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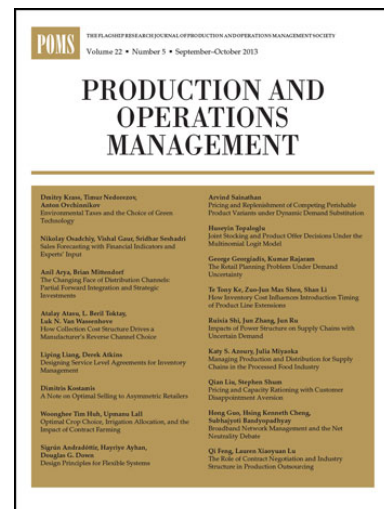
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Financial and Operational Risk Management:
Inventory Effects in the Gold Mining Industry

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Abstract

Financial and operational risk management are central concepts at the intersection of finance, operations, and commodity risk management. Yet, empirical evidence on their effects on inventory is lacking. We use a fine-grained data set comprising the financial and operational risk management decisions of gold miners from 2003 to 2011 to empirically assess the effects of risk management on inventory. Faced with volatile gold prices, miners may manage (output) risk financially by committing to sell future gold production and lock in prices. They may also manage (input) costs operationally by varying the quality of ore they extract and process, thereby altering the costs they incur and influencing inventory holdings. In addition to affecting profitability, we show that these two risk management strategies have implications for inventory holdings. We find that a one-standard deviation increase in financial risk management (FRM) is associated with an 14.3% decrease in inventory, as FRM decreases the option value of delaying processing inventory. On the other hand, a one-standard deviation increase in operational risk management (ORM) is associated with a 3.5% increase in inventory. We also find evidence that, in this context, FRM and ORM could be viewed as complements.

Key words: financial risk management, operational risk management, gold mining, empirical OM, inventory

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“We are out of the hedging business. There is no gold price that we are going to be (restarting our) hedging.”

Jamie Sokalsky, CFO, Barrick Gold Corp, 2009Q3 Earnings Call

“When Jamie Sokalsky, our new CEO, was appointed in mid-2012, [...] Jamie decided to mine only the most profitable ounces [...]”

Barrick Gold Corp, Annual Report 2013

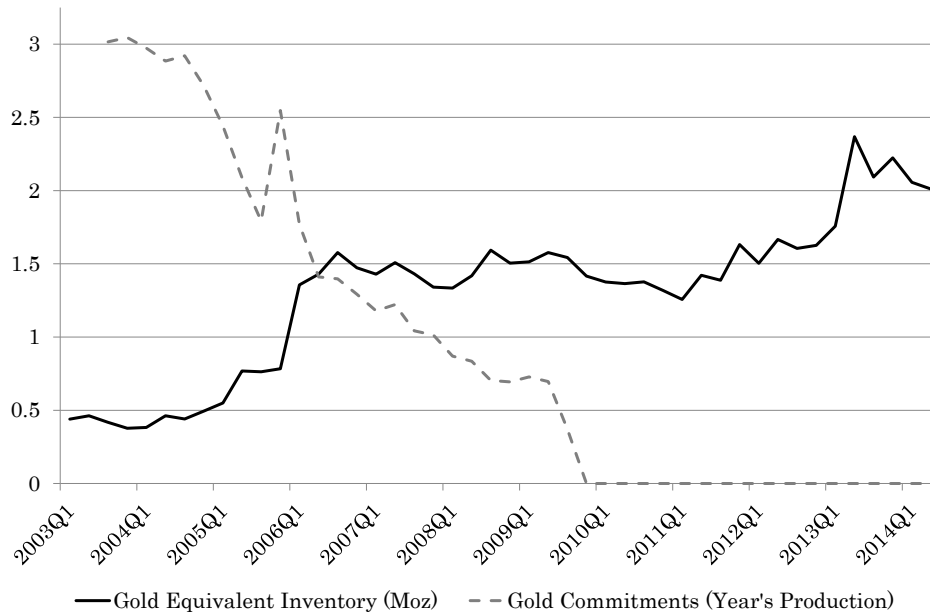
1 Introduction

Financial and operational risk management are central concepts at the intersection of finance, operations, and commodity risk management, yet evidence of their effects on inventory is lacking. In the mining industry, inventory is a particularly salient feature. Not only are stockpiles of metal ores physically massive, but they also represent a significant line item on miners' balance sheets. For example, at Barrick Gold Corp., one of the world's largest producers of gold by volume, the value of gold in inventory in 2019 totaled \$3.3 billion, and it routinely accounts for between 50%–80% of working capital.¹ In other words, a substantial amount of unused cash is sitting in inventory as stockpiles of ore. Against this realization, miners have recently started drawing down their stockpiles in attempts to liberate cash from their working capital (Ker, 2015). However, the value of this gold ore also varies according to fluctuations in the spot price of gold. Although a miner may excavate ore out of the Earth at prevailing spot prices, by the time the ore is processed and transformed into saleable bars over the next several weeks, its market price will have changed.

Miners manage this risk financially and/or operationally. Financial instruments allow miners to lock in the selling price of their output (gold doré bars). Yet, miners can also selectively mine and process ore from different parts of a mine, directly influencing their input costs through their operational decisions. In fact, Barrick was at one point the most aggressive financial hedger of gold with more than three years' worth of its gold production under contract (see Figure 1). Yet, as the

¹<https://apps.indigotools.com/IR/IAC/?Ticker=GOLD&Exchange=NYSE>, accessed Aug 1, 2020.

Figure 1: Inventory and Gold Commitments at Barrick Gold



Notes: Gold equivalent inventory in millions of ounces and gold commitments at Barrick over time. Gold Equivalent Inventory is the end-of-quarter book value of inventory scaled by the gold spot price. Commitments is the total ounces of gold committed to be sold through futures and calls scaled by the one-year forward-looking amount of gold produced.

quotes at the beginning of this paper show, Barrick made the decision to stop managing risk with derivatives, and it had completely unwound its positions by 2010. Its focus shifted to mining only the most profitable ounces: ore with the highest gold content and least waste per ton of earth. Throughout this period, inventory steadily increased, which had the additional implication that valuable working capital was stuck in large, unprocessed stockpiles.

In this paper, we examine the relationship between firm-level financial/operational risk management (FRM/ORM) and inventory against the backdrop of the gold mining industry. To the best of our knowledge, the implications and trade-offs of FRM and ORM on inventory have not been rigorously tested empirically. One reason for this is that there is a dearth of detailed and standardized information on companies' risk management practices. However, the gold mining industry provides a particularly interesting research setting. As we describe below, both FRM and ORM are prevalent, inventory ties up a substantial part of total assets, and the mining context allows access to detailed data on the nature and extent of firm risk management practices.

Our data set comprises the total amount of gold that miners have committed to sell at the firm-

quarter level from 2003Q3 to 2011Q2. We supplement this data with information on operational decisions concerning gold extraction and processing, hand-collected from firm quarterly statements. This unique data set on the activities of gold miners combines detailed information on financial and operational risk management decisions at the level of the firm.

We hypothesize and demonstrate that FRM and ORM have opposite effects on the inventory levels of gold miners. On the one hand, the use of FRM through the use of financial instruments is associated with a substantial reduction in gold miners' inventories: a one-standard deviation increase in gold selling commitments is correlated with a 14.3% reduction in inventory. By benefiting from stable selling prices, miners reduce the uncertainty around the economic feasibility of processing their stockpiles. Rather than delay the option to process the inventory, miners draw inventory down and process it.

On the other hand, ORM allows miners to actively manage their inputs in response to volatile prices by extracting and processing varying grades (quality) of gold ore. As gold prices fluctuate, miners may respond by deviating from their mining plans and adjusting the quality of ore that they excavate and process. This directly influences their costs. Yet, introducing variation into the mining and production process is associated with a significant increase in gold inventory: a one-standard deviation increase in variational grading is correlated with a 3.5% increase in inventory. Given that miners' processing resources have capacity and space constraints and often operate at high levels of utilization, varying the grades and quantities of ore increases inventory. When we decompose miners' grading decisions into "expected" and "unexpected" components, we find that expected deviations from the mining plan do not seem to be associated with changes in inventory, whereas unexpected deviations are.

Having documented these opposing effects of FRM and ORM, we then explore whether commitments and grading are complements or substitutes. We find that the joint use of FRM and ORM is associated with a reduction in inventory, suggesting that FRM strategies increase the value of ORM strategies, and vice versa. This supports the idea that gold selling commitments and grading could be seen as complementary risk management strategies, at least in the case of inventory reduction in the gold mining industry.

In an extension section, we provide more details on how miners approach risk management. We first provide empirical evidence of how production decisions are adjusted according to prevailing gold prices, and we assess the extent to which firms use FRM and ORM. We show that miners tend to substitute FRM and ORM, and that they adjust ORM in response to volatile gold prices. To conclude, we also explore how miners' risk management decisions affect profitability and show that FRM and ORM have clear associations with profit and profit variance.

Our context, data set, and econometric strategy allow us to make the following contributions. First, we explore how FRM and ORM are associated with a firm's inventory performance, and we highlight the need to consider both in a combined manner. There is research offering a normative basis for jointly considering FRM and ORM in more general settings (Chod et al., 2010; Ding et al., 2007). However, many practitioners take a standalone approach to managing risk (Protopappa-Sieke and Seifert, 2010). Financial officers are responsible for setting a strategy to financially manage price risk, and operations executives are charged with responding to this risk operationally. In the gold mining industry, FRM decisions (in particular) are made usually with a view to managing profitability and gold price volatility, without explicit consideration for their effect on inventory. Such an approach is concerning in that FRM/ORM decisions do not account for any boundary-spanning implications of the two strategies. We highlight that risk management decisions need to be aligned with inventory decisions, in conjunction with the objective of maximizing profits. To the best of our knowledge, our paper is the first to provide empirical evidence for such relationships in the Operations literature.

Second, we investigate the gold mining industry, draw several insights from it, and offer implications for managers. Where prior research has studied commodities industries such as beef (Boyabatli et al., 2011) and energy markets (Secomandi and Kekre, 2014), gold mining (and the extraction and transformation of other metals and raw materials) is an important sector of the world economy, and of individual countries' economies, that has not received equivalent treatment. In addition, it is a sector that is still characterized by high levels of inventory. The mining industry has come under intense scrutiny in recent years for its environmental, societal, and governmental externalities. Understanding how inventory performance may be improved is important for all stakeholders.

Finally, our hand-collected data set allows us to capture the concepts of FRM and ORM in a more

fine-grained manner than prior research on the subject. As alluded to above, we measure the extent of FRM as a continuous variable by capturing the extent of ounces that gold mining companies have committed to selling in the future. We similarly capture ORM as a continuous variable, based on the variability in the grade of gold mined and processed. This allows us to capture how miners adjust the cost of their input in response to changing market conditions. The interplay of these two variables provides new insights into the association of FRM and ORM with inventory.

Our paper is structured as follows. We review the relevant literature in §2. §3 provides a synopsis of the gold mining industry and process, which we use to motivate hypotheses. We discuss our data and econometric model in §4, and §5 analyzes the results of our estimation model. §6 provides several extension analyses around grading and profitability, and §7 provides several robustness checks. Finally, §8 offers a discussion and concludes.

2 Literature Review

Early work on risk management looked to explain why and how firms manage risk. [Smith and Stulz \(1985\)](#) and [Graham and Smith \(1999\)](#) suggested that any hedging that is able to reduce the volatility in taxable income is also able to reduce a firm's tax obligations. Other research has suggested that FRM reduces financial distress or bankruptcy costs ([Smith and Stulz, 1985](#)) and problems of underinvestment ([Froot et al., 1993](#)), and it may be used by managers to maximize their personal utility functions ([Stulz, 1984](#); [Smith and Stulz, 1985](#)). Recent empirical work has tested these theories by examining the relationship between hedging and firm value (e.g., [Jin and Jorion, 2006](#); [Carter et al., 2006](#)) and profitability and cash flows (e.g., [Petersen and Thiagarajan, 2000](#); [Guay and Kothari, 2003](#)). This body of empirical work nevertheless finds only modest support for the above theories of risk management ([Aretz and Bartram, 2010](#)).

Against this backdrop of mixed empirical evidence for Finance-based reasons for and consequences of hedging, prior research in Operations has used analytical models to understand risk management's implications for operational factors. Early work in inventory theory showed that risk-neutral agents are indifferent to variable profits and thus are not concerned with hedging inventory risk in a mean-variance utility framework. [Eeckhoudt et al. \(1995\)](#) was seminal in expanding such models to the

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case of a risk-averse decision maker, and research since then has shown that a risk-averse agent's utility-maximizing order quantity is less than the profit-maximizing quantity (Agrawal and Seshadri, 2000a,b). This result leads to the reasonable assumption that FRM is of some operational value, at least, to risk-averse agents. Building off the above studies, Gaur and Seshadri (2005) analytically examine financial hedging for a risk-averse retailer and show that hedging works to increase the order quantity (and inventory) to one that is close to the value-maximizing quantity. Kouvelis et al. (2013) extend this work and find that in a multi-period setting, financial hedging may lead to inventory reduction. More recently, Kouvelis and Turcic (2020) study how firms may use different types of financial hedges to protect day-to-day operations.

Beyond the financial hedge, firms can operationally manage risk. For example, in the context of multinational corporations exposed to exchange rate fluctuations, operational flexibility has been identified as the most widespread operational hedging strategy (Boyabatli and Toktay, 2004). Other research has examined how to mitigate foreign exchange and commodity price risks using excess capacity (Huchzermeier and Cohen, 1996; Kazaz et al., 2005), production switching (Kogut and Kulatilaka, 1994; Huchzermeier and Cohen, 1996), sourcing flexibility (Mello et al., 1995), production hedging (Park et al., 2017), capacity allocation strategies (Chowdhry and Howe, 1999; Ding et al., 2007), and contract choices (Turcic et al., 2021).

Given the large body of normative work examining the links between FRM/ORM and operational decisions, there is a notable dearth of research which *empirically* investigates the implications of risk management on inventory. The lack of rigorous empirical evidence is notable for two reasons. First, several studies analytically and numerically demonstrate clear, theoretical effects of financial and operational risk management on inventory (Gaur and Seshadri, 2005; Ding et al., 2007; Chod et al., 2010; Kouvelis et al., 2013). Second, inventory is an important operational variable that has been examined in its own right. Gaur et al. (2005), Rumyantsev and Netessine (2007), and Chen et al. (2007), to name a few, provide impactful data-driven insights into the drivers of firms' inventory levels. We contribute to the above literatures by empirically examining the effects of financial and operational risk management on inventory decisions. As we show below, in the gold mining context, inventory is to some degree a consequence of risk management. As such, we shift focus from analyzing financial

outcomes and metrics (e.g., firm value and profitability), and we instead examine the influence of FRM and ORM on operational performance and decisions.

Our paper is also related to a large literature focusing on optimizing mine planning and production (Lane, 1988; Mardones, 1993; Cairns and Shinkuma, 2003; Goycoolea et al., 2020). Most of these early papers assume no downstream price uncertainty. Thompson and Barr (2014) relax this assumption and show that incorporating stochastic market prices can fundamentally alter mining decisions, as miners can exercise real options to mine and process different grades of ore. Markou and Corsten (2017) also examine the gold mining industry and provide preliminary evidence of a relationship between gold prices, risk management, and consequences for mining operations. However, their analysis is limited: it does not seek to theoretically explain why and how FRM or ORM should influence operations. We complement this literature by providing empirical evidence for how miners adjust production in the face of downstream price risk, and what such risk management means for inventory performance.

3 Contextual Background and Hypotheses

In this section, we provide necessary background information into the gold mining industry, the process of gold mining, and how miners manage risk financially and operationally. We then motivate testable hypotheses within this context.

3.1 The Gold Mining Process

Although the entire mining process involves many sub-processes, gold mining can generally be divided into three stages: exploration, mining, and reclamation. In the exploration stage, mining companies heavily invest in exploring the Earth's crust in order to quantify the ounces contained in the ground. Once a suitable area is identified, geologists strategically drill into the Earth and recover samples of ore. Miners track the locations of these samples and create a 3D-model of the mineral deposits of the area. These geological models show sediments of different grades of ore. Mining and processing the areas of high grade ore is more cost effective and profitable as they contain a greater ratio of gold ounces per ton of earth compared to areas of low grade ore.

Under strict reporting standards, miners must then undertake feasibility studies and make careful

estimations of the ounces of gold that might be underground. The “Proven and Probable Reserves” in the ground refer to the amount of gold that miners can (and are expected to) extract after considering reasonable costs, for instance, for excavation and treatment but also legal and administrative matters. Upon discovery of adequate Reserves, miners create a detailed mining plan. The objective of this plan is to maximize the Net Present Value over the mine’s lifespan by defining the sequence in which miners will mine the different areas of land and thereby how much ore they will excavate and stockpile (Lane, 1988; Dimitrakopoulos and Sabour, 2007; Zhang and Kleit, 2016). A mining plan must balance the costs incurred from excavation and processing, the potential revenue from gold sales, and the time value of money.

A mining plan must achieve an optimal mix of high and low grade ore. High-grade (low-grade) ore comprises more (less) ounces of gold, i.e. less (more) waste, per ton of earth and is therefore more (less) cost effective to excavate and treat. Were the company to mine only the highest grade/lowest cost ore possible, it could find itself with considerable reserves of valuable low-grade gold ore that could not be mined cost-effectively (King and Newman, 2018). Unless gold prices would increase considerably, the miner would be left with “cash in the ground.” On the other hand, mining the lowest grades (although providing longer mine life and more overall gold production) comes with high costs. To avoid this situation, companies optimize their mining plans by extracting and processing a balance of low and high grade gold.

Ore that has been extracted from the ground is considered raw material inventory.² The miner can send this inventory straight to be processed, or it will be placed into massive heaps of earth known as stockpiles. Ore that is above some economic cut-off grade is processed immediately in order to maximize the volume of saleable production. Lower-grade ore that does not fit into the mining plan is stockpiled for future processing (Zhang and Kleit, 2016). Raw material inventory constitutes the largest share of a mine’s inventory. At Barrick, ore in raw materials inventory accounted for more than 75% of total inventory in 2018 (Barrick Gold Corp, 2019).

Gold in the processing cycle is considered work-in-process inventory. The objective of this series of steps is to separate gold from other minerals and waste. There are two general methods for processing

²Some excavated underground ore can fall into this category as well.

gold ore depending on the type of mine, and grade and type of ore extracted. Milling involves a series of mechanical grinding steps and is generally used for higher-grade excavated ore. Leaching is more chemically intensive and is typically used to process lower grade ore. The production process takes anywhere from a few days (milling) to several weeks (leaching). After this has been achieved, the gold is smelted down and poured into molds. Finished goods inventory consists of the final product—the gold doré bar. Doré bars are almost immediately sold and shipped to refineries, where they are processed into pure gold bars. As such, finished goods make the smallest portion of inventory on the balance sheet. Overall, from extraction to sale, the gold production process can take anywhere from a few days to a several weeks.

Gold inventory and stockpiles are important for several reasons. Stockpiles are massive, often spanning several thousand square feet in area. Mining plans must therefore take the location and size of stockpiles into account when scheduling extraction and processing. Physical dimensions notwithstanding, the value of the gold ounces in these stockpiles is substantial in both relative and absolute terms: At the end of 2018, Barrick had more than \$2 billion worth of gold in stockpiles. Stockpiles are essentially nonproductive assets: they tie up cash which, if processed, could otherwise be invested in other projects and exploration activities. Miners have recently begun to realize this issue, and they have started processing their stockpiles in attempts to liberate cash from their balance sheets (Ker, 2015).

The eventual value of the gold in inventory fluctuates and depends on the price of gold. Historically, the price of gold was set in a process called “fixing” by the London Gold Fixing Company. This fixed price acted as the international benchmark for the spot price of gold and was used in the pricing of many transactions, including those of financial instruments.³ Pricing doré bars is not a decision variable in the gold mining industry, and the control of its output price is generally outside the influence of any single miner. This is due primarily to two reasons. First, a large proportion of the world’s annual gold supply is due to recycling.⁴ Second, there are several large players in the gold industry,

³The price fixing process was replaced by an electronic discovery process in 2015. Our data set runs through 2011, and so the transition from price fixing to price discovery is unlikely to have influenced miners’ decisions.

⁴O’Connor et al. (2015, pg.191) note: “A key feature of gold is its difference to other storable commodities, such as copper, as new gold supply is small relative to its existing stock at about 1% annually. This creates a very large (and ever increasing) stock of gold relative to its flow.”

leading to a competitive industry where individual firms are unable to influence the sale price of their product (Petersen and Thiagarajan, 2000).

3.2 Managing Gold Price Risk

Volatility in gold spot prices is the dominant economic risk confronting gold miners. Variations in the spot price of gold directly influence miners' top and bottom lines, since gold is their most important (and often sole) product. Substantial price changes can negatively influence sales and profitability in the short and long run beyond the company's control. Price fluctuations can also adversely affect the economic viability of projects. Since the mining plan assumes a given price of gold, such variations can render parts of a mine unprofitable. Although miners do not have direct control over the gold price, they do have other tools to manage fluctuating commodity prices. However, as we will argue later, their decisions have substantial ramifications for their inventory.

First, gold miners may resort to several different types of financial instruments to alleviate price uncertainty. FRM in the gold mining industry has been widespread in the last two decades. In the second quarter of 2011, for example, miners had committed to sell approximately 28% of all global mine production through financial contracts, representing 6.4 million troy ounces of gold. Among the various financial tools at their disposal are forwards, call and put options, spot-deferred contracts, and gold bullion loans.

Second, miners may adjust their production decisions to alleviate their exposure to volatile gold prices. The quotations from Barrick's former CFO and CEO that lead into this paper highlight how, although miners can and do use financial instruments to manage output price fluctuations, they can regulate the grade ("quality") of the ore they mine and thereby influence their costs. We concentrate on this practice of "variational grading" (or simply "grading"). When gold prices are relatively stable, miners maximize their net present value (NPV) by excavating and processing an economically optimal combination of high- and low-grade ore that was predetermined in the mining plan. However, when confronted with significant price fluctuations, miners may adjust their mining strategy to remain profitable, influencing operational variables such as inventory.

3.3 Hypotheses

The gold mining process is one of removing waste: miners extract ore from the ground and incur costs in order to process the ore and remove waste, leaving behind gold. As miners follow their mining plan and extract ore, ore that is above some economic cutoff grade will be sent to processing immediately. Typically, this cutoff grade is higher than the breakeven cutoff grade (Lane, 1988; King and Newman, 2018), the minimum grade which is economical to process. Thus, ore which has been extracted, but is closer to the breakeven, will be stockpiled for later processing (Zhang and Kleit, 2016).

When gold miners sell to the spot market, they are exposed to sell their product at prices dictated by the market. Since processing ore is (continuous but) not instantaneous, the price at which the gold will be sold is uncertain when the ore is excavated and processed. The decision to begin processing stockpiles is thus an irreversible investment opportunity with an uncertain payoff. Combined with the fact that ore in inventory and stockpiles is of a grade that is close to break-even, swings in gold prices significantly manipulate the profitability of processing the inventory in the gold industry. This means that extracting and stockpiling ore for future processing is akin to holding a real option (Zhang and Kleit, 2016; Dimitrakopoulos and Sabour, 2007). As such, there is an incentive to delay the processing of inventory and wait for more information (Dixit and Pindyck, 1994).

Financial instruments which establish a fixed selling price for gold are able to mitigate the uncertainty in gold price. By committing to sell gold production at a fixed price in the future, miners reduce uncertainty in the price of their output. It follows that as the future value of inventory becomes more certain, the option value of delaying processing inventory diminishes, and miners should be more likely to process the ore. We therefore expect miners which financially manage risk to hold less gold in inventory and stockpiles than miners which do not.

Hypothesis 1. *(FRM). Financial risk management in the form of gold selling commitments is associated with less inventory.*

Under relatively stable gold prices, miners will extract and process gold ore according to a balanced mining plan which keeps gold grades relatively stable. Yet, when faced with price fluctuations, miners

can influence their incurred costs by adjusting the grade of gold ore they process. Variational grading is an operational response to changing market risks that focuses on extracting and processing higher or lower grades of gold (Kitco, 2013).

Grading involves changing several logistical, operational, and chemical/metallurgical processing steps: the decision to source ore from a different mine or a different location within a mine involves shifting resources (workers, trucks, and other equipment) to new areas for ore excavation. Extracting and processing ore from different ore bodies or areas of the mine may also require different resources and processing steps. For example, low-grade, oxide deposits are usually treated as a whole ore and crushed prior to dump or heap leaching processes. High-grade ores and ores resistant to cyanide leaching at coarse particle sizes, to the contrary, require further processing in order to recover the gold values. As such, grading increases variability in how and how fast ore is processed.

At the same time, mining is a process characterized by capacity constraints and high resource utilization. As ore is excavated from the mine, it moves through leach pads or mills, smelters, and refineries and is processed. This ore in-circuit can only be processed as fast as excavators can excavate earth, and processing centers can process the ore. Moreover, capacity utilization throughout the mining industry is generally between 80%-90% (U.S. Geological Survey, 2020). In the gold mining industry specifically, capacity utilization has been around 95% the last few decades (Federal Reserve Bank of St. Louis, 2020).

A well-known consequence of increasing processing variability is that, for a given resource infrastructure and capacity utilization, inventory will increase (Buzacott, 1999; Kingman, 1962). As such, we expect that deviating from a stable mining plan and processing ores with greater variability in their compositions will increase inventory. In particular, variational grading should lead to greater work-in-process and gold stockpiles (raw material inventory).

Hypothesis 2. *(ORM). Operational risk management in the form of variational grading is associated with more inventory.*

A large portion of prior research on the complementarity and substitutability of FRM and ORM has looked at risk management in the context of exchange rate risk. In this setting, multinational companies are exposed to movements in the currency markets. They can mitigate these risks through

financial instruments or through operational strategies such as shifting production between countries. However, [Allayannis et al. \(2001\)](#), for example, argue and empirically show that companies which utilize operational hedging strategies do not necessarily reduce their exposure to exchange rate risk, and that operational risk management is not an effective substitute for FRM. Rather, operational risk management adds value to the firm only if used in conjunction with financial instruments. [Ding et al. \(2007\)](#) argue that the main impact of a financial hedge is to counterbalance the cash flow from operations to reduce the total variance of the profit. They find numerically that the joint use of financial and operational hedging strategies leads to an improvement in the firm's mean-variance objective that is significantly larger than that from an either-or hedging strategy.

Less conclusively, [Boyabatli and Toktay \(2006\)](#) show that the interaction between ORM and FRM is influenced by a variety of contextual factors such as firm size, risk management costs, and market considerations. In a similar vein, [Chod et al. \(2010\)](#) show that, depending on the type of operational risk management available and the correlations of underlying assets, financial hedging and operational hedging (in the form of flexibility) may be either complements or substitutes.

Although the received theories do not offer consensus on the direction in which financial risk management strategies augment operational ones and vice versa (they rather show that interactions between financial and operational risk management are context-specific), it does offer consensus on the general notion that financial and operational strategies interact with each other. Therefore, we expect a non-zero association between using both strategies and inventory levels. We propose the following two-sided hypothesis.

Hypothesis 3. *(Joint FRM and ORM). The joint use of financial and operational risk management (in the form of gold selling commitments and variational grading) has a non-zero association with inventory.*

4 Data and Variable Definitions

In this section, we first describe our sample of hand-collected data on gold selling commitments and ore production and processing decisions. We then discuss our main variables and covariates, and

our econometric model to estimate the relationship between FRM, ORM, and inventory. Table 1 lists all variables (along with their calculation, descriptive statistics, and the source for the data) included in the base analysis, and Table 2 displays correlations of all the variables.

4.1 Sample Construction

The gold mining industry is unique in that it offers a transparent and detailed look into FRM and ORM at the level of the gold miner. We draw on reports which cover worldwide gold trends and the absolute amount of gold ounces committed to be sold by gold miners on a quarterly basis. Our data on gold selling commitments were compiled quarterly by Mr. Ted Reeve, mining analyst and CEO of Haliburton Mineral Services, Inc., along with several other sponsors. These reports were known as the Gold and Silver Hedge Outlook and were published during Mr. Reeve's tenure at Scotia McLeod through 1999, but they have changed names and formats over the years, seemingly since sponsors of the reports have changed. The reports we have access to begin in 2003Q4 and end in 2011Q2.⁵

These reports cover the details of the risk management programs of mining companies across the globe, accounting for 69% of global gold production and more than 95% of global producer hedging. Scholars have used similar reports to study corporate risk management policies (Tufano, 1996) and the effects of hedging on shareholder value (Adam and Fernando, 2006). They catalog the exact amount of gold (in ounces) that the firms have *committed* to sell in the future through the selling of linear instruments (forwards, gold bullion loans, spot-deferred contracts) and call options. For example, if Company A has sold 100,000 ounces of forwards and has also sold 50,000 ounces of call options, then it is said to have committed a total of 150,000 ounces.

⁵These reports are titled: *The Hedge Book* from 2003Q4 to 2007Q3, published by Mitsui Global Precious Metals, Haliburton Mineral Services, and Virtual Metals Research & Consulting; *Fortis Hedging and Financial Gold Report* from 2007Q4 to 2009Q1, published by Fortis Bank SA/NV and VM Group/Haliburton Mineral Services; *BNP Paribas Fortis Hedging and Financial Gold Report* from 2009Q2 to 2009Q3, published by BNP Paribas/Fortis Bank SA/NV and VM Group/Haliburton Mineral Services; *Gold Hedging Report* from 2009Q4 to 2010Q1, published by Fortis Bank Nederland and VM Group/Haliburton Mineral Services; and *ABN AMRO Gold Hedging Report* from 2010Q2 to 2011Q2, published by ABN AMRO Bank N.V. and VM Group/Haliburton Mineral Services.

Table 1: Variables and Descriptive Statistics

Variable	Description/Proxy	Calculation	n	Mean	Std.Dev.	25%	50%	75%	Source
<i>GoldInvRatio</i>	Gold Oz. in Inventory	See Eq. 1	915	0.0018	0.0019	0.0008	0.0015	0.0022	Compustat
<i>InvOverCOGS</i>	Alt. Inventory Measure	$Inventory_{i,q}/COGS_{i,q}$	915	1.307	1.274	0.646	1.046	1.562	Compustat
<i>Commitments</i>	FRM	See Eq. 2	915	0.396	0.831	0.000	0.000	0.439	Gold Hedge Reports
<i>Grading</i>	ORM	See Eq. 4	915	0.146	0.154	0.063	0.103	0.168	Annl & Qtrly Reports
<i>CapIntensity</i>	Capital Intensity	$\frac{\sum_{s=0}^3 PPE_{i,q-s}}{\sum_{s=0}^3 Inventory_{i,q-s} - \sum_{s=0}^3 PPE_{i,q-s}}$	915	0.894	0.074	0.864	0.911	0.945	Compustat
<i>GrossMargin</i>	Gross Margin	$\frac{Revenue_{i,q} - COGS_{i,q}}{Revenue_{i,q}}$	915	0.267	0.859	0.249	0.425	0.533	Compustat
<i>TBillRate</i>	Holding Costs	$3MonthTBillRate_q$	915	2.223	1.836	0.21	2.01	4.30	U.S. Dept of the Treasury
<i>SalesGrowth</i>	Speed of Chg. In Sales	$\frac{COGS_{i,q+1} - COGS_{i,q}}{COGS_{i,q}}$	915	0.200	1.486	-0.087	0.038	0.226	Compustat
<i>DaysAP</i>	Lead Time	$\frac{365}{4(COGS_{i,q}/AcctPayable_{i,q})}$	915	103.932	131.073	59.193	83.579	116.707	Compustat
<i>Production</i>	Gold Production (koz.)	$GoldProduction_{i,q}$	915	206.998	406.249	21.399	50.421	137.332	Compustat
<i>Demand</i>	World Prod. (tonnes)	$Demand_q$	915	903.340	120.753	800.7	864.6	1016.3	World Gold Council
<i>GoldPriceVol</i>	Coeff. Var. Gold Price	$\frac{\sqrt{\frac{1}{3} \sum_{s=0}^3 (Price_{q-s} - \frac{1}{4} \sum_{s=0}^3 Price_{q-s})^2}}{\frac{1}{4} \sum_{s=0}^3 Price_{q-s}}$	915	0.075	0.030	0.049	0.075	0.085	World Gold Council
<i>GoldPrice</i>	Gold Price (\$/oz.)	$Price_q$	915	758.716	282.215	554.100	680.100	922.200	World Gold Council

Table 2: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) <i>goldinratio</i>	-											
(2) <i>invovercogs</i>	0.729											
(3) <i>commitments</i>	-0.096	-0.155										
(4) <i>grading</i>	0.078	0.145	-0.062									
(5) <i>capintensity</i>	-0.340	-0.493	0.183	-0.001								
(6) <i>grossmargin</i>	-0.078	0.212	0.016	0.003	-0.047							
(7) <i>tbillrate</i>	0.132	-0.124	0.009	0.002	-0.031	-0.108						
(8) <i>salesgrowth</i>	0.292	0.299	0.018	0.030	0.045	0.151	0.054					
(9) <i>daysap</i>	0.349	0.357	0.007	0.145	0.145	0.117	0.065	0.364				
(10) <i>production</i>	-0.105	-0.091	0.193	-0.150	0.164	0.286	0.009	-0.055	-0.1803			
(11) <i>demand</i>	-0.072	-0.040	-0.009	-0.061	-0.000	-0.039	-0.245	-0.080	-0.102	0.017		
(12) <i>goldpricevol</i>	-0.078	0.090	-0.082	0.059	0.022	0.122	-0.093	0.028	0.063	-0.016	-0.092	
(13) <i>goldprice</i>	-0.216	0.198	-0.151	0.065	-0.025	0.187	-0.581	-0.010	-0.017	-0.042	0.133	0.393

Correlations in bold are significant at the 95% confidence level.

Our measure of FRM captures those ounces that a miner has committed to produce. Even though other alternative instruments exist (such as purchasing a put option), these are not included in our measure since they do not represent commitments on the part of miners. Commitments are important, since these derivative positions signify a level of production that the miner must meet, and inventory and production decisions directly affect miners' abilities to deliver on these commitments.

The forward instruments are straightforward: they lock in prices and ounces of gold to be sold and delivered at some future period. By selling a call option, however, the firm gives the counterparty the right, but not the obligation, to buy gold at a future price specified by the option. For the counterparty, the greater the increase in gold prices over the term of the option, the more valuable it becomes to exercise the option (i.e. the option is in the money). On the other hand, the call option is unlikely to be exercised by the counterparty if there is a substantial drop in gold prices, as the call option would be out of the money. Although we cannot know whether an option was exercised, the price of gold did appreciate by over \$1,300 per troy ounce over the span of our data set. We therefore assume that the call options were indeed exercised by the counterparty. Even in the unlikely case that firms chose not to exercise the options, however, then the results we obtain should at the least be considered conservative. If it is assumed that no call options were exercised, then any significant results we do find should be considered as a lower bound on the effect of FRM on inventory. In Section 7, we provide robustness tests on commitments which were made only through forwards.

We supplement this data with further quarterly mining production and processing data. Detailed operational data on mining companies is not available in a central database, but it is generally available in public company reports. We therefore hand-collect grades of gold processed by firms per quarter from US and Canadian quarterly reports and Management Discussion and Analysis (MD&A) publications.

Firm financial information comes from the Compustat database. Quarterly company mining data (e.g. gold production, cash costs, etc.) is obtained from the Compustat Segment Specific database.

4.2 Inventory

We are concerned with how financial and operational risk management policies affect inventory. We obtain the value of inventory at quarter's end from Compustat. However, it would be incorrect to test how the book value of inventory changes, as this may vary according to the prevailing price of gold. For example, it may be the case that a company reduces the ounces of gold in inventory over the year, but its reported year-on-year inventory value increases due to a substantial rise in prevailing spot market gold prices. To overcome this, we scale the inventory value from Compustat by the spot price of gold at the end of the quarter. What is obtained is a measure of the gold equivalent ounces (GEOs) contained in inventory, representing the number of ounces of gold equal to the value of inventory at market prices.

This measure makes the implicit assumption that the only item contained within company inventories is gold. This is unlikely to be the case, since many companies may also produce copper, silver, or other metals as a byproduct of the gold mining process. Unfortunately, we cannot capture the exact breakdown of inventory by metal, but this measure is still appropriate. Kinross Gold, for example, produces and sells silver along with gold, but as it considers itself a gold producer, its public reports list the results from its operations in GEOs.

Following Gaur et al. (2005) and Rumyantsev and Netessine (2007), for each firm i in quarter q , we scale GEOs by COGS to achieve a measure of relative inventory and to control for flow rate.

$$GoldInvRatio_{i,q} = \frac{GEO_{i,q}}{COGS_{i,q}} \quad (1)$$

4.3 Financial and Operational Risk Management

Prior research outside the gold industry has been unable to effectively capture financial risk management activities in detail: annual reports typically report only unstandardized information on whether firms hedge or not. The uniqueness of the current data set overcomes these limitations. The gold hedging reports compile the absolute amounts (in troy ounces) of future gold production each firm has committed to selling in a quarter.

We capture financial risk management as the fraction of the firm's next-year production that is committed to be sold (Haushalter, 2000). This measure is also conceptually similar to Carter et al.'s (2006) measure of the percentage of next year's fuel requirements hedged by airlines.

We measure the selling commitments of a firm i in a quarter q as follows:

$$Commitments_{i,q} = \frac{GoldOzCommitted_{i,q}}{\sum_{s=0}^3 GoldOzProduced_{i,q+s}} \quad (2)$$

Our second measure of interest is the amount of variation in a firm's processed gold grades. Ideally, we would like a measure that captures grading at the mine-level. Unfortunately, there is no standard guideline to report processed gold grades in company filings: some companies report a tonnage-weighted average grade at the level of the firm, others publish gold grades for each mine, and several do not even publish processed gold grades. Where available, we first aggregate these grades into the same tonnage-weighted metric used by companies which report at the firm-level in order to ensure the data is all at the same level of analysis. Thus, the grade of gold processed by a firm i in quarter q is the tonnage-weighted average of the gold grade processed by each mine m in the same quarter:

$$GoldGrade_{i,q} = \frac{\sum_1^m (GoldGradeProcessed_{i,m,q} \times TonsOreProcessed_{i,m,q})}{\sum_1^m TonsOreProcessed_{i,m,q}} \quad (3)$$

To capture variational grading, we measure the coefficient of variation (sample standard deviation divided by the mean) of gold grades processed over a period of four quarters:

$$Grading_{i,q} = \frac{\sqrt{\frac{1}{3} \sum_{s=0}^3 (GoldGrade_{i,q-s} - \frac{1}{4} \sum_{s=0}^3 GoldGrade_{i,q-s})^2}}{\frac{1}{4} \sum_{s=0}^3 GoldGrade_{i,q-s}} \quad (4)$$

As we highlight in Section 3, miners typically follow a mining plan which specifies extracting and processing a balanced blend of gold grades. In periods of high volatility, they can alter this balance and focus on higher- or lower-grade ore in order to mitigate the effect of changes in gold prices. However, by measuring operational risk management in this manner, we are likely quantifying a "smoothed" version of risk management: to the extent that each mine can be seen as an individual project in a

miner's overall portfolio, we capture some form of portfolio diversification. The coefficients on our measures in the econometric models are thus likely to be ex ante biased towards zero.

4.4 Controls

We include several controls in our model which have been shown in prior work to be generally correlated with inventory (Gaur et al., 2005; Rumyantsev and Netessine, 2007; Kesavan et al., 2010). Calculations for each of the variables are provided in Table 1.

We control for capital intensity in order to control for the level of investment a firm makes in plant, property, and equipment. We expect capital intensity to be negatively correlated with inventory, as firms which invest more in machinery and processing capabilities/technologies should be able to increase processing capacity and reduce the accumulation of inventory. We also include the three-month T-bill rate as a control. Rumyantsev and Netessine (2007) consider this as a proxy for the opportunity cost of holding inventory. However, given gold's reputation as a safe haven for investors and its countercyclical nature (Baur and Lucey, 2010; Markou et al., 2021), the T-bill rate also captures macroeconomic forces which may be correlated with miners' production and inventory decisions. We control for a firm's gross margin, and also for sales growth in order to capture any second-order effects between sales and inventory: as sales growth increases, we expect firms to build up and process more inventory. We control for lead time as well, and we expect that longer lead times are correlated with more inventory.

We also include several controls that are specific to the gold mining industry and that are likely to be correlated with inventory decisions. Specifically, we control for a miner's quarterly gold production, the quarterly global demand for gold in tonnes, and gold price volatility. Our main models also include firm- and quarterly-fixed effects.

4.5 Model Specification

Previous research on inventory has specified multiplicative models that transform the variables and covariates using a natural logarithm. Unfortunately, such a transformation in our data would result in many observations dropping out of our regressions, as logarithmic transformations cannot handle

negative numbers or observations with a value of zero.⁶ For this reason, we transform our variables using the inverse hyperbolic sine function (see Appendix B for a detailed explanation). We denote variables obtained after transformation by lowercase letters, e.g., *commitments*.

We estimate the following two equations of inventory as follows:

$$\begin{aligned}
 \text{goldinratio}_{i,q} = & \beta_0 + \beta_1 \text{commitments}_{i,q} + \beta_2 \text{grading}_{i,q} + \beta_3 (\text{commitments}_{i,q} \times \text{grading}_{i,q}) + \\
 & \beta_4 \text{capintensity}_{i,q} + \beta_5 \text{grossmargin}_{i,q} + \beta_6 \text{billrate}_q + \beta_7 \text{salesgrowth}_{i,q} + \\
 & \beta_8 \text{daysap}_{i,q} + \beta_9 \text{production}_{i,q} + \beta_{10} \text{demand}_q + \beta_{11} \text{goldpricevol}_q + \\
 & F_i + Q_q + \epsilon_{i,q}
 \end{aligned} \tag{5}$$

and

$$\begin{aligned}
 \text{invovercogs}_{i,q} = & \beta_0 + \beta_1 \text{commitments}_{i,q} + \beta_2 \text{grading}_{i,q} + \beta_3 (\text{commitments}_{i,q} \times \text{grading}_{i,q}) + \\
 & \beta_4 \text{capintensity}_{i,q} + \beta_5 \text{grossmargin}_{i,q} + \beta_6 \text{billrate}_q + \beta_7 \text{salesgrowth}_{i,q} + \\
 & \beta_8 \text{daysap}_{i,q} + \beta_9 \text{production}_{i,q} + \beta_{10} \text{demand}_q + \beta_{11} \text{goldpricevol}_q + \beta_{12} \text{goldprice}_q + \\
 & F_i + Q_q + \epsilon_{i,q}
 \end{aligned} \tag{6}$$

where F_i denotes firm-specific effects for firm i ; Q_q denotes quarter-specific effects for quarter q ; and $\epsilon_{i,q}$ denotes the error term. Coefficient β_1 is used to test the hypothesis that gold commitments are negatively associated with inventory (Hypothesis 1), and β_2 is used to test the hypothesis that variational grading is positively associated with inventory (Hypothesis 2). The coefficient β_3 on the interaction term is used to test the hypothesis that the effect of one risk management strategy on inventory is moderated by the other (Hypothesis 3). To the extent that one strategy moderates the effect of the other, β_3 will be significantly different from zero. If $\beta_3 = 0$, Hypothesis 3 is rejected and the strategies are neither complements nor substitutes; i.e., the use of one neither amplifies nor attenuates the effect of the other. If $\beta_3 \neq 0$, this provides evidence that one strategy moderates the effect of the other.

Regarding model estimation, the Breusch-Pagan test rejects the null hypothesis of homoscedasticity

⁶In our data, more than half of all firm-quarters have zero gold commitments.

in the errors ($\chi^2(1) = 515.4; p < 0.001$), and Wooldridge's test of serial correlation in panel data (Wooldridge, 2002; Drukker, 2003) rejects the null hypothesis of no autocorrelation ($F = 36.0; p < 0.001$). Since our data suffer from heteroscedasticity and serial correlation, we implement a feasible generalized least squares estimator (FGLS). We assume that errors are heteroskedastic across firms in the cross-section, are uncorrelated across firms in the cross-section, but that they are AR(1)-correlated within firms over time, with each firm having its own specific autocorrelation coefficient.⁷

That said, although FGLS is our preferred estimator for the above reasons, it is but one potential estimator. Therefore, in Section 7 we provide additional results under several further model specifications and assumptions. In particular, we provide estimates from models which also consider lagged dependent variables and from models which are estimated with the fixed effects estimator.

Finally, we note that in the ensuing analysis, we refer to our findings only as associations. Clearly, there are many variables which are unobservable (for example, the geological composition of a mine or the technology required to process extracted ore) which may influence both risk management practices and inventory decisions. We therefore do not test for or impose causal relationships.

5 Analysis of Gold Price Risk Management

In this section, we present the results of our analysis. In addition to our main results, we also present results on gold stockpiles and expected/unexpected grading.

5.1 Inventory and Risk Management

Table 3 shows the results from our inventory models. Models I and II concern estimates for the baseline dependent variable *goldinvratio*. Models III and IV show that the results are robust to an alternative, commonly used specification of inventory (inventory scaled by COGS; *invovercogs*). However, we urge caution in interpreting Models III and IV as they do not disentangle gold prices from inventory.

⁷The following command in Stata 16 is used to estimate Eqn 5: `xtgls goldinvratio c.commitments##c.grading capintensity grossmargin tbillrate salesgrowth daysap production demand goldpricevol i.comp_id i.q.id, force p(h) c(psar1)`. Since some firms do not report, e.g., processed gold grades or FRM activity in certain quarters, we specify the `force` command to deal with gaps in the panels. Additionally, `p(h)` specifies heteroskedasticity across panels with no cross-sectional correlation, and `c(psar1)` specifies panel-specific AR(1) autocorrelation in the errors.

Table 3: FRM, ORM, and Inventory

	(I)	(II)	(III)	(IV)
	<i>goldinvratio</i>		<i>invovercogs</i>	
<i>commitments</i>	-0.00006 (0.00008)	-0.00024*** (0.00009)	-0.02847 (0.02655)	-0.05126** (0.02561)
<i>grading</i>	0.00085*** (0.00024)	0.00066*** (0.00024)	0.30952*** (0.09033)	0.15051** (0.06206)
<i>commitments</i> × <i>grading</i>	-0.00072** (0.00030)	-0.00064** (0.00028)	-0.13269 (0.11924)	-0.23288*** (0.06937)
<i>capintensity</i>		-0.01006*** (0.00125)		-2.99178*** (0.32913)
<i>grossmargin</i>		-0.00035*** (0.00009)		0.01593 (0.01956)
<i>tbillrate</i>		0.00193** (0.00084)		0.59953 (1.64042)
<i>salesgrowth</i>		0.00074*** (0.00006)		0.28732*** (0.01359)
<i>daysap</i>		0.00053*** (0.00006)		0.16590*** (0.01386)
<i>production</i>		-0.00009 (0.00007)		-0.00415 (0.01592)
<i>demand</i>		-0.00201 (0.00287)		0.11462 (0.79251)
<i>goldpricevol</i>		0.00492 (0.01531)		-0.17633 (2.95386)
<i>goldprice</i>				0.33663 (1.04158)
Constant		0.02190 (0.02126)		-1.14731 (3.99690)
Firm Effects	No	Yes	No	Yes
Quarter Effects	No	Yes	No	Yes
Observations	911	911	911	911
Firms	58	58	58	58
Wald χ^2	17.06***	1660.58***	16.89***	4276.53***
R^2	0.016	0.540	0.040	0.768

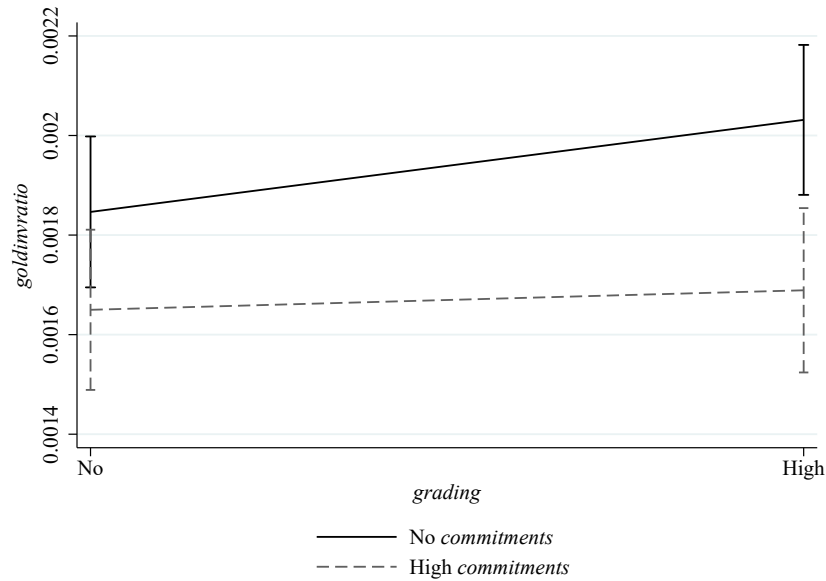
R^2 is the square of the correlation between actual and predicted values of the dependent variable in the model. Standard errors correcting for heteroskedasticity across firms and autocorrelation within firms are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

We first interpret the results on the main effects of financial and operational risk management on inventory. In Models II and IV, the main effect of financial risk management is negative and statistically significant, supporting Hypothesis 1 that gold commitments are negatively associated with inventory. Hypothesis 2 is also supported, as operational risk management in the form of grading is associated with an increase in gold inventory. Interpreting the sizes of the main effects, Model II suggests that a one-standard deviation increase in FRM is associated with an 14.3% decrease in inventory.⁸ Analogously, a one-standard deviation increase in variational grading is associated with a 3.5% increase in inventory.

Turning to Hypothesis 3, the interaction terms in Models II and IV test how the joint use of

⁸See Appendix B for a detailed calculation.

Figure 2: Interaction of FRM and ORM



FRM and ORM affects inventory. Statistically significant coefficients on the interaction terms support Hypothesis 3 that the use of one risk management strategy moderates the second. Considering that a reduction in inventory is generally favorable, the negative coefficient sign further provides evidence that gold commitments and variational grading could be viewed as complements in the gold industry.

We decompose the two-way interaction and examine the conditional effects of gold commitments and grading on inventory. We restrict attention to results from Model II and plot *goldinratio* against various levels of commitments and grading in Figure 2. The horizontal axis corresponds to no ORM (*grading* = 0; “No”) and ORM at one standard deviation above the mean (*grading* = 0.282; “High”). The levels of FRM correspond to no gold selling commitments (*commitments* = 0; “No”) and gold selling commitments at one standard deviation above the mean (*commitments* = 0.807; “High”).

At first look, more variable gold grading seems to be associated with greater levels of inventory: for each level of gold commitments, moving from smaller to larger levels of ORM results in an increase in average gold inventory. Yet, the impact of the FRM strategy on inventory levels is particularly noteworthy. Without any gold selling commitments in place, moving from no variational grading to a high level of variational grading is associated with a significant increase in gold inventory ($\beta = 0.0007$; $p < 0.01$).

However, by selling gold commitments, miners are able to completely negate this effect. For gold

miners that have committed to selling a large portion of their production forward, grading is associated with a change in inventory that is statistically indiscernible from zero ($\beta = 0.0001$; $p > 0.10$). In terms of magnitude, firms going from no commitments to high levels of commitments achieve a 16.6% reduction in gold inventory.

Taken together, we first find that if one objective of a miner is inventory reduction, it is always beneficial to sell gold commitments. This result is also consistent with prior research (Kouvelis et al., 2013). We also find that although miners may use ORM in times of volatile prices, doing so comes at the cost of higher inventory levels. This consequence seems to be able to be mitigated with a large enough future selling commitment. Yet, miners which locked in gold prices were unable to benefit from increasing gold prices over the sample period. Our analysis suggests that financial and operational risk management strategies in the gold mining industry may negate these trade-offs and could be seen as complementary.

5.2 FRM, ORM, and Gold Stockpiles

Our hypotheses stem from the notion that FRM and ORM impact the amount of ore that is excavated, stockpiled, and processed. As a more direct test, we would therefore expect that it is primarily the raw materials inventory (primarily gold in stockpiles) that is associated with changes in risk management strategies, and less so the finished goods (as-of-yet unsold doré bars). As a robustness check, we decompose total inventory into (i) raw materials (RM), (ii) work-in-process (WIP), and (iii) finished goods (FG) inventory. We define the variables *rm_goldinvratio*, *wip_goldinvratio*, and *fg_goldinvratio*, respectively, by adapting Equation 1 to measure RM, WIP, and FG inventory. We re-estimate our model with these measures as the dependent variables and display the results in Table 4. However, our sample size drops substantially due to missing data on inventory: although this approach allows us to disentangle the effects of FRM and ORM on different types of inventory, Compustat unfortunately does not have full information for all firms.

We find partial support for H1. On the one hand, Model V does not seem to show a relationship between raw materials inventory and commitments, although this may be attributed to sample issues and missing data on inventory data in Compustat. On the other hand, we find that *commitments*

Table 4: RM, WIP, and FG Inventory

	(V)	(VI)	(VII)
	<i>rm_goldinratio</i>	<i>wip_goldinratio</i>	<i>fg_goldinratio</i>
<i>commitments</i>	0.00004 (0.00005)	0.00010** (0.00004)	0.00003 (0.00003)
<i>grading</i>	0.00025** (0.00011)	0.00034*** (0.00011)	0.00007 (0.00007)
<i>commitments</i> × <i>grading</i>	-0.00043*** (0.00012)	-0.00024*** (0.00009)	-0.00002 (0.00006)
All Controls	Yes	Yes	Yes
Firm Effects	Yes	Yes	Yes
Quarter Effects	Yes	Yes	Yes
Observations	434	453	422
Firms	45	45	44
Wald χ^2	7840.06***	3853.56***	2411.01***
R^2	0.742	0.737	0.646

R^2 is the square of the correlation between actual and predicted values of the dependent variable in the model. Standard errors correcting for heteroskedasticity across firms and autocorrelation within firms are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

is associated with an increase in work-in-process inventory. As firms draw down their raw materials inventory, more of it is processed, and so WIP inventory increases. We do find strong support for H2 and H3 in Models V and VI, which looks at how risk management is associated raw material and work in process inventory. In particular, variational grading is associated with a significant increase in raw material inventory, and joint FRM and ORM are associated with a decrease in raw material inventory.

Importantly, H1, H2, or H3 are all rejected when we regress finished goods inventory on our variables. As expected, we do not find that finished goods inventory (gold doré bars) vary with gold commitments and variational grading.

5.3 Expected and Unexpected Grading

Hypothesis 2 posits that ORM through grading is associated with greater inventory due to an increase in variation in capacity-constrained processes. Extending this line of argumentation one step further, we would expect that firms which are able to ex ante anticipate such variation would also be better positioned to counteract it. They can take precautions and plan their resources accordingly. On the other hand, to the extent that the deviations are unexpected, they cannot. Here, we examine how the relationship between variational grading and inventory differs according to whether changes in the mining plan might have been expected or unexpected. We do so by disentangling deviations

from the mine plan that might be “expected” from those that might be “unexpected.”

We proceed in two steps. First, we estimate $grading_{i,q} = \gamma_0 + \gamma_1 grading_{i,q-1} + \gamma_2 goldpricevol_q + \gamma_3 goldprice_q + F_i + Q_q + \epsilon_{i,q}$.⁹ We use the coefficients from this model to predict a firm’s level of ORM in a given quarter ($\widehat{grading}_{exp}$). We interpret this as the “expected” level of ORM in a given quarter; that is, a level of variational grading that is expected under a mining plan and prevailing gold prices and volatility. We then calculate the absolute deviation $|grading - \widehat{grading}_{exp}| = \widehat{grading}_{unexp}$ as the “unexpected” component of ORM that a firm undertook in a given quarter. If increases in inventory are primarily driven by deviations from the mining plan, we would expect a positive association between *unexpected* grading and inventory.

Table 5 shows the results from estimating models of inventory on FRM and expected/unexpected ORM. Across Models VIII and IX, we find support for H1, that FRM is associated with a reduction in inventory. Turning to the relationship between expected and unexpected variational grading, Model VIII suggests that there is no association between anticipated changes in the mining plan and inventory. This suggests that, to the extent that a large variation in extracted and processed gold grades is planned, this has no significant effect on inventory levels. On the other hand, Model IX shows a clear relationship between unexpected variational grading and inventory. This provides evidence that increases in inventory are being driven by unplanned changes in the grade of gold, further corroborating Hypothesis 2.

6 Extensions

In this section, we extend our analysis along two dimensions, in order to paint a more comprehensive picture of risk management in the gold mining industry. First, we explore whether miners that primarily employ FRM differ substantially from miners that primarily use ORM to manage gold price risk. Second, we explore the link between FRM, ORM, and profitability.

⁹See Appendix C.2 for the results.

Table 5: Expected and Unexpected Grading

	(II)	(VIII)	(IX)
	Main Result	Expected Grading	Unexpected Grading
<i>commitments</i>	-0.00024*** (0.00009)	-0.00030*** (0.00010)	-0.00035*** (0.00008)
<i>grading</i>	0.00066*** (0.00024)		
<i>commitments</i> × <i>grading</i>	-0.00064** (0.00028)		
$\widehat{grading}_{exp}$		0.00051 (0.00044)	
<i>commitments</i> × $\widehat{grading}_{exp}$		-0.00041 (0.00050)	
$\widehat{grading}_{unexp}$			0.00083** (0.00041)
<i>commitments</i> × $\widehat{grading}_{unexp}$			-0.00070* (0.00040)
All Controls	Yes	Yes	Yes
Firm Effects	Yes	Yes	Yes
Quarter Effects	Yes	Yes	Yes
Observations	911	862	860
Firms	58	56	56
Wald χ^2	1660.58***	1831.59***	1599.09***
R^2	0.540	0.542	0.537

The dependent variable is *goldinvratio*. Model II is reproduced from Table 3. R^2 is the square of the correlation between the actual and predicted values of the dependent variable in the model. Standard errors correcting for heteroskedasticity across firms and autocorrelation within firms are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

6.1 Financial or Operational Risk Management

In their analysis of two large gold miners, Petersen and Thiagarajan (2000) find that firms may have diametrically opposed price risk management strategies. They show that the choice of FRM or ORM depends, to a large extent, on a miner’s ability to adjust operating costs. We therefore first examine whether firms in our sample also display a similar pattern.

In Figure 3, we plot histograms of the extent to which firms use FRM and ORM, split according to whether they have above-average (“high”) or below-average (“low”) ORM and FRM. In the left panel, we note that the distribution of firms with low ORM is skewed somewhat more to the right than the distribution of firms with high ORM. In other words, we obtain some evidence that firms which use ORM to a greater extent also tend to use FRM to a lesser extent: high ORM users have around 9.1% less gold commitments on average,¹⁰ although this difference is not statistically significant (see Table 6). In the right plot, the distribution of low FRM users is shifted more to the right than the distribution of firms with high FRM. We document that high FRM firms have around 19.3% lower

¹⁰The average *commitments* for above-average ORM users is 0.279 and for below-average ORM users is 0.307.

Figure 3: Distributions of *commitments* and *grading*

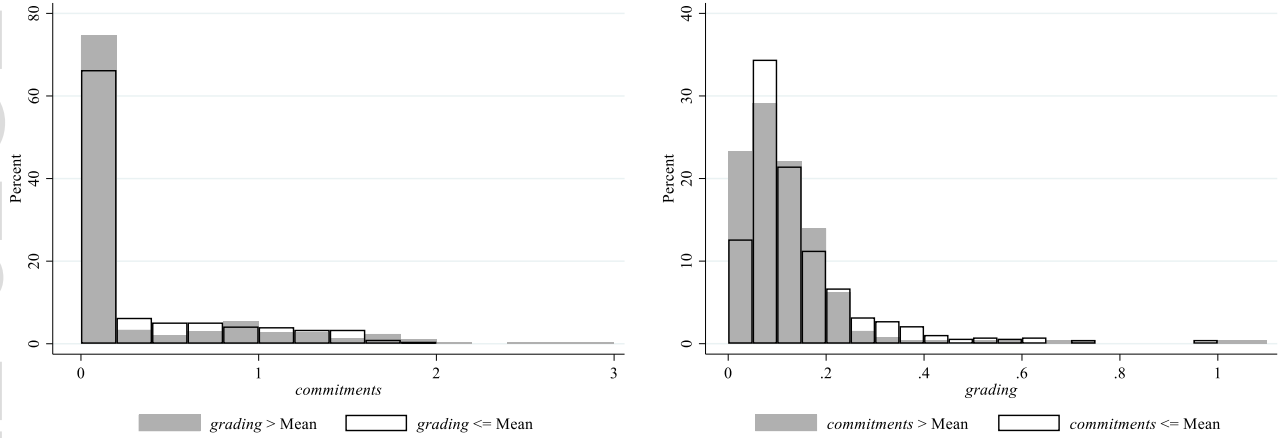


Table 6: Univariate Tests of FRM and ORM

	<i>grading</i> > Mean	<i>grading</i> <= Mean	<i>t</i> -test Difference	<i>commitments</i> > Mean	<i>commitments</i> <= Mean	<i>t</i> -test Difference
<i>goldinratio</i>	0.00204 (0.00015)	0.00174 (0.00006)	0.00031** (0.00014)	0.00149 (0.00005)	0.00197 (0.00009)	-0.00049*** (0.00014)
<i>invovercogs</i>	1.046 (0.030)	0.931 (0.019)	0.115*** (0.035)	0.860 (0.022)	1.011 (0.021)	-0.150*** (0.036)
<i>commitments</i>	0.279 (0.031)	0.307 (0.020)	-0.028 (0.036)			
<i>grading</i>				0.121 (0.008)	0.150 (0.006)	-0.029*** (0.010)

Standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

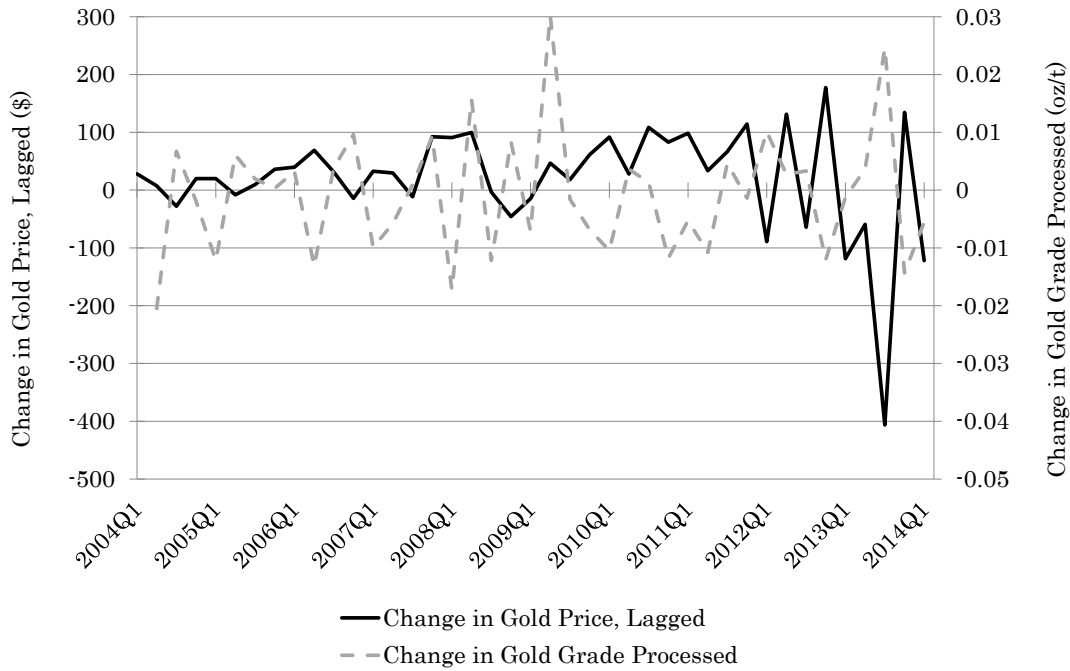
ORM on average,¹¹ and this difference is statistically significant. As such, it seems as though gold miners have a tendency to use FRM in lieu of ORM, and vice versa.

6.2 Gold Prices, Gold Grades, and Profitability

Risk management is primarily used to manage profit and profit variance. Although profitability is not the main focus of this paper, in this section, we explore the relationships between FRM/ORM and financial performance to provide richer insights into the gold mining industry. We first examine how miners respond to changing gold prices by adjusting the grade of gold ore they process and excavate, and then we link such decisions to revenues, costs, and profit.

¹¹The average level of *grading* for above-average FRM users is 0.121 and for below-average FRM users is 0.150.

Figure 4: Gold Price and Ore Grade Processed at Agnico Eagle Mines



In addition to the quotes at the beginning of the chapter, consider the operational decisions by Agnico Eagle Mines depicted in Figure 4. The solid line represents the quarter-on-quarter change in gold prices (lagged by one quarter). The dashed line is the quarter-on-quarter change in gold grade which was processed by the firm. Following substantial, downwards movements in gold prices (in 2013, for example), Agnico Eagle responded by increasing the grade of gold processed. Moreover, such operational responses are not only confined to reductions in gold prices. Between 2010 and 2011, Agnico Eagle responded to increases in prices by processing lower grade ore. At face value, it seems that adjusting operations is used as a strategy to counteract volatile prices.

We are also concerned not only with *whether* firms adjust their mining strategy in response to prices, but also with the *extent* of these adjustments. We expect that greater price volatility is associated with larger changes in processed gold grades: firms should respond to heightened price volatility by increasing their use of ORM and variational grading. We assess the validity of this conjecture by regressing *grading* on the coefficient of variation of gold prices, controlling for gold production and firm-fixed effects. The results in Table 7 show that greater volatility in gold prices is

Table 7: Variational Grading and Gold Price Volatility

	(X)
	<i>grading</i>
<i>coefvargoldprice</i>	0.130** (0.053)
<i>production</i>	-0.022*** (0.004)
Constant	0.332*** (0.054)
Firm FE	Yes
Observations	911
Firms	58
Wald χ^2	323.78***
R^2	0.382

R^2 is the square of the correlation between actual and predicted values of the dependent variable in the model. Standard errors correcting for heteroskedasticity across firms and autocorrelation within firms are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

associated with greater levels of variational grading. In other words, the more volatility in gold prices firms face, the greater the extent to which they implement variational grading.

We take this finding one step further and examine how variational grading impacts a firm’s profitability. Intuitively, if firms do use variational grading as a strategy to improve profitability, we would expect a positive relationship between profitability and the gold grade processed. We regress gross margin and the coefficient of variation of gross margin (i.e., profit variance) on the quarterly grade of gold processed by the firm and selling commitments, and controlling for quarterly gold production, gold prices, and the miner’s total cash costs. Table 8 displays the results of these models, with Models XI and XIII estimated on our base sample, and Models XII and XIV estimated on the subsample of “pure” gold miners in SIC 1040. As expected, we find a significant and positive coefficient on *goldgrade*, suggesting that higher gold grades are indeed associated with greater profitability. Also, as evidence of a profit smoothing function of ORM, we find that higher gold grades are associated with a reduction in gross margin variability. Taken together, the results in Tables 7 and 8 present strong evidence of gold miners adjusting gold grades to protect profits in response to adverse price movements. We also find that firms with a greater amount of gold selling commitments tend to be more profitable.

Table 8: Gold Grades and Profitability

	(XI) All Firms Gross Margin	(XII) SIC 1040 Gross Margin	(XIII) All Firms CV Gross Margin	(XIV) SIC 1040 CV Gross Margin
<i>goldgrade</i>	0.677*** (0.191)	0.690*** (0.194)	-0.935*** (0.321)	-0.937*** (0.324)
<i>commitments</i>	0.050*** (0.018)	0.056*** (0.018)	0.053 (0.038)	0.050 (0.038)
<i>production</i>	0.161*** (0.019)	0.165*** (0.020)	-0.049* (0.027)	-0.053*** (0.027)
<i>goldprice</i>	0.180*** (0.035)	0.160*** (0.037)	0.118** (0.049)	0.120** (0.049)
<i>cashcost</i>	-0.012*** (0.004)	-0.013*** (0.004)	0.003 (0.005)	0.004 (0.005)
Constant	-2.712*** (0.334)	-2.613*** (0.349)	-	-
Firm Effects	Yes	Yes	Yes	Yes
Quarter Effects	Yes	Yes	Yes	Yes
Observations	748	689	748	692
Firms	51	46	50	46
Wald χ^2	1331.58***	1050.46***	8861.96***	13448.09***
R^2	0.394	0.389	0.287	0.282

The dependent variable in Models XI and XII is gross margin, and in Models XIII and XIV is the coefficient of variation of gross margin. R^2 is the square of the correlation between actual and predicted values of the dependent variable in the model. Standard errors correcting for heteroskedasticity across firms and autocorrelation within firms are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

7 Robustness Tests and Alternative Model Specifications

We perform several additional analyses and robustness checks in order to ensure that our findings are not being driven by other explanations. First, we assess the robustness of our results by considering only gold commitments in the form of forward contracts. Second, we re-run our models on a subsample of “pure” gold firms in SIC 1040. Third, we consider several alternative model specifications with lagged dependent variables and the fixed effects estimator.

7.1 Forward Contracts Subsample

Our baseline empirical measure of financial risk management considers the proportion of gold production that is managed under sold forwards and call options. We first argue that although we cannot capture whether call options were indeed executed, the fact that gold prices were increasing during the sample period meant that the options were “in the money” for those parties which purchased the options, and they were indeed likely to be executed. To alleviate such concerns, we re-estimate the baseline model by recalculating commitments as the proportion of the next year’s gold production

Table 9: Further Robustness Checks

	(XV) Forwards Only	(XVI) SIC 1040
<i>commitments</i>	-0.00030*** (0.00010)	-0.00022** (0.00010)
<i>grading</i>	0.00056** (0.00023)	0.00104*** (0.00037)
<i>commitments</i> × <i>grading</i>	-0.00064* (0.00034)	-0.00094** (0.00039)
Constant	0.02150 (0.02194)	0.02951 (0.02493)
All Controls	Yes	Yes
Firm Effects	Yes	Yes
Quarter Effects	Yes	Yes
Observations	896	760
Firms	57	48
Wald χ^2	1602.64***	1310.03***
R^2	0.543	0.521

The dependent variable is *goldinratio*. R^2 is the square of the correlation between actual and predicted values of the dependent variable in the model. Standard errors correcting for heteroskedasticity across firms and autocorrelation within firms are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

under forward contracts only. The results are displayed in Table 9. The estimates in Model XV are statistically significant and consistent with the previous models.

7.2 Gold Firm (SIC 1040) Sample

Several of the firms in the baseline sample are miners of other commodities and metals, and their primary outputs are not gold. Practically, this fact means that the measure of inventory used in the previous analyses is not only composed of gold, but of other materials as well. As a robustness check, we subsample on those firms which are in SIC 1040 Gold & Silver Ores. This approach gives us a “purer” and more homogeneous sample of gold miners. We re-estimate Model II from Table 3. The results in Table 9 Model XVI corroborate those from Table 3. Moreover, the coefficients on *grading* and *commitments* × *grading* are stronger than in the baseline results.

7.3 Alternative Model Specifications

We test the robustness of our results to several alternative model specifications in Table 10. Specifically, we estimate lagged dependent variable (LDV) models of inventory using the FGLS estimator (Models XVII and XVIII) and the Arellano-Bond (Arellano and Bond, 1991) estimator (Models XIX

Table 10: Alternative Model Specifications

	(XVII) LDV - FGLS	(XVIII)	(XIX) LDV - Arellano-Bond	(XX)	(XXI) Fixed Effects Model	(XXII)
<i>commitments</i>	-0.00009 (0.00006)	-0.00573 (0.02328)	-0.00046** (0.00021)	-0.05127 (0.06826)	-0.00046* (0.00025)	-0.029 (0.058)
<i>grading</i>	0.00048*** (0.00018)	0.10347* (0.05680)	0.00050 (0.00035)	0.14422 (0.09845)	0.00066 (0.00064)	0.210 (0.164)
<i>commitments</i> × <i>grading</i>	-0.00082*** (0.00021)	-0.26063*** (0.07243)	-0.00048 (0.00030)	-0.15801* (0.09057)	-0.00052 (0.00055)	-0.199 (0.125)
<i>goldinratio</i> _{q-1}	0.18717*** (0.02398)		0.16400*** (0.05217)			
<i>invovercogs</i> _{q-1}		0.15474*** (0.02224)		0.11665** (0.04992)		
Constant	0.02169 (0.01442)	-2.35268 (4.47473)	0.01330*** (0.00331)	3.69001*** (0.91075)	0.01606 (0.02201)	-5.491 (6.023)
All Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	895	895	834	834	915	915
Firms	56	56	56	56	62	62
Wald χ^2	4087.58***	6010.49***	1121.88***	906.28***	-	-
R^2	0.765	0.813	0.497	0.545	0.427	0.510

The dependent variable in Models XVII, XIX, and XXI is *goldinratio*, in Models XVIII, XX, and XXII is *invovercogs*. R^2 is the square of the correlation between actual and predicted values of the dependent variable in the model. Standard errors are in parentheses. Models XIX-XX estimate the Huber/White standard error, and in Models XXI-XXII, errors are clustered by firm. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

and XX). We also estimate our baseline models using a fixed effects estimator with firm-level clustered standard errors (Models XXI and XXII).

Across the various models in Table 10, we note that statistical significance on our main variables is sensitive to model specification. For example, although *commitments*, *grading*, and their interaction are generally significant when estimated with the FGLS estimator (see also Table 3), they do lose significance under the Arellano-Bond and fixed effects estimators. One potential reason for this result could be that, for example in Models XXI and XXII, although the OLS estimator is more robust to correlation assumptions, it requires a relatively larger sample size than FGLS for efficient estimation. As such, some caution is required in interpreting the results. Reassuringly, however, all results are directionally consistent with our hypotheses and the main results in Table 3.

8 Conclusion

The interface of finance, operations, and commodity risk management has received increasing interest from scholars in Operations Management (Babich and Kouvelis, 2018). This paper sets out

to empirically examine the relationship between financial and operational risk management practices, and inventory. To do so, we turn to the gold mining industry, where inventory management is a salient concern. In this context, gold price risk is the dominant economic uncertainty. To protect profit and minimize risk, miners seek to protect themselves from price volatility through certain financial and operational practices. Specifically, financial instruments allow miners to lock in the selling price of their output (gold doré bars). Alternatively, miners can selectively excavate and process ore from different parts of a mine, directly influencing their inputs.

Our analysis suggests that FRM and ORM are associated with different effects on inventory levels. On the one hand, as miners commit a greater proportion of their production to be sold at a certain, locked-in price, this reduces the option value of holding and waiting to process gold stockpiles. Accordingly, we find that FRM is associated with lower levels of inventory. On the other hand, as miners implement ORM practices, they deviate from their mining plan to selectively excavate and process different grades of ore. This allows miners to vary input costs, but it also induces variability in mining processes. We find that such a strategy is associated with higher levels of inventory. We also find that miners which use *both* FRM and ORM may be able to achieve significant reductions in inventory, suggesting that financial and operational risk management (in the form of commitments and variational grading) in the gold industry could be viewed as complementary risk management strategies. This is notable, since we also find some evidence that miners may be substituting FRM for ORM.

This paper has implications for managers, and especially those charged with managing the firm's risk profile. Firms typically set and execute on their risk management strategies with the objective of maximizing profitability and/or minimizing risk. CFOs would deploy FRM primarily to manage price risk and top line sales, whereas COOs use ORM to manage cost and bottom line profit. In the gold mining industry, however, there is a noticeable disconnect between corporate operations and finance. On the one hand, FRM decisions are often made at the most senior, headquarters-level of the firm. Finance executives make decisions to sell gold forward or enter into other derivative contracts without consulting or relaying these decisions to operations managers. Likewise, individual mines are often left to manage their own production decisions in a largely decentralized fashion. At the same time, several interviews with Finance and Operations managers also confirmed that in their quest to

manage profitability and risk, miners were not always aware of the (unintended) consequences of ORM and FRM on inventory. For example, one senior mine director noted that in the process of trying to hit financial targets, stockpiles at one mine started becoming so physically massive that the mine ran out of space. Our paper highlights that FRM/ORM decisions need to be aligned with inventory considerations: in addition to maximizing profits or minimizing risk, firms need to consider optimizing inventory when making risk management decisions. Were CFOs and COOs to align FRM and ORM decisions, several of the trade-offs we highlight above may be able to be resolved.

Our study does come with several limitations; yet these also open the door for fruitful research in the future. First, as with all single industry studies, the operational specifics of the gold mining industry are unique: FRM is used to manage output risk, and ORM to manage input cost. Moreover, whereas in other contexts inventory may enable operational flexibility, in mining we show that it may also be a consequence of FRM and ORM practices. Nevertheless, prior studies have focused on the gold mining industry due to its richness and transparency in risk management strategies, and we believe that the results are generalizable to at least other commodity and mining contexts. Second, the data we leverage only captures a portion of miners' FRM portfolios through forward and call options. Although such instruments represent commitments to produce and sell gold, other derivatives exist as well, and future work could test how these also influence operational performance.

Finally, although we examine the relationship between FRM/ORM and operational outcomes, an equally interesting research avenue would ask a preceding question of how firms make the decision to use one strategy or both. In other words, when are FRM and ORM strategies used, and when are they used as complements and substitutes? Although prior normative research in Operations Management has provided theoretical foundations for such questions (Chod et al., 2010), future research can empirically study the antecedents of both commodity risk management strategies as complements and/or substitutes, and whether the market rewards firms that manage operational risks accordingly.

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