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Revenue forecasting in the mining industries

A data-driven approach

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Abstract: Robust forecasting of mining sector revenues is key to effective budgeting (and broader fiscal management) in many resource-rich countries. However, this is challenging in practice, given commodity market volatility, the extended lags (and often opaque processes) between resource discoveries and fiscal yields, and the heterogeneity of taxable entities within the sector. Such issues are exacerbated by capacity deficits: quantitative sector assessment frameworks are seldom employed or maintained by revenue authorities. In contrast, commercial mining entities typically have well-developed tools for analysing future cash flows and profitability. This paper identifies considerable scope to strengthen public revenue forecasts by drawing more heavily on industry best practices and data sources, including through bottom-up analysis of the tax base and a more rigorous approach to modelling key uncertainty drivers.

Key words: corporate income tax, extractive industries, mineral tax, minerals, mining, revenue forecasting, royalty

JEL classification: H20, H25, L72, N50

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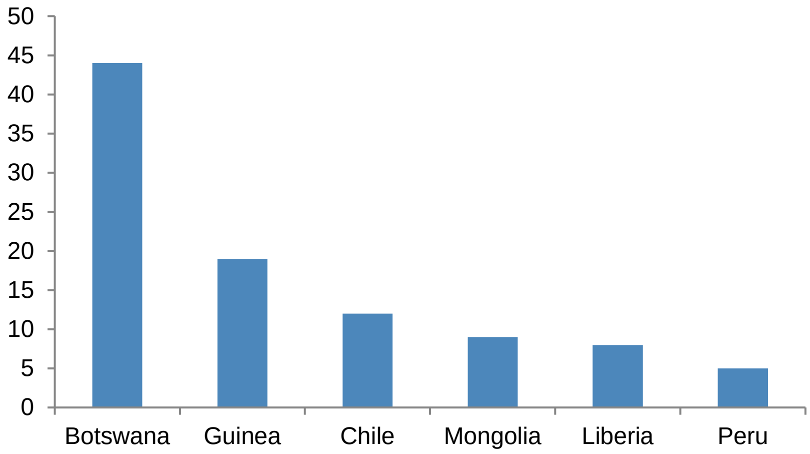
1 Introduction

Robust revenue forecasting is key to effective budgeting, including execution of public investment and expenditure programmes, debt and financial management, and the formation and implementation of wider tax and public policy frameworks.[1] However, weak institutions and a procyclical general tax base present perennial barriers to robust, unbiased revenue projections, particularly in developing countries (Avellan and Vuletin 2015; Frankel 2011).

Forecasting fiscal revenues in the mining sector is particularly challenging given commodity price volatility (and other complex market forces shaping investment flows), the extended lags between resource discoveries, extraction decisions (which are often subject to opaque processes), fiscal yields, and the substantial heterogeneity which exists among taxable entities. This is a key issue in resource-rich countries, given the importance of the mining sector as a source of fiscal revenues (Figure 1, for example, illustrates receipts from a selection of countries).

Figure 1: Mining industry receipts, selected countries, % of average annual government revenue, 2000–07



Source: IMF staff calculations reported in Boadway and Keen (2009).

There are many examples in which future revenue streams from resources sectors have been misevaluated. The Cobre Panama copper mining project provides a recent case in point. The copper was originally discovered in the mid-20th century, and the project was projected to commercialize in 2015. However, following a series of technical issues, social disturbances, and other development delays, production eventually came online only in 2019 and at around 10 per cent higher than forecast capital costs. For a project valued at three to four per cent of national gross domestic product (GDP), such considerations have major macro-fiscal implications.[2]

[1] Commodity-rich countries may also face particular challenges relating to expenditure management, including political incentives to sustain budgets and accumulate debt as a countercyclical measure (see e.g., Arezki and Bruckner 2010).

[2] Such examples are certainly not limited to the mining sector. In Ghana, for example, oil production from its Jubilee Field began in 2010. The government projected significant corporate tax receipts from 2011, but the first payments did not arrive until 2013 (Roe 2018a, 2018b). Massive gas finds in the Indian Ocean around the United Republic of Tanzania provide a further (rather extreme) case in point: the gas was initially discovered in 2011, but after a series of false dawns, plant construction is now only expected in 2022 (with fiscal revenues unlikely before the middle of the decade).

A robust, yet suitably 'risked', view on the potential revenue contribution of the mining sector is thus a critical foundation for public policy. However, in many developing countries, these judgements are commonly based on highly simplified assumptions and analytical frameworks which take limited account of key determining factors (and the uncertainty to which these are subject). Such factors potentially include, but are not limited to, future commodity market conditions as well as relevant technical, geological, and economic factors shaping the size and tax liability of the domestic mining industry and key operators within it.

A recent review of 20 resource-rich African countries by the African Development Bank (AfDB 2017) highlighted pervasive capacity gaps in the analysis of fiscal revenues in extractives sectors. In particular, the report found that where financial models are used at all, they are rarely updated regularly and seldom used for revenue monitoring. In addition, the authors found significant gaps in access to and availability of key data, including in relation to detailed production, reserves, and cost data.[3]

In stark contrast to the institutional context in many developing countries, commercial mining entities typically have a range of well-developed planning tools to help understand the potential outlook for cash flows and profitability, under different potential outcomes. These tools are commonly based on detailed (often but by no means universally private) technical and commercial information regarding the operating asset, ore body, offtaking arrangements, and future investment and marketing plans.

Clearly, such highly developed industry toolkits are beyond both the scope of responsibility and the internal capacity and resources of most public revenue forecasting units within the revenue authorities of finance ministries in resource-rich developing countries (whose starting point, as indicated, could often not be further removed from their well-resourced and highly specialized commercial-scale industry counterparts). But this is not to suggest that lessons from industry planners cannot be brought to bear for the public benefit. In fact, quite the opposite.

This paper argues that there is indeed considerable scope to improve the rigour of public revenue forecasting in the mining sector by drawing more heavily from relevant industry best practices and data sources. It outlines a set of potential approaches based on widely utilized commercial practices, emphasizing the importance of proper (but parsimonious) identification and evaluation of the key revenue generation parameters, use of high-quality data inputs, and detailed sensitivity analysis to take account of the inherent uncertainties affecting industry revenues.

In this context, it is noteworthy that a number of international agencies and non-governmental organizations have sought to improve the rigour of extractive tax and revenue analysis, drawing on models which integrate a view on industry cash flows with key fiscal parameters. Perhaps the best known of these is the International Monetary Fund's (IMF) Fiscal Analysis of Regime Industry (FARI) model, for example. Such capacity development tools are extremely welcome for better informing relevant extractive tax policy parameters, as well as latterly for supporting improved revenue forecasting (IMF 2016).

However, to date, quantitative assessment tools have tended to focus on supporting tax policy analysis in the oil and gas industries (CCSI 2017; OpenOil 2017a, 2017b, 2018, 2019). This reflects,

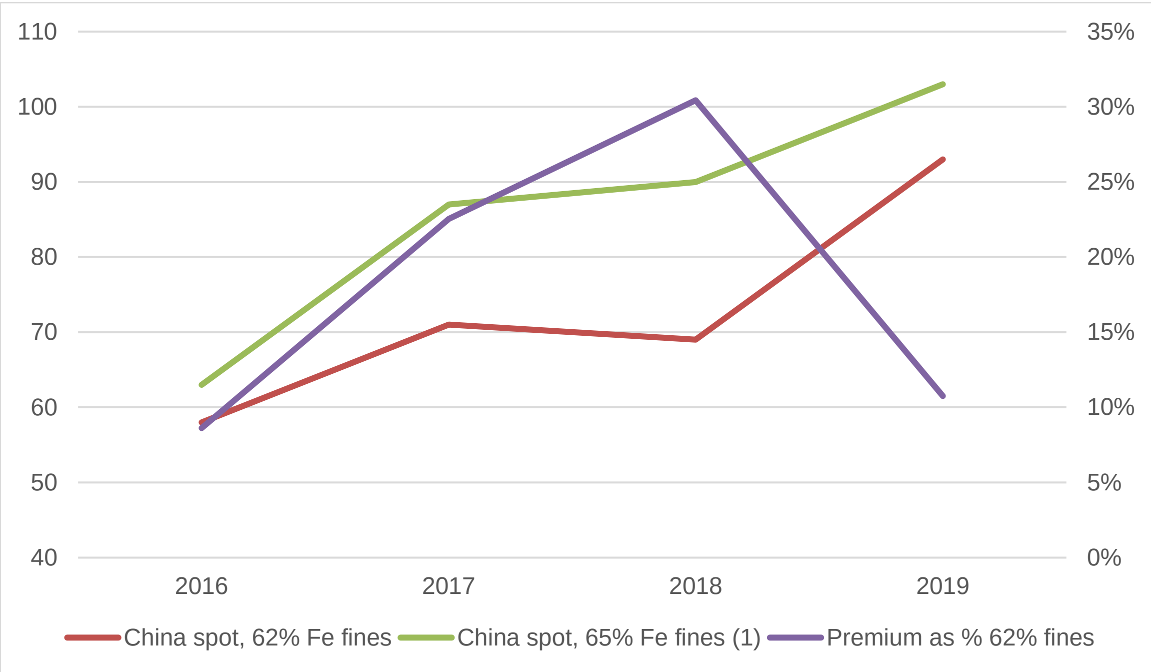
[3] AfDB (2017) identified only infrequent use of commercial databases, set against the backdrop of frequent deployment of expensive consultancy reports. Such databases limit the need to collect and interpret often disparate data from financial statements and other publicly available records, which are rarely reported at the asset level on a like-for-like basis.

at least in part, the tendency for petroleum industries to make greater contributions than the mining sector to fiscal revenues across many countries (IMF 2010). Where financial models have been more specifically tailored to the mining sector (e.g., CCSI 2015; IMF 2016; NRGI 2017; OpenOil 2015; World Bank 2006), these are typically founded on highly stylized assumptions (including in relation to production costs and their sensitivity to exchange rates).

The challenge of addressing such capacity gaps in the context of revenue forecasting should perhaps not be underestimated, for a number of reasons. First, existing fiscal-financial models have typically been developed for complementary, yet rather distinct, advisory purposes, including for example to inform tax policy decisions or to support negotiations. As such, they are commonly parameterized on a limited number of projects or assets, rendering them most suitable, at least in their most immediate form, for revenue forecasting in highly concentrated extractives sectors. Extending the applicability of these toolkits for revenue forecasting purposes thus commonly requires analysis of, and aggregation over, a broader set of industry input data.[4]

A second set of challenges arises from economic and technical particularities of the mining sector which have often been weakly addressed in fiscal-financial modelling to date. For example, mineral chains are typically highly complex and multi-staged, raising the need to understand processing costs and investment returns in more detail (relative to, say, the oil and gas industries). Ore grade and beneficiation are of critical importance for value creation in many bulk commodities. During 2018, for example, the premium for 65 per cent over 62 per cent iron-containing ore reached around 30 per cent, before collapsing to around 10 per cent in 2019 (see Figure 2). In base metals industries, proper accounting for different revenue streams is essential for a representative picture of operating margins in polymetallic mines (such as, for example, the value of precious metals from products recovered in the mining of nickel or copper).

Figure 2: Iron ore prices by grade, 2016–19, US$ per tonne



Source: author's illustration based on CRU data.

[4] See Mesa Puyo and Watson (2018) for a broader discussion of technical issues relating to the extension of the FARI model for revenue forecasting purposes.

This paper is intended to provide practical support to ongoing efforts to develop and parameterize existing fiscal-industry cash flow models (such as FARI), and to strengthen fiscal policy capacity in the mining sector more generally, through robust, quantitatively founded guidance on analysing revenue drivers and outlook. In particular, it highlights the potential for more extensive use of bottom-up analytical techniques—widely used as part of mining industry cash flow and market-related analysis—to improve the modelling of fiscal revenues from the sector.

The paper argues that when suitably calibrated—using, for example, commercially available data resources relating to production profiles and costs of individual mining assets (such as those provided by CRU)—such methodologies may obviate the need for the complex and often fragile assumptions required to model revenues using top-down techniques based on the representative mining operation (thereby providing a more technically robust basis for analysing the future and revenue base and outlook).

However, recognizing the preferences among some policymakers for the latter approaches to undertaking revenue projections, this paper also provides guidance on the determination and calibration of aggregated input assumptions in an industry which is widely characterized by different economic scales, operating efficiencies, ore qualities and values, and logistics and other relevant costs.

Finally, it offers technical support for modelling stochastic revenue outcomes. This is intended as an alternative to the tendency for forecasts to be based on current or forward-looking production data taken from the mine plans of larger operators, without due consideration for the market and technical risks to which they may be subject. In addition, revenue forecasts are commonly generated based on single ad hoc price assumptions, without taking robust account of the volatility that is inherent to these product markets and the potential implications for the size of the future tax base.

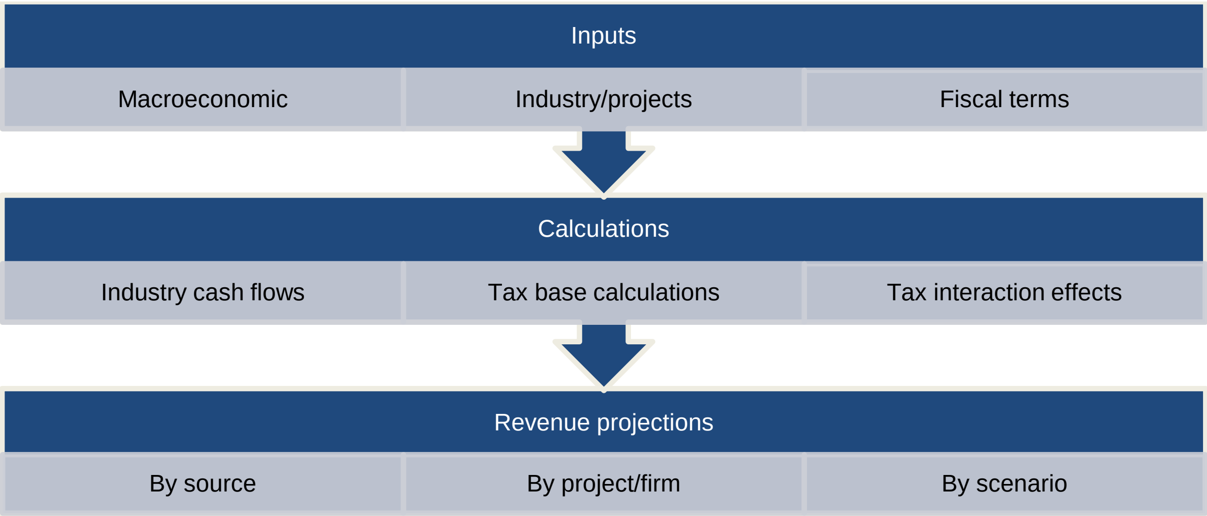
The rest of this paper is divided into three sections. Section 2 discusses general methodology and data issues relating to fiscal revenue forecasting in the mining sector, and then moves on to a more in-depth discussion of key macro, mining industry, and fiscal-related data input assumptions and model calibration issues. Section 3 discusses the evaluation of uncertainty in forecasting mining revenues, and illustrates a statistical approach to analysing a downside price and production scenario. Section 4 concludes.

2 Forecasting methodologies and inputs

Fiscal policymakers looking to inform tax and revenue-related decisions in the extractives sectors are increasingly employing techno-economic bottom-up forecasting and evaluation frameworks (such as the FARI model used by the IMF). This paper provides guidance on the selection, evaluation, and sourcing of key data inputs, as well as broader methodological choices relating to the development and implementation of these models for the purpose of fiscal revenue forecasting.

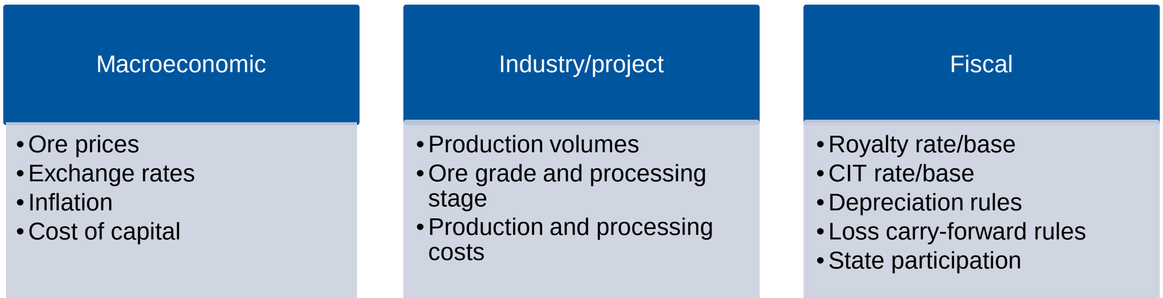
At the core of these models is a representation of project cash flows (based on estimates of the intertemporal incidence of revenues and costs), which are integrated with key tax policy-related parameters to provide guidance on the tax take (outlined in Figure 3). The variables of importance in this regard will vary to some extent across mines and industry segments. However, they will commonly include macro variables such as commodity prices, industry or project inputs such as production volumes and costs, and key fiscal parameters such as corporate income tax (CIT), royalty rates, capital outlays, and allowances (illustrated in Figure 4).

Figure 3: Overview of revenue forecasting using fiscal-industry cash flow methodology



Source: author's illustration.

Figure 4: Key input variables to mining tax revenue forecasting



Source: author's illustration.

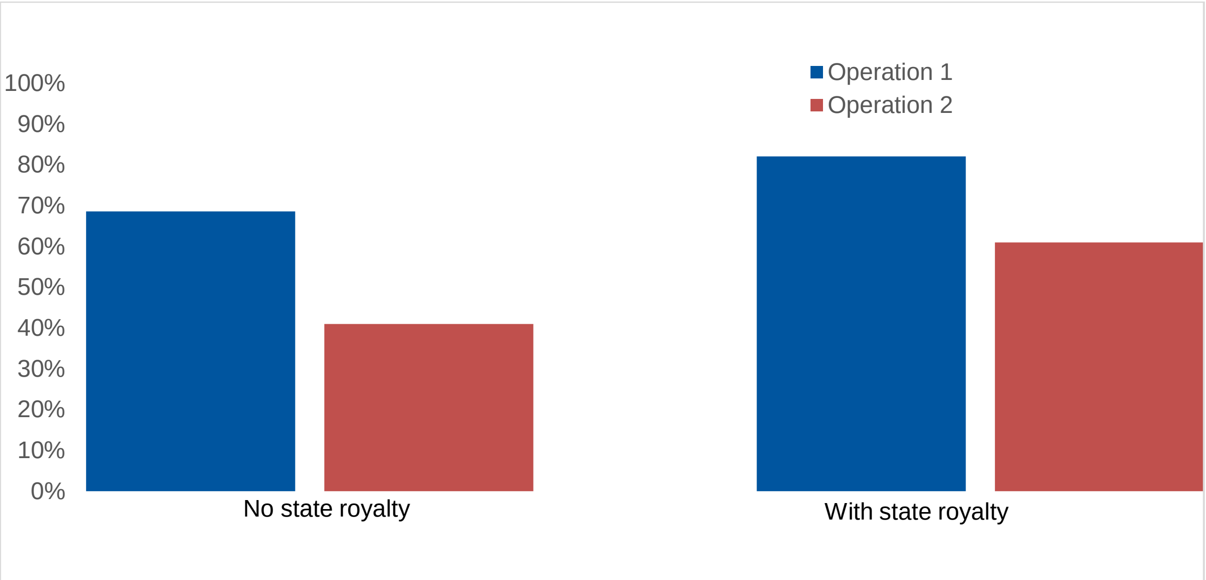
In terms of macroeconomic factors specifically, commodity prices are clearly a primary driver of mining industry revenues. In addition, variables such as inflation, exchange rates, and the cost of capital are important determinants of project costs, thereby impacting on the profitability of a particular mining project or the industry as a whole (and thus the size of the tax base). Robust and transparent assumptions regarding these variables are thus key to building a picture of the economic viability of the sector and the outlook for revenues in the short, medium, and longer terms.

Understanding the implications of these broader market conditions for the local tax base also requires a sound representation of the economics of the domestic mining industries. Key factors shaping the size of the domestic revenue base include production volumes, the output mix, and average capital and operating costs. A robust view on the outlook for these variables—which is grounded on both commercial and technical operating conditions as well as broader market realities—is thus critical for developing a robust and coherent revenue forecast.

This raises key methodological issues in the representation of the tax base. Many finance and economics ministries would typically employ a top-down approach to revenue forecasting (in which expected cash flows are a function, for example, of economic and/or industry aggregates as well as fiscal indicators such as average effective tax rates). However, this approach renders the resulting projections highly sensitive to the assumptions regarding the representative mine, which may be challenging to formulate in a sector characterized by different economic scales, operating efficiencies, ore qualities and values, and logistics and other relevant costs.

To illustrate this point, Figure 5 details the results of cash flow simulations for two different iron ore mines in Brazil, drawing on in-depth technical, economic, and fiscal data analysis and modelling of those operations. It shows that the government tax take on these mines, adjusting for differences in state royalty rates applicable across the two mines (to improve the like-for-like basis for comparison), is around two thirds higher in the case of Operation 1 compared with Operation 2. This largely reflects the significantly lower unit costs of the former.

Figure 5: Government tax take as percentage of total project net present value in selected Brazilian mining operations, 2017



Source: author's illustration based on data from Davis and Smith (2019) and CRU.

The example in Figure 5 provides a brief snapshot of the challenges associated with forming a duly representative assumption regarding a single taxable entity (or a small subset of taxable entities). This issue raises particular complexities for revenue projections relating to diversified mining industries, including those featuring different commodities, mining technologies, and processes (underground compared with open pit, for example). In the case shown in Figure 5, the differences in average tax takes arise, at least in major part, from different costs and technical operating issues between two operations.[5]

Reflecting these complexities, this paper advocates the use of a bottom-up approach to revenue forecasting, drawing on industry best practices and, where necessary, commercially licensed industry data resources (pertaining to a broad sample of mining operations). While more data-intensive by design (and requiring some upfront investment to develop), such approaches have a number of attractive features. First, they readily permit accurate revenue analysis in countries employing concession-specific fiscal terms. Second, they avoid the need to formulate challenging and often fragile assumptions (given the heterogeneity of the industry) regarding a representative

[5] Note that these differences will also impact on how production and investment respond across the two operations to different market conditions.

mine and tax take. Third, they facilitate revenue analysis at a subnational level. Fourth, they enable revenue projections to adjust appropriately to structural industry dynamics, including, for example, changing productivity, or a shift from greenfield to brownfield development projects. This is particularly helpful for forecasting over highly differentiated tax codes (in Chile, for example, mines with different operating scales and margins are subject to different tax rates).

The emerging application of the FARI model to revenue forecasting is a welcome development in the use of such bottom-up techniques. However, employing these and other similar tools for the purpose of forecasting cash flows from more diffuse and complex national mining industries requires parameterization and simulation of a broader set of mining assets and operations. By way of illustration of the wider technical possibilities in this space, this paper presents the results of bottom-up revenue simulations from individual mining assets covering the vast majority of industry production in the countries and regions in question, and subsequently aggregated into a single cash flow projection.[6] In so doing, it employs data resources which are widely utilized (often on license, in this case from CRU) by mining industry investment planners. While undoubtedly a challenge to more traditional revenue forecasting practices, it is noteworthy that such data-rich approaches can also complement top-down representative taxpayer models by permitting more accurate calibration of key input variables such as average costs and margins and effective tax rates, thereby helping to overcome the complex judgement calls involved with top-down simulations over a potentially highly heterogeneous collection of taxable entities.

2.1 Macroeconomic inputs: ore prices

Market prices are a key determinant of profitability and investment in new and expanded mined production. As such, robust—yet suitably conservative—assumptions regarding future ore values lie at the core of any revenue forecast (addressing the uncertainty that is inherent in commodity prices for the purpose of revenue forecasting is discussed in the next section).

There are a number of possible approaches to formulating such assumptions. One is to use the present value of a relevant ore. Another option is to employ a long-run average price. The latter approach may be more appropriate than the former as a basis for long-run forecasting (given the underlying cyclicality of the industry).[7] However, these approaches do not take account of future market price dynamics. To provide a recent example, high domestic steel prices in North America arising from Section 232 and other import restrictions created powerful investment incentives. As a result, domestic production of hot-rolled coil (an important steel product class) increased by nearly 10 per cent between 2016 and 2018, with excess capacity—rather predictably—contributing to a roughly 30 per cent decline in hot-rolled coil prices during 2019 (CRU 2019).

As such, it may be preferable to incorporate forward-looking price assumptions in one of three ways.

First, for mined commodities which have well-developed financial derivatives and other related markets (such as copper and iron ore), the forward curve could potentially be employed. However, the future ore prices implied by such measures must be carefully interpreted, due to the influence of various factors—including interest rate differentials, risk premiums, and storage and insurance costs—on the term structure. Moreover, these forward curves are unavailable for many mined

[6] This analysis was initially developed as part of research undertaken for the IADB's (2017) Latin American and Caribbean Macro Report.

[7] Longer-term ore price forecasts are also potentially exposed to structural economic development and technology trends, including for example the shift to a low-carbon economy (World Bank 2017).

commodities, and are unreliable for most revenue forecasting horizons (typically being only very thinly traded beyond a roughly six-month horizon).

Second, a detailed bottom-up analysis of supply and demand fundamentals can be employed. Commercial advisors in the mining industry tasked with evaluating the revenue outlook over the longer term will commonly estimate long-run marginal production costs using bottom-up techniques. This will typically involve a forward-looking view (drawing on detailed market intelligence) of production costs—not only of current (particularly high-cost) producers, but also considering the investment plans of existing players and potential new market entrants. Importantly, in markets where additional supply volumes are required to meet demand, an understanding of the likely marginal 'incentive' price (i.e. the level sufficient to recover both operating and amortized capital costs) is particularly critical.

These techniques require a detailed breakdown of production costs covering the majority of assets in the market, and a breakdown of the various sources of competitive advantage (or disadvantage) that distinguish them from one another. Differential inflation rates are commonly applied, with 'controllable' inputs (e.g., labour, equipment, and consumables) disaggregated from 'non-controllable' inputs (such as energy and those arising from foreign exchange volatility) as a basis for evaluating the outlook for production costs of each given operator. The required level of knowledge, data, and technical sophistication here is almost certainly beyond the capability of most developing-country finance and mining ministries.[8]

A third approach that may be employed for smaller-scale and junior industry operators (due to the lesser requirements in terms of internal capabilities and data resources) is to use a statistical time series method and historical price data to calibrate a plausible base case price forecast. This approach is relatively simple to implement and can also provide an informed basis for thinking about revenue forecasting errors. This approach is further elaborated upon below, including a stylized example.

2.2 Industry input variables

Production volumes

A robust view on future production volumes is central to evaluating the size of the tax base. Mining production is typically determined by a wide range of factors, including technical (such as recovery rates), geological (including ore grades and depth), financial (in particular, the scale and efficiency of investment), and commercial (especially sector- and site-level profitability) factors.

The appropriate approach to forming such a production outlook is context-specific, depending, for example, on the forecasting horizon as well as the structure and maturity of the industry. For short-term revenue projections, current production estimates are likely to provide a sound proxy, with any adjustments principally required in the case of planned maintenance or shuttering of large-scale operations.

In the case of longer-term forecasts, where these apply to mature or highly consolidated industries (with production and tax payments dominated by a limited number of players), for example, it may be sufficient—in discussion with the relevant line ministries and senior industry representatives—

[8] Chile is perhaps a notable exception in this regard: the government of Chile receives in-depth copper market research and data analytics from Cochilco, the Chilean copper commission (and also benefits from the sophisticated industry knowledge retained within Codelco, the national copper miner).

to form a view based, at least in large part, on the stated production plans of a limited number of major assets.

Figure 6: Analysing project risk by decision factor

	Speculative	Possible	Probably	Committed	Operating
Current focus of work					
Geology					
Metallurgy/technology					
Engineering					
Social/environmental					
Marketing/commercial					
Transport					
Ownership					
Financial	Funds in place for speculative drilling programme	Funds in place for more extensive drilling programme	Funds in place for final feasibility study	Funds in place for construction with adequate contingency reserves	Positive free cash flow from operations under a range of market conditions

Source: author's illustration based on CRU international documentation.

However, particularly where an industry is developing rapidly, it may be necessary to undertake a broader and more risk-based approach to production forecasting. A common method adopted in the private sector for evaluating medium- and longer-term supply fundamentals is to collate market intelligence on mining projects and then derive a framework to inform judgements on the likelihood and timing of their becoming approved and operational.

To this end, a shortlist of progress thresholds or milestones is established in relation to key geological, technical, financial, and regulatory requirements for successful resource development, and each mining project is tracked against these. The logic behind this approach is relatively straightforward. Take, for example, finance-related considerations: clearly, a project without adequate funds in place to undertake preliminary exploratory drilling has little if any prospect of yielding output. By contrast, the existence of funding for feasibility analysis or plant construction implies a much higher chance of supplying the market.

Overall, an aggregate risk score is ascribed to each project, and an associated probability weighting applied to all production plans in receipt of a given risk score. For example, CRU, a leading industry mining market intelligence and forecasting firm, maintains a detailed database on mining projects which can be highly informative for evaluating future production outlooks. For the purpose of supply forecasting, CRU ascribes mining projects into risk categories ('committed', 'probable', 'possible', or 'speculative') and then risk weights potential project volumes against each. A stylized summary of decision indicators by risk category is outlined in Figure 6.

Ore grades and impurities

The quality of domestically produced ore is a key determinant of the sales price, particularly in bulk commodities, where the mineral content and associated impurity levels are a key factor affecting downstream processing costs and product quality. For markets where there is a lack of transparent price data for different product grades or subclasses, or for mining jurisdictions where produced ores significantly depart from relevant product benchmarks, a 'value in use' model may be required. This is an industry term describing a technical approach for estimating the impacts of a deviation in the quality of output from a given product benchmark on its value. It comprises two fundamental steps. The first is to select a relevant benchmark. The second is to undertake a statistical evaluation of the impact of key product and quality considerations on ore value.

Methodologies to evaluate the second step must naturally be tailored to the specifics of each individual value chain. In the case of iron ore, for example, key determinants of product value include: the contained mineral content; the specific iron ore product, such as lump, pellet, or fine (premiums for high-grade products are closely related to the profitability of the steel industry); the levels of impurities such as silica, alumina, and sulphur; and the grain size (which affects processing costs). Such adjustments can involve fairly complex calculations but potentially have an important bearing on understanding the value of a royalty base, for example (and may require support from external industry specialists in the first instance).[9]

Production costs

Understanding industry costs is critical, given the importance of industry profitability to the revenue base. One possible approach is to estimate average industry margins based on a broad sample of the domestic production costs. While this approach has the disadvantage of being relatively data-intensive, this challenge is far from insurmountable, particularly if policymakers are equipped with access to the sorts of comparable industry 'cost curves' that are widely available to industry players.[10]

An alternative approach is to estimate average margins based on a representative operation. On the face of it, this may be a somewhat easier undertaking, particularly for an industry which is highly consolidated around a limited number of large producers. However, the challenges of selecting and evaluating the margins from such representative operations can be far from straightforward, for various reasons, as follows.

First, operating costs can vary widely across mines and operations. This reflects different geological conditions, operating scales and productivities, degrees of vertical integration, and structural heterogeneity in freight and other charges.[11] To illustrate this point, Figure 7 provides an overview of the distribution of production costs in the global nickel industry. It highlights that the interquartile range in operating costs is around US$5,000 to US$6,000 per tonne, roughly equivalent to half the 2018 London Metal Exchange sale price.[12]

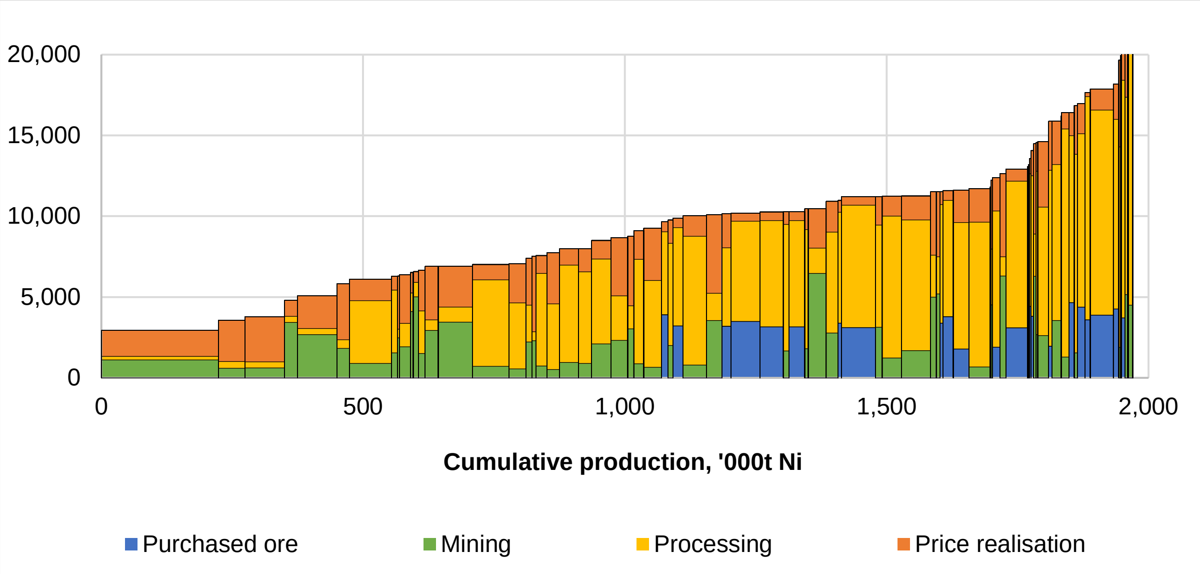
[9] These calculations can be incorporated into pricing formulas which provide a robust value basis for royalty and other concessionary payments under different market and industry environments. Please contact the author for further details.

[10] Monitoring costs, and ensuring their comparability across multiple operators and commodity markets, is a complex and involved task, often sourced by industry from specialized third-party data providers such as CRU.

[11] The profitability of bulk materials in particular is highly sensitive to transport costs (which vary widely between road and rail, and with the distance from a port).

[12] It also highlights the widely divergent breakdown of costs according to different line items, including mining (or purchased ore in the case of non-mining processing facilities), processing, and realization (sales, shipping, general administrative expenses, and treatment and recovery charges required to achieve the benchmark price).

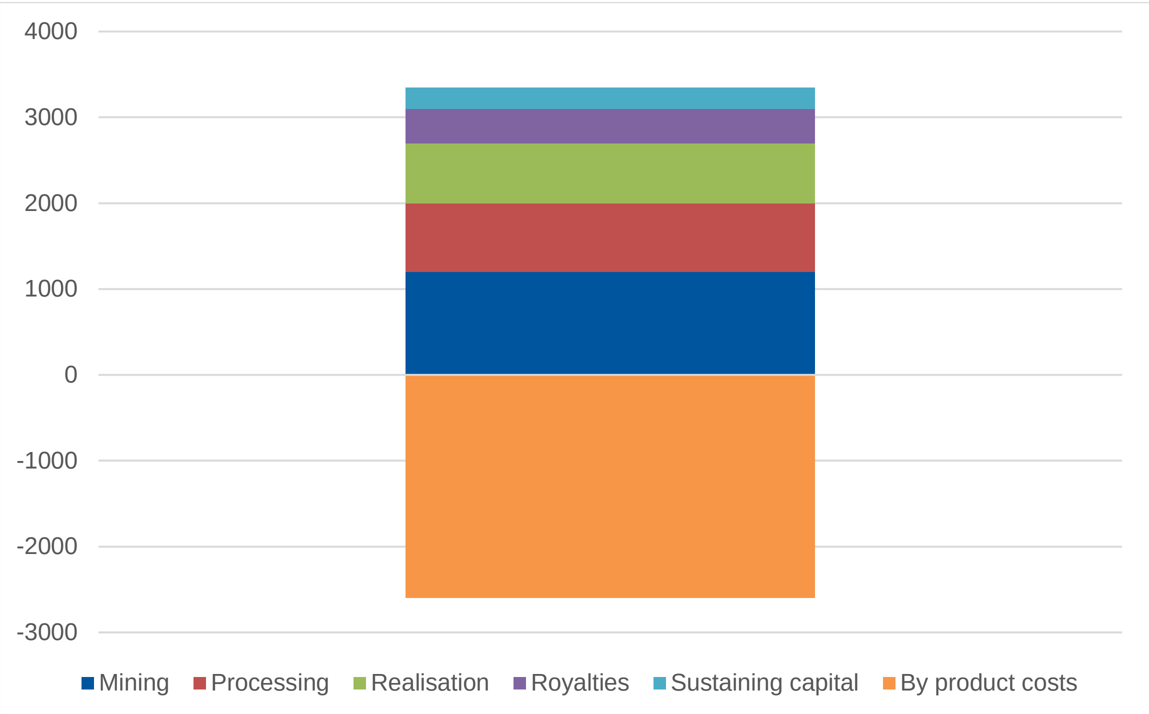
Figure 7: Global nickel production costs by asset, US$ per tonne



Source: CRU 2016 nickel cost model.

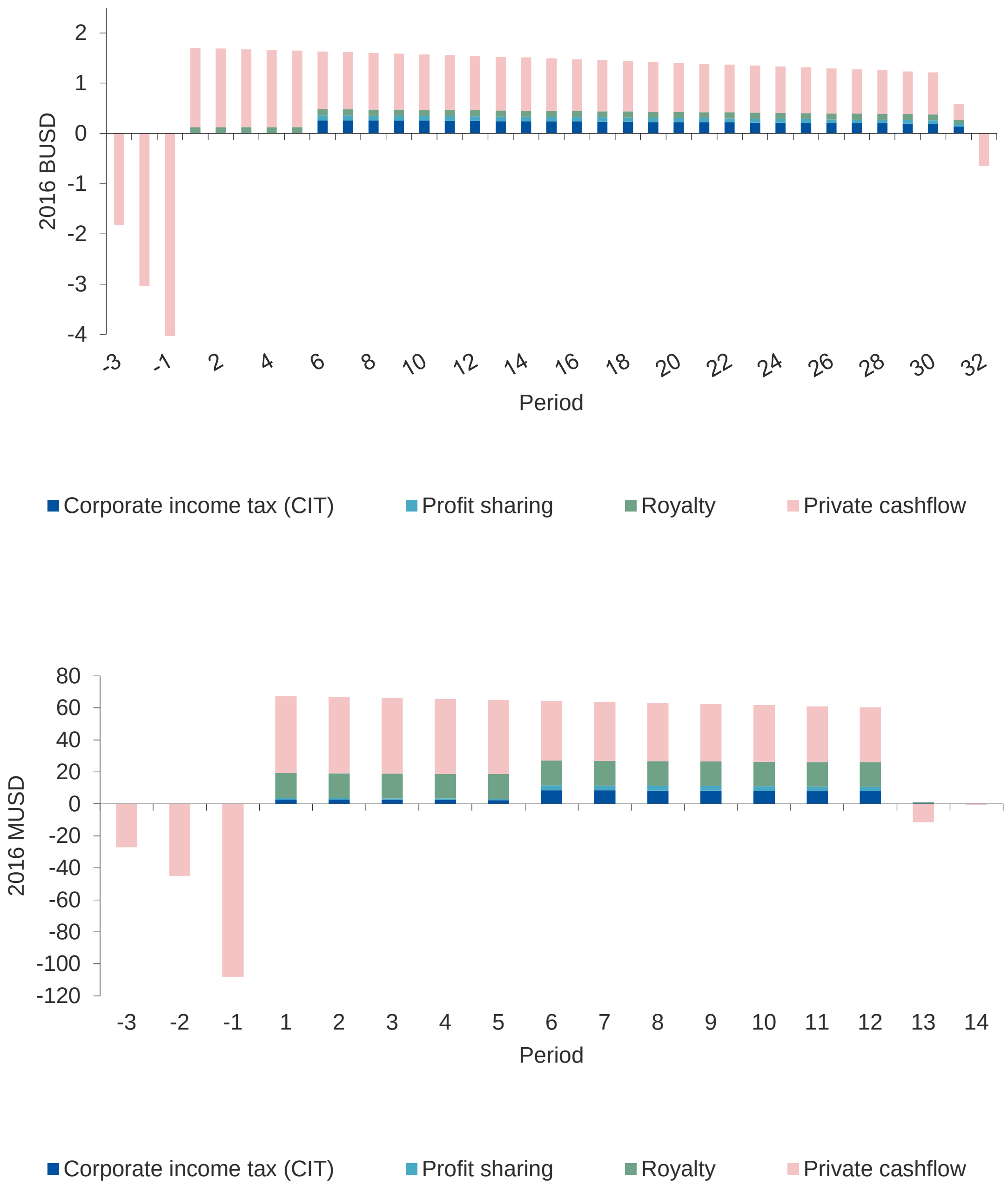
A second major issue, particularly in base metals industries, concerns the prevalence of polymetallic production. In such instances, a true picture of margins and costs requires an adjustment to estimated operating costs associated with the value of by-products. It would be simply impossible to form a judgement on the profitability of an asset such as Nornickel's nickel-cobalt-platinum group metal mines (which have a highly diversified product mix, including some high-value precious metal by-products) without this consideration. This point is illustrated in Figure 8 for a particular polymetallic copper mine in which these by-product credits increase the operating margin by around US$2,500 per tonne (this is equivalent to around 40 per cent of the final sales price for copper).

Figure 8: Illustration of by-product credits in total operating costs, selected copper producer, US$ per tonne



Source: author's illustration based on CRU data.

Figure 9: Estimated annual undiscounted cash flows by Brazilian iron ore mining operations



Notes: top panel, Operation 1, US$ billion; bottom panel, Operation 2, US$ million.

Source: author's illustration based on CRU data.

A third important consideration affecting costs concerns the degree of industry maturity. Early-stage mining operations (either exploration or development) are typically loss-making. Free cash flows only emerge once production begins to ramp up and associated upfront capital expenditures begin to taper off. The structural balance of costs and revenues generally reverses once a mine reaches the end of its operational life and rehabilitation and closure costs begin to inflate. However, these cash flow dynamics differ widely across and within industries, making the choice of representative operating entity challenging to determine: some minerals (such as copper and iron ore) are structurally more capital-intensive to extract than others (such as gold). Moreover, capital costs also differ significantly across producers within a given industry. To illustrate this latter point, Figure 9 presents an estimated time path of cash flows for our two illustrative iron ore mines in Brazil: Operation 1, a large open-pit mine, entails capital outlays approaching US$10 billion over three years, following an operating mine life of 25 to 30 years. By contrast, Operation 2 requires capital expenditure of roughly US$250 million, with a mine life of roughly 10 years.

2.3 Fiscal input variables

Key tax-related variables need to be incorporated into the revenue forecasting calculations. Given heterogeneity in the form and structure of fiscal regimes for the mining industry across countries (and even subnational regions), the appropriate choice of policy variables will be regime-specific. In general terms, however, tax and royalty schemes, comprising taxes on production (commonly known as 'royalties') and CIT on profits, typically form the bedrock of fiscal regimes in the mining industry (production sharing contracts, by contrast, are widely prevalent in fiscal regimes for the oil and gas industries; see IMF (2010) for more detail).

Royalties, for example, are typically levied on production, charged either as a fixed fee per unit of production ('specific' royalties) or as a percentage of the value of production ('*ad valorem*' royalties). These different choices regarding the basis on which royalties are applied can have significant implications for government revenue. The precise nature of the royalty base differs from country to country (and even within subnational regions). However, as applicable in 2016 in the case of the mining operations presented above, this was as follows:

$$\text{Royalty Base} = \text{Net Revenue in period t} = (\text{Market Price x Production}) - (\text{Taxes on revenue} + \text{Transportation} + \text{Insurance}) \text{ in period t} \quad [1]$$

CIT is calculated on taxable income and is broadly defined as net revenues less allowable deductions. Naturally, the form of the CIT base will differ across fiscal regimes, including with regard to the expensing or amortization of pre-production capital costs, the deductability of the royalty, and the carry-forward of losses. The amount and timing of such carry-forward are commonly subject to limits, in order to preserve a minimum tax base and limit delays to fiscal payments. These latter considerations have an important bearing on the timing of revenues, particularly where fiscal regimes permit substantial carry-forward of losses either within the accounts of a given asset or within the portfolio of a given resource producer (in cases where losses from producing the asset are not ring-fenced).

In the Brazilian case study presented above, the definition of net revenues includes exploration costs, intangible capital expenditure, depreciation of capital expenditure, operating costs, royalty costs, and interest paid, while the carry-forward of prior losses is limited to a maximum of 30 per cent of annual taxable income. This is represented as follows:

$$\text{CIT Base} = (\text{Net Revenue} - \text{Royalty} - \text{Opex} - \text{Capex Depreciation} - \text{Interest}) \text{ in period t} + (\text{permissible}) \text{ Loss Carry Forward in period t}-1 \quad [2]$$

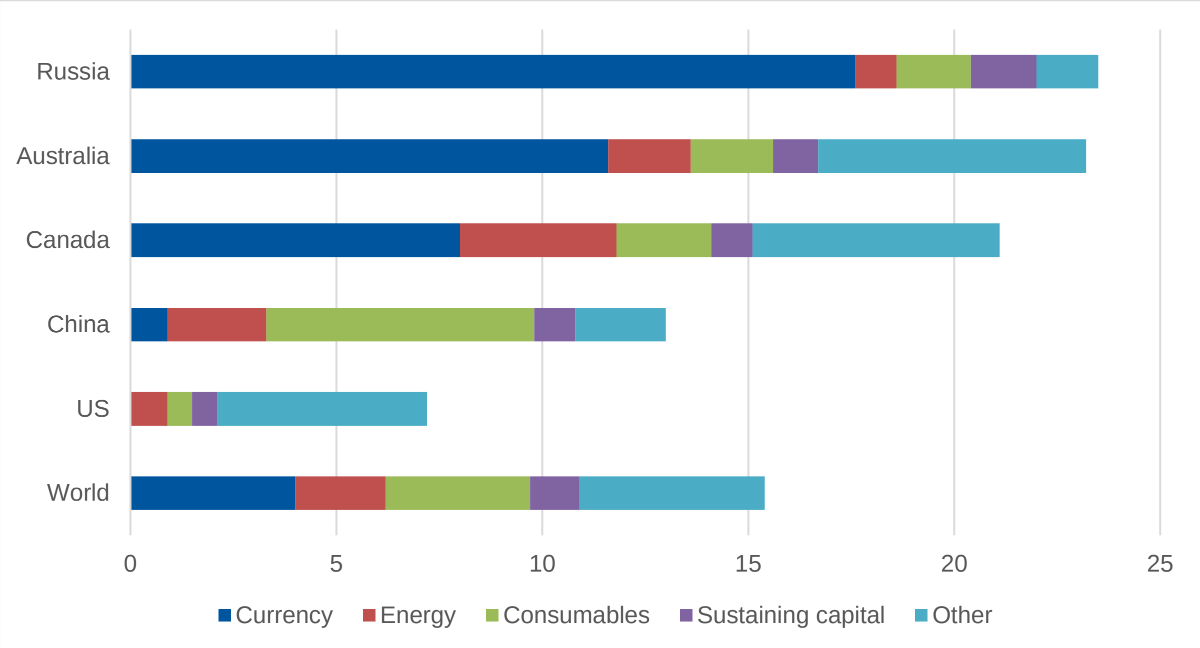
In addition, royalty- and CIT-based fiscal instruments are sometimes complemented by additional rent or profits taxes such as variable income taxes, surcharges on cash flows, or windfall taxes (among other fiscal policies). Revenues may also be impacted on by the extent and nature of any government participation in the mining industry, either on a 'free' basis (in which case the state shares the profits but not the costs) or on a 'carried' basis, where costs and profits are shared in some form.[13] Finally, mining industry activities can influence revenues from payroll taxes, as well as indirect tax revenues such as import duties and value-added tax.[14]

3 Analysing revenue uncertainty

Fiscal revenues from mining are highly uncertain. In particular, commodity prices fluctuate widely. This is because demand is closely associated with the level and growth rate of economic activity (and technological change), while supply is insensitive to prices in the short term due to investment lags (a typical greenfield copper mining project takes around 12 years to bring to market, for example).

However, such uncertainties also extend to a wide range of other factors, including production costs. In the recent commodity downcycle in 2015–16, for example, the unit costs of hard coking coal production fell by the order of 15 to 25 per cent, due to foreign exchange adjustments in key producing regions such as the Russian Federation and Australia (such changes in the terms of trade adjustments in fact serve as a (partial) hedge against cyclicity in margins).[15] This is shown in Figure 10.

Figure 10: Metallurgical coal production costs, 2015, US$ per tonne, year-on-year change



Source: author's illustration based on CRU data.

[13] Free carry is fiscally equivalent to a tax on dividend distributions and can be modelled like an additional withholding tax on dividends. Under carried interest, the investor usually meets all the costs attributable to the government prior to the production phase (these advances may or may not be compensated by the state). Carried equity is thus similar to a resource rent tax, in the sense that the state cash contributions initially met by the investor are repaid from the government's share of net profits.

[14] These effects can be substantial in some situations, but are not discussed further in this paper.

[15] The knock-on impact of this margin hedge on fiscal revenues is not included in the simulations presented in this paper.

Capital costs are also uncertain, being at risk of blowouts, particularly on large-scale greenfield projects. In a study of planned versus out-turn expenditures across a sample of 63 international mining projects, for example, Bertisen and Davis (2008) found that one in 13 projects overran by more than 100 per cent of initially projected costs. Such trends can have substantial implications for revenue projections, particularly for major projects (total capex in Operation 1, for example, was roughly equivalent to five per cent of the total Brazilian tax take in 2015).

These and other stochastic factors create conditions in which the tax base can expand and contract substantially according to shifting market and industry conditions. This can have dramatic consequences for public finances. In Chile, for example, copper revenues fell by around 10 per cent of total government revenues between 2008 and 2009 following the global financial crisis, principally due to collapsing copper prices (AfDB 2015).

As such, narrowly deterministic projections can result in erroneous revenue projections, potentially undermining the basis for effective public financing and investment decisions. A more risk-based approach to revenue analysis, which takes appropriate account of the various layers of uncertainty underpinning any projected cash flows, is thus generally desirable (as this enables fiscal planners to make more informed decisions regarding national expenditure and savings plans, taking account of a range of possible revenue outcomes).

There are various potential approaches to modelling such uncertainty. Revenue forecasts based on fully stochastic modelling approaches can be developed based on estimated distributional assumptions over (and covariances between) key determining variables. However, such approaches are complex and time-consuming to develop, and the results are sensitive to underlying assumptions (such as the stability and predictability of relationships between key statistical drivers, including commodity prices, production volumes, and costs).

In general, structured, data-driven sensitivity analyses are perhaps a more pragmatic approach to understanding the range of potential future revenue outcomes. The basic idea here is to determine the key drivers of revenue outcomes, formulate a range of plausible (and internally consistent) assumptions regarding the future outlook for these drivers under different plausible 'states of the world', and then evaluate the impact of these inputs on revenue outcomes based on analysis into fundamental statistical or model-based relationships. A practical (albeit somewhat simplified) example of this approach is shown below for the case of uncertainty over commodity prices.

3.1 Drivers of price uncertainty

Commodity prices are inherently volatile, given the cyclicality of demand growth, for example, and the inelasticity of short-term supply of mined products. However, the extent of this uncertainty differs across commodities. This is illustrated in Table 1 for a selection of ores and processed metals. It shows, for example, that the (normalized) standard deviation of molybdenum is around two and seven times greater than those of copper and aluminium respectively. These differences exist for a number of reasons.

Table 1: Price volatility by selected commodity, 1937–2010: normalized standard deviation, index (2037 prices=100)

Aluminium	Copper	Cobalt	Nickel	Molybdenum
150	555	739	820	1020

Source: author's compilation based on USGS data.

First, volatility is impacted on by the overall scale of the market and the degree of demand diversification across sectors and end uses. Some commodities, such as copper and aluminium, are used widely across the economy, while others, including cobalt and nickel for example, are highly exposed to particular applications and technologies (such as, in these cases, the production of batteries and stainless steel respectively). The resulting elevated levels of volatility are also perpetuated by the relatively small size of these markets.[16]

Second, supply responses differ in scale and timing due to technical and commercial aspects of production. For example, copper is geologically scarcer than, say, bauxite (the principal raw material in aluminium production) and is also commonly highly capital-intensive to develop (particularly in the form of greenfield projects). By contrast, the supply of aluminium projects is quicker and more flexible (taking perhaps one to two years to construct in China), yielding greater potential for investment responses to mitigate sustained price spikes.

Third, polymetallic industries tend to be inherently more volatile. This is because incentives to invest in expanding production in one commodity are a function of prices in another. Cobalt and molybdenum are perhaps the most extreme examples of this issue, since virtually all of these minerals are produced as by-products of other mined commodities: in this way, copper prices are more important determinants of supply for these commodities than their own individual prices (thereby creating conditions for deeper market imbalances).

3.2 Approaches to price scenario calibration

These structural differences mean that revenue forecasting scenarios should be tailored to particular country circumstances, in particular reflecting the structure of the domestic resources industry and the nature of its resource endowment and production. One possible approach in this regard—outlined further below—is thus to evaluate the degree of uncertainty for relevant commodities, and then to weight these individual commodities according to their importance to the overall revenue basket.

In terms of evaluating commodity price uncertainty, there are—broadly speaking—three possible approaches.

First, one could analyse the distribution of mineral price predictions implicit in option prices as a basis for scenario calibration. The disadvantage of this approach is that not all mineral prices have reliable or liquid option markets. Moreover, even where derivatives markets exist, these are typically not liquid enough to support estimates more than six months to a year or so out into the future.

A second approach would be to carry out an economic scenario of a sudden demand shortfall on the cost structure of the industry. This would inform the immediate price implication of a demand reduction but cast little light on longer-term implications (price slumps can lead to extended periods where 30 or 40 per cent of producers are loss-making). Capturing the full reaction of prices requires modelling the interplay between prices and overcapacity at a global level for a given commodity on an asset-by-asset basis. This would be complex to evaluate and communicate to decision makers.

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[16] This is particularly the case for cobalt, for which total annual global demand currently amounts to a little over 100,000 tonnes. This compares with tens of millions of tonnes demanded annually in the cases of copper and aluminium (nickel demand, by contrast, is around 2.5 million tonnes annually).

A third approach is to use a statistical time series method and historical price data to calibrate a plausible scale for how much a base case price forecast is likely to be wrong (in this case focusing on the potential downside risks). An overview of this third approach is presented below.

3.3 Illustrating a statistical approach to price scenario calibration

This section details the analysis of uncertain commodity price forecasts produced by an auto-regressive integrated moving average model. These are estimated using real benchmark commodity price data from 1900 up until five years before the year we are trying to predict. These forecasts are conditioned on a simple shortlist of key macro indicators including dollar exchange rates, US inflation, and global GDP growth. The model specification is chosen each year by a variation of the Hyndman and Khandakar (2008) algorithm, which combines unit root tests, minimization of the Akaike information criterion, and maximum likelihood estimates to arrive at a specification.[17]

Analysis of the resulting distribution of commodity price forecast errors facilitates an informed evaluation of the degree of uncertainty surrounding future mineral prices. The process is relatively straightforward. A first step is to adopt a suitable point in the distribution of out-of-sample forecast errors as a basis for setting the degree of uncertainty implied by the resulting revenue scenario (the choice of uncertainty threshold should reflect the appetite of policymakers for considering differing degrees of cash flow risk).

For the purposes of illustration, we have here selected the average (mean) absolute error.[18] Figure 11 compares this forecast error statistic across commodities and time periods. It reveals an average absolute forecast error ranging from 25 per cent of level values at a five-year interval in the case of zinc to approaching 60 per cent in the case of molybdenum (averaging around 40 per cent across all commodities). These results reaffirm the case for undertaking a disaggregated approach to the evaluation of structural uncertainties in mineral pricing.

The second step is to apply these estimates of structural uncertainty implied by the distribution of forecast errors to the base case developed above (or indeed to any base case, however derived) to form a statistically grounded alternative price scenario. By way of illustration, Figure 12 presents CRU's Latin American composite commodity index, which is developed according to the regionwide weight of individual mineral commodity production by value as a share of total mining revenues. Under this downside price scenario, the basket of mineral prices is approximately one third lower than in the base case in 2022.

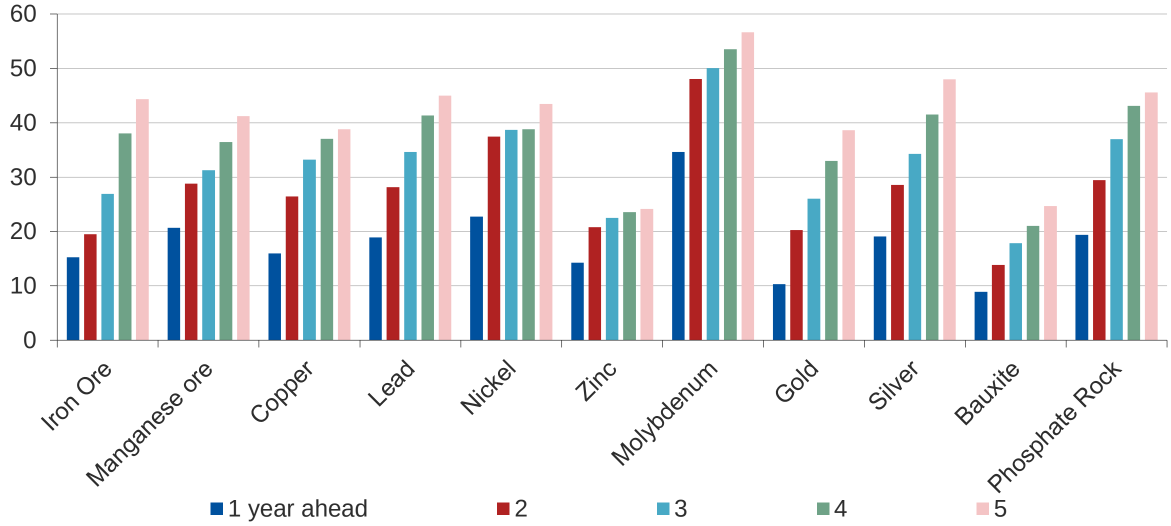
An alternative approach to calibrating a downside scenario, not discussed previously, is to analyse the distribution of cash costs for a given market. This is because when prices fall below a certain level, higher-cost producers tend to shutter production, thereby fostering a price correction. Figure 13, for example, illustrates the relationship between the unit costs of copper and zinc production at different points in the distribution of operating costs. In particular, it shows that the 90th percentile in copper and roughly the 50th percentile of production costs in zinc correlate closely

[17] This analysis has been undertaken on open-source software, using automated regression algorithms which require little time or explicit statistical training, and minimal time to update.

[18] While the models and price errors are estimated in real terms, forecasts are presented in nominal terms.

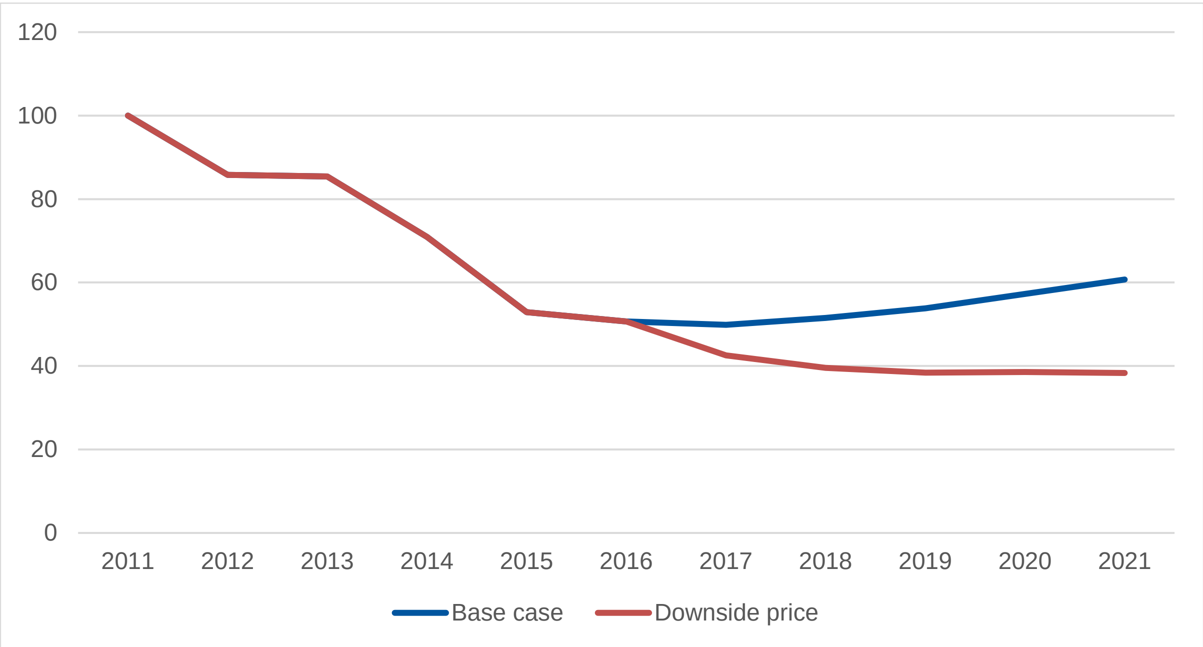
with historical turning points in prices.[19] These prices can be used as a basis for the determination of a price forecast as an alternative to the statistically derived approach

Figure 11: Average absolute forecast errors, selected commodities, % real prices



Source: author's illustration based on USGS data.

Figure 12: CRU Latin American composite commodity price, by scenario, index (2011=100)



Source: author's illustration based on data from USGS and CRU.

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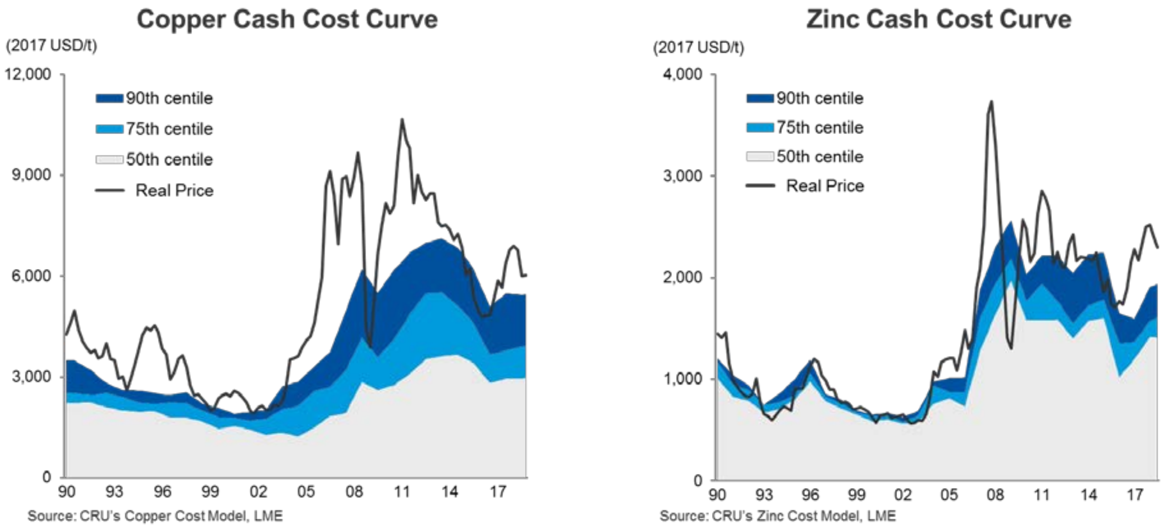
[19] The implication that a cyclical low results in a larger proportion of loss-making producers in zinc relative to copper reflects a number of factors, including the greater role of other markets such as lead and silver in driving investment returns in zinc, leading to a tendency for a deeper mismatch between supply and demand.

Figure 13: Price and distribution of cash costs in copper and zinc production, US$ per tonne

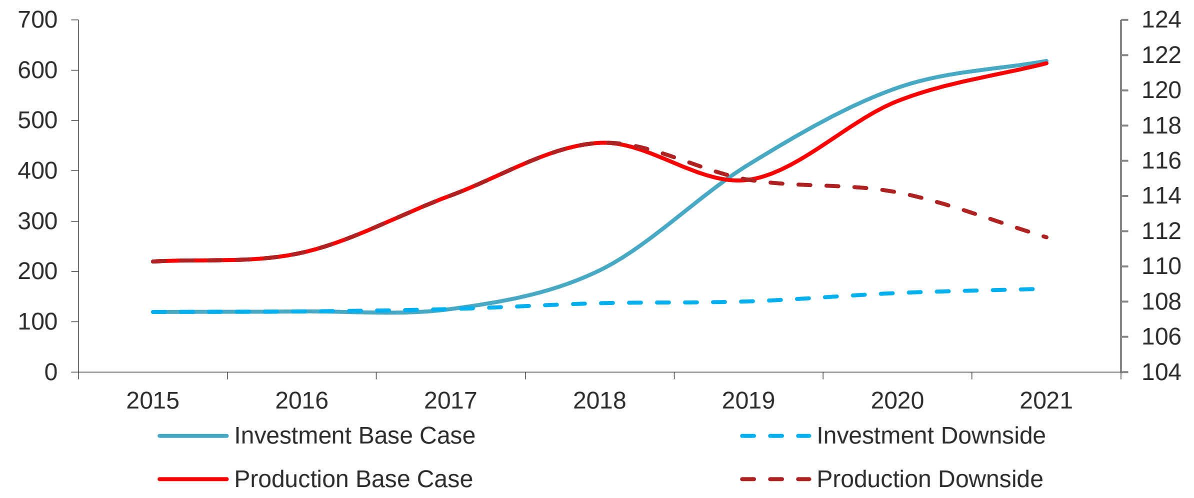


Source: CRU copper cost and zinc cost models 2018.

One key lesson for longer-term forecasting is that prices and production volumes are correlated (albeit with a lag in many cases). As such, particularly for medium- and longer-term forecasting exercises, it may be desirable to consider feedback loops from price to production in order to adequately proxy the future tax base. In the stylized scenario presented below, we have assumed that the negative price shock of around one third (in weighted average terms) is sufficient to choke off the lion's share of new sector investment.

Drawing on the risk-based approach to project pipeline analysis outlined previously, all projects for which a final investment decision has not been taken are thus presumed not to take place while no *ex post* review is undertaken of any committed investments (in practice some projects may be scaled down, while some project development may take place under lower prices). Figure 14 illustrates copper investment and production forecasts by scenario for a region of Chile. It identifies a roughly 10 per cent adjustment in production, but a roughly fourfold fall in investment in 2021 in the downside scenario compared with the base case.

Figure 14: Chilean copper production and investment by price scenario, 2011–21, index (2011=100)



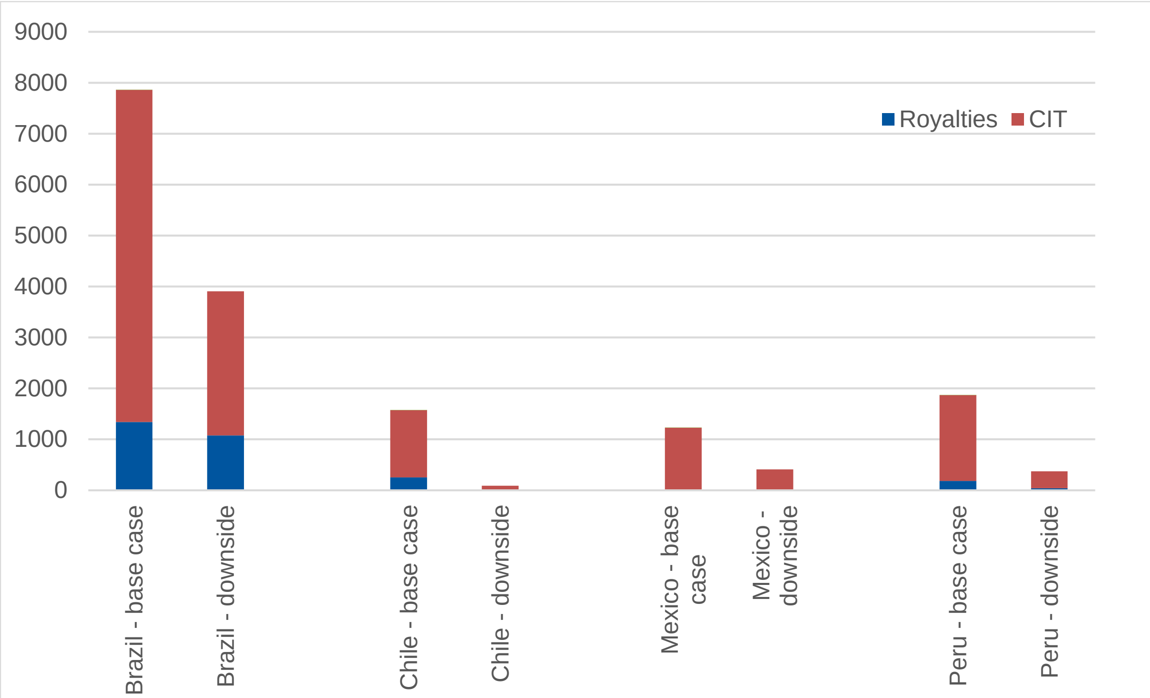
Source: CRU.

3.4 A sample of scenario-based revenue projections

This section illustrates the results of revenue projections (originally undertaken in 2016) for a selection of mining-rich industries across Latin America. These projections focus on royalty and the indicative revenue potential from CIT receipts.

Tax revenues are shown to be highly sensitive to prices. Figure 15, for example, illustrates the substantial reductions in simulated tax receipts—amounting to US$9.3 billion combined across the commodities and regions in scope—in 2020 in the downside price scenario compared with the baseline. Although the details of the fiscal terms differ substantially in terms of their rate and base across regions and producers, royalty (relative to CIT) revenues are generally found to be more robust to the downside price scenario.

Figure 15: Forecast tax revenues by price scenario in 2020, selected countries, US$ million



Source: CRU.

In the case of Chile, for example, fiscal revenues range from US$1.1 billion to US$1.4 billion under the baseline price scenario between 2016 and 2021. However, in the downside price scenario, fiscal revenues erode almost entirely, due to declining profitability and the profit-related nature of the tax base (affecting copper). In addition, the analysis identifies a decline in gold and silver revenues of around US$ 0.9 billion, and an uptick in earnings from copper of around US$0.2 billion, between 2016 and 2021 under the baseline; while in the low-price scenario, revenues effectively fall to zero, reflecting the profit-related tax based and the relative inflexibility of the cost base.

4 Conclusions, limitations, and extensions

Robust fiscal revenue forecasts in the mining sector are key to effective budgeting, including support for investment and public expenditure programmes, debt management and public financing operations, and the formation and implementation of wider tax and public policy frameworks in resource-rich countries. However, in many developing countries, forecasts are commonly based on highly simplified assumptions and analytical frameworks which take limited account of key determining factors (and associated uncertainties) (AfDB 2017).

This paper argues that there is considerable scope to improve the rigour of public revenue forecasting relating to the mining sector, including by drawing more heavily on relevant industry best practices and data resources. In particular, it emphasizes the importance of proper (but parsimonious) identification and evaluation of key revenue generation parameters, the use of high-quality data inputs, and detailed sensitivity analysis to account for the inherent uncertainties affecting industry revenues.

Overall, the paper is intended to provide practical support to ongoing efforts to close current capacity gaps in forecasting mining sector revenues, with a particular focus on mining-rich developing countries. It provides specific guidance on the development and parameterization of existing fiscal-industry cash flow models (such as FARI) as they attempt to broaden their application from tax policy analysis to revenue forecasting support tools.

Underpinning the bottom-up modelling approaches outlined in this paper are commercial industry data resources (in this case provided by CRU) which provide detailed information on individual assets comprising the tax base. Although requiring some upfront investment to access and utilize effectively, such tools have significant potential to limit the need to collect and interpret often disparate data from financial statements and other publicly available records (which are rarely reported at the asset level on a like-for-like basis). They may also support the broader execution of fiscal policy and administration, including more targeted revenue-monitoring and audit functions.

Drawing on analysis undertaken by CRU to support preparations for prepared for the IADB's 2017 Latin American and Caribbean Macro Report, this paper details both the methodological steps and the resulting revenue forecasts for a number of Latin American countries. It includes a detailed overview of the calibration and evaluation of a downside price scenario and other structural sensitivity analyses as a basis for analysing the inherent uncertainties affecting mining sector revenue projections in a structured, communicable, and quantitatively rigorous fashion.

However, while the methodologies presented above are technically sophisticated relative to current practices in many resource-rich developing countries, it should be reiterated that these approaches also have some benefits in terms of limiting the need for formulating complex and often fragile assumptions regarding the representative mining operation underpinning top-down revenue forecasts (since the mining industries and operating assets are characterized by often wildly different economic scales, operating efficiencies, ore qualities and values, and logistics and other relevant costs).

Finally, it should also be recognized that the results are based on a series of stylized (and often unrealistic) assumptions, the validity of which may require further due consideration. These simplifications include, for example, the presumption that revenue collection is fully efficient, that there are no international tax planning or other accounting responses which materially undermine the revenue base, and that there is no opportunity to deduct costs from one project against revenues from another in the absence of a well-defined fiscal boundary (or ring fence) around the project (indeed, important CIT parameters such as depreciation and loss carry-forward rules are generally ignored in this particular evaluation). There is also limited treatment of specific concessional terms (although contracts can be readily incorporated into bottom-up fiscal cash flow models).

A further area of active research in this area concerns the simplifying assumption that individual mining assets, once operating, are not impacted upon by the fiscal regime. In fact, fiscal parameters are routinely sensitized as part of commercial mining project evaluations and operational decisions, particularly in riskier jurisdictions where fiscal policy is perceived as less stable and predictable. Analysis by CRU in this context, for example, finds that owners of iron ore Operation 1 would optimally adjust its scale of operation and cut-off grade in response to fiscal parameters, with potentially decisive implications for cash flows: such behavioural adjustments are found to increase private sector net present value by around US$0.5 billion over the life of the mine.

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