Managerial Biases and Corporate Risk Management*

Tim R. Adam
School of Business and Economics, Humboldt University of Berlin
Dorotheenstr. 1, 10117 Berlin, Germany
Tel.: +49 / 30 2093 5641; Fax: 49 / 30 2093 5643
E-mail: tim.adam@wiwi.hu-berlin.de

Chitru S. Fernando
Price College of Business, University of Oklahoma
307 West Brooks, Norman, OK 73019, USA
Tel.: (405) 325-2906; Fax: (405) 325-7688
E-mail: cfernando@ou.edu

Evgenia Golubeva
Price College of Business, University of Oklahoma
307 West Brooks, Norman, OK 73019, USA
Tel: (405) 325-7727; Fax: (405) 325-7688
E-mail: janya@ou.edu

Abstract

We show that managerial behavioral biases, which have been found to influence a number of corporate financial decisions, also affect corporate risk management. We find that managers reduce their hedge positions when the market moves against a hedge, but do not systematically increase their hedge positions when the market moves in favor of the hedge. This asymmetric response is consistent with managerial loss aversion coupled with mental accounting, two behavioral biases that have been documented in other corporate contexts. Furthermore, we find that managers increase their speculative activities, measured by the volatility of hedge positions, following speculative gains, but do not reduce their speculative activities following speculative losses. This finding is consistent with managerial overconfidence. Our findings provide the first evidence that corporate risk management practices are affected by managerial behavioral biases, and suggest that recognizing the presence of these biases will help bridge the gap between the theory and practice of corporate risk management.

This version: July 14, 2010

JEL Classification: G11; G14; G32; G39

Keywords: corporate risk management; manager behavior; speculation; mental accounting; loss aversion; overconfidence.

---

* We thank Alex Butler, Sudheer Chava, Louis Ederington, Gary Emery, Dirk Jenter, Swami Kalpathy, Leonid Kogan, Shimon Kogan, Nan Li, Gustavo Manso, Bill Megginson, Darius Miller, Jun Pan, Roberto Rigobon, Martin Ruckes, Antoinette Schoar, Oliver Spalt, Per Stromberg, Rex Thomson, Pradeep Yadav, and seminar participants at MIT, University of Oklahoma, Humboldt University, University of Texas at Dallas, Southern Methodist University, Texas Christian University, ESMT Berlin, 2008 FMA Europe meetings, 2008 FMA meetings, 2009 EFA meetings and 2010 AFA meetings for valuable discussions and comments. We are grateful to Ted Reeve for providing us with his derivatives surveys of gold mining firms and Leung Kam Ming for excellent research assistance. We also thank Anthony May and Jesus Salas for valuable assistance. This research has been partially supported by the Research Grants Council of Hong Kong (Grant No. HKUST6138/02H). A part of this research was conducted when Chitru Fernando was a visiting professor at the SMU Cox School of Business. He thanks SMU for their gracious hospitality and the National Science Foundation (Grant No. ECS-0323620) for financial support. We are responsible for any remaining errors.

Managerial Biases and Corporate Risk Management

Abstract

We show that managerial behavioral biases, which have been found to influence a number of corporate financial decisions, also affect corporate risk management. We find that managers reduce their hedge positions when the market moves against a hedge, but do not systematically increase their hedge positions when the market moves in favor of the hedge. This asymmetric response is consistent with managerial loss aversion coupled with mental accounting, two behavioral biases that have been documented in other corporate contexts. Furthermore, we find that managers increase their speculative activities, measured by the volatility of hedge positions, following speculative gains, but do not reduce their speculative activities following speculative losses. This finding is consistent with managerial overconfidence. Our findings provide the first evidence that corporate risk management practices are affected by managerial behavioral biases, and suggest that recognizing the presence of these biases will help bridge the gap between the theory and practice of corporate risk management.

JEL Classification: G11; G14; G32; G39

Keywords: corporate risk management; manager behavior; speculation; mental accounting; loss aversion; overconfidence.

For years, hedging made Southwest Airlines Co. the most consistently profitable airline in the U.S. But included in its third-quarter earnings, released Thursday, was a $247 million accounting charge, which reflected the decline in the value of its hedges as the price of oil dropped during the quarter. The charge caused Southwest, which had a healthy operating profit, to post a quarterly net loss for the first time in 17 years. "Southwest is looking for opportunities to "de-hedge" some of its fuel," Gary Kelly, the airline's chief executive, said Thursday. "Low fuel prices are a good thing...and an opportunity that we'll want to take the best advantage of that we can." *Wall Street Journal*, "Fuel Hedges Cloud Airline Results," October 17, 2008.

"Ask any gambler - on the way up it's all about skill, on the way down it's damned bad luck." *Financial Times*, "Southwest's Loss," October 16, 2008.

1. Introduction

The traditional theories of corporate risk management have derived conditions under which managers who act rationally in the interest of shareholders can add value by reducing the effects of market frictions, such as taxes, bankruptcy costs, agency costs, information asymmetries, and undiversified stakeholders of the firm.[1] However, empirical tests of the predictions of these theories have met with only limited success.[2] While individual empirical studies uncover evidence that can be interpreted as being consistent with one or more of the theories of hedging, there is little consistency across studies. In addition, much of the variation in firms' derivatives strategies, both cross-sectionally and over time, remains unexplained. This disparity between theory and practice is remarkably consistent with an argument advanced nearly 50 years ago by Working (1962), that the "traditional" risk avoidance notion of hedging – matching one risk with an opposing risk – is deficient when it comes to explaining hedging behavior in practice. Indeed, the growing evidence that many managers systematically incorporate their market views into their risk management programs[3] but fail to generate positive cash flows from this "selective

[1] See, for example, Stultz (1984), Smith and Stultz (1985), Froot, Scharfstein and Stein (1993), DeMarzo and Duffie (1995), Leland (1998), Breeden and Viswanathan (1998) and Mello and Parsons (2000).
[2] See, for example, Tufano (1996), Mian (1996), Geczy, Minton and Schrand (1997), Graham and Smith (1999), Haushalter (2000) and Graham and Rogers (2002).
[3] See, for example, Dolde (1993), Stultz (1996), Bodnar, Hayt and Marston (1998), and Glaum (2002).

hedging" strategy[4] provides support for the notion that managerial behavior can deviate from the pure rationality assumed by the neoclassical theories of hedging.

In this paper, we study the risk management activities of a sample of North American gold mining firms and present new evidence that lends strong support for behavioral explanations of some practices associated with corporate hedging. A growing body of literature, both theoretical and empirical, studies the impact of managerial behavioral biases on corporate decisions.[5] Several managerial biases, including loss aversion, mental accounting, and overconfidence, have been found to affect corporate investment policies, capital structure decisions, mergers and acquisitions, security offerings, and investment bank relationships.[6] To the best of our knowledge, ours is the first study to examine whether managerial behavioral biases also affect corporate risk management decisions.

First, we find that managers tend to reduce their hedge positions when the market moves against the hedge. The reaction is asymmetric: when the market moves in favor of the hedge, managers do not systematically increase their hedge positions. This asymmetry is inconsistent with the existing theories of hedging, but consistent with the presence of behavioral biases such as loss aversion (Kahneman and Tversky (1979); Tversky and Kahneman (1991)) which implies a higher sensitivity to losses than to gains of equal magnitude. For example, while oil prices were rising, Southwest Airlines' fuel hedging activities were regarded as state-of-the-art, but when oil prices fell and the fuel hedges began to generate losses, Southwest Airlines moved swiftly to unwind its hedge positions despite realizing offsetting gains from lower fuel prices. Similar to

[4] See Adam and Fernando (2006) and Brown, Crabb and Haushalter (2006).

[5] Baker, Ruback, and Wurgler (2007) provide a comprehensive review of the literature on behavioral corporate finance.

[6] Studies include Roll (1986), Loughran and Ritter (2002), Heaton (2002), Ljungqvist and Wilhelm (2005), Malmendier and Tate (2005, 2008), Ben-David, Graham and Harvey (2007), Billett and Qian (2008), Goel and Thakor (2008), Sautner and Weber (2009), and Gervais, Heaton and Odean (2009).

the case of Southwest Airlines, hedging losses in our sample of gold mining firms are offset by gains in their underlying gold holdings. Yet, gold mining firms seem to treat these hedging losses as "real" losses and react accordingly. A possible explanation for treating hedging losses as "real" losses without regard to the gain in the underlying position arises from mental accounting. The concept of mental accounting was first proposed by Thaler (1980, 1985) and summarized by Grinblatt and Han (2005) as follows: "The main idea is that decision makers tend to segregate different types of gambles into separate accounts … by ignoring possible interactions." Thus, mental accounting implies that managers regard losses on derivatives positions separately from simultaneous gains on the underlying position. A risk management policy influenced by loss aversion and mental accounting implies that managers will implement hedging strategies that minimize derivatives losses. In contrast, to the extent rational theories of hedging imply an asymmetric response to gold price movements, we would expect firms to respond more promptly to downward gold price movements to protect against financial distress.

The second main finding of our paper is that managers tend to increase the level of their speculative activities using derivatives, measured by the volatility of hedge positions, following speculative gains, but do not reduce their speculative activities following speculative losses. This asymmetric response, which persists after controlling for several firm characteristics, is again difficult to reconcile with rational theories of risk management, but is consistent with the presence of managerial overconfidence. The managerial overconfidence hypothesis (e.g., Heaton (2002); Malmendier and Tate (2005, 2008)) implies that managers may be overconfident in their ability to beat the market, engaging in excessive position shifting under the mistaken belief that they have a relative information advantage. In particular, overconfidence is expected to increase following successes, but decrease less (if at all) following failures. This asymmetric response follows from selective self-attribution: successes tend to be attributed to one's own skill, while failures tend to be attributed to bad luck.

In summary, we document new evidence about the time-series properties of corporate derivatives practices that is consistent with the possibility that managerial behavioral biases affect derivatives strategies. Our findings are robust to numerous controls for alternative rational explanations, and contribute to the growing literature on behavioral biases by showing that managerial behavioral biases can also impact corporate risk management. Recognizing that managers sometimes deviate from strict rationality is likely to improve our understanding of corporate risk management decisions and help close the gap between the observed practice of risk management and the extant neoclassical theory that seeks to explain it.

The remainder of the paper is organized as follows. Section 2 discusses the relevant behavioral theories and derives testable hypotheses. Section 3 describes our sample, the construction of our variables and the empirical methodology. Section 4 presents the empirical evidence on how hedging responds to gold price changes. Section 5 presents the empirical evidence on how speculation responds to speculative gains and losses. Section 6 summarizes the results and presents our conclusions.

2. Empirical Hypotheses

The objective of this paper is to test whether managerial behavioral biases are likely to affect corporate risk management decisions. As documented by Baker, Ruback, and Wurgler (2007) in their excellent review of the growing literature on behavioral corporate finance, several managerial behavioral biases have been shown to affect corporate decisions. We are investigating the potential effects on corporate risk management decisions of three managerial behavioral biases: mental accounting, loss aversion and overconfidence.

Mental accounting (Thaler (1980, 1985)) implies that managers maintain separate mental accounts for different decision variables. Mental accounting may lead to sub-optimal decisions if managers ignore the possible interdependencies of the decision variables when making decisions, i.e., managers make decisions for each mental account separately. For example, Sautner and Weber (2009) report that managers are more likely to sell shares acquired from exercising options than shares acquired through required stock investments. This behavior is consistent with mental accounting. Loughran and Ritter (2002) provide an explanation for IPO underpricing based on mental accounting: managers do not mind underpricing as long as it is not larger than the “gain” between the midpoint of the filing-price range and the first-day closing price. Ljungqvist and Wilhelm (2005) show that behavioral factors can explain the likelihood that firms will switch IPO underwriters for subsequent offerings and the fees that underwriters charge for such offerings. Coleman (2007) uses an experimental survey setting to study managerial choices over risky alternatives and finds evidence that the surveyed managers maintain separate mental accounts for the consequences of decision outcomes and for the probabilities of those outcomes. In the context of risk management, mental accounting implies that managers maintain one account for derivatives-related gains and losses, and a separate account for the gains and losses on the underlying asset. Thus, managers exhibiting mental accounting may make decisions related to their derivatives portfolio while disregarding the gains/losses on the underlying asset.

The literature on cognitive biases ties mental accounting to another behavioral bias known as *loss aversion* (Kahneman and Tversky (1979); Tversky and Kahneman (1991)). Loss aversion implies that individuals are more sensitive to losses than they are to gains of equal magnitude. That is, they exhibit non-standard utility functions.

Mental accounting coupled with loss aversion implies that individuals tend to be loss averse over specific accounts rather than their overall position. For example, Barberis and Huang (2001) argue that investors exhibit loss aversion over individual stocks in their portfolios rather than over their overall portfolios. In the corporate risk management context, mental accounting coupled with loss aversion implies that managers are more sensitive to derivatives losses than to derivatives gains, and at least partially ignore any offsetting effects in the hedged positions. Moreover, Tversky and Kahneman (1991) review considerable prior evidence which suggests that managers who are loss averse will also react more intensely to losses than to gains by moving to reverse actions that led to the loss (see also Thaler and Johnson (1990)). Therefore managers who exhibit mental accounting and loss aversion will reduce their hedge positions when they result in hedging losses, but will not systematically increase their hedge positions when they result in hedging gains.[7]

Recent anecdotal evidence shows that, like in the aforementioned case of Southwest Airlines, gold mining firms moved swiftly to cut or eliminate their hedges after losing money on contracts due to rising gold prices. According to the Wall Street Journal (March 17, 2008), "last year, in the largest cut since 2002, gold mining companies reduced their committed hedged positions by 35%." One prominent example is the de-hedging of Barrick Gold (Wall Street Journal, July 28, 2004) when facing rising gold prices: "Barrick reduced its hedge position to 13.9 million ounces, down 850,000 ounces in the quarter," which contributed to its 42% drop in quarterly net income. We have uncovered no public announcements or other anecdotal evidence

[7] Loss aversion has been commonly associated in the investments literature with a reluctance to sell losing investments, i.e., the disposition effect (Shefrin and Statman (1985)), which arises when the heightened sensitivity to losses generates an attempt to gamble out of a sure loss (unless the sensitivity to losses is itself dynamically affected by the loss, in which case the disposition effect may not obtain (Thaler and Johnson, (1990)). However, drawing a parallel to the disposition effect is not straightforward in the context of corporate hedging since one cannot clearly say that keeping a hedge open is more of a gamble than closing it out. Nonetheless, the basic premise of loss aversion – the higher sensitivity to losses than to gains of equal magnitude – implies that managers will more likely notice and act upon a derivatives loss associated with corporate hedging.

to suggest a similarly swift response when gold prices are moving downwards. In contrast, to the extent rational theories of hedging imply an asymmetric response to gold price movements we would expect firms to respond more promptly to downward gold price movements to protect against financial distress.

Another managerial behavioral bias that has been widely documented in recent studies is managerial *overconfidence* (see, for example, Russo and Schoemaker (1992), Griffin and Tversky (1992) and Heaton (2002)). Overconfident managers systematically overestimate the probability of good outcomes (and correspondingly, underestimate the probability of bad outcomes) resulting from their actions (Heaton (2002)). In a dynamic setting, overconfidence coupled with biased self-attribution (Miller and Ross (1975)), where managers credit themselves for successes while blaming outside factors for failures, cause managerial overconfidence to increase following successes but not commensurately decrease following failures (Daniel, Hirshleifer and Subrahmanyam (1998); Gervais and Odean (2001)). The implications for corporate financial decisions are that overconfident managers act more decisively and aggressively, and that this behavior intensifies following successes. Several studies, including Malmendier and Tate (2005, 2008), Ben-David, Graham and Harvey (2007), Billett and Qian (2008), and Malmendier, Tate and Yan (2010), report empirical evidence consistent with overconfident managers, while Barber and Odean (2000) report similar evidence in the context of overconfident individual investors.

We test the overconfidence hypothesis in the context of corporate risk management. There is ample evidence that managers incorporate their market views into their hedging decisions, and thus hedge "selectively."[8] Adam and Fernando (2006) and Brown, Crabb and

[8] See Dolde (1993), Stultz (1996), Bodnar, Hayt and Marston (1998), and Glaum (2002).

Haushalter (2006) document significant time-series variation in the size of the hedge positions of gold mining firms, which may reflect managers' changing market views about future gold prices. In the absence of an information advantage with respect to gold prices, however, incorporating a manager's private market view into a hedging program is inconsistent with neoclassical theories of risk management. Indeed, Adam and Fernando (2006) and Brown, Crabb and Haushalter (2006) do not find systematic gains from selective hedging, which implies that managers of gold mining firms do not possess an information advantage on average. Thus, the significant time-series variation in firms' hedge positions is likely to be inconsistent with rational explanations of corporate hedging.

The managerial overconfidence hypothesis applied in the context of corporate speculation implies that managers grow more overconfident following past speculative successes, leading to a more aggressive pursuit of speculative strategies, while past failures would diminish managers' willingness to speculate to a lesser degree, if at all. Hence, we expect an asymmetric relation between speculative activities and the past performance of speculative positions, where managers increase their speculative activities following successes in speculation, while they do not commensurately decrease speculation following failures in speculation.

It could be argued that shareholders, rather than managers, are potentially affected by some of the above behavioral biases and exert pressure on rational managers to react asymmetrically. However, while shareholders observe gold price changes, they do not fully observe dynamic hedging strategies or the resulting variation in derivatives cash flows. Therefore, it is unlikely that shareholder pressure can fully underlie all our empirical hypotheses. We discuss other alternative explanations in subsection 3.3 below.

Our mental accounting / loss aversion hypothesis predicts that managers will close out hedges following losses while our overconfidence hypothesis predicts that they will speculate more following past speculative success. These hypotheses may seem contradictory since in the first case managers react sharply to "losses" while in the latter case they react sharply to "gains." Note, however, that a "speculative success" does not imply a "hedging gain" i.e., a drop in the price of gold. Likewise, the act of speculation (dynamically varying derivatives positions in response to changes in market views) does not imply a directional response of a hedge position to a change in the price of gold. For example, a speculative contrarian manager and a speculative momentum manager would react in opposite ways to the same price change. Therefore, the two hypotheses test two quite independent behavioral phenomena.

3. Data and Methodology

3.1 Data and variables

Our sample consists of 92 gold mining firms in North America, which are included in the *Gold and Silver Hedge Outlook*, a quarterly survey of derivatives activities conducted by Ted Reeve, an analyst at Scotia McLeod, from 1989 through 1999, when he discontinued the survey.[9] These 92 firms represent the majority of firms in the gold mining industry (see Tufano (1996) and Adam and Fernando (2006)). Firms not included in the survey tend to be small or privately held corporations.

The survey contains information on all outstanding gold derivatives positions, their size and direction, maturities, and the respective delivery prices for each instrument (forwards, spot-

[9] While some post-2000 hedging data is available from accounting disclosures and other sources, this data lacks the level of detail and consistency across firms that has made the Scotia McLeod survey data invaluable for many empirical studies of corporate hedging, including Tufano (1996, 1998), Fehle and Tsyplakov (2005), Adam and Fernando (2006), and Brown, Crabb and Haushalter (2006).

deferred contracts, gold loans and options). This derivatives data is described in detail in Adam (2002). We hand-collect operational data: gold production (in ounces), production costs per ounce of gold, and gold reserves, from firms' annual reports. The data on firm characteristics such as size, market-to-book, leverage, liquidity, existence of a credit rating, and payment of quarterly dividends comes from Compustat. Data on managerial compensation is from ExecuComp, supplemented by hand collection from proxy statements where necessary. All variable notations and definitions are provided in Appendix 1.

We measure the extent of derivatives usage at a given point in time *t* with time to maturity *i* by a hedge ratio $HR(i)_t$, defined as follows:

$$HR(i)_t = \frac{N(i)_t}{E_t[\text{Prod}_{t+i}]}, \tag{1}$$

where $N(i)_t$ is the sum of the firm's derivatives positions in place at time *t* (in ounces of gold) that mature in *i* years, weighted by their respective deltas, as in Tufano (1996). $E_t[\text{Prod}_{t+i}]$ is the firms's expectation of its gold production (in ounces of gold) at time t+i as of time *t*. The maturity *i* of a derivatives position can be 1, 2, 3, 4, or 5 years, although most derivatives activity takes place with contracts that mature within three years. To check robustness of our results we aggregate (a) contracts with 1-3 years maturity and (b) contracts with 1-5 years maturity.

The derivatives survey reports the expected production for each hedge horizon *i* whenever a firm has derivatives positions outstanding that mature in *i* years. If a firm does not hedge a particular maturity, then the expected production figures are missing. In this case we use the actual gold production in year t+i. Since most firms do not hedge their gold production beyond three years, the problem of missing expected production figures increases with the hedge horizon. Therefore, we also define an alternate hedge ratio, $HR_{\text{Res}}(i)_t$, that does not rely on expected production but scales a firm's total derivatives position by its total gold reserve (see Jin and Jorion (2006)):

$$HR_{\text{Res}}(i)_t = \frac{N(i)_t}{\text{Gold Reserve}_t}. \tag{2}$$

In addition to helping overcome potential issues associated with missing production data, scaling by reserves is also a useful robustness check of our analysis using production-based hedge ratios, due to the possibility that some time-series variation in the production-based hedge ratio may be due to unplanned variations in expected production rather than a change in the firm's derivatives positions.

We observe the above hedge ratios every quarter from December 1989 to December 1999. This data allows us to measure the extent of speculation (selective hedging) by the time-series volatility in hedge ratios. To obtain quarterly volatility estimates while also maximizing the number of observations in our relatively small sample, we follow the existing literature on volatility estimation and calculate volatility by the absolute change in a firm's hedge ratio. Alizadeh, Brandt, and Diebold (2002) review the large body of literature that estimates time-varying volatility using two daily observations: either open and close, or high and low. They argue, in particular, that the range, or the difference in log prices between daily high and daily low, is a good proxy for daily volatility. To quote, "…the discretized stochastic volatility model is difficult to estimate because the sample path of the asset price within each interval is not fully observed…. In practice, we are forced to use discretely observed statistics of the sample paths, such as the absolute or squared returns over each interval, to draw inferences about the discretized log volatilities and their dynamics…" The measure advocated by Alizadeh et al. (2002) has been used not only in market microstructure but also, for example, in asset pricing research. Ang, Hodrick, Xing, and Zhang (2006) mention using the range-based volatility measure as a proxy for innovations in aggregate market volatility, in order to estimate whether exposure to these innovations is a priced risk.

Thus, we define the extent of speculation in quarter *t*, V_t, as the absolute value of the difference in the natural logarithms of the hedge ratios at the beginning and the end of each quarter.[10]

$$V_t = ABS[LN(HR_t / HR_{t-1})] \tag{3}$$

This approach permits us to obtain quarterly volatility estimates, in contrast to (at best) annual volatility estimates that we would obtain using the time-series standard deviation of hedge ratios.[11]

We use several constructs to measure the past performance of firms' derivatives activities. First, we compute the quarterly total cash flows generated from derivatives positions per ounce of gold hedged, as in Adam and Fernando (2006). Second, we recalculate the quarterly cash flows assuming a firm had maintained a constant hedge ratio ("benchmark cash flows"). The difference between the total derivatives cash flow and the cash flow computed using this fixed hedge ratio benchmark is the cash flow that we attribute to selective hedging.[12] Positive selective hedging cash flows constitute "speculative gains" and negative selective hedging cash flows constitute "speculative losses." Selective hedging cash flow is an attractive measure because it reflects the part of the cash flow that results directly from managerial market timing,

[10] For the purpose of measuring percentage changes, whenever a firm reports a zero hedge (unless it reports a zero value in *both* the beginning and the end of the quarter), we substitute a very small value. The percentage change is then calculated as the difference of the natural logarithms from quarter (t-1) to quarter t.

[11] An apparent refinement would be to estimate predicted hedge ratios as in Adam and Fernando (2006) and use the hedge ratio residuals to compute speculation. However, as demonstrated by Adam and Fernando (2006) in their robustness checks, speculation computed using hedge ratio residuals does not yield substantively different results to speculation computed using total hedge ratios, which may be due in part to the inability of fundamental variables to explain the variation in hedge ratios.

[12] Adam and Fernando (2006) provide details on the computation of these cash flows.

i.e., speculative, actions.[13] Finally, in addition to the above cash flow measures, we also calculate the quarterly derivatives book profit (or loss), which is computed as the quarterly change in the value of derivatives positions in dollars per ounce hedged. Please refer to Appendix 2 for the calculation of quarterly changes in the book value of derivatives positions.

Tables 1 and 2 show the descriptive statistics and the correlations for the different hedge ratios and hedge ratio volatility measures.

[Place Tables 1 & 2 about here]

Several observations emerge from these tables. Consistent with Adam and Fernando (2006), selective hedging cash flows average at around zero, suggesting that selective hedging does not add value to the firm on a systematic basis. We notice that the hedge ratios of different maturities are all significantly correlated with one another. However, the correlations are weaker between shorter-maturity and longer-maturity hedge ratios. The aggregate hedge ratios are less than perfectly correlated with one another, substantiating the need to check robustness of our results with respect to different hedge ratio definitions. The same general conclusions hold for the hedge ratio volatilities.

3.2 Basic methodology

Our basic methodology is to run panel regressions with firm fixed effects in order to focus on the time-series variation in hedge ratios. We estimate the loss aversion hypothesis on the whole sample and, for robustness, on the subsample of firms that hedge in the sample period (i.e., have at least one non-zero hedge ratio). We test our hypothesis on both groups of firms to avoid the

[13] For example, suppose a manager believes that the gold price is going to rise and therefore reduces the hedge ratio relative to the benchmark. If she is correct in her forecast, then the total derivatives cash flow will be negative (since she is short overall) but the selective component will be positive: the firm does not lose as much on the hedge as it could have.

possibility that sample selection bias could affect the results for the subsample of hedgers and because we do not know *ex ante* that non-hedgers will persist in not hedging throughout our sample period. Keeping non-hedgers in the sample will make a finding in support of the loss aversion hypothesis less likely, *ex post*. A firm that has a zero hedge ratio will not reduce the hedge ratio in response to a gold price increase. At the same time, a firm that has a zero hedge ratio may increase the hedge ratio in response to a gold price decrease. Therefore, by keeping non-hedgers in the sample we decrease (increase) the unconditional probability of observing a significant reaction to increases (decreases) in the price of gold, which would work against the loss aversion hypothesis. We then check the robustness of our results by taking non-hedgers out of the sample.

In our initial tests, we estimate the sensitivity of the hedge ratio to past changes in the price of gold while controlling for firm characteristics that may affect the fundamental hedging needs of the firm, as well as seasonal dummies and a time trend. Subsequently, we consider the possibility that the initial level of the hedge ratio may affect the firm's reaction to the gold price change.

For robustness we repeat our tests using the two-step Heckman (1979) procedure with selection. In the first stage, we model the existence of hedging activity as a function of variables that are predicted by extant hedging theory to be determinants of hedging -- firm size, market-to-book ratio, liquidity, leverage, dividend payment, credit rating, and the likelihood of financial distress (Tufano (1996), Haushalter (2000)). We say that a firm has hedging activity if two conditions hold: (1) the beginning or the end-of-quarter hedge ratio is non-zero; and (2) cash flows from derivatives positions in the previous quarter are non-zero. In the second stage of the Heckman two-step procedure, we test whether the hedge ratio is sensitive to past changes in the price of gold for the firms that exhibit hedging activity as described above. Further methodological details are provided in Section 4.

Our test of managerial overconfidence, which is based on the relationship between hedge ratio volatility and past speculative gains and losses, needs to be restricted to active hedgers only (i.e., firms that have non-zero hedge ratios and report non-zero cash flows in the previous period). This requirement is due to the fact that the overconfidence hypothesis conditions managerial activity on the results of previous activity. In addition, leaving non-hedging firm-quarters in the sample may lead to a spurious regression result with zero past cash flows from derivatives positions "explaining" zero hedge ratio volatility next period. Hence, we estimate the panel regression with firm fixed effects on a reduced sample of active hedgers. As in our previous tests, for robustness we repeat our overconfidence tests using the two-step Heckman (1979) procedure with selection. The first stage of the Heckman two-step procedure is described above. In the second stage we test whether the hedge ratio volatility is driven by past success of the derivatives positions for the firms that exhibit hedging activity as described above. Further methodological details are provided in Section 5.

Our unique data permits us to employ a methodology that is distinct from and complements the techniques employed in the other studies of corporate managerial biases. Existing studies fall under two categories: surveys, as in Ben-David, Graham, and Harvey (2007); and cross-sectional studies, as in Malmendier and Tate (2005). These studies examine a variety of characteristics that are likely to affect the degree to which managers exhibit behavioral biases. Examples include personal and professional characteristics (age, tenure, education, etc.) and personal wealth management practices (the tendency to hold disproportionate amounts of one's own firm's stock, and the failure to exercise vested options). The question in these studies is whether cross-sectional differences across managers explain actions that are attributable to behavioral biases. Our work complements the prior studies by focusing on time-series patterns that may characterize behavioral biases, examining how managers as a group respond to market movements and their own past performance. As noted before, this complementary perspective is made possible by our unique data set, which contains quarterly observations on all outstanding gold derivatives positions of a sample of 92 North American gold mining firms from 1989-1999. The key advantage of this data set is that we are able to infer actual derivatives transactions and the corresponding cash flows as well as observe the estimates of expected production, which is a unique feature of our data set.

3.3 Controlling for alternative explanations

An alternative explanation for closing out losing derivatives positions may be liquidity pressure or financial distress (Mello and Parsons (2000)). In particular, if a firm had insufficient liquidity or be otherwise financially constrained, it is possible that managers may be forced to close out losing positions due to margin calls. Therefore, we control for a firm's liquidity and likelihood of financial distress to allow for this possibility by including a dividend dummy, rating dummy, quick ratio, leverage and Altman's (1968) Z-score as control variables.

A second alternative explanation for the propensity to close out losing positions is the possibility that book losses draw more scrutiny than book profits. We control for this possibility by including derivatives book profits and losses in our regressions.[14]

[14] The FAS 133 accounting standard, which made a significant departure from past accounting practice by requiring derivatives contracts to be marked to market, could also potentially affect the way managers react to market movements. However, our findings are unlikely to be affected by this change since our sample ends around the same time FAS 133 went into effect (in mid-1999).

An alternative explanation for an increase in speculation following high derivatives cash flows derived from speculation is that managers simply have more cash to use at their discretion or that positive cash flows from speculation improve the firm's financial strength. We control for a firm's liquidity and financial strength to account for this possibility.[15]

Another possibility is that although selective hedging does not benefit shareholders, it may benefit managers due to incentive compensation (Stulz (1996)). While the potential link between selective hedging and managerial compensation is explored in several recent studies, the results are mixed, with only weak evidence that managerial compensation significantly affects selective hedging and no consensus on the direction of the relationship.[16] Nevertheless, we control for managerial compensation variables to allow for this possibility in our hedging sample.

Finally, as pointed out by Campbell and Kracaw (1999), financially constrained firms with good projects may speculate more to generate more funds for optimal investment. Investment opportunities may also affect the degree to which firms choose to hedge due to the need to raise external financing (Froot, Scharfstein and Stein (1993)). We account for both financial constraints and growth opportunities by including standard control variables such as debt-to-equity and market-to-book ratios.

[15] It is important to note, however, that in contrast to positive speculative cash flows from derivatives, positive total derivatives cash flow need not make the overall financial position of the firm stronger because positive hedge cash flows on derivatives positions would typically offset losses due to gold price declines.

[16] Géczy, Minton and Schrand (2007) find that CEO stock price sensitivity is negatively related to speculation while CFO stock price sensitivity is positively related. Beber and Fabbri (2006) find no consistent relation between CEO delta and selective hedging. Brown, Crabb and Haushalter (2006) find no systematic relationship between selective hedging and several ownership and compensation measures.

4. Empirical Results: Hedging Response to Gold Price Changes

In this section, we test the loss aversion hypothesis, which predicts that managers systematically reduce their hedge positions when they produce hedging losses but do not systematically increase their hedge positions when they produce hedging gains. Initially, we test this hypothesis by examining how the change in the hedge ratio is related to the previous quarter's change in the gold price, while allowing for asymmetry effects and controlling for relevant firm characteristics. Thereafter, we repeat our tests while allowing for the possibility that the relation between hedge ratio changes and gold price changes may be affected by the initial level of the hedge ratio. We conclude by carrying out robustness checks.

4.1 Initial tests

We begin with a simple question: Does the hedge ratio respond to past changes in the price of gold? We normalize past changes in the price of gold by the initial gold price level, thereby making gold *returns* our main independent variable of interest:

$$RTNGOLD_{t-1} = \Delta GOLD_{t-2,t-1}/GOLD_{t-2}, \tag{4}$$

since a given dollar change in the price of gold is likely to be perceived differently depending on the prevailing gold price level.[17]

Table 3 reports the results of the regression:

$$\Delta HR_t = a + b \cdot RTNGOLD_{t-1} + CONTROLS_{t-1} + \varepsilon_t \tag{5}$$

[17] While we report regression results that employ gold return as the independent variable, we also repeated our tests using dollar changes in the price of gold. The results of those tests are available upon request and are similar to the results obtained using gold returns.

We control for past changes in firm characteristics which may also explain a hedge ratio adjustment following a change in the gold price. As our control variables, we choose the change in size, liquidity (quick ratio), leverage, market-to-book, Altman's Z-score, dividend dummy, and credit rating dummy, to accommodate the possibility that a change in the price of gold may change the fundamental hedging needs of the firm, or cause liquidity pressure and financial distress. In addition, we control for seasonal variation using seasonal dummies, clustering of some observations across quarters, and a time trend. The time trend is a variable equal to zero for the first sample observation (December of 1989) and increasing by 0.25 each quarter. Finally, in Models (3), (6), (9), and (12), we report the results obtained on a reduced sample with non-hedgers (i.e. firms reporting a zero hedge ratio for the entire sample period) excluded from the sample.

[Place Table 3 about here]

The evidence in Table 3 suggests that firms adjust hedge ratios in response to changes in the price of gold, and that this adjustment occurs primarily for short hedge horizons. The coefficient is highly significant, both statistically and economically, for the one-year hedge ratio. A one standard deviation (5.27%) increase in the price of gold makes the average firm reduce its one-year hedge ratio by about ten percent relative to the sample mean. For the aggregate three-year and five-year hedge ratios, the gold return coefficient is smaller in magnitude and sometimes insignificant, although the sign is still negative.[18] Overall, the results indicate that gold price changes affect hedging decisions.

We also notice that hedge ratios respond to changes in liquidity and that this effect too occurs at short horizons. A reduction in the quick ratio, which indicates a decrease in liquidity,

[18] Our finding of especially strong results when we use the short-term hedge ratio (i.e., up to one-year maturity), is consistent with prior studies showing that hedgers are more active in the shorter-term maturities (see, for example, Bodnar, Hayt and Marston, 1998).

makes the firm reduce its one-year hedge positions, and *vice versa*. However, the long-term hedge positions appear to be unaffected by liquidity changes.

The main hypothesis tested in this section is that the response of hedge ratio to gold price is asymmetrically stronger for gold price increases. Forcing an equal response to gold price increases and decreases in our regression specification (5) does not allow for this effect to show. Therefore, we next run the following regression to capture any asymmetric response:

$$\Delta HR_t = a + b_1 \cdot RTNGOLD_{t-1} \cdot I_1 + b_2 \cdot RTNGOLD_{t-1} \cdot I_2 + CONTROLS_{t-1} + \varepsilon_t \qquad (6)$$

In this regression, I_1 is a dummy variable that equals one if the change in the gold price during the last quarter was positive, and equals zero otherwise; and I_2 is a dummy variable that equals one if the change in the price of gold was negative, and equals zero otherwise. The sensitivity of hedge ratios to gold price increases is determined by b_1, while the sensitivity to gold price decreases is determined by b_2.

The results, presented in Table 4, are striking. In every model, regardless of the hedge ratio specification and presence of control variables, the coefficient b_1 is strongly negative and statistically significant. At the same time, the coefficient b_2 is always statistically insignificant. That is, increases in the price of gold are followed by significant de-hedging while decreases in the price of gold are not followed by a systematic increase in hedging. This result is robust to the inclusion of changes in firm characteristics that may affect the firm's hedging needs. The result is also economically significant. A one standard deviation (5.27%) percentage increase in the price of gold leads to a reduction of around 17 percent in the one-year hedge ratio relative to its sample mean, with the magnitude of the reaction diminishing with the hedging horizon. Finally, we continue to observe that at short horizons, hedge ratio adjustments are sensitive to variations in liquidity. Once again, Models (3), (6), (9), and (12) present the results obtained on a reduced sample with non-hedgers excluded.

[Place Table 4 about here]

4.2 Effect of initial hedge ratio

We next allow for the changes in hedge ratio to be affected by the initial hedge ratio. If a firm has a low hedge ratio or does not hedge, the subsequent change in the hedge ratio is likely to be positive, all else equal. A non-hedger may either remain a non-hedger or decide to start hedging, thus making the hedge ratio adjustment positive, on average, for such firms. In addition, firms with very low levels of hedge ratios are more likely to under-hedge, thereby increasing the likelihood of a subsequent increase in hedging. Following the same logic, a firm with a very high level of hedging is more likely to reduce its hedge ratio, all else equal. Hence, we expect to observe a negative relationship, all else equal, between the initial level of hedge ratio and the subsequent change. In other words, we can posit a systematic negative impact of the initial hedge ratio on the subsequent change, which exists irrespective of changes in the price of gold or other factors. In this section, we test whether our earlier results are robust to the inclusion of this permanent impact into the regression. We re-run regression (6) with one more term added to the specification:

$$\Delta HR_t = a + b_1 \cdot RTNGOLD_{t-1} \cdot I_1 + b_2 \cdot RTNGOLD_{t-1} \cdot I_2 + CONTROLS_{t-1} + c \cdot HR_{t-1} + \varepsilon_t \qquad (7)$$

In (7), HR_{t-1} is the beginning-of-quarter level of the hedge ratio. We expect the coefficient c to be negative. We also expect the coefficient b_1 to be negative and b_2 to be zero, consistent with the results reported in Table 4.

Table 5 presents the results of our regression (7) with firm characteristics, seasonal dummies, and a time trend used as controls, as in Table 4. For additional robustness, models (3), (6), (9), and (12) in Table 5 report the regression results on the reduced sample with non-hedgers excluded. We can see that our hypothesis regarding the systematic effect of the initial level of hedge ratio is confirmed: the coefficient for HR_{t-1} is universally negative and strongly significant. We observe a marked improvement in the model fit as evidenced by the increase in R^2 compared to those reported in Table 4. Therefore, including the initial level of hedge ratio in the regression is important for modeling hedging adjustments of firms. At the same time, our inference regarding the effect of changes in the price of gold remains virtually unaffected. The coefficient b_1 is still negative and significant: a one standard deviation (5.27%) percentage increase in the price of gold leads to a 10 percent reduction in the one-year hedge ratio relative to the sample mean, with economic significance diminishing with hedging horizon as before. This result indicates that firms robustly reduce their hedge ratios in response to increases in the price of gold. At the same time, we observe no response to decreases in the price of gold: the coefficient b_2 remains insignificant in all specifications.

[Place Table 5 about here]

As an additional robustness check, we control for the possibility of selection bias in our sample by allowing for the two sequential decisions of the firm, (1) whether or not to be a hedger and (2) conditional on being a hedger, the choice of the level of hedging. We estimate the two-step Heckman procedure with selection. In the first stage, we estimate a PROBIT model, where the dependent variable is the "hedging activity" dummy equal to zero if (1) either the firm has zero hedge ratios in both the beginning and the end of quarter t; or (2) the firm had zero cash flows from hedging operations in quarter t-1.[19] We estimate the likelihood of hedging activity as a function of several firm characteristics: size, market-to-book ratio, the ratio of book debt to book equity, quick ratio, dividend-payer status, existence of a credit rating, and Altman's Z-score. In the second stage, we estimate the relationship between the changes in hedge ratio and past changes in the price of gold conditional on the firm being an active hedger.

The results from the two stages of the Heckman procedure are presented in Tables 6 and 7, respectively. From Table 6, we observe that firms that exhibit hedging activity are large firms with low growth opportunities (as indicated by low market-to-book ratios), conservative leverage policies, and higher financial constraints/low liquidity. These results are consistent with the previously reported findings by Geczy, Minton and Schrand (1997), Bodnar, Hayt and Marston (1998) and Haushalter (2000).

[Place Table 6 about here]

Table 7 presents the Heckman second-stage results. The results reported in Table 7 are consistent with our previous findings reported in Table 5. We continue to observe a negative relationship between changes in hedge ratio and past changes in the price of gold only when those changes were positive, and the relationship is the strongest for the short-horizon hedge ratio. We observe no relationship between changes in hedge ratio and past decreases in the price of gold. As before, the initial level of the hedge ratio is negative and significant across all hedging horizons.

[Place Table 7 about here]

[19] We also run the first stage estimation using only the first condition (non-zero hedge ratios) to define hedging activity and obtain similar results. They are not reported due to space constraints but are available on request.

4.3 Controlling for alternative explanations

As mentioned in Section 3.3, in all our specifications we control for alternative explanations based on extant hedging theories that may help explain firms' hedge ratio adjustments following gold price changes. In particular, we control for firm characteristics such as liquidity and financial distress using a firm's quick ratio, leverage, Altman's Z-score, dividend dummy, and credit rating dummy. These additional controls do not affect our principal results in any of the specifications that we employ. We also include these variables in a non-linear fashion, for example, by including the interaction of the change in liquidity with the change in gold price. These additional tests do not affect our findings either and are available upon request. As mentioned previously, we repeat all our tests using the dollar change in the price of gold in place of gold return, with robust results. Finally, our results are robust to including the gold dummy as a separate independent variable, to allow for the intercept term to vary with the direction of gold price change.

5. Empirical Evidence: Speculation Response to Speculative Gains and Losses

In this section, we test the managerial overconfidence hypothesis by examining the relation between speculation (measured by hedge ratio volatility) and past speculative gains and losses. The overconfidence hypothesis maintains that, all else equal, if past speculative activity was successful, resulting in cash flow gains, then the manager will increase his/her speculative activities in the next period. If, however, past speculative activity was unsuccessful, resulting in cash flow losses, then there would be no commensurate reduction in speculative activities. In other words, we expect an asymmetric relation between the degree of speculative activity and past speculative cash flows.

5.1 Initial panel regression without asymmetry effects

We begin by examining the general relationship between derivatives cash flows and subsequent speculative activity. Tables 8 and 9 show the results of the firm fixed effects panel regressions of the hedge ratio volatility on past cash flows and book profits from derivatives positions per ounce of gold hedged. Similar to Table 3, we present the results for the volatility of the one-year hedge ratio, the three-year aggregate hedge ratio scaled by expected production, the three-year aggregate hedge ratio scaled by reserves, and the five-year hedge ratio scaled by reserves. Table 8 reports the results for a specification that employs total derivatives cash flows along with derivatives book profit as independent variables. Our interest in this specification is to investigate whether speculative activity responds to past derivatives cash flows and/or book profits. Table 9 reports the corresponding results using selective hedging cash flows (i.e., the speculative component of total derivatives cash flows), which is our primary variable of interest.

[Place Tables 8 and 9 about here]

Since we are interested in testing the hypothesis that successful past speculative derivatives activity will lead to higher speculation in the future, we perform these regressions after eliminating firm quarters where the firm had zero cash flows from derivatives positions, and also eliminating observations where *both* beginning-of-quarter and end-of-quarter hedge ratios were zero. In all of the models, we include seasonal dummy variables as controls; however, doing so is mostly a concern with the one-year hedge ratio, which exhibits some seasonal variation, whereas the aggregate hedge ratios exhibit virtually no seasonal variation. As discussed in Section 3.3, we also control for firm characteristics that may affect a firm's level of speculative activity, such as liquidity, financial strength, and growth opportunities.

As evident from Table 8, we observe a positive relationship between hedge ratio volatility and previous quarter total derivatives cash flows, which is robust to model specification in terms of both magnitude and statistical significance. However, we do not observe any relationship with the book profit. This result indicates that speculation responds to derivatives cash flows but not to book profits. We then refine the specification to employ the selective hedging component of derivatives cash flows. From Table 9, we observe that the relationship between hedge ratio volatility and selective hedging cash flows is positive and significant, providing evidence in favor of the hypothesis that the success of past selective hedging leads to higher levels of speculation in the future. Again, we do not find a significant relationship with book profits. Nonetheless, speculation is also positively related to benchmark cash flows, which is consistent with our observation in Table 8 for total derivatives cash flows.

Given that the tests reported in Tables 8 and 9 were performed on a reduced sample, we next perform robustness checks to control for the possibility of selection bias by allowing for the two sequential decisions of the firm, (1) whether or not to be a hedger and (2) conditional on being a hedger, how much to speculate. We estimate the two-step Heckman procedure with selection. The first stage is the same PROBIT model described above in Section 4.2 and presented in Table 6. In the second stage, we estimate the relationship between hedge ratio volatility and past cash flows and book profits from derivatives positions conditional on the firm being an active hedger.

Table 10 presents the Heckman second-stage results. The results reported in Table 10 are consistent with our previous findings reported in Tables 8 and 9. In all regression specifications, we observe a positive and significant relationship between hedge ratio volatility and past cash flows from derivatives positions, whether total derivatives cash flows or selective hedging cash flows and benchmark cash flows. We observe no relationship between hedge ratio volatility and past book profits from derivatives positions.

[Place Table 10 about here]

We next perform one more robustness check to control for managerial compensation as discussed in Section 3.3. Tables 11 and 12 present the results of the regressions of hedge ratio volatility on past cash flows while controlling for the managerial compensation variables (delta and vega) of the CEO and the CFO. The regressions are univariate due to the limited number of managerial compensation observations in our sample. However, the regressions indicate that overall, our inference regarding the effect of derivatives cash flows on speculation remains unaffected while the managerial compensation variables are statistically insignificant.

[Place Tables 11 and 12 about here]

5.2 Accounting for asymmetry effects

Having established the relation between speculation and derivatives cash flows, we now turn to our test for the presence of managerial overconfidence in our sample firms. We do so by examining the asymmetry in the relationship between derivatives cash flows and speculation. For this purpose, we run the following regression with dummy variables:

$$V_t = a + b_1 SCF_{t-1} \cdot I_1 + b_2 SCF_{t-1} \cdot I_2 + CONTROLS_t + \varepsilon_t \qquad (8)$$

In this regression, I_1 (I_2) is a dummy variable that equals one if the selective hedging cash flow during the last quarter was positive (negative) and zero otherwise. We choose selective hedging cash flow to be the dependent variable because selective hedging cash flow is the direct consequence of speculative decisions made by the manager in the past, and therefore is more directly related to the extent to which past speculation was successful than total cash flows. We include the benchmark cash flow, along with the firm characteristics, in the matrix of control variables.[20]

We estimate this regression first on a reduced sample of firm-quarters for active hedgers and next, using the Heckman two-step procedure for robustness. The results of the panel regressions on the reduced sample are presented in Table 13, and the results of the second-stage Heckman procedure with controls are presented in Table 14. While the asymmetric response of hedge ratio volatility to selective cash flow persists in this alternative specification, the significance of the benchmark cash flow variable is diminished.

[Place Tables 13 & 14 about here]

From both Table 12 and Table 13, we observe that the relationship between hedge ratio volatility and past selective hedging cash flows is strongly positive *only* if the past selective hedging cash flows are positive. A one-standard deviation increase in selective hedging cash flow leads to a 0.2774 increase in the quarterly volatility of the one-year hedge ratio, which is 22.5% of the sample mean of 1.2325. When selective hedging cash flows are negative, however, we observe no significant relationship except in the case of one-year hedge ratio volatility. However, while we would still expect a positive coefficient for one-year hedge ratio volatility with negative selective hedging cash flows if the relation between speculation and selective hedging cash flow is symmetric (since speculation should decrease as speculation losses increase) this is the opposite of what we observe for one-year hedge ratio volatility. Thus, our evidence here strongly supports an asymmetric relation between speculative activity and selective hedging cash flows, which confirms the managerial overconfidence hypothesis for our sample firms. Managers increase speculative activity following successes (as their

---

[20] Nevertheless, we check robustness of the results to using total derivatives cash flow and find that the general result is similar in spirit although less significant. The results are not reported but are available upon request.

overconfidence rises) but do not symmetrically reduce it following failures. This result is robust to the inclusion of firm characteristics that may affect the fundamental hedging needs of the firm, as well as to controlling for possible selection biases.

5.3 Other robustness checks

In addition to controlling for the rational explanations as laid out in Section 3.3, we also perform a few more robustness checks. First, past cash flows as well as derivatives book profits may be related to movements in the price of gold over the same quarter. This concern is mitigated by the fact that derivatives cash flows are the result of hedging decisions taken in the distant past as well as more current decisions and therefore, the recent change in the price of gold may not have a strong effect. Additionally, this issue is much less of a concern for selective hedging cash flows, which is our main variable of interest. Nevertheless, in unreported tests we include the change in the price of gold in our regressions without a substantive effect on our results. In the two-stage Heckman framework, we also allow for the relationship between hedge ratio volatility and past selective hedging cash flows to be a function of the beginning-of-quarter hedge ratio. In these robustness tests, also available upon request, we continue to find that hedge ratio volatility is positively related to past derivatives cash flows and that the relationship is robustly stronger for positive selective hedging cash flows, consistent with our managerial overconfidence hypothesis.

6. Conclusions

We add to the growing body of literature that documents the presence of managerial behavioral biases in a variety of corporate finance settings, including investment and capital structure policy, mergers and acquisitions, security offerings and investment bank relationships, by showing that the effect of these behavioral biases also extends to corporate hedging decisions. We study how firms change their hedge positions in response to past changes in the gold price and past performance of their hedging portfolios, using a 10-year sample of North American gold mining firms that has been widely studied in the literature. Consistent with anecdotal evidence, we find that managers systematically decrease their hedge positions following past increases in the gold price, while they do not systematically increase their hedges following past gold price declines. We interpret this evidence as consistent with managerial loss aversion and mental accounting, i.e., managers act to minimize losses from derivatives positions, while paying less regard to the performance of the underlying position. We also document a positive relationship between speculation and past speculative gains, without a corresponding relation between speculation and past speculative losses. This asymmetry supports the conjecture that the financial success of past hedging decisions increases managerial overconfidence, leading managers to elevate their levels of speculation. Our findings provide the first evidence that corporate risk management practices are affected by managerial behavioral biases, and suggest that recognizing the presence of these biases will help bridge the gap between the theory and practice of corporate risk management.

Appendix 1: Variable Notations and Definitions

<u>Hedge Ratios</u>:

HR1 – HR5 are the hedge ratios from one- to five-year maturities, respectively;

A3 is the aggregate hedge ratio that aggregates the hedge positions over one-, two-, and three-year horizons, scaled by the expected production;

A3R is the aggregate hedge ratio that aggregates the hedge positions over one-, two-, and three-year horizons, scaled by gold reserves;

A5R is the aggregate hedge ratio that aggregates the hedge positions over one-, two-, three-, four- and five-year horizons, scaled by gold reserves.

<u>Hedge Ratio Volatility</u>:

V1 – V5 are the quarterly volatilities of the one- through five-year hedge ratios, respectively. Quarterly volatility is the absolute value of the difference in the natural logarithms of the end-of-quarter and beginning-of-quarter hedge ratio levels.

V6 – V8 are the corresponding quarterly volatilities for A3, A3R, and A5R, respectively.

<u>Derivatives Cash Flows</u>:

CF are the total cash flows from derivatives positions (in $ per ounce hedged) estimated as in Adam and Fernando (2006);

SCF and **BCF** are the selective and the benchmark cash flows, estimated as in Adam and Fernando (2006);

RBK is the change in the book value of the derivatives positions per ounce hedged (see Appendix 2).

<u>Firm Characteristics</u>:

SIZ is the logarithm of the market value of assets ($ million);

MB is the market-to-book ratio of assets;

DE is the ratio of book debt to book equity;

QCK is the quick ratio;

DIV is a dummy variable equal to one if the firm paid quarterly dividend;

RAT is a dummy variable equal to one if a firm reports a credit rating;

Z is the Altman's (1968) Z-score (higher value of Z corresponds to lower probability of bankruptcy).

DELTA_CEO (CFO) is the change in the dollar value of the CEO's (CFO's) wealth derived from ownership of stock and stock options in the firm when the firm's stock price changes by one percent, calculated according to the methodology of Core and Guay (2002). We calculate the aggregate delta of the executive's compensation as the sum of the deltas of the options holdings and the delta of the stock holdings.

VEGA_CEO (CFO) is the change in the dollar value of the CEO's (CFO's) wealth derived from ownership of stock and stock options in the firm when the annualized standard deviation of the firm's stock price changes by 0.01, following Core and Guay (2002). We calculate the aggregate vega of the executive's compensation as the sum of the vegas of the executive's options holdings, following Coles, Daniel and Naveen (2006).

GLD is the change in the price of gold over the quarter;

Appendix 2: Calculation of Quarterly Derivatives Book Profits

For the calculations of derivatives book profits, we use delta of the linear positions (which is equal to -1) and delta of option positions, which we back out from the total delta of the firm. We calculate the delta of option positions at the end of the quarter as the firm's total delta plus the number of linear contracts:

$$\Delta_{t,Option} = \Delta_{t,Total} + N_{t,Forward} + N_{t,Spot} + N_{t,Loan} \quad \text{(A1)}$$

In (A1), $\Delta_{t,Total}$ is the total delta of the firm, $N_{t,Forward}$ is the number of forward contracts, $N_{t,Spot}$ is the number of spot contracts, and $N_{t,Loan}$ is the number of loan contracts. Then, for each quarter, we calculate the minimum of the two hedge positions,

$$MIN_{NLIN,t} = \min(N_{t,Linear}, N_{t-1,Linear}) \quad \text{(A2)}$$

$$MIN_{NOPT,t} = \min(N_{t,Option}, N_{t-1,Option}) \quad \text{(A3)}$$

Above, $MIN_{NLIN,t}$ is the smaller of the beginning-of-quarter and end-of-quarter linear positions (forward plus spot plus loan) and $MIN_{NOPT,t}$ is the smaller of the beginning-of-quarter and end-of-quarter option positions. Obviously, at this step we lose observations where the size of the position is missing either at the beginning or at the end of the quarter.

Next, we calculate the delta $M\Delta_{t,Option}$ of option positions as the beginning-of-quarter delta $\Delta_{t-1,Option}$, divided by the beginning-of-quarter option position $N_{t-1,Option}$, multiplied by the smaller of the beginning-of-quarter and the end-of-quarter positions:

$$M\Delta_{t,Option} = \Delta_{t-1,Option} \cdot MIN_{NOPT,t} / N_{t-1,Option} \quad \text{(A4)}$$

If both option positions $N_{,t,Option}$ and $N_{t-1,Option}$ are zero, then delta is set to zero. Next, we use the option delta $M\Delta_{t,Option}$ to calculate the total book profits from linear positions $BK_{t,Linear}$, from option positions $BK_{t,Option}$, and from all positions BK_t, where $GOLD_t$ is the price of one ounce of gold at the end of quarter t:

$$BK_{t,Linear} = MIN_{NLIN,t} \cdot (GOLD_{t-1} - GOLD_t) \qquad \text{(A5)}$$

$$BK_{t,Option} = M\Delta_{t,Option} \cdot (GOLD_{t-1} - GOLD_t) \cdot (-1) \qquad \text{(A6)}$$

$$BK_t = BK_{t,Linear} + BK_{t,Option} \qquad \text{(A7)}$$

Finally, to adjust for the scale effect, we scale the total profits by the average size of the firm's position to obtain relative book profits from option positions $RBK_{t,Option}$, from linear positions $RBK_{t,Linear}$, and from all positions $RBK_{t,}$. The average size of the linear position $\overline{N}_{Linear}$ is equal to the average number of linear contracts reported by the firm over all quarters of the sample period in which a non-zero linear position is reported. The average size of the option positions $\overline{N}_{Option}$ is computed similarly.

$$RBK_{t,Option} = BK_{t,Option} / \overline{N}_{Option} \qquad \text{(A8)}$$

$$RBK_{t,Linear} = BK_{t,Linear} / \overline{N}_{Linear} \qquad \text{(A9)}$$

$$RBK_t = RBK_{t,Linear} + RBK_{t,Option} \qquad \text{(A10)}$$

References

Adam, Tim, 2002, Do Firms Use Derivatives to Reduce their Dependence on External Capital Markets? *European Finance Review* 6, 163-187.

Adam, Tim, and Chitru Fernando, 2006, Hedging, Speculation, and Shareholder Value, *Journal of Financial Economics* 81, 283-309.

Alizadeh, Sassan, Michael W. Brandt, and Francis X. Diebold, 2002, Range-Based Estimation of Stochastic Volatility Models, *Journal of Finance* 57, 1047-1092.

Altman, Edward I., 1968, Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *Journal of Finance* 23, 589-609.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The Cross-Section of Volatility and Expected Returns, *Journal of Finance* 61, 259-299.

Baker, Malcolm, Richard S. Ruback, and Jeffrey Wurgler, 2007, Behavioral Corporate Finance: A Survey, in *The Handbook of Corporate Finance: Empirical Corporate Finance*, edited by Espen Eckbo. Elsevier/North Holland, New York.

Barber, Brad M., and Terrance Odean, 2000, Trading is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors, *Journal of Finance* 55, 773-806.

Barberis, Nicholas, and Ming Huang, 2001, Mental Accounting, Loss Aversion, and Individual Stock Returns, *Journal of Finance* 56, 1247-1292.

Beber, Alessandro, and Daniela Fabbri, 2006, Who Times the Foreign Exchange Market? Corporate Speculation and CEO Characteristics, Working Paper.

Ben-David, Itzhak, John R. Graham, and Campbell R. Harvey, 2007, Managerial Overconfidence and Corporate Policies, Working Paper.

Billett, Matthew T., and Yiming Qian, 2008, Are Overconfident CEOs Born or Made? Evidence of Self-Attribution Bias from Frequent Acquirers, *Management Science* 54, 1037-1051.

Bodnar, Gordon N., Gregory S. Hayt, and Richard C. Marston, 1998, Wharton Survey of Derivatives Usage by U.S. Non-Financial Firms, *Financial Management* 27, 70-91.

Breeden, Douglas, and S. Viswanathan, 1998, Why Do Firms Hedge? An Asymmetric Information Model, Working Paper.

Brown, Gregory W., Peter R. Crabb, and David Haushalter, 2006, Are Firms Successful at Selective Hedging*? Journal of Business*, 79, 2925-2949.

Campbell, Tim S. and William A. Kracaw, 1999, Optimal Speculation in the Presence of Costly External Financing. In "Corporate Risk: Strategies and Management," Gregory Brown and Donald Chew, editors, Risk Publications, London.

Coleman, Les, 2007, Risk and Decision Making by Finance Executives: A Survey Study, *International Journal of Managerial Finance* 1, 108-124.

Daniel, Kent D., David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor Psychology and Security Market Under- and Over-Reactions, *Journal of Finance* 53, 1839 – 1867.

DeMarzo, Peter M. and Darrell Duffie, 1995, Corporate Incentives for Hedging and Hedge Accounting, *Review of Financial Studies* 8, 743 – 772.

Dolde, Walter, 1993, The Trajectory of Corporate Financial Risk Management, *Journal of Applied Corporate Finance* 6, 33-41.

Fehle, Frank, and Sergey Tsyplakov, 2005, Dynamic Risk Management: Theory and Evidence, *Journal of Financial Economics* 78, 3-47.

Froot, Kenneth.A., David S. Scharfstein, and Jeremy C. Stein, 1993, Risk Management: Coordinating Corporate Investment and Financing Policies, *Journal of Finance* 48, 1629 – 1658.

Géczy, Christopher C., Bernadette A. Minton, and Catherine Schrand, 1997, Why Firms Use Currency Derivatives, *Journal of Finance* 52, 1323-1354.

Géczy, Christopher C., Bernadette A. Minton, and Catherine Schrand, 2007, Taking a View: Corporate Speculation, Governance and Compensation, *Journal of Finance* 62, 2405 – 2443.

Gervais, Simon, J.B. Heaton, and Terrance Odean, 2009, Overconfidence, Compensation Contracts and Labor Markets, Working Paper.

Gervais, Simon, and Terrance Odean, 2001, Learning to be Overconfident, *Review of Financial Studies* 14, 1-27.

Glaum, Martin, 2002, The Determinants of Selective Exchange-Risk Management – Evidence from German Non-Financial Corporations, *Journal of Applied Corporate Finance* 14, 108 - 121.

Goel, Anand, and Anjan Thakor, 2008, Overconfidence, CEO Selection and Corporate Governance, *Journal of Finance* 63, 2737- 2784.

Griffin, Dale and Amos Tversky, 1992, The Weighing of Evidence and the Determinants of Confidence, *Cognitive Psychology* 24, 411-435.

Grinblatt, Mark, and Bing Han, 2005, Prospect Theory, Mental Accounting, and Momentum, *Journal of Financial Economics* 78, 311-339.

Haushalter, G. David, 2000, Financing Policy, Basis Risk, and Corporate Hedging: Evidence from Oil and Gas Producers, *Journal of Finance* 55, 107 – 152.

Heaton, J.B., 2002, Managerial Optimism and Corporate Finance, *Financial Management*, Summer, 33-45.

Heckman, James J., 1979, Sample Selection as a Specification Error, *Econometrica* 47, 153 – 161.

Jin, Yanbo, and Philippe Jorion, 2006, Firm Value and Hedging: Evidence from U.S. Oil and Gas Producers, *Journal of Finance* 61, 893 – 919.

Kahneman, Daniel, and Amos Tversky, 1979, Prospect Theory: An Analysis of Decisions under Risk, *Econometrica* 47, 313-327.

Leland, Hayne E., 1998, Agency Costs, Risk Management, and Capital Structure, *Journal of Finance* 53, 1213-1243.

Ljungqvist, Alexander, and William J. Wilhelm, Jr., 2005, Does Prospect Theory Explain IPO Market Behavior? *Journal of Finance* 60, 1759-1790.

Loughran, Tim, and Jay R. Ritter, 2002, Why Don't Issuers Get Upset About Leaving Money on the Table in IPOs? *Review of Financial Studies* 15, 413-443.

Malmendier, Ulrike, and Geoffrey Tate, 2005, CEO Overconfidence and Corporate Investment, *Journal of Finance* 60, 2661 – 2700.

Malmendier, Ulrike, and Geoffrey Tate, 2008, Who Makes Acquisitions? CEO Overconfidence and the Market's Reaction, *Journal of Financial Economics* 89, 20-43.

Malmendier, Ulrike, Geoffrey Tate, and Jon Yan, 2010, Managerial Beliefs and Corporate Financial Policies, Working Paper.

Mello, Antonio, and John Parsons, 2000, Hedging and Liquidity, *Review of Financial Studies* 13, 127 – 153.

Miller, Dale T., and Michael Ross, 1975, Self-Serving Biases in the Attribution of Causality: Fact or Fiction? *Psychological Bulletin* 82, 213-225.

Roll, Richard, 1986, The Hubris Hypothesis of Corporate Takeovers, *Journal of Business* 59, 197–216.

Russo, J. Edward, and Paul J.H. Schoemaker, 1992, Managing Overconfidence, *Sloan Management Review* 33, 7–17.

Sautner, Zacharias, and Martin Weber, 2009, How Do Managers Behave in Stock Option Plans? Clinical Evidence from Exercise and Survey Data, *Journal of Financial Research* 32, 123-155.

Shefrin, Hersh, and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long: Theory and evidence, *Journal of Finance* 40, 777 – 790.

Smith, Clifford W., and Rene M. Stulz, 1985, The Determinants of Firms' Hedging Policies, *Journal of Financial and Quantitative Analysis* 20, 391-405.

Stulz, René M., 1984, Optimal Hedging Policies, *Journal of Financial and Quantitative Analysis* 19, 127 – 140.

Stulz, René M., 1996, Rethinking Risk Management, *Journal of Applied Corporate Finance* 9, 8-24.

Thaler, Richard H., 1980, Towards a Positive Theory of Consumer Choice, *Journal of Economic Behavior and Organization* 1, 39-60.

Thaler, Richard H., 1985, Mental Accounting and Consumer Choice, *Marketing Science* 4, 199-214.

Thaler, Richard H., and Eric J. Johnson, 1990, Gambling with the House Money and Trying To Break Even: The Effects of Prior Outcomes on Risky Choice, *Management Science* 36, 643-660.

Tufano, Peter, 1996, Who Manages Risk? An Empirical Examination of Risk Management Practices in the Gold Mining Industry, *Journal of Finance* 51, 1097-1137.

Tufano, Peter, 1998. The Determinants of Stock Price Exposure: Financial Engineering and the Gold Mining Industry, *Journal of Finance* 53, 1051-1052.

Tversky, Amos, and Daniel Kahneman, 1991, Loss Aversion in Riskless Choice: A Reference-Dependent Model, *Quarterly Journal of Economics* 106, 1039-1061.

Working, Holbrook, 1962, New Concepts Concerning Futures Markets and Prices, *American Economic Review* 52, 431 – 459.

Table 1
Descriptive Statistics of Hedge Ratios, Hedge Volatility, Cash Flows, and Firm Characteristics
Descriptive statistics are estimated on the pooled dataset. The sample consists of quarterly observations from 1989-1999 for a sample of 92 North American gold mining firms as reported in *Gold and Silver Hedge Outlook*. The table reports summary statistics for the following variables: hedge ratios of various maturities as well as aggregate hedge ratios estimated as the sum of the firm's derivatives positions in place in quarter *t* (in ounces of gold), weighted by their respective deltas, scaled either by expected production or by reserves; hedge ratio volatilities estimated as the absolute value of the ratio of natural logarithms of the end-of-quarter to the beginning-of-quarter hedge ratio; total cash flows from derivatives positions per ounce hedged as well as selective and benchmark cash flows, which are estimated as in Adam and Fernando (2006); derivatives book profit equal to the change in the book value of the derivatives positions per ounce hedged (see Appendix 2 for calculation); change in the price of gold per ounce; firm size measured as the logarithm of the market value of assets; market-to-book ratio of assets; ratio of book debt to book equity; quick ratio; dividend dummy variable equal to one if the firm paid quarterly dividend; credit rating dummy variable equal to one if a firm reports a credit rating; and Altman's (1968) Z-score. Firm characteristics are from Compustat.

Variable	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
One-year hedge ratio	0.2874	0.3179	0.0000	1.0000	1875
Two-year hedge ratio	0.1552	0.2418	0.0000	1.0000	1879
Three-year hedge ratio	0.0779	0.1722	0.0000	1.0000	1901
Four-year hedge ratio	0.0363	0.1135	0.0000	1.0000	1935
Five-year hedge ratio	0.0271	0.1092	0.0000	0.9990	1952
Aggregate 3-yr. ratio, prod.	0.1716	0.2402	0.0000	1.0000	1460
Aggregate 3-yr. ratio, res.	0.0465	0.0738	0.0000	0.6620	1460
Aggregate 5-yr. ratio, res.	0.0575	0.0961	0.0000	0.9857	1460
Volatiliy, 1-yr. ratio	1.2325	2.9044	0.0000	12.4055	1665
Volatility, 2-yr. ratio	1.2304	2.9902	0.0000	12.7594	1660
Volatility, 3-yr. ratio	0.8524	2.5275	0.0000	11.5129	1694
Volatility, 4-yr. ratio	0.8324	2.5702	0.0000	11.5129	1732
Volatility, 5-yr. ratio	0.5135	2.0428	0.0000	11.4742	1761
Volatility, 3-yr. agg. ratio, prod.	0.6838	2.0897	0.0000	11.5000	1253
Volatility, 3-yr. agg. ratio, res.	0.6477	1.8500	0.0000	10.5740	1262
Volatility, 5-yr. agg. ratio, res.	0.6867	1.8970	0.0000	11.2149	1304
Total derivative cash flow	4.8063	16.2041	-95.9039	180.1249	1788
Selective cash flow	0.3680	10.5898	-66.7713	201.8647	1801
Benchmark cash flow	4.4377	16.7540	-90.4059	180.1249	1788
Derivative book profit	2.1401	16.4882	-181.3730	106.0881	1750
Change in the price of gold	-3.0569	17.7753	-48.9000	52.0000	1781
Size	5.5771	1.7608	1.0460	9.3604	1858
Market-to-Book ratio	1.9381	1.1137	0.2985	9.0819	1647
Debt-to-Equity ratio	0.4619	1.0772	0.0000	21.2707	1205
Quick ratio	4.2476	9.7254	0.0065	141.5172	1161
Dividend dummy	0.4701	0.4993	0.0000	1.0000	1289
Rating dummy	0.2454	0.4305	0.0000	1.0000	1312
Altman's Z-score	4.9900	13.5111	-22.8560	126.8310	1618

Table 2

Correlations Across Hedge Ratios and Across Hedge Ratio Volatilities

Correlations are estimated on the pooled dataset. The sample consists of quarterly observations over 1989-1999 for a sample of 92 North American gold mining firms as reported in *Gold and Silver Hedge Outlook*. *HR1 – HR5* are hedge ratios with one- to five- year maturity, respectively; *V1 – V5* are their respective volatilities; *A3* is the aggregate 3-year hedge ratio scaled by expected production, *A3R* is the aggregate 3-year hedge ratio scaled by reserves, and *A5R* is the aggregate five-year hedge ratio scaled by reserves, and *V6 – V8* are their respective volatilities. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Panel A: Correlations of the hedge ratios

	HR1	HR2	HR3	HR4	HR5	A3	A3R	A5R
HR1	1.0000							
HR2	0.5841 ***	1.0000						
HR3	0.4208 ***	0.7195 ***	1.0000					
HR4	0.2591 ***	0.4611 ***	0.6717 ***	1.0000				
HR5	0.1646 ***	0.2625 ***	0.4029 ***	0.5356 ***	1.0000			
A3	0.7462 ***	0.9340 ***	0.8608 ***	0.5576 ***	0.3345 ***	1.0000		
A3R	0.6457 ***	0.6901 ***	0.5993 ***	0.4317 ***	0.2919 ***	0.7750 ***	1.0000	
A5R	0.5721 ***	0.6381 ***	0.6387 ***	0.5767 ***	0.4904 ***	0.7366 ***	0.9194 ***	1.0000

Panel B: Correlations of hedge ratio volatilities

	V1	V2	V3	V4	V5	V6	V7	V8
V1	1.0000							
V2	0.2773 ***	1.0000						
V3	0.1105 ***	0.2754 ***	1.0000					
V4	0.0426 *	0.0556 **	0.1512 ***	1.0000				
V5	0.0380	0.0542 **	0.1226 ***	0.3893 ***	1.0000			
V6	0.8096 ***	0.5182 ***	0.3571 ***	0.0623 **	0.0900 ***	1.0000		
V7	0.7703 ***	0.3981 ***	0.2248 ***	0.1044 **	0.1142 ***	0.9894 ***	1.0000	
V8	0.7644 ***	0.3618 ***	0.2129 ***	0.0927 ***	0.1020 ***	0.9785 ***	0.9827 ***	1.0000

Table 3

Relationship between Hedging and Past Gold Returns

The table presents the results of the panel regressions with firm fixed effects of hedge ratio changes in the current quarter, ΔHR_t, on past relative changes in the price of gold, $RTNGOLD_{t-1} = \Delta GOLD_{t-2,t-1}/GOLD_{t-2}$. We control for changes in the following firm characteristics: *SIZ,* firm size measured as the logarithm of the market value of assets; *MB,* market-to-book ratio of assets; *DE,* ratio of book debt to book equity; *QCK,* quick ratio; *DIV,* dummy variable equal to one if the firm paid quarterly dividend; *RAT,* dummy variable equal to one if a firm reports a credit rating; and *Z,* Altman's Z-score. Models (3), (6), (9), and (12) are estimated on a reduced sample with non-hedgers excluded. All of the models include seasonal dummy variables and a time trend, and ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics accounting for cluster effects are given in parentheses.

	One-year hedge ratio			Aggregate 3-year ratio scaled by production			Aggregate 3-year ratio scaled by reserves			Aggregate 5-year ratio scaled by reserves		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.0264 **	-0.0012	-0.0010	0.0212 ***	0.0251 *	0.0266 *	-0.0043 *	-0.0051	-0.0054	-0.0056	-0.0043	-0.0044
	(2.19)	(-0.06)	(-0.05)	(2.53)	(1.65)	(1.69)	(-1.79)	(-1.07)	(-1.07)	(-1.50)	(-0.61)	(-0.60)
RTNGOLD	-0.3926 ***	-0.5979 **	-0.6013 **	-0.1935 ***	-0.3174 **	-0.3230 **	-0.0183	-0.0495	-0.0513	-0.0501	-0.1205 *	-0.1223 *
	(-3.05)	(-2.47)	(-2.42)	(-3.09)	(-2.09)	(-2.06)	(-0.75)	(-1.55)	(-1.56)	(-1.39)	(-1.68)	(-1.66)
ΔSIZ		0.0521	0.0543		0.0329	0.0342		0.0063	0.0063		0.0014	0.0001
		(1.11)	(1.11)		(1.16)	(1.15)		(0.84)	(0.82)		(0.15)	(0.13)
ΔZ		-0.0011	-0.0012		0.0000	0.0000		0.0000	0.0000		-0.0002	-0.0002
		(-1.45)	(-1.61)		(0.01)	(-0.09)		(-0.16)	(-0.14)		(-0.50)	(-0.52)
ΔQCK		0.0017 ***	0.0017 ***		0.0006 **	0.0007 **		0.0000	0.0000		0.0002	0.0002
		(4.35)	(4.34)		(2.00)	(2.02)		(0.29)	(0.24)		(1.45)	(1.44)
ΔMB		0.0166	0.0168		0.0115	0.0120		-0.0014	-0.0015		0.0055	0.0056
		(1.04)	(1.01)		(0.89)	(0.89)		(-0.51)	(-0.53)		(1.18)	(1.16)
ΔDE		-0.0307	-0.0290		0.0622	0.0641		0.0064	0.0065		-0.0040	-0.0039
		(-1.56)	(-1.42)		(1.41)	(1.42)		(1.10)	(1.09)		(-0.38)	(-0.36)
ΔDIV		-0.0399	-0.0393		-0.0231	-0.0227		-0.0025	-0.0025		-0.0045	-0.0044
		(-0.48)	(-0.47)		(-0.61)	(-0.59)		(-0.39)	(-0.39)		(-0.40)	(-0.39)
ΔRAT		0.0857	0.0978		-0.0070	0.0018		-0.0032	-0.0034		0.0064	0.0070
		(1.48)	(1.55)		(-0.29)	(0.08)		(-0.53)	(-0.52)		(1.32)	(1.39)
R^2	0.0582	0.0785	0.0804	0.0474	0.0808	0.0832	0.0045	0.0234	0.0243	0.0046	0.0167	0.0169
F-statistic	7.30	3.25	3.25	7.66	3.06	3.48	1.11	1.78	1.81	1.34	1.42	1.42
Observations	1501	618	596	1266	523	501	1344	581	559	1510	661	639
Clusters	93	37	36	88	36	35	81	38	37	82	38	37

Table 4

Relationship between Hedging and Past Gold Returns: Asymmetric Response

The table presents the results of the panel regressions with firm fixed effects of hedge ratio changes in the current quarter, ΔHR_t, on past relative changes in the price of gold in the previous quarter, $RTNGOLD_{t-1} = \Delta GOLD_{t-2,t-1}/GOLD_{t-2}$, while allowing for an asymmetric response in the hedge ratio to gold price increases and decreases. Indicator variables I_1 (I_2) are equal to 1 if gold return was positive (negative). We control for changes in the following firm characteristics: *SIZ,* firm size measured as the logarithm of the market value of assets; *MB,* market-to-book ratio of assets; *DE,* ratio of book debt to book equity; *QCK,* quick ratio; *DIV,* dummy variable equal to one if the firm paid quarterly dividend; *RAT,* dummy variable equal to one if a firm reports a credit rating; and *Z,* Altman's Z-score. Models (3), (6), (9), and (12) are estimated on a reduced sample with non-hedgers excluded. All of the models include seasonal dummy variables and a time trend, and ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics accounting for cluster effects are given in parentheses.

	One-year hedge ratio			Aggregate 3-year ratio scaled by production			Aggregate 3-year ratio scaled by reserves			Aggregate 5-year ratio scaled by reserves		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.0424 ***	0.0131	0.0132	0.0311 ***	0.0336 *	0.0353 *	-0.0022	-0.0034	-0.0036	-0.0034	-0.0015	-0.0016
	(3.29)	(0.64)	(0.63)	(2.95)	(1.88)	(1.91)	(-0.69)	(-0.65)	(-0.66)	(-0.86)	(-0.22)	(-0.23)
$RTNGOLD \cdot I_1$	-0.6905 ***	-0.9432 ***	-0.9624 ***	-0.3622 ***	-0.5091 **	-0.5257 **	-0.0615 **	-0.0877 **	-0.0919 **	-0.0954 **	-0.1813 *	-0.1849 *
	(-3.60)	(-3.24)	(-3.21)	(-3.28)	(-2.13)	(-2.13)	(-2.00)	(-2.56)	(-2.62)	(-2.06)	(-1.97)	(-1.96)
$RTNGOLD \cdot I_2$	0.0182	-0.0636	-0.0400	0.0547	-0.0089	0.0054	0.0429	0.0168	0.0195	0.0147	-0.0190	-0.0174
	(0.10)	(-0.22)	(-0.13)	(0.48)	(-0.05)	(0.03)	(0.73)	(0.26)	(0.28)	(0.18)	(-0.14)	(-0.12)
ΔSIZ		0.0461	0.0487		0.0266	0.0279		0.0052	0.0053		0.0000	-0.0001
		(0.99)	(1.00)		(0.97)	(0.97)		(0.70)	(0.68)		(-0.01)	(-0.01)
ΔZ		-0.0010	-0.0011		0.0000	0.0000		0.0000	0.0000		-0.0001	-0.0001
		(-1.29)	(-1.43)		(0.10)	(0.00)		(-0.11)	(-0.08)		(-0.45)	(-0.47)
ΔQCK		0.0017 ***	0.0017 ***		0.0006 *	0.0006 *		0.0000	0.0000		0.0002	0.0002
		(4.13)	(4.10)		(1.92)	(1.93)		(0.24)	(0.19)		(1.38)	(1.37)
ΔMB		0.0127	0.0124		0.0100	0.0102		-0.0018	-0.0020		0.0047	0.0048
		(0.89)	(0.84)		(0.82)	(0.80)		(-0.66)	(-0.70)		(1.06)	(1.03)
ΔDE		-0.0317	-0.0295		0.0605	0.0628		0.0062	0.0063		-0.0044	-0.0042
		(-1.69) *	(-1.53)		(1.38)	(1.39)		(1.07)	(1.07)		(-0.42)	(-0.39)
ΔDIV		-0.0408	-0.0403		-0.0235	-0.0231		-0.0026	-0.0027		-0.0048	-0.0047
		(-0.49)	(-0.48)		(-0.62)	(-0.60)		(-0.44)	(-0.44)		(-0.43)	(-0.42)
ΔRAT		0.0929 *	0.1080 *		-0.0019	0.0089		-0.0022	-0.0020		0.0078	0.0088
		(1.67)	(1.82)		(-0.08)	(0.39)		(-0.35)	(-0.29)		(1.39)	(1.43)
R^2	0.0620	0.0851	0.0873	0.0504	0.0849	0.0878	0.0064	0.0259	0.0270	0.0053	0.0182	0.0185
F-statistic	7.10	3.67	3.87	7.33	2.85	3.38	1.56	2.12	2.25	1.38	1.54	1.54
Observations	1501	618	596	1266	523	501	1344	581	559	1510	661	639
Clusters	93	37	36	88	36	35	81	38	37	82	38	37

Table 5

Relationship between Hedging and Past Gold Returns: Effect of Initial Hedge Ratio

The table presents the results of the panel regressions with firm fixed effects of hedge ratio changes in the current quarter, ΔHR_t, on past relative changes in the price of gold in the previous quarter, $RTNGOLD_{t-1} = \Delta GOLD_{t-2,t-1}/GOLD_{t-2}$, while allowing for the effect of the initial hedge ratio and asymmetry effects. Indicator variables I_1 (I_2) are equal to 1 if gold return was positive (negative). HR_{t-1} is the level of the hedge ratio at the beginning of quarter. We control for changes in the following firm characteristics: *SIZ,* firm size measured as the logarithm of the market value of assets; *MB,* market-to-book ratio of assets; *DE,* ratio of book debt to book equity; *QCK,* quick ratio; *DIV,* dummy variable equal to one if the firm paid quarterly dividend; *RAT,* dummy variable equal to one if a firm reports a credit rating; and *Z,* Altman's Z-score. Models (3), (6), (9), and (12) are estimated on a reduced sample with non-hedgers excluded. Non-hedgers are firms that report no hedging over the entire sample period. All of the models include seasonal dummy variables and a time trend, and ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics accounting for cluster effects are given in parentheses.

	One-year hedge ratio			Aggregate 3-year ratio scaled by production			Aggregate 3-year ratio scaled by reserves			Aggregate 5-year ratio scaled by reserves		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.1291 ***	0.1077 ***	0.1119 ***	0.0552 ***	0.0528 ***	0.0559 ***	0.0090	0.0039	0.0040	0.0028	0.0022	0.0025
	(5.93)	(3.20)	(3.25)	(4.28)	(2.95)	(3.01)	(1.63)	(0.44)	(0.45)	(0.38)	(0.17)	(0.19)
$RTNGOLD \cdot I_1$	-0.3968 **	-0.7120 ***	-0.7303 ***	-0.2135 **	-0.3963 *	-0.4138 *	-0.0233	-0.0573 *	-0.0611 *	-0.0280	-0.1022	-0.1050
	(-2.42)	(-3.74)	(-3.71)	(-2.41)	(-1.92)	(-1.93)	(-0.74)	(-1.74)	(-1.82)	(-0.70)	(-1.55)	(-1.55)
$RTNGOLD \cdot I_2$	-0.1364	-0.2125	-0.1889	-0.0043	-0.0846	-0.0624	0.0164	-0.0140	-0.0107	-0.0362	-0.0962	-0.0936
	(-0.86)	(-0.81)	(-0.71)	(-0.04)	(-0.54)	(-0.38)	(0.37)	(-0.27)	(-0.20)	(-0.57)	(-0.87)	(-0.83)
HR_{t-1}	-0.4672 ***	-0.5360 ***	-0.5358 ***	-0.3298 ***	-0.3009 ***	-0.3009 ***	-0.3486 ***	-0.2531 ***	-0.2536 ***	-0.3499 ***	-0.3280 ***	-0.3285 ***
	(-13.13)	(-10.39)	(-10.38)	(-8.32)	(-7.00)	(-6.95)	(-9.67)	(-8.94)	(-9.00)	(-11.51)	(-9.63)	(-9.65)
CONTROLS		YES	YES		YES	YES		YES	YES		YES	YES
R^2	0.1509	0.1452	0.1504	0.0603	0.0721	0.0756	0.1265	0.0746	0.0766	0.1055	0.0956	0.0972
F-statistic	33.59	28.00	29.21	15.42	12.00	12.09	20.12	12.58	12.46	25.15	64.56	64.16
Observations	1501	618	596	1266	523	501	1344	581	559	1510	661	639
Clusters	93	37	36	88	36	35	81	38	37	82	38	37

Table 6

Determinants of Hedging Activity: First Stage of the Two-Step Heckman Regression With Selection

The table reports the results of the PROBIT model. The dependent variable is the hedging activity dummy equal to zero if (1) either the firm had zero hedge ratios in both the beginning and the end of quarter *t*; or (2) the firm had zero cash flows from hedging operations in quarter *t-1*. The independent variables are: firm size measured as the logarithm of the market value of assets; market-to-book ratio of assets; ratio of book debt to book equity; quick ratio; dummy variable equal to one if the firm paid quarterly dividend; dummy variable equal to one if a firm reports a credit rating; and Altman's Z-score. Z-statistics are in parentheses and ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

	Probability of Hedging
Intercept	0.5409 **
	(2.10)
Size	0.2403 ***
	(4.50)
Market-to-book	-0.3013 ***
	(-3.91)
Debt-to-Equity	-0.2064 ***
	(-2.82)
Quick ratio	-0.0789 ***
	(-4.98)
Dividend dummy	-0.487 ***
	(-3.25)
Credit rating dummy	0.0916
	(0.61)
Altman Z-score	-0.0193
	(-1.25)
Pseudo-R^2	0.1051
Chi^2	86.57
Observations	792

Table 7
Relationship between Hedging and Past Gold Returns Conditional on Hedging Activity: Second Stage of the Two-Step Heckman Regression with Selection

The table reports the results of the second stage of the two-step Heckman procedure. In the first stage (see Table 6), we estimate the likelihood of hedging activity in a given quarter. In the second stage, we regress hedge ratio changes in the current quarter, ΔHR_t, on past relative changes in the price of gold in the previous quarter, $RTNGOLD_{t-1} = \Delta GOLD_{t-2,t-1}/GOLD_{t-2}$, while allowing for the effect of the initial hedge ratio and asymmetry effects. Indicator variables I_1 (I_2) are equal to 1 if gold return was positive (negative). We control for the level of the hedge ratio at the beginning of quarter as well as for changes in the following firm characteristics: firm size measured as the logarithm of the market value of assets; market-to-book ratio of assets; ratio of book debt to book equity; quick ratio; dummy variable equal to one if the firm paid quarterly dividend; dummy variable equal to one if a firm reports a credit rating; and Altman's Z-score. The regressions include the Inverse Mills ratio estimated on the first stage of the Heckman procedure. All of the models include seasonal dummy variables and a time trend, and ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics accounting for cluster effects are given in parentheses.

	One-year hedge ratio	Aggregate 3-year ratio scaled by production	Aggregate 3-year ratio scaled by reserves	Aggregate 5-year ratio scaled by reserves
	(1)	(2)	(3)	(4)
Intercept	0.1623 ***	0.0337	-0.0040	0.0053
	(3.71)	(1.36)	(-0.42)	(0.49)
$RTNGOLD \cdot I_1$	-1.1368 ***	-0.4991 *	-0.0665	-0.1389
	(-4.13)	(-1.80)	(-1.20)	(-1.50)
$RTNGOLD \cdot I_2$	0.0805	-0.3583	-0.0584	-0.1552
	(0.25)	(-1.59)	(-0.80)	(-1.04)
HR_{t-1}	-0.2344 ***	-0.0705 **	-0.1019 ***	-0.1907 ***
	(-3.27)	(-2.06)	(-2.95)	(-5.24)
Inverse Mills Ratio	-0.1254 ***	-0.0275 **	-0.0072	-0.0259 **
	(-3.08)	(-2.17)	(-1.47)	(-2.63)
CONTROLS	YES	YES	YES	YES
R^2	0.2161	0.1478	0.0646	0.1061
F-statistic	5.22	9.39	6.36	11.62
Observations	432	366	430	495

Table 8
Relationship between Speculation and Past Total Derivatives Cash Flows

The table presents the results of the panel regressions with firm fixed effects. The dependent variable is the volatility of the hedge ratio. Hedge ratio volatility is estimated as the absolute value of the difference in the logs of the hedge ratio in the end and the beginning of the quarter. The independent variables are as follows: *CF* is the total derivatives cash flow in the previous quarter; *RBK* is the change in the book value of derivatives positions in the previous quarter. Seasonal dummies are included in each of the models. The regressions include the following firm characteristics as control variables: *SIZ,* firm size measured as the logarithm of the market value of assets; *MB,* market-to-book ratio of assets; *DE,* ratio of book debt to book equity; *QCK,* quick ratio; *DIV,* dummy variable equal to one if the firm paid quarterly dividend; *RAT,* dummy variable equal to one if a firm reports a credit rating; and *Z,* Altman's Z-score. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics corrected for cluster effects are reported in parentheses.

	Volatility of one-year hedge ratio		Volatility of aggregate 3-year ratio scaled by production		Volatility of aggregate 3-year ratio scaled by reserves		Volatility of aggregate 5-year ratio scaled by reserves	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.9315 ***	2.9375	0.7202 ***	3.7069 *	0.6400 ***	1.6145	0.7448 ***	1.2300
	(5.29)	(1.10)	(5.46)	(1.93)	(4.75)	(0.80)	(6.40)	(0.77)
CF	0.023 ***	0.0181 **	0.0213 ***	0.0113	0.0237 ***	0.0209 ***	0.0164 ***	0.0150 **
	(3.60)	(2.24)	(3.03)	(1.53)	(3.54)	(2.95)	(3.53)	(2.89)
RBK	0.0019	-0.0017	-0.0011	-0.0017	-0.0020	-0.0038	-0.0003	-0.0021
	(0.91)	(-0.72)	(-0.69)	(-0.74)	(-1.29)	(-1.68)	(-0.23)	(-0.97)
SIZ		-0.1817		-0.3584		-0.0319		0.0572
		(-0.39)		(-1.18)		(-0.09)		(0.20)
Z		0.0730 *		0.0787		0.0458		0.0490 *
		(1.36)		(1.64)		(1.29)		(1.91)
QCK		0.0212		-0.0208		-0.0342		-0.0127
		(0.27)		(-0.57)		(-1.24)		(-0.44)
MB		-0.5594 ***		-0.2617 *		-0.2153		-0.2190 **
		(-2.64)		(-1.76)		(-1.53)		(-1.98)
DE		-0.1862		-0.2467		-0.4726 ***		-0.3233 **
		(-1.12)		(-1.28)		(-4.46)		(-2.32)
DIV		0.2905		-0.2261		-0.2401		-0.6023 ***
		(0.68)		(-0.70)		(-1.07)		(-3.52)
RAT		-0.3583		-0.0684		-0.1324		-0.2063
		(-0.68)		(-0.19)		(-0.43)		(-0.77)
Dummies	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.0304	0.0382	0.0263	0.0330	0.0379	0.0519	0.0204	0.0364
F-statistic	4.70	1.62	3.85	1.64	3.44	5.82	3.27	2.84
Observations	1112	638	788	465	854	529	1005	621
Clusters	84	65	65	48	61	51	63	53

Table 9

Relationship between Speculation and Past Selective Hedging Cash Flows

The table presents the results of the panel regressions with firm fixed effects. The dependent variable is the volatility of the hedge ratio. Hedge ratio volatility is estimated as the absolute value of the difference in the logs of the hedge ratio in the end and the beginning of the quarter. The independent variables are as follows: *SCF* is the selective hedging cash flow in the previous quarter; *BCF* is the benchmark cash flow in the previous quarter; *RBK* is the change in the book value of derivatives positions in the previous quarter. Seasonal dummies are included in each of the models. The regressions include the following firm characteristics as control variables: *SIZ,* firm size measured as the logarithm of the market value of assets; *MB,* market-to-book ratio of assets; *DE,* ratio of book debt to book equity; *QCK,* quick ratio; *DIV,* dummy variable equal to one if the firm paid quarterly dividend; *RAT,* dummy variable equal to one if a firm reports a credit rating; and *Z,* Altman's Z-score. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics corrected for cluster effects are reported in parentheses.

	Volatility of one-year hedge ratio		Volatility of aggregate 3-year ratio scaled by production		Volatility of aggregate 3-year ratio scaled by reserves		Volatility of aggregate 5-year ratio scaled by reserves	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.9468 ***	2.9597	0.7154 ***	3.9226 **	0.6301 ***	1.7182	0.7338 ***	1.3219
	(5.50)	(1.11)	(5.39)	(2.02)	(4.65)	(0.84)	(6.31)	(0.82)
SCF	0.0174 *	0.0199	0.0237 ***	0.0210 **	0.0273 ***	0.0263 ***	0.0202 ***	0.0212 ***
	(1.66)	(1.54)	(2.97)	(2.80)	(3.43)	(3.45)	(3.14)	(3.02)
BCF	0.0249 ***	0.0173 **	0.0209 ***	0.0092	0.0224 ***	0.0180 **	0.0153 ***	0.0124 **
	(3.56)	(2.15)	(2.95)	(1.26)	(3.39)	(2.50)	(3.40)	(2.49)
RBK	0.0021	-0.0117	-0.0012	-0.0020	-0.0021	-0.0040 *	-0.0004	-0.0023
	(0.96)	(-0.73)	(-0.72)	(-0.86)	(-1.36)	(-1.77)	(-0.30)	(-1.08)
SIZ		-0.1851		-0.3901		-0.0454		0.0413
		(-0.40)		(-1.28)		(-0.13)		(0.14)
Z		0.0736		0.0825		0.0493		0.0514 **
		(1.37)		(1.70)		(1.36)		(1.96)
QCK		0.0205		-0.0239		-0.0382		-0.0156
		(0.26)		(-0.65)		(-1.39)		(-0.54)
MB		-0.5615 ***		-0.2738 *		-0.2282 *		-0.2202 **
		(-2.64)		(-1.87)		(-1.64)		(-2.00)
DE		-0.1871		-0.2505		-0.4789 ***		-0.3268 **
		(-1.12)		(-1.31)		(-4.65)		(-2.36)
DIV		0.2899		-0.2042		-0.2401		-0.5993 ***
		(0.68)		(-0.67)		(-1.10)		(-3.58)
RAT		-0.3553		-0.0431		-0.1203		-0.1940
		(-0.67)		(-0.12)		(-0.40)		(-0.73)
Dummies	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.0308	0.0384	0.0267	0.0349	0.0399	0.0567	0.0229	0.0434
F-statistic	3.88	1.50	3.62	1.98	3.15	6.15	3.02	2.90
Observations	1112	638	788	465	854	529	1005	621
Clusters	84	65	65	48	61	51	63	53

Table 10
Determinants of Hedge Ratio Volatility Conditional on Hedging Activity:
Second Stage of the Two-Step Heckman Regression with Selection

The table reports the results of the second stage of the two-step Heckman procedure. In the first stage (see Table 6), we estimate the likelihood of hedging activity in a given quarter. In the second stage, we estimate the relationship between hedge ratio volatility in quarter *t* versus cash flows and book profits from derivatives positions in quarter *t-1*, conditional on hedging activity. Hedge ratio volatility is estimated as the absolute value of the difference in the logs of the hedge ratio from the beginning to the end of the quarter. *CF* is the total derivatives cash flow; *SCF* is selective hedging cash flow; *BCF* is the benchmark cash flow; *RBK* is the change in the book value of derivatives positions. Seasonal dummies are included in each model. The regressions control for the following firm characteristics: firm size measured as the logarithm of the market value of assets; market-to-book ratio of assets; ratio of book debt to book equity; quick ratio; dividend dummy variable equal to one if the firm paid quarterly dividend; credit rating dummy variable equal to one if a firm reports a credit rating; and Altman's Z-score. The regressions include the Inverse Mills ratio estimated on the first stage of the Heckman procedure. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics corrected for cluster effects are reported in parentheses.

	Volatility of one-year hedge ratio		Volatility of aggregate 3-year ratio scaled by production		Volatility of aggregate 3-year ratio scaled by reserves		Volatility of aggregate 5-year ratio scaled by reserves	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	4.4363 ***	4.4151 ***	2.3099	2.2593	3.1157 **	3.0198 **	2.5783 **	2.437 **
	(2.99)	(2.94)	(1.13)	(1.11)	(2.41)	(2.32)	(2.37)	(2.22)
CF	0.00221 **		0.0234 **		0.0215 ***		0.0161 ***	
	(2.53)		(2.35)		(3.39)		(3.07)	
SCF		0.0238 *		0.0288 **		0.0263 ***		0.0224 ***
		(1.96)		(2.67)		(4.10)		(3.68)
BCF		0.0212 **		0.0223 **		0.0184 ***		0.0129 **
		(2.29)		(2.27)		(2.73)		(2.49)
RBK	-0.0006	-0.0007	-0.0023	-0.0025	-0.0025	-0.0026	-0.0016	-0.0017
	(-0.31)	(-0.32)	(-0.84)	(-0.90)	(-1.18)	(-1.24)	(-0.75)	(-0.83)
Inverse Mills	-3.7381	-3.7044	-1.2069	-1.0787	-3.1570	-2.9739	-1.5532	-1.3087
Ratio	(-1.38)	(-1.36)	(-0.29)	(-0.26)	(-1.25)	(-1.17)	(-0.82)	(-0.69)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Dummies	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.0769	0.0770	0.0738	0.0749	0.0879	0.0916	0.0738	0.0786
F-statistic	5.32	4.96	2.97	2.73	3.10	3.33	2.44	2.99
Observations	585	585	442	442	526	526	614	614
Clusters	53	53	42	42	51	51	53	53

Table 11
Determinants of Hedge Ratio Volatility Conditional on Hedging Activity: Controlling for Managerial Compensation (CEO)

The table reports the results of the second stage of the two-step Heckman procedure. In the first stage (see Table 6), we estimate the likelihood of hedging activity in a given quarter. In the second stage, we estimate the relationship between hedge ratio volatility in quarter *t* versus cash flows and book profits from derivatives positions in quarter *t-1*, conditional on hedging activity. Hedge ratio volatility is estimated as the absolute value of the difference in the logs of the hedge ratio from the beginning to the end of the quarter. *CF* is the total derivatives cash flow; *SCF* is selective hedging cash flow; *BCF* is the benchmark cash flow; *DELTA_CEO* and *VEGA_CEO* are the managerial compensation sensitivities for the CEO. The regressions include the Inverse Mills ratio estimated on the first stage of the Heckman procedure. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics corrected for cluster effects are reported in parentheses.

	Volatility of one-year ratio		Volatility of aggregate 3-year ratio scaled by production		Volatility of aggregate 3-year ratio scaled by reserves		Volatility of aggregate 5-year ratio scaled by reserves	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.2460	0.2453	1.4696	1.4616	1.0222	1.0261	1.7445	1.7351
	(0.21)	(0.21)	(0.81)	(0.81)	(0.78)	(0.78)	(1.26)	(1.24)
CF	0.0159		0.0183		0.0161 **		0.0171 **	
	(1.35)		(1.19)		(2.08)		(2.82)	
SCF		0.0143		0.0169		0.0182 **		0.0212 **
		(0.79)		(0.81)		(2.03)		(2.74)
BCF		0.0164		0.0186		0.0155 **		0.0159 **
		(1.47)		(1.25)		(2.05)		(2.72)
DELTA_CEO	-0.1665	-0.1638	-0.1755	-0.1725	-0.1250	-0.1291	-0.1260	-0.1346
	(-0.96)	(-0.95)	(-0.88)	(-0.91)	(-1.12)	(-1.20)	(-1.18)	(-1.31)
VEGA_CEO	0.2002	0.1963	0.0822	0.0788	0.0738	0.0791	0.0176	0.0291
	(1.18)	(1.18)	(0.35)	(0.35)	(0.53)	(0.58)	(0.12)	(0.19)
Inverse Mills	0.1638	3.1772	1.9141	1.9362	1.0782	1.0549	0.2416	0.2517
Ratio	(1.76)	(1.75)	(1.09)	(1.11)	(0.87)	(0.86)	(0.32)	(0.34)
R^2	0.0545	0.0544	0.037	0.0371	0.0407	0.0409	0.0466	0.0478
F-statistic	2.08	1.64	1.46	1.16	2.19	1.91	3.41	3.30
Observations	146	146	106	106	127	127	155	155
Clusters	41	41	31	31	39	39	42	42

Table 12
Determinants of Hedge Ratio Volatility Conditional on Hedging Activity: Controlling for Managerial Compensation (CFO)

The table reports the results of the second stage of the two-step Heckman procedure. In the first stage (see Table 6), we estimate the likelihood of hedging activity in a given quarter. In the second stage, we estimate the relationship between hedge ratio volatility in quarter *t* versus cash flows and book profits from derivatives positions in quarter *t-1*, conditional on hedging activity. Hedge ratio volatility is estimated as the absolute value of the difference in the logs of the hedge ratio from the beginning to the end of the quarter. *CF* is the total derivatives cash flow; *SCF* is selective hedging cash flow; *BCF* is the benchmark cash flow; *DELTA_CFO* and *VEGA_CFO* are the managerial compensation sensitivities for the CEO. The regressions include the Inverse Mills ratio estimated on the first stage of the Heckman procedure. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics corrected for cluster effects are reported in parentheses.

	Volatility of one-year hedge ratio		Volatility of aggregate 3-year ratio scaled by production		Volatility of aggregate 3-year ratio scaled by reserves		Volatility of aggregate 5-year ratio scaled by reserves	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-1.4314	-1.4416	-4.1473	-4.1741	-3.1787	-3.1686 *	-1.6036	-1.6082
	(-0.66)	(-0.65)	(-1.51)	(-1.46)	(-1.78)	(-1.71)	(-1.22)	(-1.21)
CF	0.0565 **		0.0499 **		0.039 ***		0.0409 **	
	(2.48)		(2.59)		(2.86)		(2.65)	
SCF		0.0749		0.0834 *		0.06 **		0.055 **
		(1.50)		(1.88)		(2.09)		(2.16)
BCF		0.0543 **		0.0465 **		0.0366 ***		0.0388 **
		(2.52)		(2.46)		(2.75)		(2.55)
DELTA_CFO	0.2539	0.2132	0.5191	0.4235	0.3593	0.3118	0.2366	0.2194
	(0.82)	(0.74)	(1.20)	(1.02)	(1.35)	(1.22)	(1.21)	(1.16)
VEGA_CFO	-0.1079	-0.0499	-0.1494	-0.0148	-0.0575	0.0109	-0.0678	-0.0478
	(-0.40)	(-0.19)	(-0.48)	(-0.05)	(-0.33)	(0.07)	(-0.47)	(-0.34)
Inverse Mills Ratio	3.3311	3.2148	2.9886	2.6094	2.0427	1.785	0.7582	0.9108
	(1.08)	(1.05)	(1.22)	(1.12)	(1.18)	(1.07)	(1.15)	(1.16)
R^2	0.1164	0.1209	0.176	0.1986	0.2023	0.2212	0.1606	0.1736
F-statistic	2.06	1.84	1.88	1.93	2.22	2.13	1.91	1.65
Observations	68	68	52	52	60	60	72	72
Clusters	22	22	17	17	20	20	23	23

Table 13
Testing for Asymmetric Volatility Response to Past Cash Flows

The table presents the results of the panel regressions of hedge ratio volatility on past cash flows from derivatives positions, while allowing for an asymmetric response. The volatility is estimated as the absolute value of the difference in the logs of the hedge ratios in the end and the beginning of the quarter. *SCF* is the selective hedging cash flow in the previous quarter. I_1 is a dummy variable that equals one if the selective hedging cash flow during the last quarter was positive, and equals zero otherwise; and I_2 is a dummy variable that equals one if the selective hedging cash flow was negative, and equals zero otherwise. Seasonal dummies are included in each model and ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics corrected for cluster effects are reported in parentheses.

	Volatility of one-year hedge ratio	Volatility of aggregate 3-year ratio scaled by production	Volatility of aggregate 3-year ratio scaled by reserves	Volatility of aggregate 5-year ratio scaled by reserves
	(1)	(2)	(3)	(4)
Intercept	0.6931 ***	0.5925 ***	0.5177 ***	0.5751 ***
	(3.50)	(4.16)	(4.07)	(5.26)
SCF×I_1	0.0262 **	0.0218 ***	0.0238 ***	0.0203 ***
	(2.43)	(2.68)	(3.45)	(3.14)
SCF×I_2	-0.0342 **	-0.0036	-0.0072	-0.0068
	(-2.15)	(-0.39)	(-0.97)	(-0.94)
Dummies	YES	YES	YES	YES
R^2	0.0366	0.0144	0.0194	0.0135
F-statistic	4.6	2.81	2.86	2.31
Observations	1151	810	868	1000
Clusters	82	66	61	62

Table 14

Testing for Asymmetric Volatility Response with Selection

The table reports the results of the second stage of the two-step Heckman procedure. In the first stage, we estimate the likelihood of hedging activity in a given quarter. In the second stage, we estimate the following regression of the three-year aggregate hedge ratio volatility on past selective hedging cash flows from derivatives positions, while allowing for an asymmetric response. The volatility is estimated as the absolute value of the difference in the logs of the hedge ratio in the end and the beginning of the quarter. *SCF* is the selective hedging cash flow in the previous quarter. *BCF* is the benchmark cash flow. I_1 is a dummy variable that equals one if the selective hedging cash flow during the last quarter was positive, and equals zero otherwise; and I_2 is a dummy variable that equals one if the selective hedging cash flow was negative, and equals zero otherwise. The Inverse Mills ratio is obtained on the first stage of the Heckman procedure. The second-stage regressions includes: firm size measured as the logarithm of the market value of assets; market-to-book ratio of assets; ratio of book debt to book equity; quick ratio; dividend dummy variable equal to one if the firm paid quarterly dividend; credit rating dummy variable equal to one if a firm reports a credit rating; and Altman's Z-score. Seasonal dummies are included in each model and ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics corrected for cluster effects are reported in parentheses.

	Volatility of one-year hedge ratio	Volatility of aggregate 3-year ratio scaled by production	Volatility of aggregate 3-year ratio scaled by reserves	Volatility of aggregate 5-year ratio scaled by reserves
	(1)	(2)	(3)	(4)
Intercept	4.6787 ***	3.5631 **	3.3262 ***	2.3019 **
	(3.04)	(2.07)	(2.91)	(2.01)
SCF×I_1	0.0369 ***	0.0280 *	0.0292 ***	0.0278 ***
	(3.85)	(1.84)	(5.09)	(4.87)
SCF×I_2	-0.0207	0.0147	0.0039	0.0025
	(-1.19)	(1.38)	(0.43)	(0.31)
BCF	0.0076	0.0097	0.0079	0.0057 *
	(1.00)	(1.57)	(1.56)	(1.82)
Inverse Mills	-4.4532 **	-3.57	-3.5717 **	-1.6059
Ratio	(-2.15)	(-1.45)	(-2.19)	(-1.08)
Dummies	YES	YES	YES	YES
Controls	YES	YES	YES	YES
R^2	0.077	0.0505	0.0879	0.0781
F-statistic	4.6	3.43	5.48	4.24
Observations	588	445	528	610
Clusters	53	41	51	53