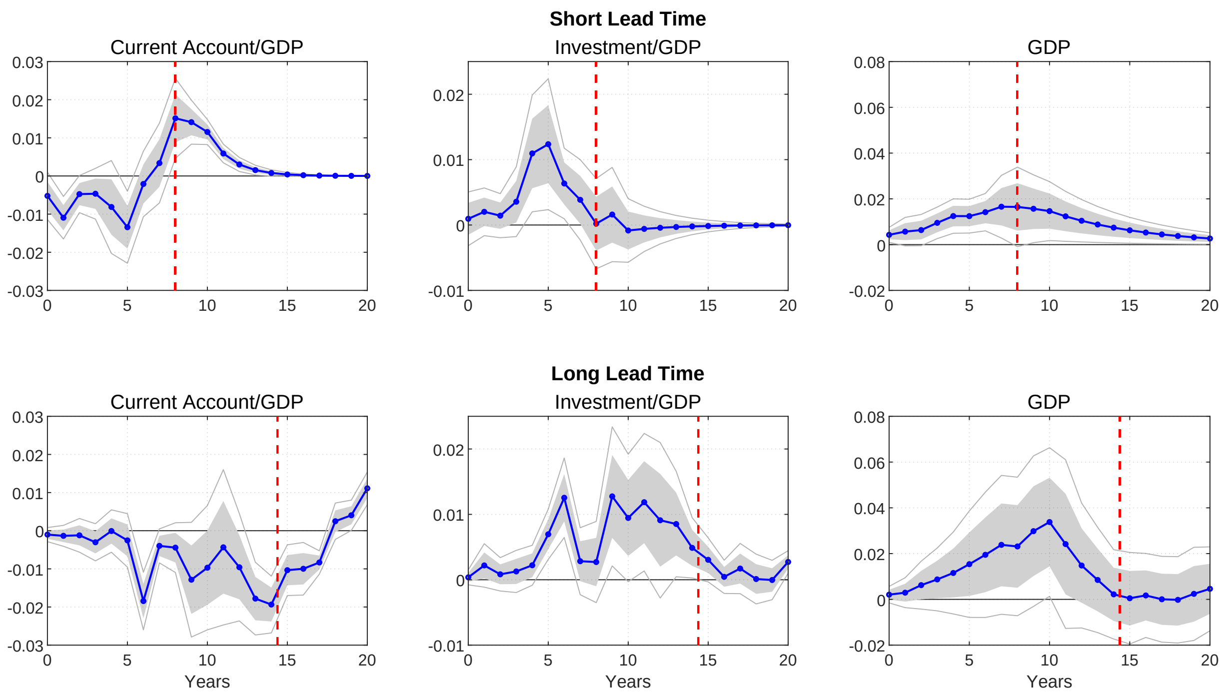


Figure 5: Impulse responses to short-run (first row) and long-run (second row) discoveries

Notes: These graphs show the estimated impulse responses of aggregate variables to a short-run discovery (first row) and to a long-run discovery (second row). The vertical red dashed line indicates the median lead time between the discovery date and the production start date for each group (8 years for short-run discoveries, 14 years for long-run discoveries). 90% and 68% confidence intervals are shown in all cases.

3.5 Robustness and Extensions

In this subsection, we perform several robustness checks of our baseline results documented in Section 3.3. We examine alternative measures of giant commodity discoveries, alternative splits by type of commodity, the effects of removing discoveries with very long or very short lead times before production start, alternative dynamic specifications, and the use of a different methodology such as local projections. All results can be found in Appendix D.

We begin by testing the robustness of our main results to alternative measures of the size of giant commodity discoveries. First, we use a dummy variable that captures the occurrence of an oil or mineral discovery event, relying solely on the timing of the discovery. This approach avoids assumptions about the construction of the monetary value of the discovery but disregards the size of the discovery relative to the economy, potentially omitting crucial information. As shown in Figure 15, the estimated responses of the three key variables to an oil or mineral discovery event are largely consistent with our baseline results. However, the output response to an oil discovery event is imprecise and not statistically distinguishable from zero. Next, we test robustness by replacing the country-specific risk-adjusted discount rate with a common discount factor of 10%. The resulting impulse responses for the key macroeconomic variables remain virtually unchanged (see Figure 16).

Second, we explore alternative splits by commodity type, leveraging heterogeneity in lead times within each category. As shown in Table 2, the median lead time for oil discoveries is shorter than for gas discoveries—6 years compared to 8 years. Similarly, the median lead time for precious metals is 6 years, whereas other mineral discoveries have a median lead time of 13 years. We estimate Equation (2) for two splits: (i) oil vs. gas, and (ii) precious metals vs. other minerals. For the first split, we set $p = q = 10$, and for the second, $p = 10$ and $q = 20$. The results are qualitatively consistent with our baseline findings, highlighting similar delayed effects of gas and other minerals discoveries relative to oil and precious metals discoveries, respectively (see Figure 10 and Figure 11).

Third, we examine whether excluding discoveries with lead times exceeding 20 years before production affects our estimates. It could be argued that such discoveries represent noise rather than genuine news shocks, and that their long lead times may be influenced by factors unrelated to technology, such as political instability or strategic timing in response to commodity price fluctuations. The results remain robust, indicating that discoveries with exceptionally long lead times are not driving the observed differences in responses to oil and mineral discovery news shocks (see Figure 12). We also check that the results are robust to excluding discoveries with lead times of less than 2 years before production, as these are less likely to represent news shocks (see Figure 13).

Fourth, we estimate the same regression on the sample of countries that experience both oil and mineral discoveries. This comparison can help rule out the possibility that the delayed effects observed after mineral discoveries are driven by different economic conditions between countries that discover minerals and those that discover oil. Figure 14 shows that these delayed effects hold in countries that discover both types of commodities.

Lastly, our findings remain robust across various dynamic specifications. Specifically, the results hold when changing the lag order of the independent variables to $p = 15$, $q = 15$, or $q = 25$ (Figure 16). In addition, we estimated alternative impulse responses using the Jordà (2005) local projection method. While local projections offer a more flexible approach to modeling dynamic effects with fewer restrictions than ADL models, this flexibility comes at the cost of reduced efficiency and the loss of a substantial number of observations, particularly at longer horizons. Despite these trade-offs, the resulting impulse response patterns align well with those from our baseline model (Figure 17). The main exception is the response of GDP to oil discovery shocks, which is no longer significantly different from zero in the medium run.

4 A Small Open Economy Model with Financial Frictions

In this section, we present a small open economy model that qualitatively illustrates how financial frictions affect the propagation of news shocks. The starting point is the two-sector small open economy model of Arezki et al. (2017), which we briefly describe in Section 4.1. We extend this model by incorporating a collateral constraint as in Mendoza (2002, 2010), which limits borrowing capacity based on the value of capital in the commodity sector. Additionally, we introduce investment irreversibility, following Pindyck (1991) and Abel and Eberly (1999), to capture the costly reallocation of capital across sectors. These two frictions fundamentally alter the economy's adjustment to news shocks by constraining the ability to finance investment through external borrowing and limiting the speed at which resources can be reallocated. The combination of these features generates delayed and nonlinear responses of macroeconomic variables, particularly investment and the current account, to long-run news. Our model demonstrates that the timing of investment depends on both the lead time—the exogenous delay between discovery and production—and the extent to which borrowing constraints bind over time. By incorporating these elements, the model provides a richer framework for understanding how financial constraints shape the macroeconomic effects of resource discoveries.

4.1 Standard Small Open Economy Model

We start by presenting ARS benchmark model. ARS model is a small open economy framework that consists of two distinct sectors: a commodity extraction sector and the rest of the economy, reflecting the dual structure common in many small open economies. The small open economy does not affect the world interest rate or world commodity prices. A key feature of this model is the explicit inclusion of lead times between the onset of the discovery news shock and its full realization when production starts, referred to as the "time to connect." This concept reflects the time required to overcome technological, regulatory, and infrastructure challenges before full production can begin. We will use this to compare the effects of news with different time horizons.

4.1.1 Firms

There are two sectors in the economy: a commodity sector and another sector, which we will call manufacturing. Sector 1, the manufacturing sector (non-resource), uses a Cobb-Douglas, constant returns to scale technology, which depends on capital at the end of period $t-1$, $K_{1,t-1}$, and labor, $N_{1,t}$:

$$Y_{1,t} = A_{1,t} N_{1,t}^{\alpha_1} K_{1,t-1}^{1-\alpha_1}$$

Sector 2, the commodity sector, uses capital $K_{2,t-1}$, labor, $N_{2,t}$, and the *stock of commodity reserves* available for production in period t, R_{t-1}, also with a Cobb-Douglas, constant returns to scale, production function:

$$Y_{2,t} = A_{2,t} N_{2,t}^{\alpha_2} K_{2,t-1}^{\alpha_k} R_{t-1}^{1-\alpha_k-\alpha_2}$$

where $0 < \alpha_1, \alpha_2, \alpha_k < 1$. Capital accumulation in each sector is subject to investment adjustment costs à la Jaimovich and Rebelo (2009):

$$K_{s,t} = I_{s,t} \left[1 - \frac{\phi}{2} \left(\frac{I_{st}}{I_{s,t-1}} - 1 \right)^2 \right] + (1-\delta) K_{s,t-1} \quad , \quad s = 1, 2$$

where s denotes the sector, $\delta \in (0,1)$, $\phi > 0$. Adjustment costs in steady state are equal to zero.

4.1.2 Households

The economy is populated by identical agents who maximize lifetime utility defined over sequences of consumption C_t and hours worked N_t. Lifetime utility is

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \frac{\left(C_t - \psi N_t^{\theta} \right)^{1-\sigma} - 1}{1-\sigma} \right]$$

It is assumed that $\theta > 1, \psi > 0$, and $\sigma > 0$. Following ARS, we opt for Greenwood et al. (1988) (GHH) preferences, which shut down the wealth effect on labor supply and are commonly used in open economy models. The household supplies capital and labor in a competitive market.

Households consume only good 1 but can exchange the commodity (good 2) for good 1 on international markets. Thus, the flow budget constraint is as follows:

$$B_t = (1 + r_t) B_{t-1} + (Y_{1,t} + p_t Y_{2,t}) - (C_t + I_{1,t} + I_{2,t})$$

where p_t is the relative price of a commodity determined exogenously in the world market.

To induce stationarity of foreign bond holdings, we follow the external debt-elastic interest rate proposed by Schmitt-Grohe and Uribe (2003):

$$r_t = r^* + \chi \left[exp(\bar{B} - B_{t-1}) - 1 \right]$$

4.1.3 Aggregation

Aggregate output, capital, investment, and domestic labor are defined as:

$$\begin{aligned} Y_t &= Y_{1,t} + p_t Y_{2,t} \\ K_t &= K_{1,t} + K_{2,t} \\ I_t &= I_{1,t} + I_{2,t} \\ N_t &= N_{1,t} + N_{2,t} \end{aligned}$$

The current account is defined as

$$CA_t = B_t - B_{t-1} = S_t - I_t$$

where S_t is aggregate saving.

4.1.4 Exogenous Processes

We model the lead time between discovery and production using the same "time-to-connect" concept as ARS. Reserves are known immediately upon discovery but become productive only once the necessary infrastructure—such as roads for minerals or pipelines for oil—has been connected to capital and labor. This process takes time. Thus, the stock of producing reserves evolves as follows:

$$R_t = \bar{R} + R_{t-1} - Y_{2,t} + \epsilon_{t-j}$$

This relation states that the producing reserves at the end of year $t-1$, R_{t-1}, are augmented with an exogenous stream $\bar{R}$, are endogenously depleted by commodity production, $Y_{2,t}$, during year t. ϵ_{t-j} captures the interaction between the news of a commodity discovery and the time-to-connect feature. At time $t-j$, the discovery news is received, leading to an immediate increase in known reserves. However, producing reserves only increase at time t, as it takes time to connect them to capital and labor. The lag on ϵ_{t-j} captures this lead time between the announcement of the discovery and the actual availability of reserves for production. We set j to 6 and 11, reflecting the median lead times for oil and mineral discoveries, respectively.

4.2 Introducing Financial Frictions

As we will show in Section 4.4, the model described previously delivers an immediate response of the current account and investment to discovery news shocks, which is not in line with our evidence in the case of mineral discoveries. The mechanism behind these results crucially relies on the country's ability to borrow externally.

However, the timing of macroeconomic responses to commodity discoveries is significantly influenced by two key factors: the lead time between discovery and production and the presence of borrowing constraints. The lead time determines how long it takes to establish productive capacity for technological reasons. In particular, mining projects face longer lead times compared to oil extraction, due to complex geological and infrastructure challenges. At the same time, developing a commodity deposit typically requires substantial upfront investments over an extended period, during which uncertainty about prices, macroeconomic conditions, and policy environments remains high. Borrowing constraints limit access to external financing, preventing the smoothing of investment over time. When borrowing constraints are binding, this can result in a delayed but sharper macroeconomic response, as financial conditions ease.

Therefore, a natural extension of the model is the introduction of borrowing constraints, a well-established feature in explaining business cycle fluctuations, particularly in emerging markets (Mendoza (2002, 2010)). As we will show, incorporating these constraints helps the model to better capture the delayed responses of investment and current account following a mineral discovery.

Collateral constraint. We opt for a particular form of borrowing constraint by assuming that the amount of borrowing is limited by the value of collateral, which depends on the capital stock in the commodity sector and a proportionality factor reflecting the pledgeability of assets. This type of collateral constraint, known as resource-backed lending, is particularly prevalent in commodity-rich countries, as we will discuss below.

$$B_t \geq \phi K_{2,t} \tag{3}$$

Collateral constraints play a critical role in explaining the excess aggregate volatility in emerging economies, as emphasized by Mendoza (2010). In these economies, access to international capital markets is often limited by external factors, such as terms-of-trade shocks or sudden stops in capital flows. When asset prices or output in the collateral-constrained sector fall, the country's borrowing capacity is reduced, leading to a sharp adjustment in consumption, investment, or both. This constraint amplifies the impact of external shocks and generates large swings in macroeconomic aggregates, contributing to the volatility commonly observed in emerging markets.

Investment Irreversibility. Turning discovery into production requires large upfront investments in the commodity sector. If the country faces borrowing constraints and cannot secure external financing, it would reallocate capital from other sectors of the economy to fund resource development. However, this reallocation can lead to a contraction in non-resource sectors, potentially causing an economic downturn—a pattern that is not strongly supported by the data. Moreover, capital reallocation may be difficult in practice due to sector-specific skills, infrastructure needs, and institutional frictions.

To limit sector reallocation, we introduce an additional constraint on investment in the rest of the economy, ensuring that capital flows into the commodity sector do not excessively disrupt overall economic activity. This adjustment allows the model to better align with observed patterns following a resource discovery.

$$I_{1,t} \geq \nu I_{1,ss} \tag{4}$$

The amount of disinvestment in the rest of the economy is limited to a lower threshold, which represents a steady-state investment level. This threshold reflects the irreversibility of capital reallocation: once resources are allocated, they cannot easily be withdrawn or redirected without incurring significant adjustment costs. This feature captures a realistic rigidity observed in many economies, where investment decisions are not only forward-looking but also constrained by sunk costs and technological limitations. Alternatively, one can think that there is specific resource-extraction capital, which is distinct from the general capital stock. Examples of oil-extraction capital include drilling rigs, pipelines, pumps, and seismic exploration tools (Bohn and Deacon, 2000). Another interpretation is that resource-extraction capital becomes productive in the periods after it is purchased, reflecting an installation lag similar to the time to build concept introduced by Kydland and Prescott (1982).

Discussion. We now present illustrative examples that support our assumption about the importance of collateral constraints in the commodity sector.

Developing commodity fields requires large upfront investments, which are often financed through borrowing. However, access to international capital markets is frequently constrained, particularly for developing economies. Resource-backed lending—where loans are collateralized by oil, minerals, or metals—has become a key financing mechanism, particularly in Latin America and Sub-Saharan Africa. According to Mihalyi et al. (2020, 2022); Wang et al. (2023), this common practice allows countries to access much-needed financing for infrastructure development and other projects without the immediate need for cash by leveraging their natural resource wealth as collateral. Resource-backed loans have been especially prevalent in commodity-rich countries, with financing typically involving natural resources as security for long-term loans from international creditors. China has been a dominant player in this form of lending, providing at least $152 billion in resource-backed loans since 2004 (Horn et al., 2021).

Our model is directly applicable to state-owned enterprises (SOEs). SOEs play a critical role in developing new commodity fields, particularly in oil, uranium, and coal. Globally, SOEs control a significant share of resource reserves and production. For example, national oil companies (NOCs) manage over $3 trillion in assets and dominate global oil and gas production (International Monetary Fund, 2019). Similarly, in mining, SOEs hold substantial reserves across key metals, including copper, iron ore, and gold, despite a decline in state control since the 1980s (World Bank, 2008). In coal, state ownership remains prevalent, driven by energy security and industrial policy considerations (U.S. Energy Information Administration, 2020; World Coal, 2022).

While SOEs dominate many commodity sectors, private companies also play a significant role in commodity extraction. Our model remains relevant in this context because private firms, especially in developing economies, often face significant financial constraints. As Baumgartner and Thöni (2019) highlight, private investment in resource-rich economies is frequently hindered by limited access to capital, creating barriers to project development and expansion. Project financing structures, which rely on collateralized borrowing, mirror the borrowing constraints faced by governments. As Esty (2004) explains, project finance plays a crucial role in funding large-scale infrastructure and resource extraction projects by structuring loans around collateralized assets and expected cash flows rather than the balance sheet of the borrowing firm. This approach allows firms with limited creditworthiness to secure funding, but it also ties investment decisions closely to the availability of collateral and the stability of future revenues. Additionally, domestic firms in resource-rich economies typically encounter greater difficulty accessing international financial markets, exacerbating financing challenges. As Venables (2016) emphasizes, both state-owned and private firms struggle with securing adequate funding for resource extraction, which in turn influences investment decisions and project timelines. Therefore, the dynamics of investment delays and financial frictions apply broadly, whether the commodity sector is state-owned or private.

4.3 Calibration

Table 4 presents the baseline calibrated parameters for our two-sector model. The values are broadly consistent with the literature, particularly ARS and Jaimovich and Rebelo (2008).

The model incorporates Cobb-Douglas production functions with constant returns to scale for both sectors. The manufacturing sector is labor-intensive, with a labor share α_1 of 64%, following Jaimovich and Rebelo (2008). In contrast, the commodity sector is capital-intensive, with a labor share α_2 of 13% and a capital share α_k of 49% (thus, the resource share is 38%). These parameters are calibrated using the estimates from Gross et al. (2013), who provide production function parameters for the Australian mining industry, which contributes approximately 13% to the country's GDP, with oil and gas accounting for around 3%. The relatively higher capital and resource shares reflect the capital-intensive nature of commodity extraction compared to manufacturing.

The depreciation rate δ is set at 10%, following ARS, reflecting the relatively high wear and tear of capital in resource extraction industries. The household sector is characterized by a discount factor $\beta = 0.909$, risk aversion $\sigma = 1$, and a Frisch elasticity $\theta = 1.2$, consistent with Jaimovich and Rebelo (2008). The disutility of labor parameter $\psi = 0.408$ and the elasticity of the interest rate with respect to debt $\chi = 0.0001$ are taken from ARS, ensuring consistency with previous

Table 4: Baseline Calibrated Parameters

Parameter	Value	Description	Target/Source
α_1	0.64	Labor Share in Manufacturing	Jaimovich and Rebelo (2008)
α_2	0.13	Labor Share in Commodity Extraction	Gross et al. (2013)
α_k	0.49	Capital Share in Commodity Extraction	Gross et al. (2013)
α_r	0.37	Reserve Share in Commodity Extraction	Gross et al. (2013)
δ	0.10	Depreciation Rate	Arezki et al. (2017)
β	0.909	Discount Factor	Arezki et al. (2017)
σ	1.000	Risk Aversion	Jaimovich and Rebelo (2008)
θ	1.200	Frisch Elasticity	Jaimovich and Rebelo (2008)
ψ	0.408	Disutility of Labor	Arezki et al. (2017)
χ	0.0001	Elasticity of Interest Rate wrt Debt	Arezki et al. (2017)
$\bar{B}$	-11.878	Steady State Debt	steady-state $\frac{TB}{Y} = 0.04$
γ_1	0.1	Investment Adjustment in Manufacturing	Arezki et al. (2017)
γ_2	0.1	Investment Adjustment in Commodity	Arezki et al. (2017)
p_c	1	Commodity Price	Arezki et al. (2017)
$\bar{R}$	2	Value of Discovery	steady-state $\frac{Y_2}{Y} = 0.06$
ϕ	-5.97	Debt Constraint	$\phi = 1.005 \times \frac{B_{ss}}{K_{ss,2}}$
ν	1.000	Investment Irreversibility in Manufacturing	Abel and Eberly (1999)

small open economy models.

To capture the economy's external borrowing capacity, we calibrate the steady-state debt level $\bar{B}$ at -11.878, which corresponds to a trade balance-to-GDP ratio of 4%, a typical value for emerging market economies. The investment adjustment costs are set to 0.1 in both the manufacturing (γ_1) and commodity (γ_2) sectors, following ARS.

We calibrate the collateral constraint parameter ϕ to -5.97 by computing the steady-state values of capital ($K_{ss,2}$) and debt (B_{ss}) in an economy without borrowing constraints and then setting $\phi = 1.005 \times \frac{B_{ss}}{K_{ss,2}}$. This ensures that the collateral constraint is not binding in the initial steady state but remains very tight. As regards the investment irreversibility constraint, we set $\nu = 1$, meaning that capital in the non-commodity sector cannot be reallocated once invested. This follows Pindyck (1991) and Abel and Eberly (1999), capturing the well-documented difficulty of shifting capital across sectors in resource-rich economies.

Finally, following ARS, the commodity price p_c is normalized to 1, and the discovery value $\bar{R}$ is calibrated to 2, so that the steady-state output ratio of the commodity sector to the total economy ($\frac{Y_2}{Y}$) is approximately 6%.

4.4 Results

Figure 6 presents the results of our baseline model (solid red line) and compares them to the model without financial frictions (dashed black line), similar to the one in ARS. The first row shows the responses to short-lead time discoveries, which serve as our proxy for short-run news. The second row displays the responses to long-lead time discoveries, our proxy for long-run news. The lead time for short-run news is 6 years, similar to the median lead time for oil discoveries, while the lead time for long-run news is 11 years, corresponding to the median lead time for mineral discoveries.

The presence of constraints in our model clearly amplifies the responses compared to the standard model.[15] However, for short-run news, the responses are qualitatively similar in both models: the current account drops immediately as investment rises, and GDP increases when reserves become available for production. In contrast, for long-run news, the responses diverge significantly. In our model, the current account remains unchanged for the first 4 years, then sharply declines. Similarly, investment and GDP stay near zero for several periods before increasing sharply. These patterns closely mirror the empirical dynamics observed for mineral discoveries. In the standard model, however, the current account, investment, and GDP all initially drop in the years immediately after the discovery news.

After a discovery, to fully capitalize on the benefits at the time of production, it is crucial to begin investing in the commodity sector to build production capacity. To finance this investment, resources are sourced through a hierarchical process: borrowing from abroad, reallocating capital between sectors, temporarily increasing output in the commodity sector using existing deposits, and increasing savings. While the borrowing constraint limits the ability to borrow from abroad, investment irreversibility restricts capital reallocation. The time available to build the capital stock in the commodity sector is crucial. Our model suggests that it takes around 5 years to build the capital stock in the economy. The shorter the time available to accumulate capital, the more viable it becomes to temporarily boost production from existing deposits, putting less pressure on consumption. As shown in Figure 20, output in the commodity sector increases quickly and gradually after the discovery in the case of short-term news, while the response is delayed and more pronounced after long-run news. Over time, this gradual rise in commodity output leads to an increase in the capital stock of the resource sector, which in turn eases the borrowing constraint.

After both short- and long-run discovery news, the borrowing constraint plays a significant role, but its impact differs. In the case of short-run news, the borrowing constraint does not bind, allowing for temporary boosts in consumption and mild amplification of the responses for other macroeconomic variables. In contrast, in the case of long-run news, the constraint binds along the first 5 years of transition, which forces a more delayed and pronounced adjustment process. Consequently, the timing of the consumption increase and the decision to allocate resources toward capital accumulation depends heavily on the interaction of the time horizon of the news shock and the borrowing constraint.

To sum up, borrowing constraints and investment irreversibility play a crucial role in generating delayed responses by limiting firms' ability to front-load investment and preventing the immediate reallocation of capital from other sectors. These features effectively capture the delayed responses observed in the data, particularly in response to long-run news. This highlights the important role of the horizon in shaping macroeconomic responses to news shocks, as both constraints and the resource allocation process influence the optimal strategies for investment and consumption decisions.

[15] One can note a discrepancy between the empirical estimates and the magnitudes of the theoretical model responses. Similar to ARS, our model is not designed to perform a quantitative matching exercise but rather to highlight the transmission mechanism.

Furthermore, the shock is normalized so that the present value of the increase in oil revenue corresponds to 1% of initial GDP. Empirically, however, oil discoveries lead to an increase in government revenue equivalent to approximately 9% of GDP, while mineral discoveries result in a smaller increase of around 2% of GDP.

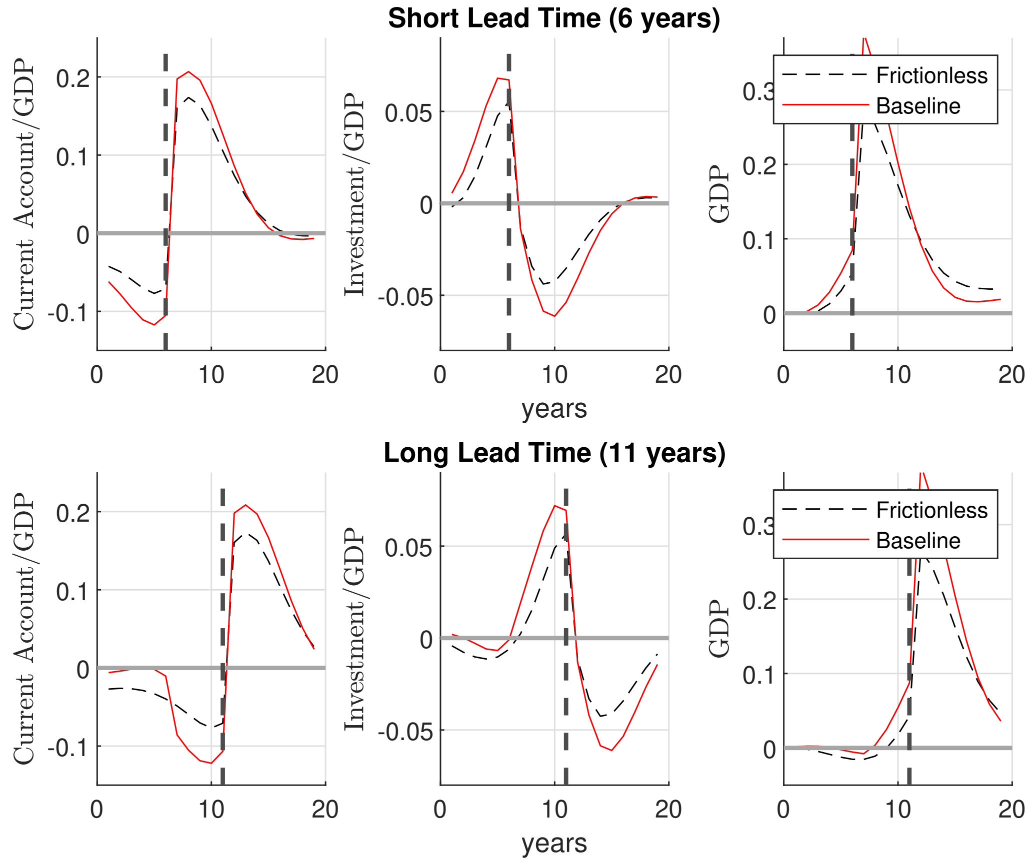


Figure 6: Impulse responses for current account, investment and GDP

Notes: This figure presents the impulse responses of the current account to GDP ratio, investment to GDP ratio, and GDP to a short lead-time discovery (first row) and to a long lead-time discovery (second row). The responses are shown for our baseline model with financial frictions (red solid lines) and without financial frictions (black dashed lines).

4.5 Additional Results and Sensitivity Analysis

We now discuss the responses of other macroeconomic variables and provide a sensitivity analysis of our findings with respect to some key parameters. All related figures are displayed in Appendix E.

Figure 19 shows the responses of savings, consumption, and hours. These responses align with our empirical results (Figure 9). In particular, in response to long lead-time discoveries, savings decrease and consumption increases with a 5-year delay following the discovery, while hours rises around the start of production. In contrast, the SOE model predicts that sectoral reallocation causes a drop in hours, with capital flowing from manufacturing to the commodity sector, leading to a large drop in manufacturing hours and a small increase in the low labor-intensive commodity sector. Savings drop and consumption jumps immediately due to the wealth effect from expected higher future income. In our baseline model, the delayed responses of savings and consumption to long-lead time discoveries reflect the gradual buildup of investment required for the long-term benefits of the discovery. Overall, our baseline model captures well the delayed responses of consumption, employment, and savings to long-run news, in line with the evidence, while the standard SOE model generates immediate responses due to sectoral reallocation and capital flows.

In Figure 21, we examine the case of a tighter borrowing constraint, setting $\phi = 1.001 \times \frac{B_{ss}}{K_{ss,2}}$. Our results indicate that a tighter borrowing constraint leads to counterfactual excess saving, as the economy is unable to borrow as much in response to shocks.

In Figure 22, we illustrate the role of investment irreversibility. In the model without irreversibility ($\nu = 0$), the responses of the current account are similar to those in the baseline model. However, we observe a significant decline in investment and GDP in the years following the discovery, driven by the reallocation of capital from the rest of the economy. This pattern, however, does not align with empirical observations. One could argue that large adjustment costs might lead to delayed responses in the current account and investment. However, as shown in Figure 22, we still observe an immediate drop in investment, even under unrealistically high adjustment costs.

5 Investigating the Mechanism

In this section, we provide evidence supporting the proposed mechanism and highlight the role of financial frictions in the transmission of discovery news shocks. First, we investigate how the macroeconomic impact of commodity discoveries varies across countries with different levels of financial openness. While responses to oil discoveries are similar across both groups, responses to mineral discoveries are delayed in financially closed countries, suggesting the presence of borrowing constraints. Second, we examine the impact of commodity discoveries on international capital flows. We find that oil discoveries lead to an immediate increase in foreign direct investment, while mineral discoveries generate a delayed response, which further points to the importance of financial frictions in the transmission of news shocks.

5.1 Split by Financial Openness

As discussed in Section 4, both the standard model and the model augmented with financial frictions produce similar qualitative responses to short-run news, while their predictions differ in response to long-run news, due to the presence of financial frictions.

To test this in the data, we examine how the macroeconomic effects of commodity discoveries vary across countries with different levels of financial openness. We split the sample of countries into two groups—financially open and financially closed—and estimate separate regressions for each group. To measure financial openness, we follow the approach of ARS and employ a de facto indicator based on the ratio of total assets and liabilities to GDP, using data from Lane and Milesi-Ferretti (2007). A country is classified as financially open if its average ratio of assets and liabilities to GDP is above the median, and financially closed if it is below the median.

Figure 7 presents the impulse responses to an oil discovery news in the first row and to a mineral discovery news in the second row. We contrast the responses for financially open countries, represented by dashed green lines, with those for financially closed countries, shown in blue. Consistent with ARS, we find that the responses of the current account, investment, and GDP to giant oil discoveries are qualitatively similar across the two groups of countries, with a significant impact in the early years following the discovery. We observe that in the financially closed group, investment and output peak about a year earlier, and the current account turns from negative to positive sooner. This can likely be explained by the slightly shorter median lead times in this group. The median lead time is 5 years for oil discoveries and 11 years for mineral discoveries, compared to 7 and 12 years, respectively, in the financially open group.

However, the responses to giant mineral discoveries, displayed in the second row, strongly differ in the two groups of countries. In the financially open group, current account drops immediately and persistently after the discovery news, whereas in the financially closed group, it only declines 5 years after the discovery. Similarly, investment increases in the years following the discovery in the financially open group, while there is no impact during the first 5 years in the financially closed group. Output drops in the financially open group, but the estimates are imprecise. Overall, these results demonstrate that the responses to mineral discoveries show a significant delay, which is observed only in financially closed countries, where borrowing constraints are more likely. In contrast, both oil and mineral discoveries lead to an immediate impact on macroeconomic variables in financially open countries. These findings align with the predictions of our model and suggest the presence of borrowing constraints.

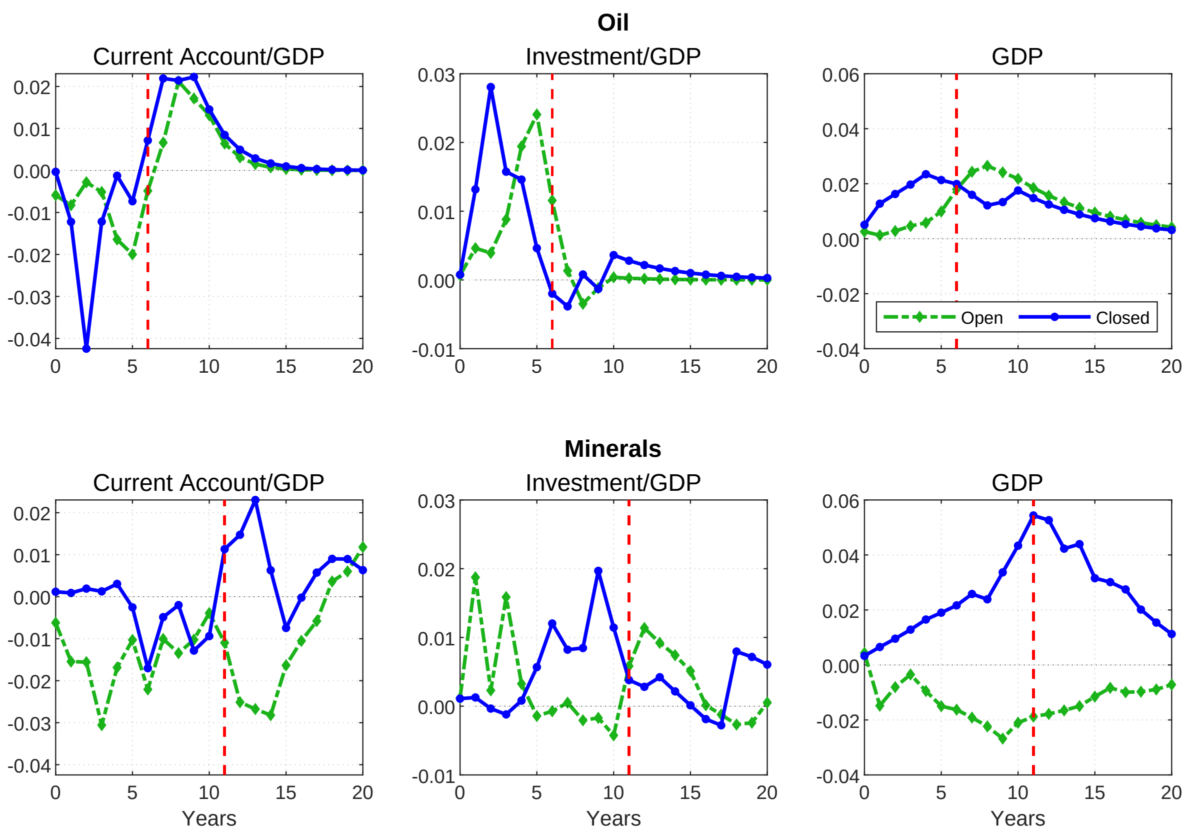


Figure 7: Impulse responses to commodity discoveries in financially open countries (green) and financially closed countries (blue)

Notes: These graphs present the estimated impulse responses of aggregate variables to giant commodity discovery news shocks. The first row shows responses to an oil discovery news shock, and the second row shows responses to a mineral discovery news shock. In each panel, the green dotted line corresponds to the response in financially open countries, and the blue solid line the response in financially closed countries. The vertical red dashed line indicates the median lead time between the discovery date and the start of production date for each type of commodity (6 years for oil discoveries, 11 years for mineral discoveries).

Importantly, studying the effects of long-run news shocks reveals the presence of borrowing constraints and helps to distinguish between the two types of models (standard vs. augmented with financial frictions), while the responses to short-run news appear qualitatively similar, regardless of the presence of financial frictions.

5.2 Evidence on Capital Flows

Net Foreign Direct Investment (FDI) has become a major type of international capital flow in recent decades and a key source of financing for capital investments. Using data on capital flows from Alfaro et al. (2014), we estimate Equation (2) for the same panel of countries as in the baseline analysis to examine the impact of oil and mineral discoveries on FDI. The impulse responses, shown in Figure 8, largely reflect the response patterns of the other macroeconomic variables. Oil discoveries lead to an increase in FDI in the first years after the discovery, while mineral discoveries trigger a delayed response, with a surge in FDI occurring approximately 5 years after the discovery, and no significant reaction in the first 5 years. For both types of discovery, the response of net FDI peaks about 2 years before production starts. This suggests that financial frictions may play a critical role in moderating the flow of foreign capital. Notably, these findings indicate that the delayed economic impact of mineral discoveries may be due to financial barriers that impede the immediate flow of FDI.

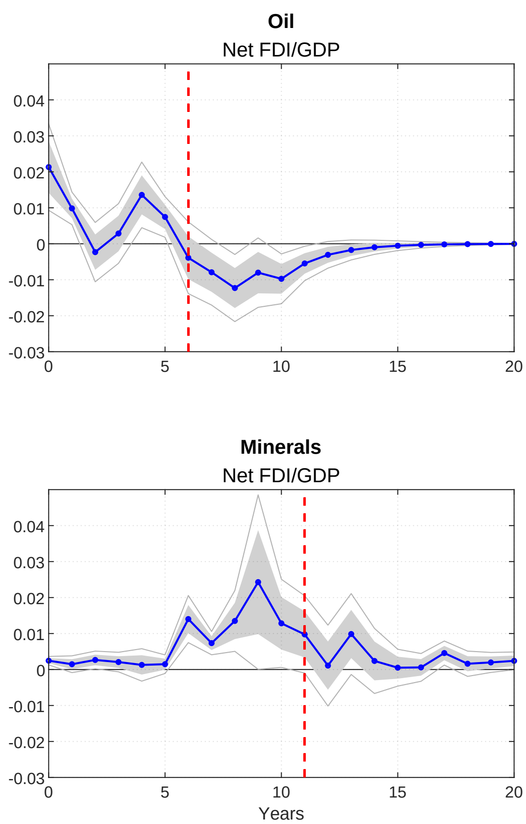


Figure 8: Impulse responses to oil (first row) and mineral (second row) discoveries

Notes: These graphs show the estimated impulse responses of net Foreign Direct Investments (FDI) to an oil news shock (first row) and to a mineral news shock (second row). The vertical red dashed line indicates the median lead time between the discovery date and the start of production date for each type of commodity (6 years for oil discoveries, 11 years for mineral discoveries). 90% and 68% confidence intervals are shown in all cases.

6 Conclusion

While most of the news shocks literature focuses on news shocks that materialize after a few quarters, this paper brings new insights by examining long-horizon news shocks that materialize after several years or even decades. Building on the work by ARS, we construct a new dataset of giant commodity discoveries worldwide for oil and for a wide range of minerals. Importantly, we gather data on both discovery and production start dates, which allows us to calculate the lead time between discovery and production. This lead time defines the horizon of the news shock. We document significant heterogeneity in lead times across commodities, which we leverage to study news events with different horizons.

The horizon of news shocks matters. First, our empirical analysis reveals that discoveries with long lead times—typically, mineral discoveries—have a delayed economic impact, with little to no response in the first 4 years following the discovery. In contrast, discoveries with shorter lead times—typically, oil discoveries—trigger significant macroeconomic fluctuations shortly after the discovery. Second, we show that both a standard small open economy model and a model with collateral constraints yield similar predictions for the effects of short-horizon discovery news. However, only the model with collateral constraints can explain the empirical findings related to long-horizon discovery news. Lastly, we further provide evidence that highlights the role of financial frictions in the transmission of discovery news shocks. Our findings have broader implications for macroeconomics. In particular, exploring how the time horizon shapes the impact of news about future fiscal or monetary policy changes could be a promising area for future research.

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A Commodity Discoveries

A.1 Definition of giant commodity discoveries

Giant commodity discoveries are defined by the size of their reserves. Table 5 provides a summary of the minimum size of these giant-sized deposits across commodities. This definition follows the criteria used by Tkachev et al. (2019) (LSLDs) for mineral deposits and by Horn (2014) for oil and gas fields. For mineral deposits, this size-based definition is broadly consistent with the criteria proposed by Minex Consulting, which is based on company-making mines that are large, are long-lived, and have a net present value (NPV) greater than 1 billion USD.

To put those sizes into perspective: a giant oil field contains over 500 million barrels, which is equivalent to the annual oil production of Algeria—a major oil producer and OPEC member. Similarly, a giant gold mine contains at least 200 tons of gold, exceeding the annual gold production of the United States, one of the world's top five gold producers, while a giant copper mine holds at least 4 million tons of copper, which corresponds to the annual output of Chile, the world's largest copper producer.

A.2 Data Construction

This section describes the sources and the construction of our data for a broad set of commodities. Our analysis is based on two key characteristics of a discovery: its size (measured as the discovered reserves multiplied by the corresponding commodity price) and the lead time between the discovery year and the start of production year.

Mineral Discoveries

The data on the size of reserves, deposit name, location, and geological characteristics of giant mineral deposits come from the Large and Super-Large Mineral Deposits (LSLDs) database, created and continually updated by the State Geological Museum of the Russian Academy of Sciences (Rundquist et al. (2006)). Most of the information is accessible online through the WEB-GIS application "World's Largest Mineral Deposits" on the Geoportal "Metallogeny" (Tkachev et al. (2019)). To the best of our knowledge, this dataset has not yet been used in the economics literature.

We complement this data by drawing on additional sources to obtain information on the year of discovery and production. The primary sources for discovery and production years is the MinEx Consulting dataset, a proprietary dataset generously provided by Richard Schodde, Managing Director of MinEx Consulting. This dataset is further supplemented with information from Global Energy Monitor (Global Energy Monitor, 2024), Porter GeoConsultancy (portergeo.com.au), Mindat, The Diggings, the International Atomic Energy Agency, Mining Technology (mining-technology.com), Rio Tinto, and De Beers, among others.

Overall, our final dataset of mineral discoveries contains a total of 220 giant discoveries of 27 commodities in 60 countries between 1960 and 2012. 23 countries in the sample experience only one mineral discovery. After merging all sources mentioned above, we obtain information on the production start date for 147 mineral discoveries.

Table 5: Giant-sized deposits

Commodity	Symbol	Unit	Giant size (from)
Oil & Gas			
Oil	–	10^6 bbl	500
Gas	–	10^6 BOE	500
Precious Metals			
Gold	Au	t	200
Silver	Ag	t	4000
Platinoids	Pt, Pd, Rh, Ru, Os, Ir	t	100
Base Metals			
Copper	Cu	10^6 t	4
Bauxite	Al_2O_3	10^6 t	40
Iron Ore	Fe	10^6 t	100
Lead	Pb	10^6 t	1
Nickel	Ni	10^3 t	500
Zinc	Zn	10^6 t	2
Tin	Sn	10^3 t	50
Cobalt	Co	10^3 t	50
Non-Metallic Minerals			
Coal	–	10^6 t	500
Potash	K_2O	10^6 t	100
Phosphorus	P_2O_5	10^6 t	40
Boron	B_2O_3	10^6 t	2
Fluorite	Flr	10^6 t	2
Specialty Metals			
Chromium	Cr_2O_3	10^6 t	4
Lithium	Li_2O	10^3 t	100
Manganese	Mn	10^6 t	10
Molybdenum	Mo	10^3 t	100
Niobium	Nb_2O_5	10^3 t	100
Titanium	TiO_2	10^6 t	2
Tungsten	WO_3	10^3 t	50
Vanadium	V_2O_5	10^3 t	250
Mineral Sands			
Zirconium	ZrO_2	10^3 t	150
Rare Earths	TR_2O_3	10^3 t	100
Other			
Diamond	Dia	10^6 ct	20
Uranium	U	10^3 t	20

Note: t means metric ton, ct carat, bbl barrel, and BOE barrel of oil equivalent.
Source: Horn (2014), Tkachev et al. (2019).

Oil Discoveries

Data on oil and gas discoveries primarily comes from the Horn dataset (Horn, 2014), updated version of 2015. This dataset, which was already used in a few previous studies (Lei and Michaels, 2014; Arezki et al., 2017; Esquivel, 2024), contains information on 1063 discoveries greater than 500 million barrels across 75 countries. It provides details on the field name, discovery year, estimated ultimate recovery (in million barrels of oil equivalent, MMBOE), location (country, latitude, longitude, offshore or onshore) and field type (oil or gas). However, it lacks information on the year of production.

We supplement this dataset with several other sources to obtain information on the year of production. These include the Petroleum Dataset compiled by the Centre for the Study of Civil War at the Peace Research Institute Oslo (PRIO) (Lujala et al., 2007), the Uppsala Giant Oil field database (Höök et al., 2014), Global Energy Monitor (GEM), and Offshore Technology (https://www.offshore-technology.com/). The Petroleum Dataset compiled by the Centre for the Study of Civil War at the Peace Research Institute Oslo (PRIO) (Lujala et al., 2007), which was used in the political science literature on conflicts (Sorens, 2011), contains information on the field name, year of discovery, year of production and location for several hundreds of discoveries in 80 countries from 1927 until 2003. 229 of these discoveries happen after 1950. Unfortunately, the year of production is missing for some observations. The Uppsala Giant Oil field database (Höök et al., 2014), which was used in Beverelli et al. (2011), contains information on estimated ultimate recovery, year of discovery, year of production and year when production reaches its peak for 264 discoveries in 40 countries between 1887 and 1999. 212 of these discoveries happen after 1950. As regards Global Energy Monitor, it contains data on more than 8000 currently operational oil and gas fields. This includes information on field name, its location, discovery year, production start year, operator, and owner.

Overall, our final dataset of oil discoveries contains a total of 792 giant discoveries in 72 countries between 1960 and 2012. 19 countries in the sample experience only one oil discovery. After merging all sources mentioned above, we obtain information on the production start date for 358 oil discoveries.

Table 6: Production date coverage 1960–2012

	Minerals	Oil
Discoveries with production date	147	358
Production date missing	73	434
Total	**220**	**792**

Table 7: Giant Discoveries Merged Data Set: value (percent of GDP) – unique country-year coverage, 1960–2012

	Obs.	Mean	Median	Std. Dev.	Min	Max
Oil	361	74	9	451	.037	8,101
Minerals	151	77	2	370	.00011	4,008
Pooled	480	80	8	442	.00011	8,101

Note: This table presents summary statistics on the number and size (as a percentage of GDP) of discoveries, after aggregation by country and year. Note that GDP data is missing for certain countries in some years.

A.3 Lead Times from Discovery to Production

Lead times in the development of commodity fields arise from a mix of technical, economic, geopolitical, and regulatory challenges, which vary across different projects. We reviewed discoveries with lead times longer than 40 years.

Several oil and gas discoveries have faced extensive lead times due to *technical difficulties*, including complex geological formations and high CO_2 content in natural gas and oil. Notable cases include **Natuna** (57 years, natural gas), **Kudu** (55 years, natural gas), **Russkoye** (50 years, oil), and **Bakken Oil** (49 years, oil). Similarly, discoveries like **Mansuriyah** (48 years, natural gas), **Semakovskoye** (47 years, oil), **Attahadi** (42 years, natural gas), and **Bovanenko** (41 years, oil) have experienced issues related to the extraction and processing of unconventional resources, delaying progress.

On the mining side, projects such as **Mutun** (58 years, iron ore), **Twangiza** (55 years, gold), **Ambatovy** (50 years, nickel), **Reko Diq** (50 years, copper and gold), **Khorat Basin** (45 years, potash), **Nyabikere** (42 years, rare earths), and **Goro** (41 years, nickel) have faced *economic challenges*, including high initial development costs, limited local demand, and the lack of necessary infrastructure. These economic barriers further slow progress in these mines, especially in regions where market conditions are unfavorable.

Geopolitical disputes and *regulatory delays* also play a crucial role in hindering the development of oil fields and mines. For example, fields like **Natuna** (57 years, natural gas), **Kudu** (55 years, natural gas), and **Dorra** (60+ years, natural gas) have been delayed by territorial disputes and conflicts over resource ownership. Meanwhile, projects such as **Mutun** (58 years, iron ore) and **Khorat Basin** (45 years, potash) have faced regulatory hurdles, including legal uncertainties and strong local opposition, particularly due to environmental concerns.

The interplay of *technical*, *economic*, *geopolitical*, and *regulatory* challenges accounts for the prolonged delays in the development of these oil fields and mines. Furthermore, at the time of discovery, it is often unclear how long it will take to develop commodity fields, as various factors can influence the timeline. The **Natuna** gas field in Indonesia is a prime example of this uncertainty. Discovered in 1973 by Agip, the field initially held great promise. However, the development timeline quickly became unclear due to a series of challenges over the years. In 1980, a joint venture was formed between the Indonesian state-owned Pertamina and Exxon to develop the Natuna D-Alpha block, but production faced significant setbacks due to the high CO_2 content in the gas. Subsequent agreements, including those signed in 1995 with Exxon and in 2008 with Pertamina, reflected ongoing difficulties in advancing the project. Even as late as 2016, despite numerous renegotiations and efforts by various companies, the development of the Natuna field remained stalled.

B Macroeconomic Data

Table 8: Variables definitions

Variable	Definition and transformations	Source
	Main Macroeconomic Variables	
log(GDP)	log of GDP in constant LCU	IMF(2013)
CA	current account (% GDP)	IMF(2013)
I	investment (% GDP)	World Bank(2013)
	Additional Variables	
S	saving as (% GDP) constructed as CA+I	-
log(C)	log of final consumption expenditures in constant LCU	IMF(2013)
EMP	employment to population ratio, percentage), male and female, age 15+	"emploare" from International Labor Organization website (www.ilo.org/kilm)
Net FDI	FDI Capital Net Flows (% GDP) (annual-FDINetF2y-ifs)	Alfaro et al. (2014)

Table 9: Macro Data 1980-2012

Variable	Years	Nb of countries	Obs	Mean	Min	Median	Max	Std
Log(GDP)	1980–2012	181	5478	553.4	-278.1	579.5	1477.8	321.6
CA	1980–2012	179	5396	-3.5	-242.2	-3.2	106.8	12.3
I	1980–2011	177	4954	22.2	-2.4	21.1	113.6	8.4
S	1980–2011	171	4711	18.8	-202.9	18.1	107.2	12.2
Log(C)	1980–2012	162	4567	576.5	-82.3	590.7	1435.6	282.5
EMP	1991–2012	160	3519	58.1	28.9	57.7	88.1	11.5
Net FDI	1980–2012	181	4652	2.6	-147.1	1.1	164.5	7.6

C Additional Results

Figure 9 shows the impulse responses of the savings rate, consumption, and the employment rate to an oil discovery news (first row) and to a mineral discovery news (second row).

After an oil discovery news, the savings rate immediately turns negative and becomes positive around production start date. Consumption increases 1 year after the discovery, but the response is small in magnitude and the estimates are imprecise, which may be due to measurement error in the consumption data, as discussed in ARS. As regards the employment rate, it falls significantly a year before production starts, reaches a trough 8 years after the discovery and gradually returns to normal.

In response to mineral discoveries, we observe a delayed impact on these variables: savings decline significantly after 6 years before turning positive around production start date, consumption increases sharply and persistently after a few years, and employment starts to fall

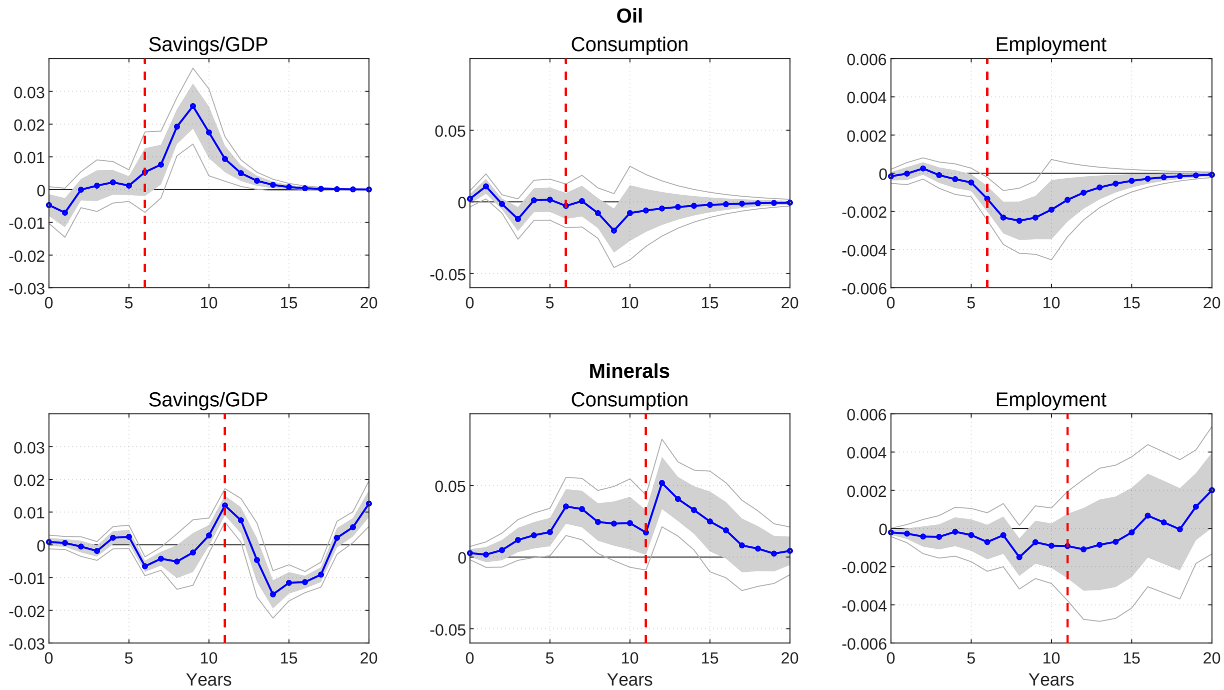


Figure 9: Impulse responses to oil (first row) and mineral (second row) discoveries

Notes: These graphs show the estimated impulse responses of aggregate variables to an oil news shock (first row) and to a mineral news shock (second row). The vertical red dashed line indicates the median lead time between the discovery date and the start of production date for each type of commodity (6 years for oil discoveries, 11 years for mineral discoveries). 90% and 68% confidence intervals are shown in all cases.

after 8 years, gradually returning to normal and even becoming positive in the long run. However, the estimates for the employment response are imprecise and not statistically different from zero. These findings support our baseline results, showing that the effects of mineral discoveries are delayed, with little impact in the first 5 years following the discovery.

Table 10: Estimates from multinomial regressions

	(1)			(2)			(3)			(4)		
	Commodity type			Commodity type			Commodity type			Commodity type		
	Oil	Minerals	Both	Oil	Minerals	Both	Oil	Minerals	Both	Oil	Minerals	Both
Land Area	0.04***	0.04***	0.05***							0.04**	0.03**	0.06***
	(0.00)	(0.00)	(0.00)							(0.00)	(0.01)	(0.00)
East Asia	-0.19	-16.51***	0.79							2.94	-38.52*	4.32***
	(0.87)	(0.00)	(0.25)							(0.17)	(0.03)	(0.00)
Latin America	-0.03	-3.04*	-0.08							1.31	-2.97	0.49
	(0.97)	(0.01)	(0.90)							(0.57)	(0.05)	(0.63)
Africa	0.31	-2.06**	-0.99							1.97	0.23	-1.48
	(0.69)	(0.00)	(0.23)							(0.44)	(0.87)	(0.24)
Life Expectancy				0.00	0.02	0.03				0.10	0.23*	-0.01
				(0.96)	(0.62)	(0.46)				(0.23)	(0.03)	(0.90)
Population Density				0.00*	0.00	0.00				0.00	0.00	-0.02***
				(0.03)	(0.16)	(0.27)				(0.62)	(0.62)	(0.00)
Population Density Coastal				-0.00	-0.00	-0.00				-0.01	0.01	-0.02**
				(0.42)	(0.14)	(0.21)				(0.16)	(0.16)	(0.01)
Fraction Population under 15				1.37	-5.77	3.18				1.00	-5.81	2.68
				(0.81)	(0.26)	(0.54)				(0.89)	(0.55)	(0.77)
GDP Per Capita							-9.22	5.37	-3.11	15.73	62.32	1.68
							(0.68)	(0.76)	(0.86)	(0.64)	(0.13)	(0.96)
Investment Price							0.00	0.00	-0.01	0.00	0.00	-0.00
							(0.87)	(0.89)	(0.49)	(0.97)	(0.78)	(0.74)
Years Open							-0.28	-0.27	-0.16	0.02	-7.12*	1.59
							(0.79)	(0.79)	(0.87)	(0.99)	(0.02)	(0.35)
Primary Schooling							-1.12	0.10	-0.09	-1.08	-3.73	-1.00
							(0.37)	(0.93)	(0.92)	(0.69)	(0.18)	(0.71)
N	139			103			113			98		
r2_p	0.29			0.08			0.02			0.43		

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table reports estimates from multinomial logistic regressions of the type of commodity discovery experienced by a country (there are four possible outcomes: discovering oil, discovering minerals, discovering both types of commodities, and discovering none, which is the base outcome) on several geographic, demographic, and economic indicators.

Table 11: Estimates from regressions of lead times on long-term economic growth determinants

	(1) Lead time	(2) Lead time	(3) Lead time	(4) Lead time
Africa	-0.21			-2.19
	(0.91)			(0.44)
Land Area	-0.31			0.01
	(0.07)			(0.96)
East Asia	-0.88			-2.74
	(0.50)			(0.48)
Latin America	-0.75			1.75
	(0.75)			(0.55)
Life Expectancy		-0.19		-0.29
		(0.08)		(0.19)
Population Density		-0.00		-0.01
		(0.21)		(0.19)
Population Density Coastal		-0.03**		-0.04**
		(0.00)		(0.00)
Fraction Population under 15		-32.13		-47.09*
		(0.09)		(0.03)
GDP Per Capita			-37.92	34.14
			(0.58)	(0.67)
Investment Price			-0.01	-0.01
			(0.25)	(0.60)
Years Open			0.80	3.03
			(0.74)	(0.44)
Primary Schooling			-4.44	-5.38
			(0.18)	(0.41)
Oil	-8.93***	-7.36***	-8.19***	-8.04***
	(0.00)	(0.00)	(0.00)	(0.00)
Gas	-5.51**	-3.95*	-4.79*	-4.46*
	(0.00)	(0.01)	(0.02)	(0.03)
Offshore	4.24	4.32*	3.63	4.47*
	(0.06)	(0.03)	(0.10)	(0.04)
N	420	367	374	345
r2	0.26	0.28	0.25	0.29

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table reports estimates from regressions of lead times between discovery and production dates on several geographic, demographic, and economic indicators. Commodity and time fixed effects are included.

D Robustness and Extensions

D.1 Other commodity splits

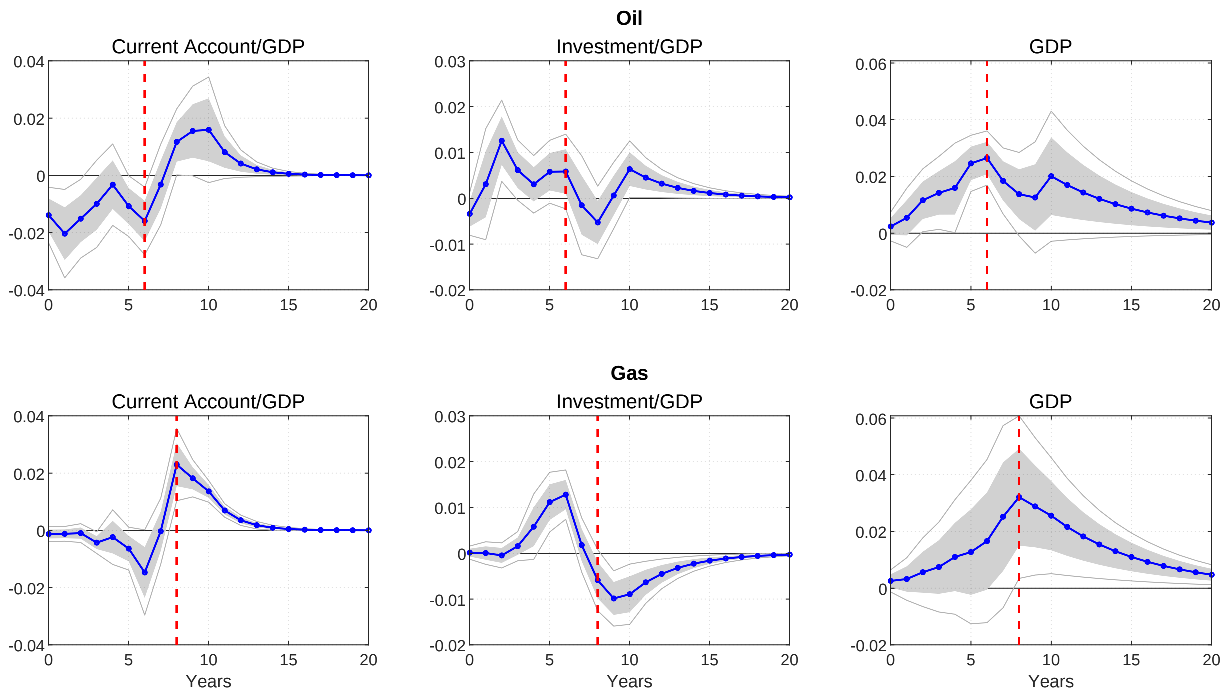


Figure 10: Impulse responses to oil (first row) and gas (second row) discoveries

Notes: These graphs show the estimated impulse responses of aggregate variables to an oil discovery news shock (first row) and to a gas discovery news shock (second row). The vertical red dashed line indicates the median lead time between the discovery date and the start of production date for each type of discovery (6 years for oil discoveries, 8 years for gas discoveries). 90% and 68% confidence intervals are shown in all cases.

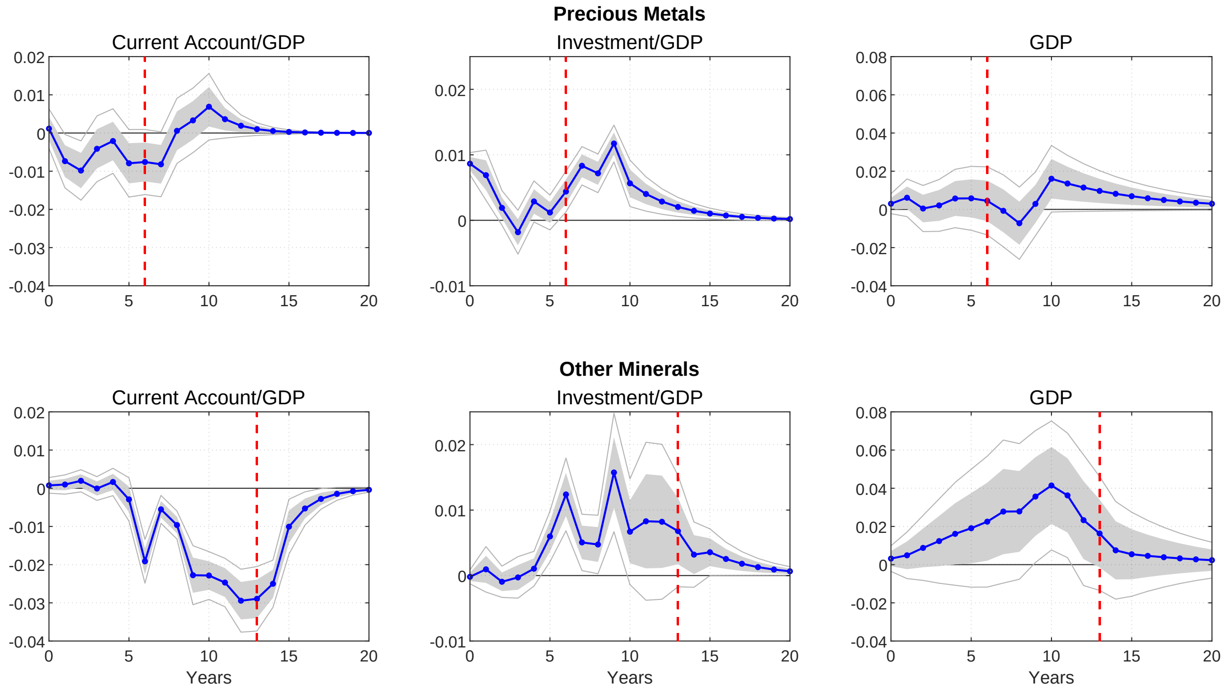


Figure 11: Impulse responses to precious metals (first row) and other minerals (second row) discoveries

Notes: These graphs show the estimated impulse responses of aggregate variables to a precious metals discovery news shock (first row) and to other minerals discovery news shock (second row). The vertical red dashed line indicates the median lead time between the discovery date and the start of production date for each type of discovery (6 years for precious metals discoveries, 13 years for other minerals discoveries). 90% and 68% confidence intervals are shown in all cases.

D.2 Excluding discoveries with lead time greater than 20 years or inferior to 2 years

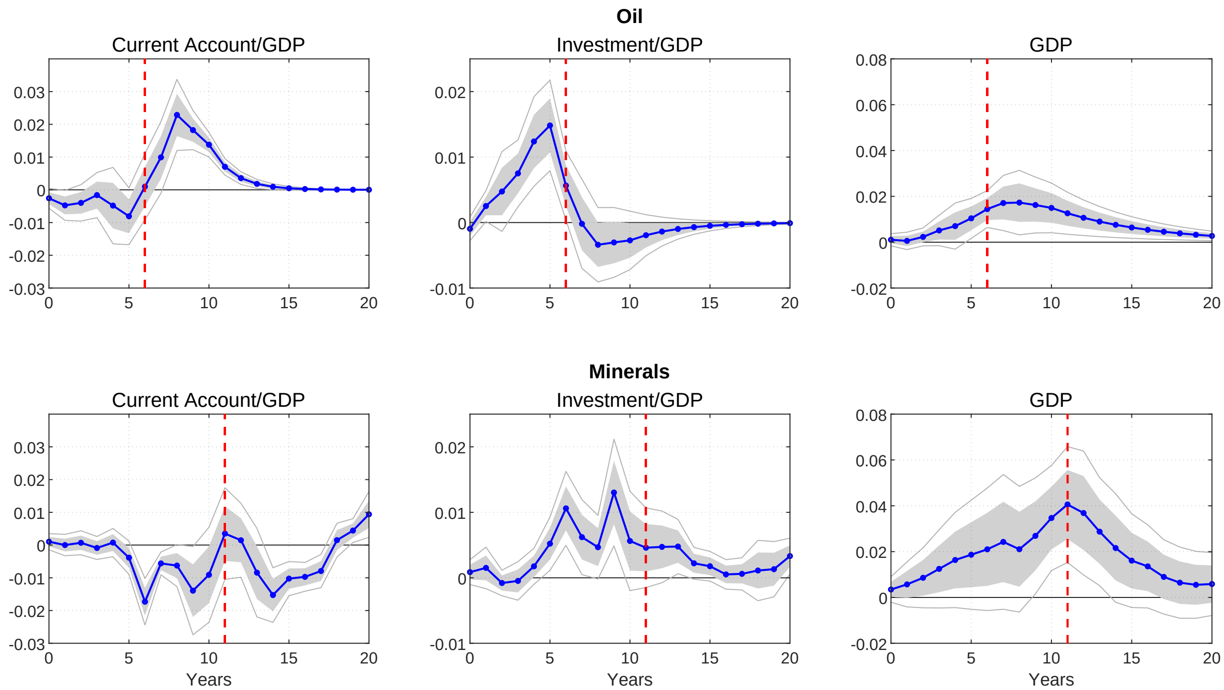


Figure 12: Impulse responses to oil (first row) and minerals (second row) discoveries with lead time inferior to 20 years

Notes: These graphs show the estimated impulse responses of aggregate variables to an oil discovery news shock (first row) and to a minerals discovery news shock (second row). The vertical red dashed line indicates the median lead time between the discovery date and the start of production date for each type of discovery (6 years for oil discoveries, 11 years for minerals discoveries). 90% and 68% confidence intervals are shown in all cases.

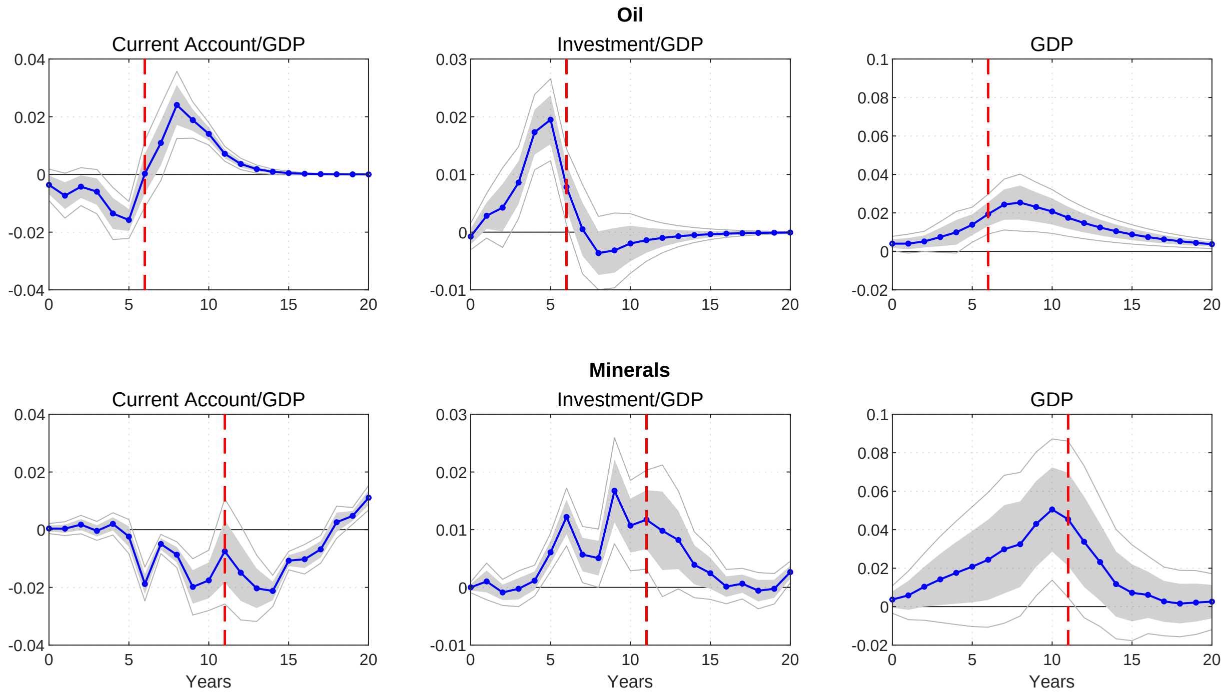


Figure 13: Impulse responses to oil (first row) and minerals (second row) discoveries with lead time greater than 2 years

Notes: These graphs show the estimated impulse responses of aggregate variables to an oil discovery news shock (first row) and to a minerals discovery news shock (second row). The vertical red dashed line indicates the median lead time between the discovery date and the start of production date for each type of discovery (6 years for oil discoveries, 11 years for minerals discoveries). 90% and 68% confidence intervals are shown in all cases.

D.3 Keeping countries experiencing both types of discoveries

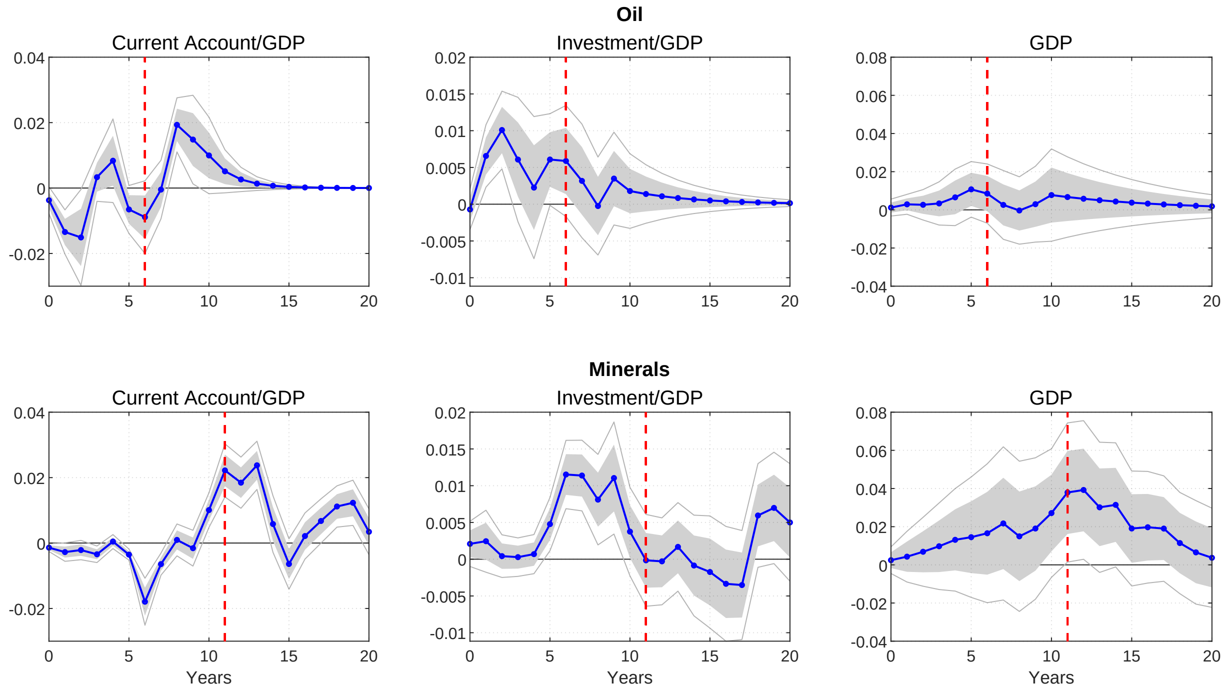


Figure 14: Impulse responses to oil (first row) and minerals (second row) discoveries

Notes: These graphs show the estimated impulse responses of aggregate variables to an oil discovery news shock (first row) and to a minerals discovery news shock (second row). The vertical red dashed line indicates the median lead time between the discovery date and the start of production date for each type of discovery (6 years for oil discoveries, 11 years for minerals discoveries). 90% and 68% confidence intervals are shown in all cases.

D.4 Alternative measure of shock (dummy)

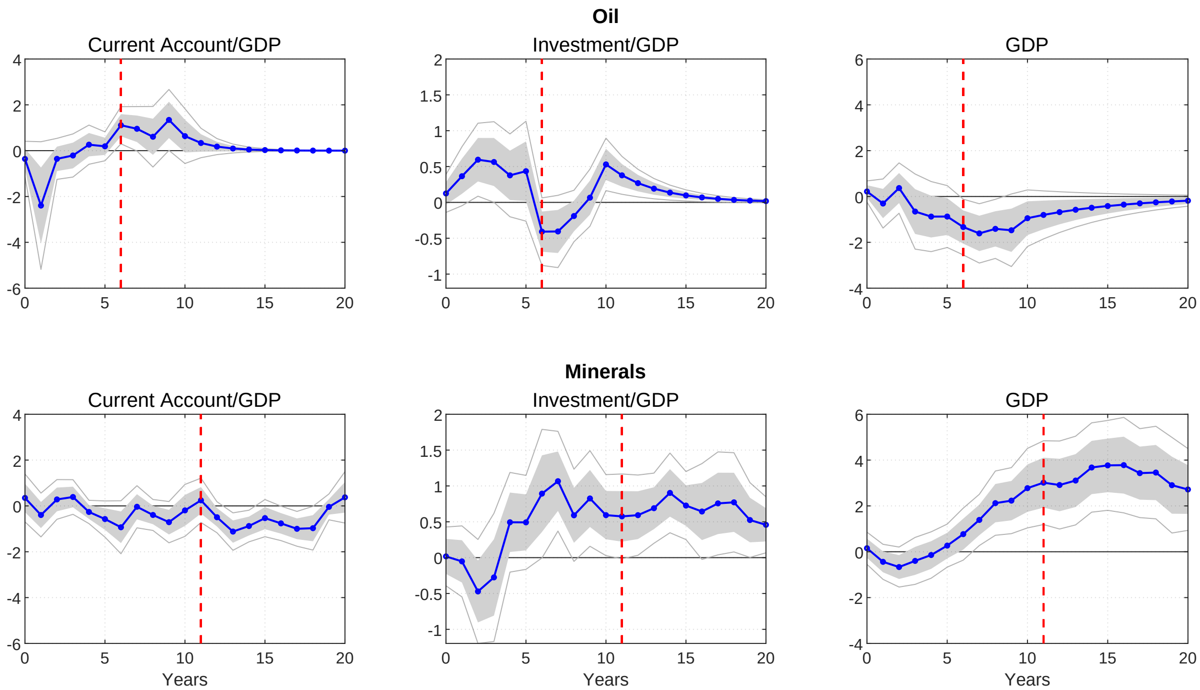


Figure 15: Impulse responses to oil (first row) and minerals (second row) discoveries

Notes: These graphs show the estimated impulse responses of aggregate variables to an oil discovery news shock (first row) and to a minerals discovery news shock (second row). The vertical red dashed line indicates the median lead time between the discovery date and the start of production date for each type of discovery (6 years for oil discoveries, 11 years for minerals discoveries). 90% and 68% confidence intervals are shown in all cases.

D.5 Alternative measure of shock (common discount rate 10%)

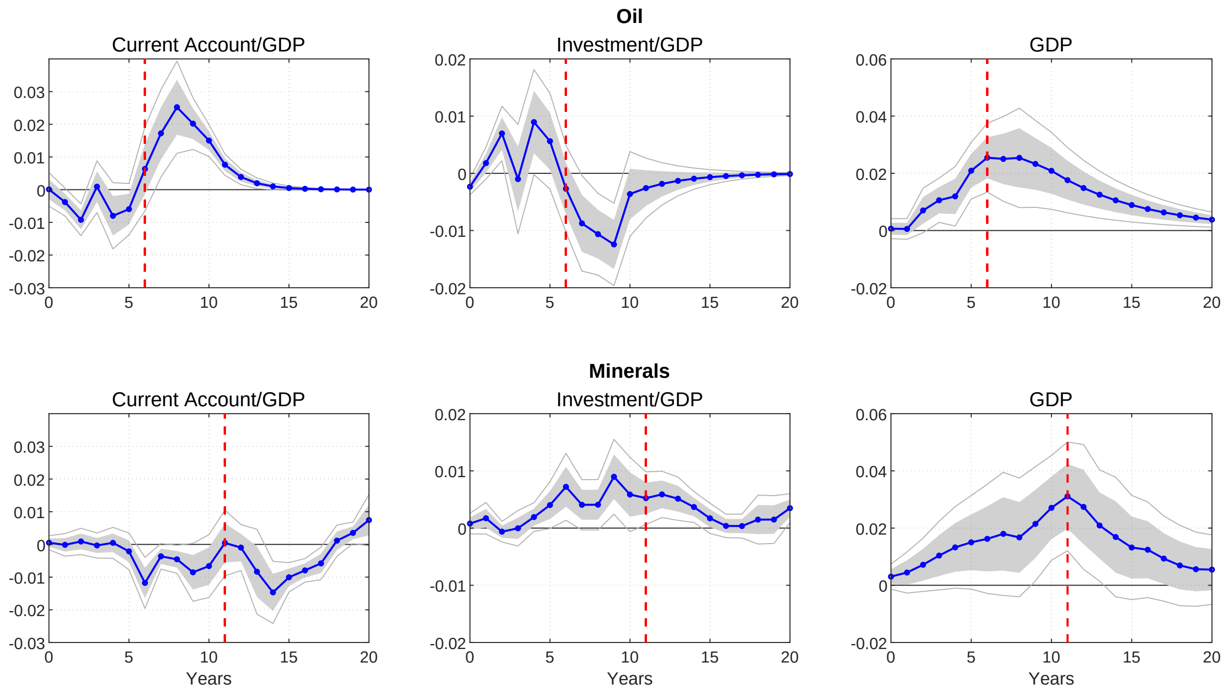
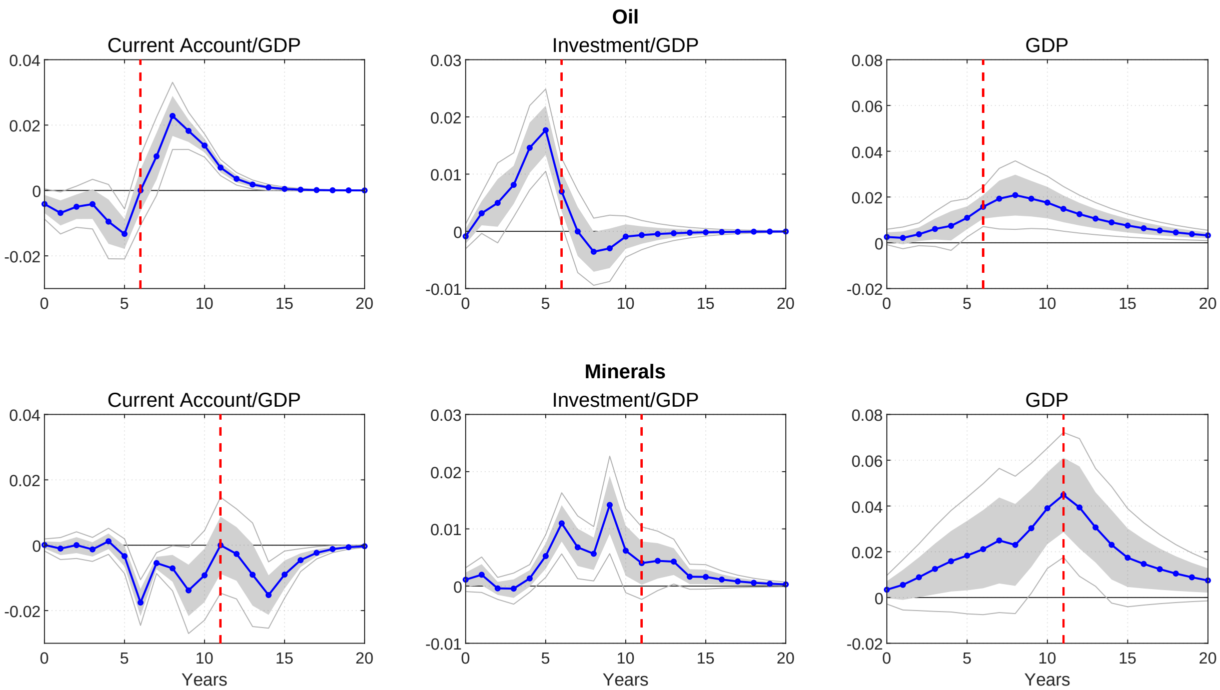


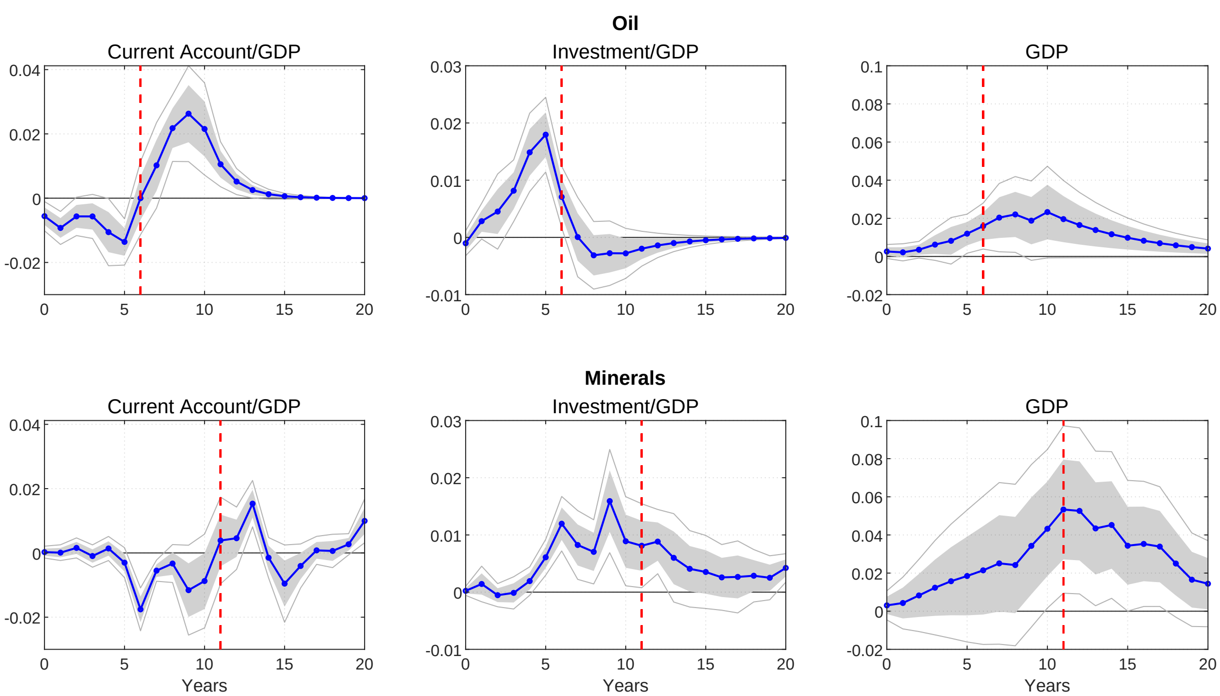
Figure 16: Impulse responses to oil (first row) and minerals (second row) discoveries

Notes: These graphs show the estimated impulse responses of aggregate variables to an oil discovery news shock (first row) and to a minerals discovery news shock (second row). The vertical red dashed line indicates the median lead time between the discovery date and the start of production date for each type of discovery (6 years for oil discoveries, 11 years for minerals discoveries). 90% and 68% confidence intervals are shown in all cases.

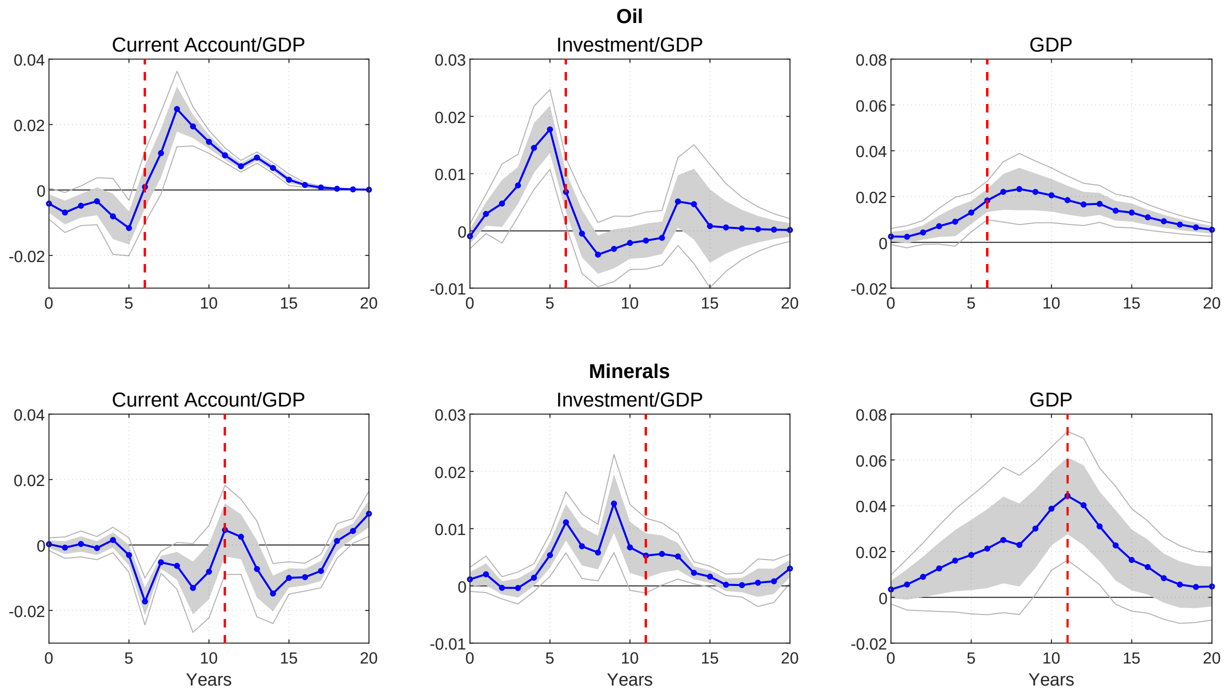
D.6 Alternative dynamic specifications



(a) $p = 10$, $q = 15$



(b) $p = 10$, $q = 25$



(c) $p = 15$, $q = 20$

Notes: These graphs show the estimated impulse responses of aggregate variables to an oil discovery news shock (first row) and to a minerals discovery news shock (second row) for different dynamic specifications. The vertical red dashed line indicates the median lead time between the discovery date and the start of production date for each type of discovery (6 years for oil discoveries, 11 years for minerals discoveries). 90% and 68% confidence intervals are shown in all cases.

Figure 16: Impulse responses to oil (first row) and minerals (second row) discoveries

D.7 Local Projections

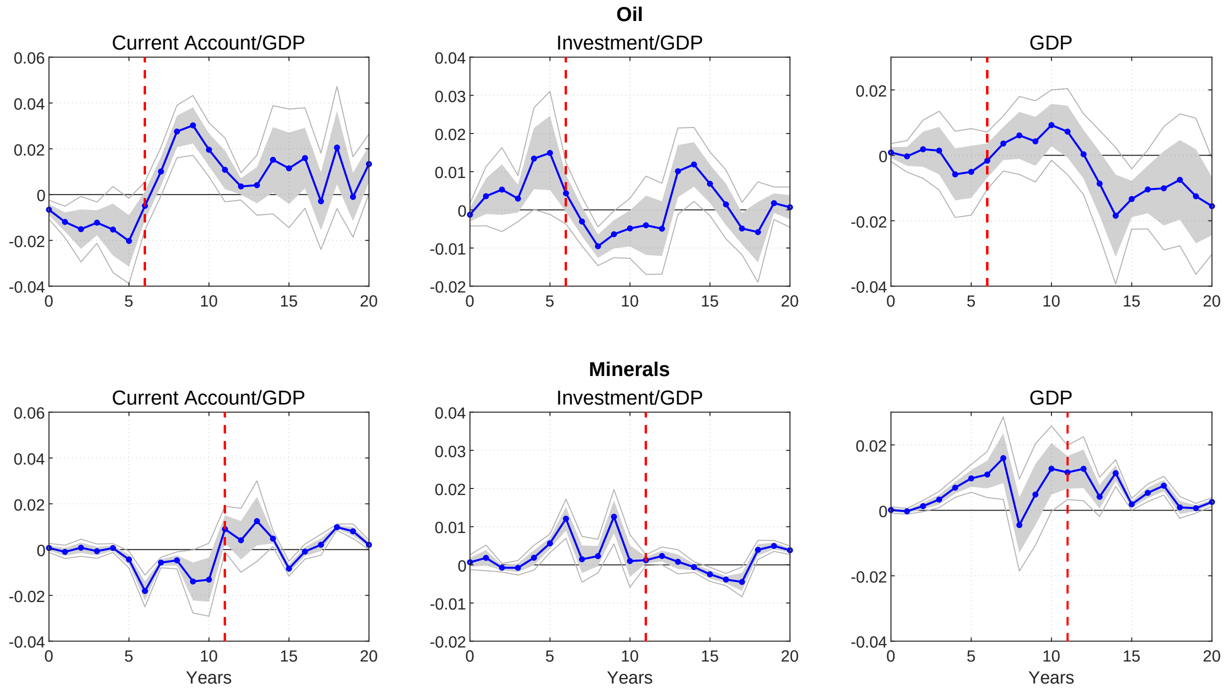


Figure 17: Impulse responses to oil (first row) and minerals (second row) discoveries

Notes: These graphs show the estimated impulse responses of aggregate variables to an oil discovery news shock (first row) and to a minerals discovery news shock (second row). The vertical red dashed line indicates the median lead time between the discovery date and the start of production date for each type of discovery (6 years for oil discoveries, 11 years for minerals discoveries). 90% and 68% confidence intervals are shown in all cases.

D.8 Split by Lead Time: Instrumental Variable Approach

Table 12: Estimates from regressions

	(1) Lead time
Distance	1.14*
	(0.04)
Commodity=2	-10.29
	(0.08)
Commodity=3	24.79*
	(0.01)
Commodity=4	18.60*
	(0.01)
Commodity=2 X Distance	2.09*
	(0.04)
Commodity=3 X Distance	-3.53*
	(0.02)
Commodity=4 X Distance	-1.42
	(0.23)
Offshore=1 X Distance	0.90**
	(0.00)
N	581
R^2	0.19

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table reports estimates from the regression of the lead time between discovery and production dates on the distance to the nearest big city, the commodity type, whether the discovery is offshore, and interaction terms. Commodity type 1 (base case) is oil, type 2 is gas, type 3 is precious metals, type 4 is other minerals. Regional and time fixed effects are included.

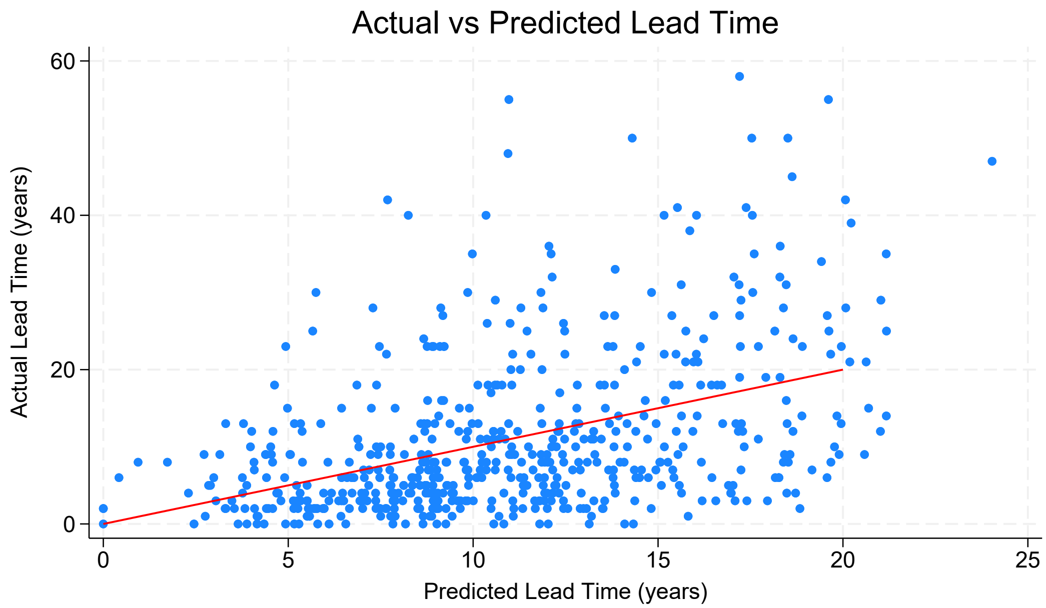


Figure 18: Actual vs. predicted lead time

E Model

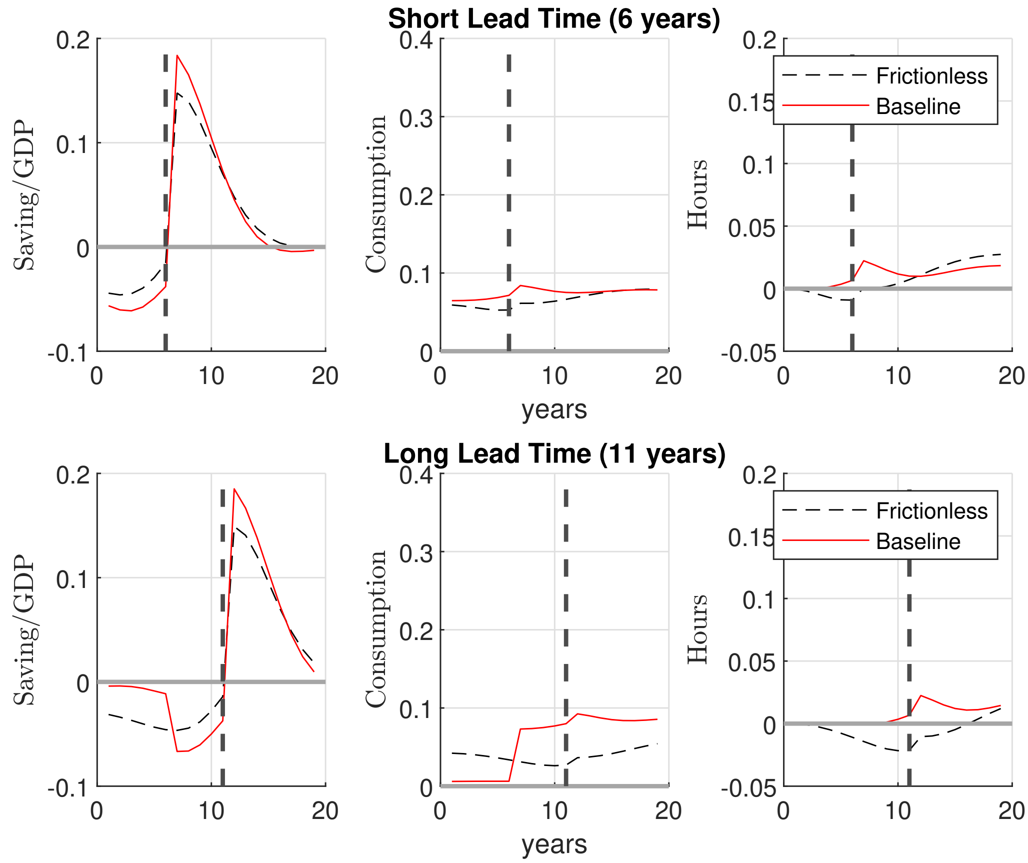


Figure 19: Impulse responses for savings, consumption, and hours

Notes: This figure presents the impulse responses of savings to GDP ratio, consumption and hours to a short lead-time discovery (first row) and a long lead-time discovery (second row). The responses are shown for our baseline model with financial frictions (red solid lines) and without financial frictions (black dashed lines).

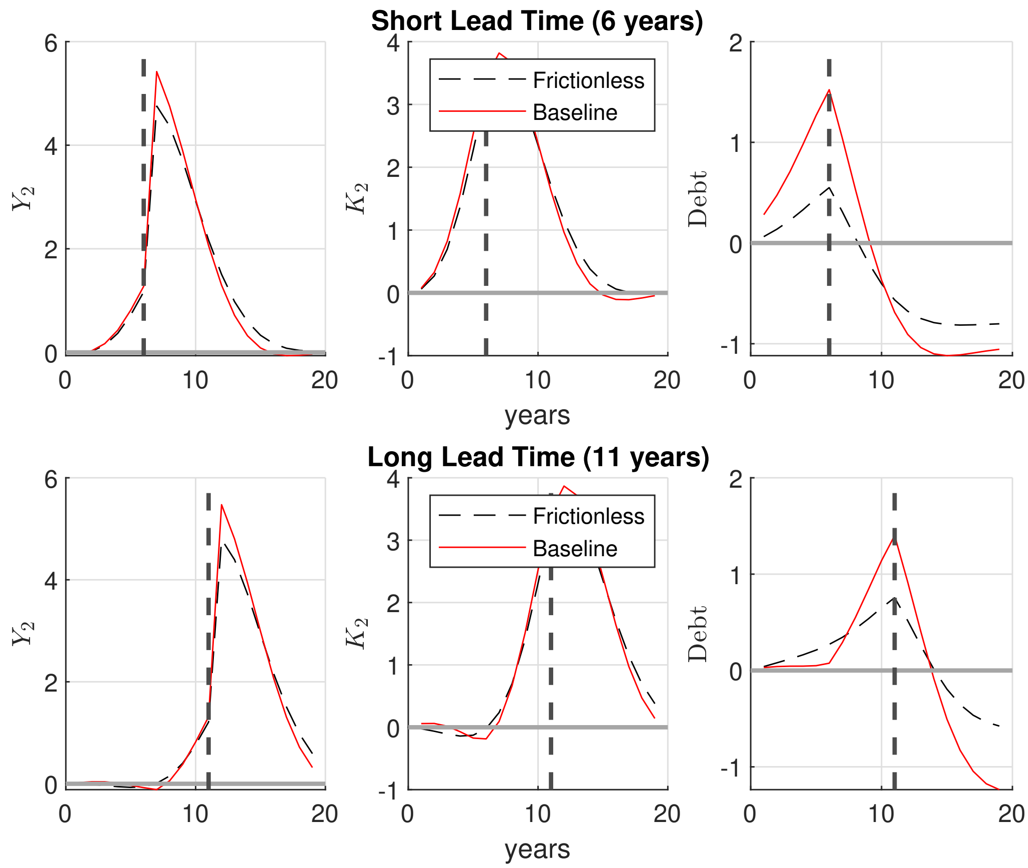


Figure 20: Impulse responses for output and capital in the commodity sector as well as debt.

Notes: This figure presents the impulse responses of output (Y_2) and capital (K_2) in the commodity sector, as well as debt, to a short lead-time discovery (first row) and a long lead-time discovery (second row). The responses are shown for our baseline model with financial frictions (red solid lines) and without financial frictions (black dashed lines).

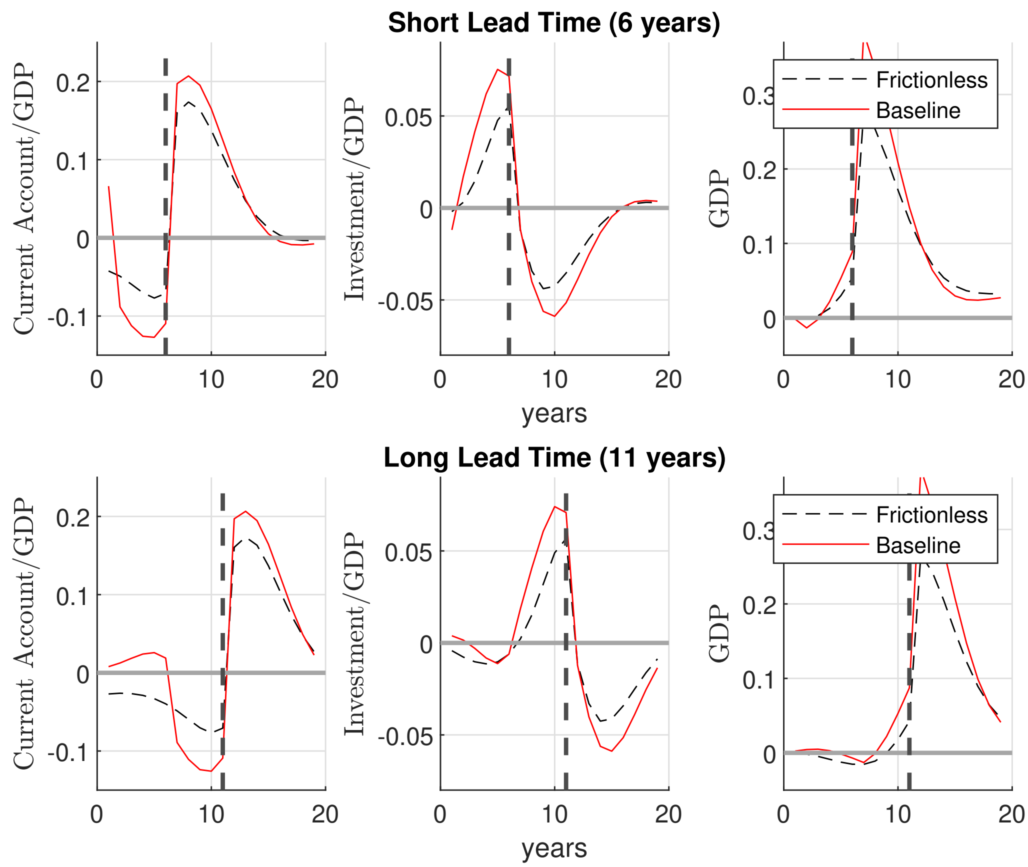


Figure 21: Impulse responses for current account, investment, and GDP with tighter borrowing constraints

Notes: This figure presents the impulse responses of the current account to GDP ratio, investment to GDP ratio and GDP to a short lead-time discovery (first row) and a long lead-time discovery (second row). The responses are shown for our baseline model with financial frictions (red solid lines) and without financial frictions (black dashed lines).

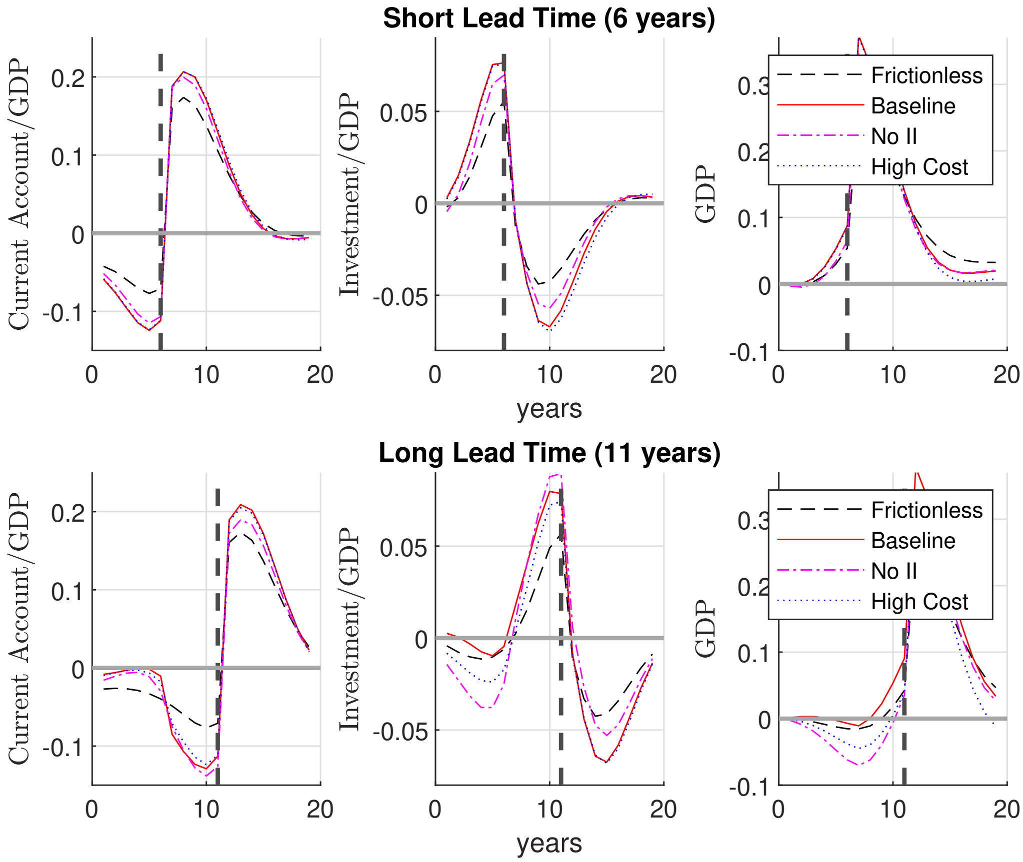


Figure 22: Impulse responses for current account, investment, and GDP for different frictions

Notes: This figure presents the impulse responses of the current account to GDP ratio, investment to GDP ratio, and GDP to a short lead-time discovery (first row) and a long lead-time discovery (second row). The responses are shown for our baseline model with financial frictions (red solid lines), without financial frictions (black dashed lines), without investment irreversibility (pink dash-dotted lines), and without investment irreversibility but with very high investment adjustment costs (dotted lines).