Managerial biases and corporate risk management*

Tim R. Adam
School of Business and Economics
Humboldt University of Berlin
Spandauer Str. 1, 10178 Berlin, Germany
Tel.: +49 / 30 2093 5642; Fax: 49 / 30 2093 5643
E-mail: tim.adam@wiwi.hu-berlin.de

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

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

February 2009

JEL Classification: G11; G14; G32; G39

Keywords: Corporate risk management; speculation; mental accounting; disposition effect; overconfidence.

---

* We thank Sudheer Chava, Louis Ederington, Gary Emery, Robin Greenwood, Nan Li, Oliver Spalt, Pradeep Yadav, and seminar participants at the University of Oklahoma, Southern Methodist University, Texas Christian University, ESMT Berlin, 2008 FMA Europe meetings and 2008 FMA 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 Jesus Salas for valuable assistance. We are responsible for any errors.

Managerial biases and corporate risk management

Abstract

We document new evidence of managerial biases in corporate finance, using as our context the risk management activity of a sample of North American gold mining firms over a 10-year period. We find asymmetry in the hedge ratio adjustment to past changes in the price of gold: managers systematically decrease their hedge positions following increases in the price of gold (hedging losses), while the same systematic negative relationship is not observed for gold price drops (hedging gains). This finding is consistent with managerial loss aversion. Since the hedging losses in our sample are offset by gains in the underlying gold holdings of our firms, this behavior is also consistent with mental accounting. Finally, we document that managers increase the volatility of their hedge positions (i.e., level of speculation) following increases in derivative cash flows but do not decrease their level of speculation following cash flow decreases, which is consistent with managerial overconfidence.

"Companies can also find themselves in awkward positions when trying to explain a hedging strategy that has generated losses." Walter Ochynski, Ochynski - Financial Consulting, October 7, 2003.

"Last year, in the largest cut since 2002, gold mining companies reduced their committed hedged positions by 35%." Wall Street Journal, March 17, 2008.

1. Introduction

A growing body of literature studies the presence of managerial behavioral biases within the corporate context, modeling managers as less-than-rational, and the market as rational.[1] The effects of managerial biases such as overconfidence, the disposition effect, and loss aversion have been addressed both theoretically and empirically in many areas of corporate finance, including investment policy, capital structure, mergers and acquisitions, and the timing of debt and equity offerings.[2] To the best of our knowledge, ours is the first paper to address similar managerial biases in the context of corporate risk management decisions. The potential presence of behavioral biases provides for several conjectures regarding the degree of hedging activity undertaken by firms and its variation over time. We document evidence that, while puzzling from the viewpoint of the traditional theories of hedging, is supportive of these conjectures.

The rational theories of corporate risk management have derived conditions under which hedging financial risks adds value because it reduces the effects of market frictions, such as taxes, bankruptcy costs, agency costs, information asymmetries, and undiversified stakeholders of the firm.[3] The traditional theories assume that derivative

---

[1] Baker, Ruback, and Wurgler (2006) provide a comprehensive review of the literature on behavioral corporate finance.

[2] Studies include Gervais, Heaton and Odean (2003), Aktas, de Bodt and Roll (2007), Ben-David, Graham and Harvey (2007), Malmendier, Tate, and Yan (2007), Sautner and Weber (2006), Loughran and Ritter (2002), and Crane and Hartzell (2007).

[3] See, for example, Stultz (1984), Smith and Stultz (1985), Stultz (1996), Froot, Scharfstein and Stein (1993), DeMarzo and Duffie (1995), and Mello and Parsons (2000).

contracts are fairly priced and that managers are rational and act in the best interest of shareholders. However, empirical tests of the predictions of these theories have met with only limited success.[4] While most empirical studies uncover evidence that could be interpreted as being consistent with one or more of the theories of hedging, there is no consistency of the empirical results across studies, i.e., there is no single theory that receives unanimous support by a majority of studies. In addition, most 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 seriously deficient when it comes to explaining hedging behavior in practice. In fact, there is considerable anecdotal evidence that managers deviate from the pure rationality assumed by the traditional theories. For example, there is extensive evidence that many managers systematically incorporate their market views into their risk management programs,[5] but fail to generate positive cash flows from this strategy.[6]

In this paper, we document new evidence that is difficult to reconcile with the predictions of the traditional theories. First, we find that managers tend to systematically reduce their hedging positions when the market moves against them, especially when the value of the total hedge book is negative, even though the underlying net position remains unchanged. The reaction is asymmetric: when the market moves in favor of the derivatives positions, managers do not increase their positions. This asymmetry is

[4] See, for example, Tufano (1996), Mian (1996), Geczy, Minton and Schrand (1997), Graham and Smith (1999), Haushalter (2000) and Graham and Rogers (2001).
[5] See, for example, Dolde (1993), Bodnar, Hayt and Marston (1998), and Glaum (2002).
[6] See Adam and Fernando, 2006) and Brown, Crabb and Haushalter (2006).

puzzling from the standpoint of the rational motives for hedging. If anything, one would expect hedge ratios to be particularly sensitive to gold prices when gold prices decline since such price declines, if they persist, will negatively impact the fundamentals of the firm and increase the probability of financial distress. However, our data suggests the opposite – that managers change their derivatives positions much more predictably in response to rising gold prices than to declining gold prices.

Second, we find that managers increase their speculative activity when their derivatives portfolios yield positive cash flows, but do not reduce their speculative activity when the derivatives portfolios yield losses. We measure the degree of speculation by the volatility of hedge ratios. The observed (asymmetric) effect of past cash flows on hedge ratio volatility, which persists after controlling for firm characteristics, is again difficult to reconcile with the traditional theories.

Following the growing literature that documents the presence of managerial behavioral biases in corporate finance, we suggest that our findings are also consistent with the presence of such biases in our sample firms. Our first finding is consistent with managerial loss-aversion. Derivatives-related losses are often scrutinized by senior management while the same is typically not the case for derivatives-related gains, leading to a higher propensity to adjust hedge positions when the market moves against them. A striking example of this pattern is the January 2008 derivative trading scandal at the French Société Générale Bank. As reported by *Fortune* (April 15, 2008): “The bank's own internal investigation into the matter shows that [Jérôme Kerviel’s] supervisors missed, ignored, or didn't take seriously 75 alerts about his [unauthorized] trading activities over a period of two years, a damning record that gives credence to the young trader's defense for his actions: His bosses were aware of his trades but largely ignored his activities as long as he was making money."

Unlike in the Société Générale episode, hedging losses in our sample are always offset by gains in the underlying gold holdings by the sample firms and yet, the firms seem to treat these 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 the concept of mental accounting, first proposed by Thaler (1980), and summarized by Grinblatt and Han (2007) as follows: "The main idea of mental accounting is that decision makers tend to segregate different types of gambles into separate accounts … by ignoring possible interactions." Thus, mental accounting implies that senior management regards losses on derivative positions separately from simultaneous gains on the underlying position. Such policy provides managers with an incentive to implement hedging strategies that minimize losses.

Our second finding, that speculation increases following high cash flows from derivative positions (but does not symmetrically decline following negative cash flows), is consistent with managerial overconfidence, which suggests a positive relationship between past successes and future speculative activity. The overconfidence hypothesis (e.g., Daniel, Hirshleifer and Subrahmanyam (1998); Gervais and Odean (2001); Gervais, Heaton and Odean (2003)) implies that managers may be overconfident in their ability to beat the market, engaging in excessive position taking 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 strategies that are difficult to reconcile with the traditional risk management theories, but are consistent with the possibility that managerial biases affect derivatives strategies (or stated alternatively, that managers have non-standard utility functions). Our findings contribute to the growing evidence on the deviation of corporate practices from full rationality and suggest that recognizing the presence of these deviations in corporate hedging may improve our understanding of risk management decisions.

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 hedging in response to gold price changes. Section 5 presents the empirical results on hedge ratio volatility in response to past derivative cash flows. Section 6 summarizes the results and presents our conclusions.

2. Theories and testable hypotheses

To arrive at testable hypotheses, our paper borrows from the growing body of literature that applies the concept of managerial behavioral biases to the corporate context, modeling the manager as less-than-rational, and the market as rational. Baker, Ruback, and Wurgler (2006) provide a thorough review of the literature on behavioral corporate finance. Although this area of research is relatively new, a close examination uncovers some common themes. First, managerial *overconfidence* is generally defined as either excessive optimism about the prospects of the firm due to overestimation of a manager's own ability to run the firm or, more frequently, as the overestimation of the precision of his private signal regarding the true value of the firm. A common theme is related to the time-series dynamics of overconfidence: it is believed to increase following successes and decrease by less (if at all) following failures (e.g., Gervais, Heaton, and Odean (2003)). The asymmetric response to past successes and failures follows from self-attribution: successes tend to be attributed to one's own skill while failures tend to be attributed to bad luck. The implication for financial decisions is that overconfident managers act more decisively and aggressively. Hence, managerial activity is hypothesized to intensify following successes. Several studies report empirical evidence consistent with overconfident managerial behavior.[7]

Another bias addressed by several recent studies is *mental accounting*. Managers can maintain separate mental accounts for different decision variables and thus may weigh those variables sub-optimally when making a decision. Sautner and Weber (2006) report that managerial option exercise behavior is consistent with mental accounting: shares acquired on option exercise are more likely to be converted into cash than those acquired as required stock investment. Coleman (2007) uses an experimental 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. 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-

[7] See, for example, Malmendier and Tate (2005), Malmendier, Tate and Yan (2007), Atkas, De Bodt and Roll (2007), and Ben-David, Graham and Harvey (2007).

price range and the first-day closing price. Crane and Hartzell (2007) find evidence of a disposition effect[8] in the behavior of REIT managers: they are found to be more likely to sell properties that have earned high cumulative returns, i.e., "winners" while showing relative reluctance to selling "losers."

The disposition effect is tied to another behavioral bias known as *loss aversion* (Kahneman and Tversky (1979)). Individuals afflicted by this bias exhibit more sensitivity to losses than they do to gains of equal magnitude.[9] That is, they exhibit non-standard utility functions.

Thus, the potential presence of psychological biases provides for several conjectures regarding the degree of hedging activity in corporate risk management. For one thing, mental accounting coupled with loss aversion would imply in the corporate risk management context that managers are more sensitive to losses on derivative positions than they are to gains. Recent anecdotal evidence shows that gold mining firms moved swiftly to cut or eliminate their hedges after losing money on contracts due to the rising gold price. 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%."[10] One prominent example is the costly 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

---

[8] Shefrin and Statman (1985) derive the main theoretical framework for the disposition effect. See also, e.g., Odean (1998) and Grinblatt and Han (2007) for evidence.
[9] See, for example, Loughran and Ritter (2002).
[10] An alternative explanation for closing out losing positions may be liquidity pressure or distress. As addressed later, controlling for changes in liquidity and likelihood of distress does not affect our inferences. Another alternative explanation is the implementation of FAS 133, which made a dramatic departure from past accounting practice by requiring derivative contracts to be marked-to-market. 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).

contributed to its 42% drop in quarterly net income. Importantly, the tendency to de-hedge when commodity prices move against the hedges does not affect just gold mining firms. For example, Southwest Airlines reported recently that it is "looking for opportunities to 'de-hedge' some of its fuel" now that oil prices are falling (Wall Street Journal, October 17, 2008). According to the Southwest CEO, "low fuel prices are a good thing… and an opportunity that we'll want to take the best advantage of that we can."

In this paper, we hypothesize and test the possibility that this behavior may be a result of loss aversion coupled with mental accounting. Namely, suppose that a manager irrationally believes that gold price changes are autocorrelated[11]; i.e., a decline (increase) in the price of gold will follow a decline (increase).[12] To address this assumption formally, suppose the manager assigns the following transitional probabilities:

$Pr\ [\Delta GOLD_t > 0 \mid \Delta GOLD_{t-1} > 0] = 1$

$Pr\ [\Delta GOLD_t > 0 \mid \Delta GOLD_{t-1} < 0] = 0$

$Pr\ [\Delta GOLD_t < 0 \mid \Delta GOLD_{t-1} > 0] = 0$

$Pr\ [\Delta GOLD_t < 0 \mid \Delta GOLD_{t-1} < 0] = 1$

where $\Delta GOLD_t = GOLD_t - GOLD_{t-1}$, the change in the price of gold from time (t-1) to time (t).

For expositional purposes, consider an example with $F_0 = S_0$ (where F_0 = time T forward price at time 0 and S_0 = time 0 spot price), zero interest rate, and zero cost of carry. The manager observes the gold price and makes a decision to hedge or not to

[11] This belief has to be irrational; at least in our sample, gold price *changes* are not highly autocorrelated, although gold price *levels* are highly first-order autocorrelated.

[12] Alternatively, the market may irrationally believe this. According to the anecdotal evidence, investors apparently reward the "de-hedgers" *despite* the negative cash flow that results from having to unwind positions. For example, according to the Wall Street Journal "to close out its hedging, Australian miner Newcrest Mining Ltd. raised 2.04 billion Australian dollars (US$1.93 billion) through an equity offering. Investors pushed up Newcrest's stock 26% in the 10 days after it announced the plan." As explained later, we do not find the sensitivity of managerial compensation to stock price to affect our inference.

hedge. According to his transition probability matrix, if gold price went up last quarter, his expected utility from *hedging* is the sum of his utility from the gain on the underlying position and his utility from the loss of the derivative position:

$E_t[U \mid \Delta GOLD_t > 0]^{hedge} = U(S_T - S_0) + U(F_0 - F_T)$

where S_T is the time T spot price, and the other variables are as defined above. Importantly, note that we do not consider the expected utility of the combined value of the underlying and derivative positions. The mental accounting hypothesis requires that we keep the two utilities separate. Similarly, if the price of gold went up last quarter, then the manager's expected utility from *not hedging* is

$E_t[U \mid \Delta GOLD_t > 0]^{no\ hedge} = U(S_T - S_0) + U(0)$

In this case the "damage" or "loss" of *hedging*, relative to not hedging, is determined by the absolute value of the difference:

$$LOSS\ INCURRED^{hedge\ if\ gold\ up} = ABS\,[U(F_0 - F_T) - U(0)] \qquad (1)$$

Note that $(F_0 - F_T)$ above is a negative value. In the same way, we can consider the managerial decision to hedge or not to hedge conditional on the last quarter's *drop* in the price of gold. As it can be easily shown, this time the "missed gain" from *not hedging*, relative to hedging, is

$$GAIN\ MISSED^{not\ hedge\ if\ gold\ down} = ABS\,[U(0) - U(F_0 - F_T)] \qquad (2)$$

Note that this time, $(F_0 - F_T)$ is a positive value. Loss aversion implies in this case that

$$ABS\,[U(0) - U(F_0 - F_T) \mid (F_0 - F_T)>0] < ABS\,[U(F_0 - F_T) - U(0) \mid (F_0 - F_T)<0]$$

That is, the "loss incurred" results in a bigger utility drop than the "gain missed." Hence, this loss aversion provides the basis for our first empirical hypothesis:

Hypothesis 1: It is more important for the manager to decrease the extent of hedging when he expects the gold price to rise than it is to increase the extent of hedging when he expects the gold price to decline.

Note that under this hypothesis, the relationship between changes in hedge ratio and changes in gold price goes in the opposite direction from what might be expected under a rational explanation based on the changing hedging needs of the firm due to movements in gold prices. Under a hedging-needs explanation, a manager would be more concerned about hedging at an increasing rate when the firm is moving closer to financial distress (i.e., when the gold price is declining).

The second conjecture stemming from the potential presence of psychological biases in our sample pertains to the implications of managerial overconfidence for how managers conduct their hedging activities. Managerial overconfidence implies that past successes resulting specifically from derivatives positions (as opposed to the underlying positions or the overall quality of the hedge) would make the manager more overconfident, leading to a more aggressive pursuit of speculation in the form of selective hedging (i.e., market timing) strategies; while past failures would affect the speculative behavior to a lesser degree. Hence, one would expect the relationship between past performance of the derivative positions and the degree of speculation in the current period to be positive on average, and more so for past gains than for past losses. Hence, we formulate our second empirical hypothesis:

Hypothesis 2: The relationship between past performance of the derivative positions and the degree of speculative activity in the current period is positive on average, and more so for past gains than for past losses.

In addition to the literature documenting the presence of managerial biases in corporate decisions, an important puzzle motivating our second hypothesis is the widely established empirical evidence that firms incorporate their market views into their hedging decisions, or hedge "selectively."[13] Stultz (1996) has advanced a rational explanation for hedging selectively to create shareholder value based upon the informational advantage in risk taking that some firms may acquire. Stulz (1996) emphasizes the importance of firms truly understanding the source of their comparative advantage, if any, noting that being a large player in a particular market does not necessarily provide such a firm information that other firms in the market do not have. In addition, notwithstanding any private firm information, selective hedging exposes it to considerably more risk relative to the case in which it engages in pure hedging. Therefore, a firm that seeks to add shareholder value by selective hedging must not only have a comparative advantage in information but also have the balance sheet and capital structure to support the extra risk taking that selective hedging entails. At the same time, Stultz (1996) notes that firms in distress may also have a higher incentive to speculate.

The criteria established by Stulz (1996) for a successful selective hedging strategy seem stringent indeed. In contrast, the available evidence suggests that selective hedging activity is widespread, perhaps too widespread to meet the Stulz criteria for success. Even in commodity industries, where firms may have access to specialized information pertaining to their industries, there is no evidence that firms are able to systematically

[13] The term is due to Stultz (1996). For empirical evidence see, for example, Dolde (1993), Bodnar, Hayt and Marston (1998), and Glaum (2002).

beat the market by selective hedging using such specialized information.[14] Another possibility is that although selective hedging does not benefit shareholders, it may benefit managers due to incentive compensation. The potential link between selective hedging and managerial compensation is explored in several recent studies. However, these studies report mixed results. Overall, there is only weak evidence that managerial compensation significantly affects selective hedging and there is no consensus on the direction of the relationship.[15] These mixed results regarding the potential motives for selective hedging suggest that our study of managerial biases may provide valuable new insights.

3. Data and methodology

Our selective hedging data is from Adam and Fernando (2006). The sample consists of 92 gold mining firms in North America, encompassing the majority of firms in the gold mining industry. These firms are included in the *Gold and Silver Hedge Outlook*, a quarterly survey conducted by Ted Reeve, an analyst at Scotia McLeod, from 1989 to 1999. 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. The derivatives portfolios consist of forward instruments (forwards, spot-deferred

[14] See, for example, Adam and Fernando (2006), and Brown, Crabb, and Haushalter (2006).

[15] Géczy, Minton and Schrand (2007) find that CEO stock price sensitivity is negatively related to speculation. Beber and Fabbri (2006) find no statistically significant 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. Adam, Fernando and Salas (2007) find that selective hedging actually decreases with stock and option compensation (for both CEOs and CFOs) and insider ownership. They also rule out the possibility that firms may be speculating in this way to exploit information and/or financial advantages.

contracts, and gold loans) and options (put and call). A total of 1,295 firm-quarters represent nonzero hedging portfolios of one-year maturity. Each of the sample firms has at least one non-zero observation for a one-year maturity hedge ratio with an average of 13 observations per firm. Out of 92 sample firms, 46 firms have more than ten quarterly observations with non-zero hedge ratio of one-year maturity. For comparison, 28 firms have more than ten nonzero observations for three year maturity and 12 firms have more than ten nonzero observations for five year maturity. Hence, our data is consistent with the findings reported in Bodnar et al. (1998) that the bulk of hedging activity is concentrated in short term maturity contracts.

Operational data, e.g., gold production figures, production costs per ounce of gold, etc., we collect by hand from firms' financial statements. The data on firm characteristics such as size, market-to-book, leverage, liquidity, existence of a credit rating, and payment of quarterly dividends come from COMPUSTAT.

To estimate quarterly volatility, we use the values of the hedge ratio at the beginning and the end of the quarter. By constructing volatility from two quarterly observations, we follow previous literature on volatility estimation. 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.

Our quarterly measure of speculation for quarter t is the hedge ratio volatility measured as the absolute value of the difference in the natural logarithms of the hedge ratios of the beginning and the end of the quarter:[16]

$$VOL_t = ABS[LN(HR_t / HR_{t-1})]$$

In this formula, HR_t is the value of the hedge ratio. In all our tests, we use: (1) the short-term hedge ratio constructed using contracts maturing within one year; and (2) the aggregate hedge ratios, which aggregate derivative contract positions of up to three (five) years to maturity. Each of these hedge ratios has its advantages. The one-year hedge ratio accounts for the bulk of hedging activity, compared to the longer maturities. On the flip side, the short-term ratio may also be the ratio that the firm is more likely to adjust for non-selective reasons such as financial distress. The aggregate hedge ratios have the advantage of cumulating hedge positions of different maturity and may enable us to capture selective activity (if any) using longer-term contracts.

[16] 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.

Our main measure for the aggregate hedge ratio is the number of ounces hedged up to three years ahead (using linear contracts and puts with a maturity of up to 3 years) divided by the expected production over the next three years:

$$AGGHR3 = \frac{N(1+2+3)}{EPROD(1+2+3)}$$

When expected production is missing, we have used actual production instead, i.e., for the production forecast i years ahead we use $E[prod(t+i)|t] = prod(t+i)$. We have not interpolated the missing production figures, as production is rather volatile. For this reason we have fewer observations in the aggregate hedge ratios than in the 1-year hedge ratio. Due to the difficulty that arises with estimating the expected production in our sample, we also use two other aggregate hedge ratios that are scaled by gold reserves. One aggregates over the contracts with one-, two-, and three-year maturities; and the other aggregates over all available contract maturities in our sample, from one through five years.

We use several constructs to measure the past performance of the derivative positions for each firm. First, we compute quarterly cash flows from derivative positions per ounce of gold hedged. We look at the total derivative cash flow as well as the component attributable to selective hedging. The latter is computed as in Adam and Fernando (2006) relative to a fixed hedge ratio benchmark, which is based on the average hedge ratio for the firm over the sample period. Selective hedging cash flow is an attractive measure because it reflects the part of the cash flow that results directly from the managerial market timing, i.e., speculative, actions.[17] However, the disadvantage of selective hedging cash flow (relative to total cash flow) is that it is harder to observe on a routine basis and to communicate to decision makers. Our second measure of past performance is derivative profit, which is computed as the quarterly change in the value of derivative positions per ounce hedged. Please refer to our Appendix for the calculation of quarterly changes in the book value of derivative positions.

Tables 1 and 2 show the descriptive statistics and the correlations for the variables of interest on a quarterly basis. In a very small number of cases, the hedge position was greater than the expected production in the year the contracts matured; hence, the maximum short-term hedge ratio is equal to 8.9583. We exclude such outliers in our robustness checks. The aggregate hedge ratios are considerably less affected by these outliers.

[Place Tables 1 & 2 about here]

Several observations emerge from these tables. First, not surprisingly, changes in gold price are negatively correlated with the derivative cash flows. Second, consistently with Adam and Fernando (2006), selective hedging cash flows are zero on average suggesting that selective hedging does not add value to the firm. We notice that the changes in the hedge ratios are strongly negatively correlated with past changes in the price of gold. We observe also that hedge ratio volatility is positively correlated with the past derivative cash flow. These findings provide preliminary univariate evidence

[17] 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 derivative 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.

supporting our hypotheses. Finally, we note that smaller firms exhibit higher volatility of hedge ratios.

Our basic methodology is to run panel regressions with firm fixed effects. Our main tests of Hypothesis 1, which addresses the decision whether or not to hedge in response to gold price changes, are performed on the whole sample of firm-quarters using panel regressions with firm fixed effects, since the hypothesis addresses directly the decision of whether or not to hedge. We also test Hypothesis 1 on two sub-samples: firms that hedge at the beginning of the quarter, and those that do not. It is on the former sub-sample that we expect to find the stronger support for the hypothesis. We confirm these results both with the firm fixed effects panel regressions and with the Heckman two-step procedure.[18] Finally, we estimate the hypothesis on the whole sample while allowing for the sensitivity of hedge ratio changes to past gold price changes to be a function of the beginning-of-quarter level of the hedge ratio. The methodology is addressed in more detail in Section 4.

Our test of Hypothesis 2, which addresses the relationship between hedge ratio volatility and past derivative cash flows, 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 derivative positions "explaining" zero hedge ratio volatility next period.

[18] These additional tests of Hypothesis 1 are available from the authors upon request. Our results are especially strong when we use the shortest-term hedge ratio (up to one-year maturity), suggesting, not surprisingly, that this may be the ratio that managers decide upon first when deciding whether or not to hedge.

Hence, we estimate the panel regression with firm fixed effects on a reduced sample of active hedgers. 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 firm size, market-to-book, liquidity, leverage, dividends, credit rating, and likelihood of distress (Haushalter (2000)). We say that a firm has hedging activity if two conditions hold: (1) either the beginning or the end-of-quarter hedge ratio is non-zero; *and* (2) cash flows from derivative positions in the previous quarter are non-zero. In the second stage of the Heckman two-step procedure, we test whether the hedge ratio volatility is driven by past success of the derivative positions for the firms that exhibit hedging activity as described above. This methodology is addressed in detail in Section 5.

Our methodology differs from the techniques employed by the other studies of corporate managerial biases. The 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 look at various cross-sectional characteristics of corporate managers that are likely to affect the degree of biases such as overconfidence. Examples include personal characteristics (age, tenure, education, etc.) as well as personal wealth management practices (the tendency to hold disproportional amounts of own firm's stock; the failure to exercise vested options). The question in these studies is whether managers labeled as biased engage in suboptimal corporate policies. In contrast, our study focuses on the time-series component.

Another important methodological advantage of our paper comes from the nature of our database. As previously noted, it 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 more precisely observe and measure actual derivatives transactions.

4. Empirical results: Hedging and gold price changes

4.1 Initial tests

In this section, we test our hypothesis that managers will hedge less in response to gold price increases; and not necessarily hedge more in response to gold price declines. By way of motivation, Figure 1 shows cross-sectional mean changes in the 3-year aggregate hedge ratios of firms following large (greater than one percent) quarterly increases in the price of gold. In nine out of 11 cases, a gold price increase is followed by a hedge ratio reduction.

[Place Figure 1 about here]

Initially, we test this hypothesis as follows. In a panel setting, we run a regression of the change in the hedge ratio on the last quarter's change in the price of gold, allowing for asymmetry effects as explained above, and controlling for some firm characteristics which may also explain hedge ratio adjustment following a change in the gold price. To test for the asymmetry effect, we introduce a dummy variable equal to one when the change in the gold price was positive last quarter; and zero if it was negative. Our regression has the following general structure:

$$\Delta HR_t = a + b\Delta GOLD_{t-1} + \varepsilon \qquad (3)$$

$$\Delta HR_t = a + b_1\Delta GOLD_{t-1} + b_2(I\{\Delta GOLD_{t-1} > 0\} \cdot \Delta GOLD_{t-1}\} + CONTROLS + \varepsilon \qquad (4)$$

We expect the coefficient b in (3) to be negative. We also expect the coefficient b_2 in (4) to be negative. The interpretation of the coefficients is a follows: the sensitivity to gold price declines is determined by b_1; and the sensitivity to gold price increases is determined by (b_1+b_2). Finding that $b_2 < 0$ and hence (b_1+b_2) is more negative than b_1, would suggest that managers adjust their hedge ratios down following gold price increases more aggressively than they adjust their hedge ratios up following declines.

As our control variables, we choose last quarter's change in size, liquidity (quick ratio), and Altman's (1968) Z-score, to accommodate for the possibility that a change in the price of gold may change the fundamental hedging needs of the firm or cause liquidity pressure or distress.

Table 3 presents the results of our regressions (3) and (4) for the one-year hedge ratio as well as for the three-year aggregate hedge ratio scaled by expected production.[19] We observe a significantly negative coefficient for the past change in the gold price in a univariate regression. Allowing for asymmetry demonstrates that the coefficient is negative and statistically significant following *positive* moves in the price of gold, and statistically insignificant otherwise. This result is robust to the inclusion of changes in the firm characteristics that may affect the firm's hedging needs such as size and the probability of financial distress. [20]

[Place Table 3 about here]

4.2 Tests of nonlinear effects

To allow for non-linear dependence of hedge ratio changes on gold price changes, we next model the rates of hedge ratio increase (decrease) following a gold price drop (rise) as a linear function of the beginning-of-quarter hedge ratio. Empirically, we estimate the following two regressions.

[19] Qualitatively similar results were obtained using the other hedge ratios.
[20] The result is also robust to modifying the regression to explicitly include gold dummy as a separate independent variable and to using size levels instead of changes.

$$\Delta HR_t = a_1 + [b_1 + b_2 I\{\Delta GOLD_{t-1} > 0\}] \cdot \Delta GOLD_{t-1} + [b_3 + b_4 I\{\cdot \Delta GOLD_{t-1} > 0\}] \cdot HR_{t-1} \cdot \Delta GOLD_{t-1} + \varepsilon_{1t}$$

$$\Delta HR_t = a_2 + [c_1 + c_2 I\{\Delta GOLD_{t-1} < 0\}] \cdot \Delta GOLD_{t-1} + [c_3 + c_4 I\{\cdot \Delta GOLD_{t-1} < 0\}] \cdot HR_{t-1} \cdot \Delta GOLD_{t-1} + \varepsilon_{2t}$$

In the first regression, as before, the dummy variable is equal to one when the change in the gold price was positive last quarter; and zero if it was negative. In the second regression we assign the dummy a value of one when the gold price *declined* in the previous quarter; and zero otherwise. In both regressions, HR_{t-1} is the initial level of the hedge ratio. In such a setting, suppose gold price *declined* in the previous quarter. The relationship between changes in the hedge ratio and past changes in the gold price will be represented by

$$\Delta HR_t = a_1 + [b_1 + b_3 \cdot HR_{t-1}] \cdot \Delta GOLD_{t-1} + \varepsilon_{1t}$$

Thus, if the gold price declines and $HR_{t-1} = 0$, the firm cannot possibly reduce its hedge ratio any further, and we expect the hedge ratio to increase, on average, corresponding to $b_1 < 0$. If, on the other hand, $HR_{t-1} > 0$, then we expect this increase in the hedge ratio to get smaller in HR_{t-1}: the higher the initial hedge ratio, the less room there is for a further increase in response to a gold price drop, corresponding to $b_3 > 0$.

Next, suppose that gold price *increases* in the previous quarter. Then, the relationship between changes in the hedge ratio and past changes in the gold price can be expressed as:

$$\Delta HR_t = a_2 + [c_1 + c_3 \cdot HR_{t-1}] \cdot \Delta GOLD_{t-1} + \varepsilon_{2t}$$

Thus if the gold price increases and $HR_{t-1} = 0$, the firm cannot reduce its hedge ratio any further; so we expect $c_1 \geq 0$. If, on the other hand, $HR_{t-1} > 0$, we expect a decrease in the hedge ratio following the rise in the gold price, and we expect this decrease to become larger in HR_{t-1}: the higher the initial hedge position, the more room there is for reducing it, corresponding to $c_3 < 0$.

Tables 3A and 3B show the regression results for the one-year hedge ratio and for the three-year aggregate hedge ratio scaled by expected production, respectively. We observe that all of the regression coefficients discussed above are statistically significant and have the expected signs. In particular, let us focus on the response of the three-year aggregate hedge ratio to gold price changes, modeled as a function of the initial hedge ratio. If gold price declines, then the relationship will be determined by

$$\Delta HR_t = 0.0152 + [-0.0011 + 0.0059 \cdot HR_{t-1}] \cdot \Delta GOLD_{t-1}$$

On the other hand, following gold price increases,

$$\Delta HR_t = 0.0152 + [+0.0007 - 0.0071 \cdot HR_{t-1}] \cdot \Delta GOLD_{t-1}$$

[Place Table 3A & 3B about here]

This evidence is in line with our hypothesis that conditional on the initial positive value of the hedge ratio, managers will lower the hedge ratio at a higher rate following a gold price rise than they would increase it following a gold price drop. Integrating the slope over all initial values of the hedge ratio, we calculate the average slope for gold price increases and for gold price declines. Consistently with the evidence reported in the previous section, the average value of the slope for increases is -0.0008; and the average slope for decreases is 0.0001. To provide the economic significance of this difference, a one standard deviation (18.45) increase in the price of gold moves the three-year aggregate hedge ratio down by one percent; and a similar decrease in the price of gold changes it by one-tenth of one percent.

4.3 Other robustness checks

Given that the markets apparently reward managers for incorporating past gold trends into hedging decisions, managers may be acting not so much out of personal irrationality but in the interest of pushing up the short-term stock price because they anticipate that investors will reward the momentum speculation. Managers will do so if their compensation is sensitive to stock price. In a separate set of tests, which we omit reporting here to save space, we find that CEO delta does not affect the sensitivity of a firm's hedge ratio to changes in the price of gold. This irrelevance of managerial compensation is consistent with Beber and Fabbri (2006) that managerial compensation does not seem to be causing selective hedging by gold producers.

In addition, we estimate our fixed-effects panel regression, similar to those reported in Table 3, on two sub-samples: one with zero initial hedge ratios, and one with positive initial hedge ratios. We also repeat these tests using the Heckman two-step procedure with selection, where we first model the positive hedge ratio as a function of firm characteristics (size, leverage, quick ratio, market-to-book, dividend dummy, credit rating dummy, and Z-score); and then we estimate the relationship between changes in the hedge ratio and changes in gold price for the firm-quarters that feature a positive hedge ratio. Our robustness tests support our main results and we omit reporting them; however, they are available upon request.

5. Empirical evidence: Hedging volatility and past cash flows

In this section, we address the hypothesis that hedge ratio volatility should positively depend on past cash flows. The overconfidence hypothesis maintains that, all else equal, if past activity was successful (in a hedging context, if the manager had correctly guessed the direction of the gold price change), then the manager will “develop an appetite” for speculation again next period. If, however, such past activity was unsuccessful (the manager had guessed wrong), then there may be less speculation subsequently, but we expect the reduction in speculation after failures, if any, to be smaller than the increase in speculation following successes.

Note that a negative cash flow from derivative positions may not indicate a “failure” and hence may not reduce managerial overconfidence. If a negative cash flow is the result of closing a losing position before the contract expired, and especially if it is “rewarded” by a positive stock return, the manager may well consider this negative cash flow to be the result of a successful decision; thus a negative cash flow, per se, need not reduce overconfidence. However, it may also be that a negative cash flow is not a result of a decision but simply a result of the contract’s expiration at a loss. In this case, a negative cash flow would not be rewarded and would not lead to higher overconfidence. On the other hand, a positive cash flow is likely to increase overconfidence whether or not it was a result of premature closing or normal expiration. Hence, the major premise of this paper that higher derivative cash flows should lead to higher hedge ratio volatility is still reasonable.

While we expect that the hedge ratio volatility should increase with past cash flows, it is more difficult to develop an unambiguous hypothesis with regard to book profits. While past book profits may represent “success” to a manager – in a way that selective cash flows do – they also reflect the decline in the price of gold. On the other hand, negative book profits – “failures “ – indicate an increase in the price of gold.

Indeed, as we show in Table 2, book profits are very strongly negatively correlated with gold price changes. Hence, both positive and negative changes in the price of gold (and, correspondingly, in the book profits from derivative positions) may lead to higher hedge ratio volatility.

As a motivating exercise, and before turning to the detailed panel framework, Figure 2 plots two aggregate time series: (i) the difference (from the same quarter of last year) in the industry cross-sectional mean of the absolute quarterly change in the one-year-maturity hedge ratio; and (ii) the *lagged* difference (from the same quarter of last year) in the cross-sectional mean of total derivative cash flow. The cross-sectional means are estimated each quarter over all gold-mining firms who report a non-zero value of hedge ratio during that quarter, i.e. over all hedging firms. The two series on the plot are visibly correlated suggesting the existence of a general relationship between derivative cash flows and hedging activity in the gold-mining industry. We next analyze this possibility in detail using a panel framework and implementing controls.

[Place Figure 2 about here]

As we proceed to our panel regressions, we first test our general hypothesis that hedge ratio volatility should increase, on average, with past derivative cash flows. Thus, we first test this general relationship without accounting for asymmetry effects, which will be addressed shortly thereafter.

5.1 Panel regression without asymmetry effects

Table 4 shows the results of the firm fixed effects panel regressions of the hedge ratio volatility on past cash flows and book profits from derivative positions per ounce hedged.

We present the results for the volatility of the three-year aggregate hedge ratio scaled by expected production, although similar results were obtained with the other hedge ratio measures. To estimate these regressions, we limited the sample to active hedgers only. We are interested in testing the hypothesis that successful past activity will lead to higher speculation in the future. Hence, we eliminate firm quarters where the firm had zero cash flows from derivative positions and those observations where *both* beginning-of-quarter and end-of-quarter hedge ratios were zero. In all of the models, we included 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. (This evidence is available from the authors upon request). We also control for the Altman (1968) Z-score since the probability of bankruptcy may affect a firm's level of speculative activity. Lastly, in one of the models we control for the beginning-of-quarter level of the hedge ratio, to allow for the possibility that volatility of those hedgers who take small positions is different from volatility of those who take larger positions, irrespective of cash flows.[21]

[Place Table 4 about here]

As evident from Table 4, in all of the models we observe a positive relationship between hedge ratio volatility and previous quarter cash flows, which is robust to model specification in terms of both magnitude and statistical significance. Importantly, the relationship with selective cash flows is significant, providing additional evidence in favor of the hypothesis that the correct managerial hunch in the past leads to larger relative adjustments of the hedge ratio in the future. At the same time, we do not find a

[21] We also allow, in the two-stage Heckman framework, for the relationship between hedge ratio volatility and past total (selective) cash flow to be a function of the beginning-of-quarter hedge ratio. In these robustness tests, we continue to find that hedge ratio volatility is positively related to past cash flow.

significant relationship with the book profits (labeled as RBK in Table 4). This result does not come as a big surprise, however, as explained above.

Given that the tests reported in Table 4 were performed on a reduced sample, we next perform robustness checks that allow for the simultaneous decision of the firm to be an active hedger and to speculate. We estimate the two-step Heckman procedure with selection. In the first stage, we estimate the PROBIT model, where 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. We estimate the likelihood of hedging activity as a function of several firm characteristics: size, market-to-book value of assets, the ratio of book debt to book equity, quick ratio, dividend-payer status, existence of credit rating, and Altman's Z-score. In the second stage, we estimate the relationship between hedge ratio volatility and past cash flows and book profits from derivative positions conditional on hedging activity.

The results from the two stages of the Heckman procedure are presented in Tables 5 and 6, respectively. From Table 5, 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, low liquidity, and high probability of financial distress. These results are consistent with our evidence reported in Table 2; as well as with the previously reported findings by Geczy, Minton and Schrand (1997), Bodnar, Hayt and Marston (1998) and Haushalter (2000)) that large firms hedge more than small firms do.

[Place Table 5 about here]

The results reported in Table 6 confirm those reported in Table 4: in all regression specifications, we observe a positive and significant relationship between hedge ratio volatility and past cash flows from derivative positions. We observe no relationship between hedge ratio volatility and past book profits from derivative positions.

[Place Table 6 about here]

5.2 Accounting for asymmetry effects

We now turn to examining our hypothesis that the effects of past cash flows on hedge ratio volatility are asymmetric. For this purpose, we run the following regression with dummy variables:

$$VOL_t = a + b_1 CF_{t-1} + b_2 (I\{CF_{t-1} > 0\} \cdot CF_{t-1}\} + \varepsilon \qquad (5)$$

In this regression, *VOL* represents the hedge ratio volatility for the chosen maturity; *CF* represents cash flows from derivative positions; and $I\{CF > 0\}$ represents a dummy variable equal to one if the derivative cash flow was positive, and to zero otherwise.

We expect the coefficient b_2 in (5) to be positive. The interpretation of the coefficients is a follows: if past cash flow is negative, then the sensitivity of hedge ratio volatility to the cash flow is determined by b_1; otherwise, it is determined by (b_1+b_2). Finding that $b_2 > 0$ and hence (b_1+b_2) is higher than b_1, would be consistent with our Hypothesis 1.

As before, we estimate this regression first on a reduced sample of firm-quarters, and next using Heckman two-step procedure for robustness. The results of the panel regressions on a reduced sample are presented in Table 7, and the results of the second-stage Heckman procedure are presented in Table 8.

[Place Tables 7 & 8 about here]

From both Table 7 and Table 8, we observe that the relationship between hedge ratio volatility and past cash flows is strongly positive *only* if the past cash flows are positive. When cash flows are negative, however, we observe a negative relationship between cash flows and future hedge ratio volatility: larger "failure" leads to more speculation, not to less. We hypothesize that this behavior may represent managerial attempts to gamble out of losses. Evidence consistent with such behavior has been reported in Brown, Harlow and Starks (1996). They show that mutual fund managers that are losers increase volatility of their positions more than winners do, in the hope of gambling out of losses by the time of performance assessment. In any event, however, we clearly observe that the positive relationship is stronger after successes than after failures: in all of the specifications, we observe that b_1+b_2 is higher than b_1.

6. Conclusions

In this paper, we establish new evidence consistent with the presence of managerial biases, using corporate risk management as the context for our study. We examine the possibility that the widespread practice of selective hedging empirically documented in recent studies may be at least partly driven by mental accounting, loss aversion, and overconfidence. We analyze the hedging practices of the North American gold mining firms over 1990 – 1999 using a unique dataset, and study the relationship between a firm's hedging activity and the past performance of its derivative positions. Our empirical investigation, consistently with the anecdotal evidence, reveals that managers appear to act as if they take a view regarding the future changes in the price of gold: they systematically decrease their hedges following past rises in gold price. Importantly, we do not find that managers are equally eager to increase their hedges in response to declines in the price of gold. We interpret this evidence as consistent with loss aversion and mental accounting: managers act to minimize losses from derivative positions, while paying less regard to the performance of the underlying position. We also document a positive relationship between the past performance of derivative positions and the subsequent amount of speculation. This positive relationship is strong following successes and non-existent following failures. This observation is in line with the conjecture that the success of the past managerial hedging decisions may increase managerial overconfidence, leading managers to speculate more in the future. Our findings contribute to the growing evidence on the deviation of corporate practices from full rationality and suggest that recognizing the presence of these deviations in corporate hedging may improve our understanding of risk management decisions.

Appendix

For the calculations, 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:

$$\Delta_{t,Option} = \Delta_{t,Total} + N_{t,Forward} + N_{t,Spot} + N_{t,Linear}$$

Then, for each quarter, we calculate the minimum of the two hedge positions,

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

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

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 of option positions as the beginning-of-quarter delta, divided by the beginning-of-quarter number of option contracts, multiplied by the minimum of the beginning-of-quarter and the end-of-quarter positions:

$$M\Delta_{t,Option} = \Delta_{t-1,Option} \cdot MIN_{NOPT,t} / N_{t-1,Option}$$

If both Nopt and lNopt are zero, then delta is set to zero. Next, we use the delta to calculate the total book profits

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

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

$$BK_t = BK_{t,Linear} + BK_{t,Option}$$

Finally, to adjust for the scale effect, we scale the total profits by the average size of the firm's position. The average size of the linear position 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 is computed similarly.

$$RBK_{t,Option} = BK_{t,Option} / \overline{N}_{Option}$$

$$RBK_{t,Linear} = BK_{t,Linear} / \overline{N}_{Linear}$$

$$RBK_{t} = RBK_{t,Linear} + RBK_{t,Option}$$

References

Adam, T., and C. Fernando, 2006, Hedging, speculation, and shareholder value, *Journal of Financial Economics* 81, 283-309.

Adam, T., Fernando, C., and J. Salas, 2007, Why do firms hedge selectively? Evidence from the gold industry," Working paper, University of Oklahoma and National University of Singapore.

Aktas, Nihat, de Bodt, Eric and Roll, Richard W., "Learning, Hubris and Corporate Serial Acquisitions," 2007, Working paper, UCLA

Alizadeh, S., Brandt, M.W., and F.X. Diebold, 2002, "Range-based estimation of stochastic volatility models," *Journal of Finance* 57, 1047-1092

Altman, E.I., 1968, "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy," *Journal of Finance* 23, 589 – 609.

Ang, A., Hodrick, R.J., Xing, Y., and X. Zhang, 2006, "The cross-section of volatility and expected returns," *Journal of Finance* 61, 259-299

Baker, M., Ruback, R.S., and J. Wurgler, 2006, "Behavioral corporate finance: A survey," Working paper, Harvard Business School and NYU Stern School of Business

Beber, A., and D. Fabbri, 2006. Who Times the Foreign Exchange Market? Corporate Speculation and CEO Characteristics, Working paper, University of Lausanne.

Ben-David, Itzhak, Graham, John R. and Harvey, Campbell R., "Managerial Overconfidence and Corporate Policies," 2007, Working paper, University of Chicago and Duke University

Bodnar, G., Hayt, G., and R. Marston, 1998, "Wharton survey of derivatives usage by U.S. non-financial firms," *Financial Management* 27, 70-91.

Brown, G., Crabb, P., and D. Haushalter, 2006, "Are firms successful at selective hedging*?" Journal of Business*, 79(6), 2925-2949.

Brown, K.C., W. Van Harlow, and L. T. Starks, 1996, "Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry," *Journal of Finance* 51, 85-110

Coleman, L., 2007, "Risk and decision making by finance executives," Working paper, University of Melbourne.

Crane, A., and J. Hartzell, 2007, “The disposition effect in corporate investment decisions: Evidence from real estate investment trusts,” Working paper, University of Texas.

Daniel, K., Hirshleifer, D., and A. Subrahmanyam, 1998, “Investor Psychology and security market under- and over-reactions.”, *Journal of Finance* 53, 1839 – 1867.

DeMarzo, P. and D. Duffie, 1995, “Corporate incentives for hedging and hedge accounting,” *Review of Financial Studies* 8, 743 – 772.

Dolde, W., 1993 “The trajectory of corporate financial risk management,” *Journal of Applied Corporate Finance* 6, 33-41.

Froot, K.A., D.S. Scharfstein, and J.C. Stein, 1993, “Risk management: Coordinating corporate investment and financing policies,” *Journal of Finance* 48, 1629 – 1658.

Géczy, C., Minton, B., and Schrand, C., 1997. Why firms use currency derivatives, *Journal of Finance* 52, 1323-1354.

Géczy, C., Minton, B., and Schrand, C., 2007. Taking a view: Corporate speculation, governance and compensation,” *Journal of Finance* 62, 2405 – 2443.

Gervais, S., J.B. Heaton, and T. Odean, 2003, “Overconfidence, Investment policy, and executive stock options,” Working paper, Duke University.

Gervais, S., and T. Odean, 2001, “Learning to be overconfident,” *Review of Financial Studies* 14, 1-27.

Glaum, M., 2002, “The determinants of selective exchange-risk management – evidence from German non-financial corporations,” *Journal of Applied Corporate Finance* 14, 108 - 121.

Graham, J. and D. Rogers, 2002, “Do firms hedge in response to tax incentives?” *Journal of Finance* 57, 815 – 839.

Graham, J. and Smith, C., 1999, Tax incentives to hedge, *Journal of Finance* 54, 2241-2262.

Grinblatt, Mark and Han, Bing, 2007, "Prospect Theory, Mental Accounting, and Momentum," Yale ICF Working Paper No. 00-71; UCLA Anderson School Finance Working Paper No. 01-18.

Haushalter, G.D., 2000, “Financing policy, basis risk, and corporate hedging: Evidence from oil and gas producers,” *Journal of Finance* 55, 107 – 152.

Heckman, J. J., 1979, “Sample selection as a specification error,” *Econometrica* 47, 153 – 161.

Loughran, T., and J. Ritter, 2002, “Why don’t issuers get upset about leaving money on the table in IPOs?” *Review of Financial Studies* 15, 413-443.

Malmendier, U., and G.A.. Tate, 2005, “CEO overconfidence and corporate investment,” *Journal of Finance* 60, 2661 – 2700.

Malmendier, U., G.A.. Tate, and J. Yan, 2007, "Corporate Financial Policies with Overconfident Managers" Stanford University, NBER, and University of Pennsylvania.

Mello, A. and J. Parsons, 2000, “Hedging and liquidity,” *Review of Financial Studies* 13, 127 – 153.

Mian, Shehzad L., 1996, Evidence on Corporate Hedging Policy, *Journal of Financial and Quantitative Analysis* 31, 419-439.

Odean, T., 1998, “Are investors reluctant to realize their losses?” *Journal of Finance* 53(5), 1775 – 1798.

Sautner, Z., and M. Weber, 2006, “How do managers behave in stock option plans? Evidence from exercise and survey data,” Working paper, University of Oxford and University of Mannheim.

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

Smith, C., and R. Stulz, 1985, “The determinants of firms’ hedging policies,” *Journal of Financial and Quantitative Analysis* 20, 391-405.

Stultz, R.M., 1984, “Optimal hedging policies,” *Journal of Financial and Quantitative Analysis* 19, 127 - 140

Stulz, R., 1996. “Rethinking risk management,” *Journal of Applied Corporate Finance* 9, 8-24.

Thaler, R. H., 1980, "Towards a positive theory of consumer choice" *Journal of Economic Behavior and Organization*, 1, 39-60.

Tufano, P., 1996, “Who manages risk? An empirical examination of risk management practices in the gold mining industry,” *Journal of Finance* 51, 1097-1137.

Working, H., 1962, “New concepts concerning futures markets and prices,” *American Economic Review* 51(2), 160 – 163.

Figure 1
Change in gold price and subsequent change in hedge ratio

The figure shows the quarters with more than a one-percent increase in the price of gold together with the corresponding change in the hedge ratio in the following quarter. %GOLD: relative increase in the price of gold over quarter (t-1). CHGHR: change in the cross-sectional mean of the 3-year aggregate hedge ratio in quarter t.

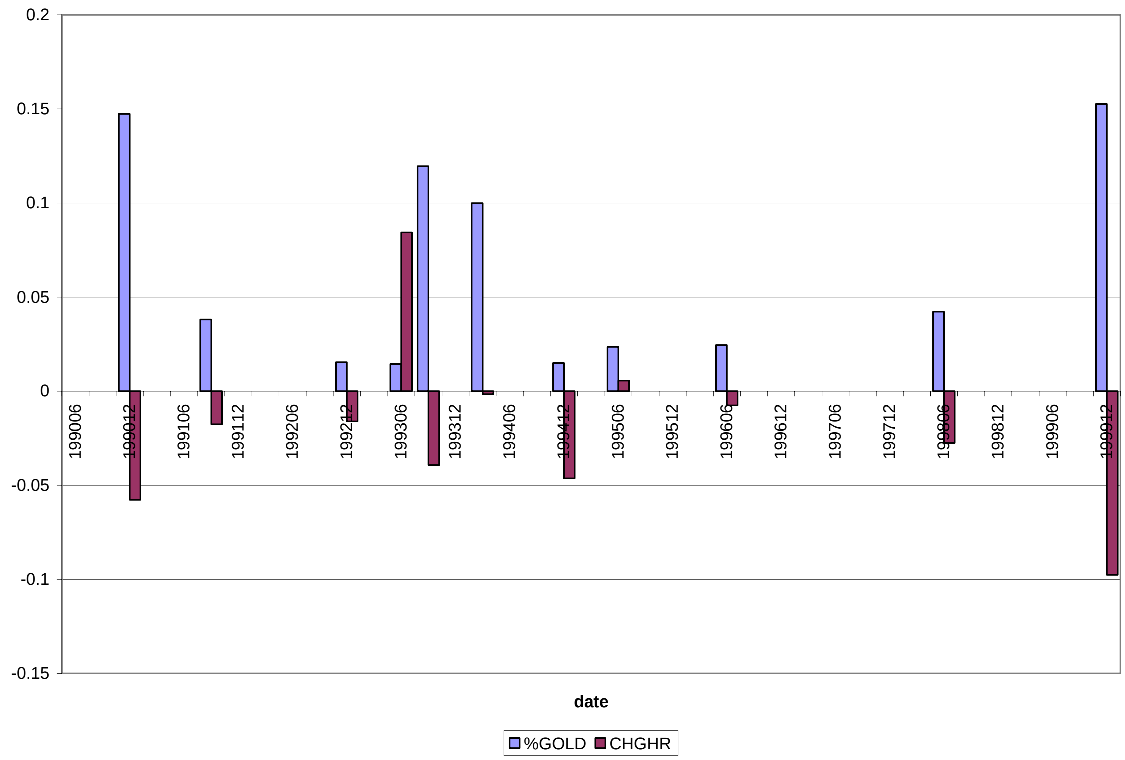

Figure 2
Hedge ratio volatility and derivatives cash flows: the industry aggregate time series

The figure shows the relationship between hedge ratio volatility and derivatives cash flows. MVH1: four-lag difference in the cross-sectional mean of the quarterly volatility of one-year-maturity hedge ratio (multiplied by 100). Quarterly volatility is computed as the absolute value of the change in the one year maturity hedge ratio over the quarter. The cross-sectional mean is estimated over all sample firms that report a nonzero value for the one year maturity hedge ratio in that quarter. MCF: four-lag difference in the cross-sectional mean of total derivative cash flows. MCF is plotted with one quarterly lag.

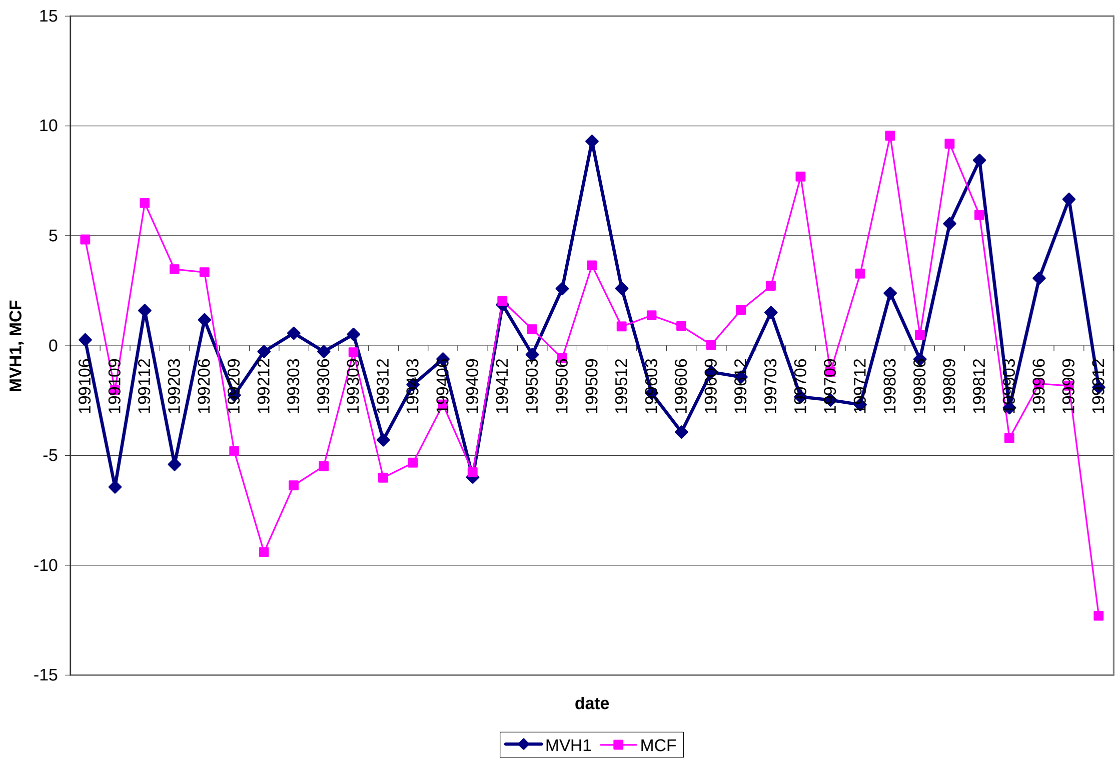

Table 1
Descriptive statistics of hedge volatility, cash flows, and firm characteristics

Descriptive statistics are estimated on the pooled dataset. The data is quarterly, 1989-1999. Variable definitions: HR1 – HR5 are the hedge ratio form one- to five-year maturities, respectively; A3 – aggregate hedge ratio that aggregates the hedge positions over one-, two-, and three-year horizons, scaled by the expected production; A3R – same as A3 but scaled by gold reserves; A5 – same as A3 but aggregating all five hedge horizons; 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; CF are the total cash flows from derivative positions per once hedged; SCF and BSF are the selective and the benchmark cash flows, estimated as in Adam and Fernando (2005); RBK is the change in the book value of the derivative positions per ounce hedged (see Appendix); GLD is the change in the price of gold over the quarter; SIZ is the logarithm of the market value of assets; 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).

Variable	Observations	Mean	St. Dev.	Minimum	Maximum
HR1	1999	0.3475	0.4407	0.0000	8.9583
HR2	2001	0.1875	0.2859	0.0000	3.4782
HR3	2019	0.0924	0.1901	0.0000	1.0540
HR4	2057	0.0423	0.1222	0.0000	1.0000
HR5	2076	0.0349	0.1432	0.0000	2.7401
A3	1708	0.2025	0.2674	0.0000	1.5794
A3R	1584	0.0611	0.0823	0.0000	0.6769
A5R	1583	0.0729	0.1007	0.0000	0.9857
V1	1785	1.2044	2.8577	0.0000	12.6554
V2	1777	1.2413	2.9964	0.0000	12.7594
V3	1803	0.8951	2.5809	0.0000	11.5656
V4	1848	0.8921	2.6466	0.0000	11.5129
V5	1882	0.5727	2.1511	0.0000	11.4742
V6	1473	0.7549	2.1984	0.0000	11.5492
V7	1448	0.8361	2.0480	0.0000	10.7767
V8	1446	0.8311	2.0564	0.0000	11.2149
CF	1914	4.7002	15.8979	-95.9039	180.1249
SCF	1927	0.0761	10.6502	-66.7713	201.8647
BCF	1914	4.6256	16.5769	-90.4059	180.1249
RBK	1876	1.8378	19.2975	-302.5117	190.6472
GLD	1907	-2.5853	18.2451	-48.9000	52.0000
SIZ	1980	5.6010	1.7469	1.0460	9.3604
MB	1029	1.8900	1.1333	0.2985	9.0819
DE	1288	0.4572	1.0503	0.0000	21.2707
QCK	1226	4.1731	9.5002	0.0065	141.5172
DIV	1372	0.4614	0.4987	0.0000	1.0000
RAT	1395	0.2394	0.4269	0.0000	1.0000
Z	1735	4.8181	13.1232	-22.8560	126.8310

Table 2

Correlations between hedge ratios, volatility, cash flows, and firm characteristics

Correlations are estimated on the pooled dataset. The data is quarterly, 1989-1999. Variable definitions: CHGHR is the change in the aggregate hedge ratio that aggregates the hedge positions over one-, two-, and three-year horizons, scaled by the expected production; VOL is the quarterly volatility of the aggregate hedge ratio. 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. LCF is the total cash flow from derivative positions per once hedged, lagged by one quarter; LSCF and LBSF are the selective and the benchmark cash flows, estimated as in Adam and Fernando (2005), lagged by one quarter; GLD is the change in the price of gold over the quarter, lagged by one quarter; SIZE is the logarithm of the market value of assets. The p-values are in parentheses.

CHGHR	VOL	GLD	LCF	LSCF	LBCF	SIZE
1.0000						
-0.1833	1.0000					
(0.0000)						
-0.1601	0.0680	1.0000				
(0.0000)	(0.0450)					
0.0791	0.0790	-0.0968	1.0000			
(0.0196)	(0.0198)	(0.0006)				
0.0931	0.0368	-0.1131	0.3140	1.0000		
(0.0059)	(0.2773)	(0.0001)	(0.0000)			
0.0038	0.0420	-0.0066	0.7127	-0.4422	1.0000	
(0.9113)	(0.2153)	(0.8159)	(0.0000)	(0.0000)		
0.0247	-0.2273	-0.0140	-0.0597	-0.0350	-0.0273	1.0000
(0.4671)	(0.0000)	(0.6395)	(0.0447)	(0.2373)	(0.3589)	

Table 3
Relationship between hedging and past gold prices

The table presents the results of the panel regressions of hedge ratio changes on past changes in the price of gold, which allow for an asymmetric response. We estimate the regression of the following general form:

$$\Delta HR_t = a + b_1 \Delta GOLD_{t-1} + b_2 (I\{\Delta GOLD_{t-1} > 0\} \cdot \Delta GOLD_{t-1}\} + CONTROLS \quad + \varepsilon$$

The dependent variable in Models 1 – 4 is ΔHR1, the change in the one-year hedge ratio. The dependent variable in Models 5 – 8 is ΔAGGHR3, the change in the three-year aggregate hedge ratio scaled by expected production. ΔGOLD is the change in the price of gold in the previous quarter. CROSSP is the cross-product of ΔGOLD and the indicator variable equal to 1 if the change in the price of gold was positive and to zero otherwise. ΔSIZE is the change in the firm size (natural logarithm of the market value of assets) in the previous quarter. ΔZSCORE is the change in the firm's Z-score computed following Altman (1968) in the previous quarter. ΔQUICK is the change in the quick ratio. All of the models include seasonal dummy variables. The regressions are estimated on the whole sample. **, *, + indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics accounting for cluster effects are given in parentheses.

	Change in HR1				Change in AGGHR3			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Intercept	0.0163	0.0447 **	0.0495 **	0.0357 +	0.0085 *	0.0193 **	0.0187 **	0.0159 +
	(1.25)	(2.89)	(2.70)	(1.89)	(1.98)	(3.44)	(2.82)	(1.88)
ΔGOLD	-0.0022 **	-0.0003	-0.0003	-0.0005	-0.0006 **	0.0001	-0.0001	0.0000
	(-3.93)	(-0.46)	(-0.46)	(-0.93)	(-3.36)	(0.49)	(-0.19)	(-0.13)
CROSSP		-0.0035 **	-0.0038 **	-0.004 **		-0.0013 **	-0.0014 *	-0.0012 +
		(-3.02)	(-3.08)	(-2.66)		(-2.66)	(-2.24)	(-1.62)
ΔSIZE			0.0909 *	0.0551			0.0536 *	0.0349
			(2.27)	(1.23)			(2.35)	(1.52)
ΔZSCORE			0.0002				0.0001	
			(0.71)				(0.14)	
ΔQUICK				0.0019 **				0.0005 **
				(4.68)				(2.60)
Dummies	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.0769	0.0846	0.0988	0.1146	0.0537	0.058	0.0804	0.0809
F-statistic	12.69	10.33	7.27	6.16	9.17	8.72	7.64	5.51
No. of Obs.	1674	1674	1297	782	1374	1374	1091	675
Clusters	97	97	73	45	90	90	66	40

Table 3A
Short-term hedging and past gold prices: nonlinear effects

The table presents the results of the panel regressions of hedge ratio changes on past changes in the price of gold, which allow for an asymmetric response as well as nonlinear effects. We estimate two regressions:

$$\Delta HR_t = a_1 + [b_1 + b_2 I\{\Delta GOLD_{t-1} > 0\}] \cdot \Delta GOLD_{t-1} + [b_3 + b_4 I\{\cdot \Delta GOLD_{t-1} > 0\}] \cdot HR_{t-1} \cdot \Delta GOLD_{t-1} + CONTROLS + \varepsilon_{1t}$$

$$\Delta HR_t = a_2 + [c_1 + c_2 I\{\Delta GOLD_{t-1} < 0\}] \cdot \Delta GOLD_{t-1} + [c_3 + c_4 I\{\cdot \Delta GOLD_{t-1} < 0\}] \cdot HR_{t-1} \cdot \Delta GOLD_{t-1} + CONTROLS + \varepsilon_{2t}$$

The dependent variable is the change in the one-year hedge ratio. ΔGOLD is the change in the price of gold in the previous quarter. I is the indicator variable: in the first regression, I = 1 if ΔGOLD > 0, and I = 0 otherwise; in the second regression, I = 1 if ΔGOLD < 0, and I = 0 otherwise. ΔSIZE is the change in the firm size in the previous quarter. ΔZSCORE is the change in the firm's Altman (1968) Z-score in the previous quarter. ΔQUICK is the change in the quick ratio. HR is the level of the hedge ratio at the beginning of the current quarter. All of the models include seasonal dummy variables. The regressions are estimated on the whole sample. **, *, + indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics accounting for cluster effects are given in parentheses.

I = 1 if ΔGOLD > 0, I = 0 otherwise				I = 1 if ΔGOLD < 0, I = 0 otherwise			
	Model 1	Model 2	Model 3		Model 1	Model 2	Model 3
Intercept	0.0200	0.0313 +	0.0233	Intercept	0.0200	0.0313 +	0.0233
	(1.31)	(1.75)	(1.24)		(1.31)	(1.75)	(1.24)
B1	-0.0059 **	-0.0064 **	-0.0055 **	C1	0.0054 **	0.0053 **	0.0046 **
	(-6.00)	(-5.23)	(-4.33)		(5.30)	(4.49)	(5.09)
B2	0.0113 **	0.0117 **	0.0101 **	C2	-0.0113 **	-0.0117 **	-0.0101 **
	(6.55)	(5.59)	(5.06)		(-6.55)	(-5.59)	(-5.06)
B3	0.0138 **	0.0143 **	0.0123 **	C3	-0.0172 **	-0.0170 **	-0.0174 **
	(6.25)	(5.78)	(5.46)		(-8.11)	(-6.79)	(-7.41)
B4	-0.0309 **	-0.0313 **	-0.0297 **	C4	0.0309 **	0.0313 **	0.0297 **
	(-9.53)	(-7.96)	(-7.59)		(9.53)	(7.96)	(7.59)
ΔSIZE		0.0847 *	0.0503	ΔSIZE		0.0847 *	0.0503
		(2.28)	(1.22)			(2.28)	(1.22)
ΔZSCORE		0.0006		ΔZSCORE		0.0006	
		(1.38)				(1.38)	
ΔQUICK			0.0020 **	ΔQUICK			0.0020 **
			(5.07)				(5.07)
Dummies	YES	YES	YES	Dummies	YES	YES	YES
R^2	0.3460	0.3801	0.5143	R^2	0.3460	0.3801	0.5143
F-statistic	22.53	16.03	15.69	F-statistic	22.53	16.03	15.69
No. of Obs.	1674	1297	782	No. of Obs.	1674	1297	782
Clusters	97	73	45	No. of Clusters	97	73	45

Table 3B
Aggregate hedging and past gold prices: nonlinear effects

The table presents the results of the panel regressions of hedge ratio changes on past changes in the price of gold, which allow for an asymmetric response as well as nonlinear effects. We estimate two regressions:

$$\Delta HR_t = a_1 + [b_1 + b_2 I\{\Delta GOLD_{t-1} > 0\}]\cdot \Delta GOLD_{t-1} + [b_3 + b_4 I\{\cdot \Delta GOLD_{t-1} > 0\}]\cdot HR_{t-1}\cdot \Delta GOLD_{t-1} + CONTROLS + \varepsilon_{1t}$$

$$\Delta HR_t = a_2 + [c_1 + c_2 I\{\Delta GOLD_{t-1} < 0\}]\cdot \Delta GOLD_{t-1} + [c_3 + c_4 I\{\cdot \Delta GOLD_{t-1} < 0\}]\cdot HR_{t-1}\cdot \Delta GOLD_{t-1} + CONTROLS + \varepsilon_{2t}$$

The dependent variable is the change in the three-year aggregate hedge ratio scaled by expected production. ΔGOLD is the change in the price of gold in the previous quarter. I is the indicator variable: in the first regression, I = 1 if ΔGOLD > 0, and I = 0 otherwise; in the second regression, I = 1 if ΔGOLD < 0, and I = 0 otherwise. ΔSIZE is the change in the firm size in the previous quarter. ΔZSCORE is the change in the firm's Altman (1968) Z-score in the previous quarter. ΔQUICK is the change in the quick ratio. HR is the level of the hedge ratio at the beginning of the current quarter. All of the models include seasonal dummy variables. The regressions are estimated on the whole sample. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics accounting for cluster effects are given in parentheses.

I = 1 if ΔGOLD > 0, I = 0 otherwise				I = 1 if ΔGOLD < 0, I = 0 otherwise			
	Model 1	Model 2	Model 3		Model 1	Model 2	Model 3
Intercept	0.0152 **	0.0152 **	0.0132 +	Intercept	0.0152 **	0.0152 **	0.0132 +
	(3.09)	(2.53)	(1.84)		(3.09)	(2.53)	(1.84)
B1	-0.0011 **	-0.0016 **	-0.0015 **	C1	0.0007 *	0.0007 +	0.0004
	(-3.11)	(-3.34)	(-3.19)		(2.00)	(1.83)	(1.24)
B2	0.0018 **	0.0024 **	0.0019 **	C2	-0.0018 **	-0.0024 **	-0.0019 **
	(2.96)	(3.02)	(2.67)		(-2.96)	(-3.02)	(-2.67)
B3	0.0059 **	0.0064 **	0.0053 *	C3	-0.0071 **	-0.0074 **	-0.0055 *
	(3.09)	(3.11)	(2.21)		(-3.46)	(-3.28)	(-2.36)
B4	-0.0130 **	-0.0138 **	-0.0108 *	C4	0.0130 **	0.0138 **	0.0108 *
	(-3.60)	(-3.51)	(-2.42)		(3.60)	(3.51)	(2.42)
ΔSIZE		0.0527 *	0.0358	ΔSIZE		0.0527 *	0.0358
		(2.48)	(1.66)			(2.48)	(1.66)
ΔZSCORE		0.0002		ΔZSCORE		0.0002	
		(0.57)				(0.57)	
ΔQUICK			0.0006 **	ΔQUICK			0.0006 **
			(2.76)				(2.76)
Dummies	YES	YES	YES	Dummies	YES	YES	YES
R^2	0.0852	0.1090	0.1046	R^2	0.0852	0.1090	0.1046
F-statistic	8.88	8.21	7.88	F-statistic	8.88	8.21	7.88
No. of Obs.	1374	1091	675	No. of Obs.	1374	1091	675
Clusters	90	66	40	Clusters	90	66	40

Table 4
Panel regressions of hedge ratio volatility on past cash flows and profits

The table presents the results of the panel regressions with firm fixed effects. The dependent variable is the volatility of the aggregate three-year hedge ratio scaled by expected production. Hedge ratio volatility is estimated as the absolute value of the difference in the logs of the three-year aggregate hedge ratio in the end and the beginning of the quarter. The independent variables are as follows: CF is the total derivative cash flow; SCF is the selective cash flow; BCF is the benchmark cash flow; RBK is the change in the book value of derivative positions; ZSCORE is the Altman's Z-score (higher value of Z-score correspond to lower chance of bankruptcy); AGGHR3: aggregate three-year hedge ratio scaled by expected production. All independent variables are taken with one quarterly lag, except for Altman's Z-score, which is contemporaneous with the dependent variable. Seasonal dummies are included in each of the models. **, *, + indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics corrected for cluster effects are reported in parentheses.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	0.8552 **	0.8487 **	0.9542 **	0.8665 **	0.8603 **	0.9067 **	1.5246 **
	(6.86)	(6.74)	(7.79)	(6.88)	(6.78)	(5.33)	(5.67)
CF	0.0164 *			0.0164 *			
	(2.46)			(2.45)			
SCF		0.0193 **			0.0195 **	0.0180 *	0.0123
		(2.53)			(2.53)	(2.16)	(1.58)
BCF		0.0160 *			0.0160 *	0.0121 *	0.0098
		(2.38)			(2.37)	(1.98)	(1.64)
RBK			-0.0015	-0.0015	-0.0016	-0.0025	-0.0029
			(-0.76)	(-0.78)	(-0.81)	(-1.14)	(-1.31)
ZSCORE						-0.0446	-0.0608 *
						(-1.39)	(-2.09)
AGGHR3							-1.8047 *
							(-2.94)
Dummies	YES	YES	YES	YES	YES	YES	YES
R^2 overall	0.0144	0.0150	0.0096	0.0149	0.0156	0.0137	0.054
F-statistic	3.66	3.42	2.44	3.22	3.06	2.51	2.37
No. of Obs.	871	871	870	870	870	786	786
Clusters	67	67	67	67	67	56	56

Table 5
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: SIZE –the logarithm of book value of assets; MKTOBK – the market-to-book ratio of assets; DBTEQ – the ratio of book value of debt to the book value of equity; QUICK – the quick ratio; DIVDUM – dividend dummy equal to one in the quarter when the a firm paid quarterly dividends; RATINGDUM – the dummy variable equal to one if the firm has credit rating; ZSCORE – Altman's Z-score (lower value of Z-score correspond to higher probability of financial distress). Z-statistics are in parentheses. Pseudo-R^2 is reported.

Intercept	0.6398	*
	(2.18)	
SIZE	0.1979	**
	(3.30)	
MKTOBK	-0.2830	**
	(-3.17)	
DBTEQ	-0.1822	*
	(-2.40)	
QUICK	-0.0910	**
	(-4.90)	
DIVDUM	-0.1949	
	(-1.12)	
RATINGDUM	0.1353	
	(0.84)	
ZSCORE	-0.0298	+
	(-1.68)	
R^2	0.1247	
Chi^2	83.01	
No. of Obs.	642	

Table 6
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. On the first stage (see Table 5), 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 derivative 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 three-year aggregate hedge ratio scaled by expected production from the beginning to the end of the quarter. The second-stage independent variables are as follows. CF is the total derivative cash flow; SCF is selective cash flow; BCF is the benchmark cash flow; RBK is the change in the book value of derivative positions; ZSCORET is the Altman's (1968) Z-score (higher value of Z-score corresponds to lower chance of bankruptcy); AGGHR3 is the three-year aggregate hedge ratio scaled by expected production. All dependent variables are taken with one quarterly lag, except for Altman's Z-score, which is contemporaneous with the dependent variable. Seasonal dummies are included in each model. The regressions include the Inverse Mill's 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.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	0.0353	0.0214	0.2113	0.0462	0.0350	0.1421	0.7875
	(0.09)	(0.05)	(0.50)	(0.11)	(0.08)	(0.33)	(1.52)
CF	0.0256 *			0.0257 *			
	(2.38)			(2.37)			
SCF		0.0360 **			0.0366 **	0.0326 *	0.0256 *
		(2.81)			(2.83)	(2.42)	(2.04)
BCF		0.0240 *			0.0240 *	0.0230 *	0.0204 +
		(2.35)			(2.34)	(2.06)	(1.94)
RBK			-0.0012	-0.0015	-0.0020	-0.0015	-0.0019
			(-0.56)	(-0.67)	(-0.84)	(-0.69)	(-0.77)
ZSCORET						-0.1420 *	-0.1107
						(-2.14)	(-1.57)
AGGHR3							-1.5725 **
							(-3.19)
Inverse Mill's	2.5284 +	2.5285 +	2.4130	2.5277 +	2.5171 +	3.5715 *	2.9712 +
	(1.73)	(1.73)	(1.66)	(1.73)	(1.73)	(2.01)	(1.70)
Dummies	YES	YES	YES	YES	YES	YES	YES
R^2	0.0594	0.0621	0.0387	0.0598	0.0626	0.0916	0.1293
F-statistic	2.59	2.49	1.66	2.18	2.13	2	2.13
No. of Obs.	396	396	396	396	396	396	396
Clusters	43	43	43	43	43	43	43

Table 7
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 derivative positions, which allow for an asymmetric response of the following general form:

$$VOL_t = a + b_1 CF_{t-1} + b_2 (I\{CF_{t-1} > 0\} \cdot CF_{t-1}\} + \varepsilon$$

VOL1 is the quarterly volatility of the one-year hedge ratio; VOL6 is the quarterly volatility of the three-year aggregate hedge ratio scaled by expected production; VOL7 is the quarterly volatility of the three-year aggregate hedge ratio scaled by reserves; VOL8 is the quarterly volatility of the five-year aggregate hedge ratio scaled by reserves. 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. CF is the total derivative cash flow in the previous quarter. CFCP is the cross-product of CF and the indicator variable I{CF >0} that takes a value of one when CF>0. Seasonal dummies are included in each model. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics corrected for cluster effects are reported in parentheses.

	VOL1	VOL6	VOL7	VOL8
Intercept	0.6737 **	0.7293 **	0.5781 **	0.6114 **
	(3.51)	(4.87)	(4.76)	(5.15)
LCF	-0.0227 **	-0.005	-0.022 **	-0.0207 **
	(-2.16)	(-0.63)	(-3.21)	(-2.86)
CFCP	0.0685 **	0.0341 **	0.0479 **	0.0456 **
	(4.73)	(2.65)	(5.42)	(5.28)
Dummies	YES	YES	YES	YES
R^2	0.0544	0.0318	0.0273	0.0257
F-statistic	9.16	3.06	7.72	7.45
No. of Obs.				
Total	1113	871	997	995
Positive	807	626	716	716
Negative	306	245	281	279
Clusters	84	67	63	63

Table 8
Testing for asymmetric volatility response with selection

The table presents the results of the second stage of the Heckman two – step procedure with selection. We estimate a linear regression of the three-year aggregate hedge ratio volatility on past cash flows from derivative positions, which allow for an asymmetric response, of the following general form:

$$VOL_t = a + b_1 CF_{t-1} + b_2 (I\{CF_{t-1} > 0\} \cdot CF_{t-1}\} + \varepsilon$$

VOL is the quarterly volatility of the three-year aggregate hedge ratio. The volatility is estimated as the absolute value of the difference in the logs of the three-year aggregate hedge ratio in the end and the beginning of the quarter. CF: total derivative cash flow; CFCP is the cross-product of CF and the indicator variable I{CF >0} that takes a value of one when CF>0. The independent variables CF and CFCP are lagged by one quarter. Control variables: SIZE is the firm size (natural logarithm of the market value of assets); ZSCORE is the firm's Z-score computed following Altman (1968). Seasonal dummies are included in each model. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Robust t-statistics corrected for cluster effects are reported in parentheses.

The inverse Mill's ratio is obtained on the first stage of the Heckman procedure. The results of the first stage are reported in Table 5. On the first stage, we estimate the PROBIT regression of hedging activity on firm characteristics: size, market-to-book, quick ratio, leverage, dividend dummy, credit rating dummy, and Altman's (1968) Z-score. Hedging activity is defined as the quarter in which the firm has at least one non-zero hedge ratio (either in the beginning or at the end of the quarter); and where past cash flows from derivative positions were non-zero.

	Model 1	Model 2
Intercept	-0.2342	2.1247 +
	(-0.57)	(1.69)
CF	-0.0163 +	-0.0164 *
	(-1.84)	(-2.07)
CFCP	0.0644 **	0.0617 **
	(2.63)	(2.46)
SIZE		-0.2837 *
		(-2.14)
ZSCORE		-0.0524
		(-0.71)
Inverse Mill's Ratio	2.6554 +	2.0877
	(1.81)	(1.09)
Dummies	YES	YES
R^2	0.0792	0.1273
F-statistic	2.49	2.49
No. of Obs.	396	396
Clusters	43	43