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Hedging, hedge accounting, and earnings predictability

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Abstract
Studies suggest that, pursuant to the implementation of SFAS 133, even sophisticated users of financial statements find it difficult to comprehend earnings implications of hedging derivatives. Moreover, due to stringent hedge accounting requirements under these standards, many economic hedges do not qualify for hedge accounting and are deemed "ineffective" for financial reporting purposes. Motivated by these considerations, we investigate the impact of hedging on earnings predictability by analyzing hand-collected hedging data from two industries that extensively use derivatives to manage price risks: the oil-and-gas exploration and production industry and the airline industry. In contrast to extant evidence, we find that overall hedging derivatives improve income predictability and increase (decrease) analysts' forecast accuracy (dispersion). We also show hedges deemed ineffective for hedge accounting can increase earnings volatility and significantly impair earnings predictability. This finding lends support to concerns expressed by some corporate managers and industry experts against stringent hedge accounting requirements.

Keywords Financial analysts · Earnings forecasts · Derivatives · Hedging · Hedge ineffectiveness

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1 Introduction

We use a sample of oil-and-gas exploration and production (henceforth "oil-and-gas companies") and airline firms to investigate the impact of derivative hedging on earnings predictability under prevailing accounting standards.[1] Under SFAS 133, when derivatives are used effectively for hedging purposes, cash flow and earnings volatility should decrease, making earnings easier to predict, all else equal. Yet evidence indicates otherwise. Campbell et al. (2015) show that financial analysts fail to understand profitability implications of unrealized hedging gains and losses from cash flow hedges once they expire, and therefore their longer term two-year and three-year-ahead earnings forecasts are adversely affected. Chang et al. (2016) find that analysts' earnings forecasts become *less accurate* and *more dispersed* following initiations of derivatives by firms for hedging purposes and attribute this result to analysts' limited ability to understand complex derivative financial instruments and their financial statement effects from the detailed disclosures provided under SFAS 133.

In many industries, such as the ones we examine in this paper, hedging is an ongoing activity, as firms try to shield themselves from risk exposures in the input and output markets. To the extent new hedges are routinely put in place to replace expiring hedges, earnings are not likely to be fully exposed to price changes in hedged items. Similarly, if derivative programs are initiated to either fully or partially mitigate the effects of existing or new risk exposures, it seems reasonable to expect earnings and cash flows to become more predictable. In essence, if hedging serves its intended purpose, the notion that the onerous reporting requirements of SFAS 133 adversely affect analysts' forecasting ability is intriguing and warrants further attention.

We provide new insights into this issue by examining how the hedge accounting requirements of SFAS 133 incorporate the economics of hedging into accounting earnings. Many practitioners and policymakers—including the former chairman of the Federal Reserve, Alan Greenspan—have expressed concern that the hedge accounting requirements of SFAS 133 introduce "artificial and inappropriate" financial statement volatility, even when firms use derivatives purely for hedging purposes (Bankers' Roundtable 1997).[2] These concerns relate to the income statement impact of "ineffective" hedges—those that offer partial risk management benefits but do not qualify for hedge accounting under SFAS 133.

Intuitively, *any* hedge should decrease income volatility to the extent it reduces some degree of the underlying risk exposure and cash flow volatility—the "economic effect." Hedging serves no purpose without this economic benefit. Despite this benefit, under SFAS 133, hedges can either be designated "effective" and qualify for hedge accounting, or "ineffective" in which case they do not qualify for hedge accounting. For an effective cash flow hedge, periodic changes in its fair value are recorded in other comprehensive income (OCI) *until* the period in which the hedge is consummated, at which time the changes in fair value of *both* the hedging derivative and the hedged item

[1] Under the FASB Accounting Standards Codification, the legacy statement SFAS 133 is covered in Topic 815. Nonetheless, throughout this paper, we refer to SFAS 133 because extant hedge accounting rules were first introduced by this standard.

[2] See Berton (1994), McKay and Niedzielski (2000), Osterland (2000), Hwang and Patouhas (2001), and MacDonald (1997).

are released to earnings.[3,4] More importantly, the income statements of the interim periods are not exposed to the changes in the fair value of effective hedges. On the other hand, for an ineffective hedge, SFAS 133 stipulates that periodic changes in its fair value flow directly to interim income statements, even as the hedge itself remains active. Thus, as critics contend, this treatment accorded to ineffective hedges results in an "accounting effect" that could increase over-time income volatility, all else equal.[5] Our objective is to empirically investigate this effect as a possible explanation for why analysts' forecasting may have been hampered by the implementation of SFAS 133.

In assessing the overall income statement impact of hedges, it is important to *jointly* consider both their economic and accounting effects. Perfect hedges that fully offset risk exposures do not give rise to accounting effects, because they will meet the hedge accounting criteria of SFAS 133. Therefore, perfect hedges should unambiguously reduce income volatility. However, perfect hedges may not always be available, in which case most firms seek imperfect hedges that offset these risk exposures to the extent possible.[6] Imperfect hedges that do not qualify as effective hedges for accounting purposes can affect income volatility in two ways—a volatility-decreasing economic effect and a volatility-increasing accounting effect. Consequently, their net income volatility effect is not clear. (In Appendix A, we provide a numerical example of the economic and accounting effects of hedges that do not qualify for hedge accounting.)[7] Moreover, because ineffective hedges comprise a significant portion of the hedging portfolios of many firms, especially in oil-and-gas and airline industries, the overall impact of a firm's hedging portfolio on income volatility is also not clear.[8]

Therefore, as firms continue to employ both effective and ineffective hedges to offset risk exposures, some important questions loom. What is the net effect of hedging derivatives on earnings predictability and the forecasting efficacy of financial analysts?

[3] For a detailed description of the hedge accounting rules that determine whether a hedge is effective or ineffective, see Appendix A.

[4] For fair value hedges that qualify for hedge accounting, both the derivative and the underlying asset or liability are marked to market every period, effectively ensuring that the income statement is shielded from fair value fluctuations since the fair value of the derivative and the underlying move in opposite directions. We do not discuss fair value hedges since the derivatives discussed in this paper are exclusively cash flow hedges.

[5] Proponents of SFAS 133 claim that these hedge accounting rules "… do not create volatility but only unmask it," contending that SFAS 133 only requires the reporting of volatility that always existed but was not previously reported (Smith et al. 1998).

[6] For example, a North Dakota-based crude oil producer may use West Texas intermediate crude price-based futures contracts to hedge price risk of its production, because the latter are the most readily available and widely traded crude oil futures on the NYMEX. While prices of crude oil from North Dakota and West Texas would be positively correlated, the correlation would not be perfect, making the derivative instrument a less than perfect hedge in managing the firm's oil price risk.

[7] As noted in Appendix A, a hedging derivative the value of which changes 75 cents in the opposite direction for every one dollar change in the price of the hedged item would substantially (albeit imperfectly) offset the underlying price risk but would not qualify as an effective hedge for hedge accounting purposes. Moreover, even highly effective hedges might be disqualified from hedge accounting in the absence of formal documentation of the hedging relationship and the entity's risk management objectives and strategy (SFAS 133, ¶20a). In these instances, the accounting effect could outweigh the economic effect resulting in a net *increase* in income volatility.

[8] Appendix B provides some illustrative examples of hedge ineffectiveness disclosures from firms in oil-and-gas and airline industries.

How do ineffective hedges impact earnings predictability? Can hedging cause earnings to become *less* predictable than without hedging? We address these questions in this paper.

As noted previously, we conduct our empirical analysis in the context of the U.S. oil-and-gas exploration and production industry and the airline industry. Oil-and-gas (airline) firms use derivative instruments, such as futures, forward contracts, swaps, and options to hedge substantial price risk associated with oil-and-gas output (jet fuel expense). Prior research identifies these industries as being ideal for investigating issues relating to derivatives because the extent of derivative usage for hedging is economically significant and can be accurately measured (Haushalter 2000; Pincus and Rajgopal 2002; Carter et al. 2006; Jin and Jorion 2006; Kumar and Rabinovitch 2013; Lobo et al. 2020). These firms are particularly useful in investigating the issue of accounting hedge ineffectiveness because they use derivatives primarily for hedging purposes and because ineffective hedges comprise a substantial portion of their overall hedging portfolios.[9]

We hand-collect data on hedging derivative usage for U.S. oil-and-gas and airline firms. We find that analysts' forecasting ability improves, on average, with the extent of overall derivative usage for both groups of firms. To further verify causality, we examine the relation between *changes* in derivative usage and *change* in analysts' forecast properties and find that increases in derivative usage are associated with increases (decreases) in earnings forecast accuracy (dispersion). These results contrast with the findings of Chang et al. (2016), who observe derivative initiations to be associated with lower analyst forecast accuracy and higher dispersion. Our findings indicate that overall the economic effects of hedging more than offset the adverse accounting effects attributable to ineffective hedges; that is, hedging improves earnings predictability, despite many firms using ineffective hedges.

We next draw our attention to the role of hedge ineffectiveness. For this purpose, we also hand-collect data on hedge ineffectiveness. Our results indicate that the presence of ineffective hedges indeed adversely affect earnings predictability associated with hedging. For both oil-and-gas and airline firms that hold some ineffective hedges, we no longer observe analysts' earnings forecasts to have higher accuracy and lower dispersion when compared with those firms with no hedging. That is, despite the economic effect, when hedge ineffectiveness is present, hedging does not appear to have an overall positive (negative) effect on forecast accuracy (dispersion).

However, the central criticism leveled against SFAS 133 is that stringent hedge accounting rules potentially make income more volatile than if there were no hedges in the first place. To directly address the validity of this criticism, we need to isolate the income volatility effects of ineffective hedges from those of effective hedges. To achieve this end, we restrict our attention to a subsample of oil-and-gas and airline firms where all hedging derivatives are disclosed as either "fully" effective or "fully" ineffective.

As expected, we find a positive association between hedging and analysts' forecasting ability for firms that hold effective hedges only. Thus, when hedges are effective, analysts do not seem to be hindered by their apparent inability to decipher detailed reporting under SFAS 133 and understand the earnings implications of hedging. Moreover, we find that hedging impairs forecasting ability for both oil-and-gas and airline firms that hold only ineffective hedges. Indeed, analyst forecasts of these firms

[9] Other heavy derivative-user industries include banking and integrated oil. Firms in these industries hold both hedging and trading derivatives, making it difficult to isolate the income statement impact of accounting hedge ineffectiveness from that of trading derivatives.

appear less accurate and more dispersed than when *no* hedges are employed.[10] In other words, the accounting treatment of ineffective hedges appears to be inducing substantial and likely artificial income volatility, supporting the critics of SFAS 133.

Our paper makes two important contributions to the understanding of how extant derivative accounting rules affect earnings predictability. First, focusing on two industries where the extent of hedging is economically meaningful and employing both level and change analyses, we find that on average derivative hedging improves earnings predictability, even though many of our sample firms hold ineffective hedges.[11] This result contrasts sharply with existing evidence on the impact of hedging on the forecasting efficacy of financial analysts (Campbell 2015; Campbell et al. 2015; Chang et al. 2016). The choice of the setting is important in derivative studies because, as argued by Guay and Kothari (2003), the economic magnitude of derivative usage tends to be rather marginal in broad industrial firms.

Second, to the best of our knowledge, ours is the first paper to directly examine the impact of hedge ineffectiveness introduced by SFAS 133 on earnings predictability. As previously mentioned, a major criticism levelled against the hedge accounting requirements of SFAS 133 is that they induce "artificial and inappropriate" income volatility. Our findings indicate that this criticism has merit. Therefore, our paper potentially informs the FASB's ongoing efforts to simplify hedge accounting rules.[12] One policy implication of our results is that regulators should perhaps consider relaxing stringent thresholds applied and be guided more by the intent to capture the economic benefit in the determination of hedge effectiveness for accounting purposes.

The paper proceeds as follows. Section 2 presents a simple theoretical framework to demonstrate how hedge accounting could either increase or decrease earnings volatility and develops our hypotheses. (The mathematical details of the model are in Appendix C.) Section 3 discusses our setting, data, and research design. Section 4 reports our main results on the link between derivative usage and analyst forecast properties. Section 5 presents results of additional analyses. Section 6 concludes.

2 Theory and hypotheses

2.1 Theoretical framework

We begin our analysis by developing a simple theoretical model to demonstrate how hedge accounting affects earnings volatility. We consider a firm that is exposed to price risk of an input/output item on an ongoing basis and wishes to hedge against period-specific fluctuations (i.e., gain or loss) of this item. Each period, the firm closes some

[10] The only exception is forecast dispersion of airline firms where we fail to find a statistically significant difference between hedging with only ineffective hedges and not hedging at all.

[11] The descriptive statistics reveal that oil-and-gas firms in our sample hedge the price risk of 44% of their output with derivatives, while airlines hedge 42% of the cost of aviation fuel with derivatives.

[12] A recent FASB Standards-update attempts to make it easier for firms to qualify their derivatives for hedge accounting by relaxing some of the onerous documentation and monitoring requirements (FASB 2017). These changes, which came into effect for fiscal years beginning after December 15, 2018, would allow firms to apply hedge accounting for more derivative instruments than before. However, the FASB update does not address the effectiveness thresholds applicable for a derivative to qualify for hedge accounting or the accounting treatment of derivatives that fail to meet these thresholds.

hedging positions, because of the culmination of underlying transactions, and opens fresh positions to cover new origination.

For hedging to be economically beneficial, the net variance in gain or loss from the risk source after hedging must be less than that before hedging. We model a *perfect* hedge as one that eliminates this risk and an *imperfect* hedge as one that only reduces but does not eliminate the risk. We model SFAS 133 as placing an upper bound on the extent of imperfection allowed in a hedge to qualify as an effective hedge for accounting purposes. Thus, in our model, a hedge can be *economically beneficial* because it offsets some of the risk but still need not qualify as an effective hedge for accounting purposes. On the other hand, an imperfect hedge can qualify as effective if the level of imperfection is considered tolerable as per SFAS 133.

We present a detailed mathematical analysis of this model in Appendix C. Two key insights emerge from this model. First, as we would expect, fully effective hedging always decreases earnings volatility. Second, hedges that are deemed ineffective under SFAS 133 could *increase* earnings volatility, because of the immediate recognition of gains and losses associated with the ineffective hedging derivatives, supporting concerns expressed by practitioners and policymakers relating to the adoption of SFAS 133 (as noted previously). These insights provide a theoretical basis for our ensuing empirical analysis.

2.2 Hypotheses

All else equal, the economic effect of hedging in offsetting risk exposures should result in more predictable income streams, making forecasting easier. Disagreements between analysts should also attenuate, resulting in lower forecast dispersion. However, studies find that market participants, including financial analysts, have difficulty understanding financial implications of derivative hedging (Campbell 2015; Campbell et al. 2015; Chang et al. 2016).

However, as our theoretical model demonstrates, whether hedges qualify for hedge accounting under SFAS 133 has important implications for income volatility. *Effective* hedges that do qualify reduce income volatility, because they are only associated with volatility-decreasing economic effect with no countervailing accounting effect. The same is not necessarily the case for the ineffective hedges that do not qualify. Ineffective hedges can have two opposing effects on earnings—a volatility-decreasing economic effect and a volatility-increasing accounting effect, as demonstrated by our model.[13] Because firms typically hold both effective as well as ineffective hedges, both economic and accounting effects are likely to co-exist in any given period. Therefore, the net effect of hedging derivatives on earnings predictability is unclear. Hence, we state our first hypothesis in the null form, as follows.

> **H1**: *Analyst forecast accuracy and dispersion are not associated with the extent of derivative usage.*

To ascertain a causal link between the extent of derivative usage and analyst forecast properties, we also test H1 using a *change* specification—that is, we study the relation between *changes* in derivative usage and *changes* in forecast accuracy and dispersion.

[13] At times, even otherwise perfect hedges may be deemed ineffective and fail to qualify for hedge accounting, due to a lack of required documentation.

Next, we focus more squarely on how hedge ineffectiveness affects analysts' earnings forecasts. Putting analysts' ability to judge financial implications of hedging aside, any hedge can be expected to have a volatility-decreasing economic benefit to the extent that it limits a firm's risk exposure. However, a hedge that does not qualify for hedge accounting (i.e., an ineffective hedge) has a volatility-increasing accounting effect as well. Therefore, we expect the presence of ineffective hedges to have an incremental adverse impact on the relationship between analysts' forecast properties and the extent of hedging, all else equal. Accordingly, we test the following hypothesis (alternative form), as follows.

> **H2**: *Ineffective hedges have an incrementally negative (positive) effect on the association between analyst forecast accuracy (dispersion) and the extent of derivative usage.*

As a stark test of the impact of ineffective hedging on earnings volatility and the forecasting efficacy of financial analysts and to obtain a clearer picture on the critique that SFAS 133 induces artificial income volatility, we also investigate a subsample consisting of observations in which firms disclose their entire derivative portfolios to be either *effective* or *ineffective* in terms of hedge accounting. When derivative portfolios comprise effective hedging derivatives only, there is no "accounting effect" to speak of. In this case, we should expect forecast accuracy to improve. Any evidence to the contrary would lend support to the notion that analysts have difficulty deciphering complex derivative disclosures.

On the other hand, if the entire derivative portfolio fails to qualify for hedge accounting, earnings volatility is then subject to both economic and accounting effects as previously discussed, and the impact of the latter effect is likely to be especially large. Therefore, examining these two subsamples will enable us to obtain a clear understanding of how the accounting effect of ineffective hedges impacts analysts' forecasts.

3 Setting, data, and research design

3.1 Setting and data

As previously noted, we examine the relation between hedging derivative usage and earnings predictability in the context of production (output) price hedging in the U.S. oil-and-gas exploration and production industry and jet fuel consumption (input) cost hedging in the U.S. airline industry.

Oil-and-gas firms extract crude oil and natural gas and sell them "as is" at the wellhead. These firms have a natural incentive to hedge fluctuations in output prices with derivative instruments to fix the prices in advance and reduce risk exposure. Because of the heavy use of derivatives, the literature has recognized the oil-and-gas industry as an ideal setting to investigate issues relating to hedging derivatives (e.g., Haushalter 2000; Pincus and Rajgopal 2002; Jin and Jorion 2006; Kumar and Rabinovitch 2013; Lobo et al. 2020).

Volatility of jet fuel prices imposes significant risks for airline companies, as jet fuel expense is a major operating cost.[14] Competition restricts the extent to which airline

[14] Jet fuel expense is either the largest or the second-largest expense line item in airline income statements. (In some periods, the largest line item is salaries, wages, and benefits.)

firms can pass on fuel price increases to customers. Airlines often manage this risk by entering into derivative contracts to fix their fuel consumptions prices (Carter et al. 2006). Since derivative contracts on jet fuel are not exchange-traded, many airlines use heating oil and crude oil derivatives as substitutes.

These industries provide us with settings in which derivative usage can be accurately measured in relation to underlying exposure (i.e., production quantity and jet fuel consumption). Carrying out industry-level analyses also alleviates omitted correlated variable problems caused by industry heterogeneity (Guay and Kothari 2003; Jin and Jorion 2006). Further, examining contexts where derivatives are used for different hedging needs—to hedge output price risk in the oil-and-gas industry and input price risk in the airline industry—enhances the generalizability of our findings. Another distinct advantage of examining these industries is that neither one employs derivatives for trading purposes. It is difficult to assess the impact of hedging on earnings predictability in such industries as banking and integrated oil because firms in these industries employ both hedging and trading derivatives, and the accounting treatment for trading derivatives and ineffective hedges is identical. Focusing on oil-and-gas firms and airlines ensures that our findings are not confounded by the presence of trading derivatives.

Both our oil-and-gas and airline industry derivative datasets are based on hand-collected data. Oil-and-gas firms provide detailed disclosures on the types, quantities, and maturities of derivative contracts that are in place to hedge the price risk of their production in their 10-K and 10-Q reports. Following Lobo et al. (2020), we hand collect detailed hedging derivative data for 53 unique oil-and-gas firms.[15] Our sample period is from 2001 to 2017.[16] We follow Haushalter (2000), Kumar and Rabinovitch (2013), and Lobo et al. (2020) and measure the extent of derivative usage for production hedging (*Derivatives*) as the ratio of the volume of oil-and-gas hedging derivative contracts exercisable in a given quarter to the total oil-and-gas production in that quarter. Since a typical firm produces and hedges both crude oil and natural gas, we apply the industry standard of one barrel of oil being equivalent to 6000 cubic feet of gas to combine the derivative usage to hedge crude oil and natural gas into a single firm-quarter measure of *Derivatives*. In essence, *Derivatives* measures the extent of derivative usage in a given period to hedge the price risk of that period's production. It can range from zero to one with a firm that does not hedge any of its production carrying a value of zero and a firm that hedges all of its production carrying a value of one.

We also hand-collect derivative data for airlines from their 10-Q and 10-K filings for the same period. (The industry's SIC is 4512.) There are 26 unique U.S.-based airlines in our sample. Instrument-level derivative disclosures in the airline industry tend to be less detailed than in the oil-and-gas industry. Nonetheless, airlines disclose the percentage of jet fuel consumption hedged with derivative contracts. This is our measure of the extent of derivative usage (*Derivatives*) for airlines.[17]

[15] The SIC code for oil-and-gas exploration-and-production firms is 1311.

[16] Lobo et al. (2020) obtain detailed quarterly hedging data for 53 unique oil-and-gas firms over the period of 1996 to 2008. However, because SFAS 133—which introduced the notions of hedge accounting and ineffective hedges—became effective for fiscal years beginning after June 15, 2000, only the fiscal periods after this date are relevant to our study. Therefore, we further extend the sample period by hand-collecting derivative data for these firms up to the year 2017.

[17] Some small airlines have fuel reimbursement agreements with larger, partner airlines. Based on the economic substance, we code these as effective forward contracts.

Appendix D presents an illustration of how we compute the variable *Derivatives* for oil-and-gas firms and airlines. In their financial statement notes, both groups of firms disclose the income statement impact of hedge ineffectiveness for failing to meet the hedge accounting criteria of SFAS 133. We also hand-collect this data for tests of H2.

Our data offers us some unique advantages in linking derivative usage and forecasting ability. The magnitude of derivative usage in our sample is economically meaningful, and thus results can be more confidently attributed to derivative usage rather than other omitted factors (Guay and Kothari 2003). Further, as we possess detailed and accurate data on derivative usage, we are able to not just establish a general association between derivative usage and analyst forecast outcomes, but also ensure that derivative usage in a particular period (in terms of derivative contracts becoming exercisable in that period) correctly matches analyst forecasts made for that period.[18] Finally, with our data collection approach, we are able to quantify the effect of hedge ineffectiveness. To the best of our knowledge, ours is the first study to do so.

We obtain analyst forecast data from the I/B/E/S database and data for control variables from I/B/E/S, Compustat, and CRSP. The oil-and-gas (airline) sample for tests of H1 based on level specifications consists of 10,318 (3,296) quarterly analyst forecasts. Sample sizes for other tests vary due to variable availability.

3.2 Research design

3.2.1 Tests of hypothesis H1

We employ the following regression model to examine the association between the extent of derivative usage and analyst forecast accuracy and dispersion. We run separate regressions for oil-and-gas firms and airlines in this as well as in all subsequent tests. Firm and time subscripts are suppressed for ease of exposition.

$$\begin{aligned} Accuracy(Dispersion) = {} & \beta_0 + \beta_1{*}Derivatives + \beta_2{*}Analysts + \beta_3{*}Size \\ & + \beta_4{*}Intangible + \beta_5{*}Volatility + \beta_6{*}MB \\ & + \beta_7{*}Issue + \beta_8{*}Turnover + \beta_9{*}Return + \beta_{10}{*}ROA \\ & + \beta_{11}{*}Foreign + \beta_{12}{*}M\&A + \beta_{13}{*}DA \\ & + \beta_{14}{*}Num\_firm + \beta_{15}{*}Num\_ind + \beta_{16}{*}Brokerage\_size \\ & + \beta_{17}{*}Forecast\_exp + \beta_{18}{*}Forecast\_freq \\ & + \beta_{19}{*}Horizon + \gamma{*}Time\ Fixed\ Effects \\ & + \delta{*}Brokerage\ Fixed\ Effects + \varepsilon. \end{aligned} \tag{1}$$

[18] Hence, our empirical proxy for derivative usage is superior to alternative measures, such as a dummy variable indicating whether the firm holds derivatives and the total notional value of derivative instruments, regardless of their maturity period.

The dependent variable is either quarterly analyst forecast accuracy (*Accuracy*) or dispersion (*Dispersion*) obtained from I/B/E/S.[19,20] To avoid multiple forecast revisions by the same analyst for a given firm-quarter, we only use the latest forecast of each analyst. *Derivatives*, which captures the extent of derivative usage to hedge production for oil-and-gas firms and jet fuel consumption for airlines, is the variable of interest. If hedging with derivatives makes earnings less volatile and more predictable, then analysts' forecasts should be more accurate and less dispersed with greater derivative usage. Therefore, we would expect a positive (negative) β_1 with *Accuracy* (*Dispersion*) as the dependent variable. On the other hand, if the analysts' inability to understand derivatives or the accounting effect associated with ineffective hedges outweighs the economic effect, then analysts' forecasts should be less accurate and more dispersed in the presence of greater derivative usage. In that case, we would expect a negative (positive) β_1 with *Accuracy* (*Dispersion*) as the dependent variable.

We follow prior studies and include several firm-level control variables. We control for the number of analysts following a firm (*Analysts*), beginning-of-the-period total assets (*Size*), intangible assets (*Intangible*), stock return volatility (*Volatility*), and the market to book ratio (*MB*), because these factors could influence analyst forecast outcomes (Lang and Lundholm 1996; Barth et al. 2001; Tan et al. 2011). We also include a dummy variable indicating whether the firm has issued equity (*Issue*) as well as controls for share turnover (*Turnover*) and for annual stock returns (*Return*), because these factors could influence analysts' incentives to cover a given firm (e.g., Hayes 1998). We follow Chang et al. (2016) and control for profitability (*ROA*) and include dummy variables indicating whether the firm has foreign operations (*Foreign*) or engages in mergers and acquisitions (*M&A*). Because hedging and discretionary accruals might be employed as substitutes for earnings management (Barton 2001; Pincus and Rajgopal 2002), we also control for the absolute value of discretionary accruals (*DA*).[21]

Additionally, we follow the literature and control for several analyst attributes as well (Clement 1999; Jacob et al. 1999). We follow Clement (1999) and use number of firms (*Num_firm*) and number of industries (*Num_ind*) an analyst is following to proxy for each analyst's portfolio complexity. We use the size of the analyst's brokerage (*Brokerage_size*) to proxy for the analyst's access to resources. It has been argued that analysts from larger brokerages have more resources at their disposal. We control for an analyst's experience with the firm in terms of the number of quarters the analyst has followed the firm (*Forecast_exp*). We also control for forecast horizon (*Horizon*) and forecast frequency (*Forecast_freq*), as Jacob et al. (1999) find these attributes to be associated with analysts' forecast performance. All our regression models

[19] Following Chang et al. (2016), *Accuracy* and *Dispersion* are scaled by the stock price at the end of the period. However, all our results hold if these variables are instead scaled by the beginning of the period stock price.

[20] Note that our unit of analysis is analyst-firm-quarter. Therefore, forecast dispersion changes as new analyst forecasts are issued.

[21] However, Kilic et al. (2013) argue that the use of derivatives for earnings management has become significantly more difficult after the introduction of SFAS 133.

employ time fixed effects to control for time trends.[22] We also employ brokerage fixed effects to account for brokerage-level factors that might affect analyst forecast properties.[23] Standard errors are clustered by the firm and the analyst. All variable definitions are in Appendix E.

3.2.2 Tests of hypothesis H2

Hypothesis H2 investigates how ineffective hedges affect the relation between earnings predictability and the extent of derivative usage. We modify regression model (1) by introducing the variable *Ineffective* as follows.

$$\begin{aligned} Accuracy\ (Dispersion) = {} & \beta_0 + \beta_1 {*} Derivatives + \beta_2 {*} Ineffective \\ & + \beta_3 {*} Derivatives {*} Ineffective + \beta_4 {*} Analysts + \beta_5 {*} Size \\ & + \beta_6 {*} Intangible + \beta_7 {*} Volatility + \beta_8 {*} MB + \beta_9 {*} Issue \\ & + \beta_{10} {*} Turnover + \beta_{11} {*} Return + \beta_{12} {*} ROA \\ & + \beta_{13} {*} Foreign + \beta_{14} {*} M\&A + \beta_{15} {*} DA \\ & + \beta_{16} {*} Num\_firm + \beta_{17} {*} Num\_ind \\ & + \beta_{18} {*} Brokerage\_size + \beta_{19} {*} Forecast\_exp \\ & + \beta_{20} {*} Forecast\_freq + \beta_{21} {*} Horizon \\ & + \gamma {*} Time\ Fixed\ Effects + \delta {*} Brokerage\ Fixed\ Effects \\ & + \varepsilon \end{aligned} \tag{2}$$

As previously explained, the potentially volatility-increasing income statement effect of hedges that do not qualify for hedge accounting is reflected in ineffective gains/losses. We hand-collected this information from Forms 10-K and 10-Q and employ the variable *Ineffective* and its interaction term with *Derivatives* in model (2). Specifically, *Ineffective* is an indicator variable taking the value of one if the firm reports any ineffective gains/losses for the period, indicating the holding of hedges that do not qualify for hedge accounting during the period, and zero otherwise.

Of interest for H2 is the coefficient on the interaction term *Derivatives*Ineffective* (β_3). If the accounting effect of ineffective hedges makes earnings incrementally more difficult to predict, then β_3 should be negative (positive) with *Accuracy* (*Dispersion*) as the dependent variable. In addition, the sum of the coefficients on *Derivatives* (β_1) and

[22] The time fixed effects employed in tabulated results are year and quarter fixed effects. Our inferences remain unchanged if we instead employ quarter-year fixed effects, quarter fixed effects only, or year fixed effects only. Our results are also not sensitive to excluding quarter fixed effects and instead including a fourth quarter dummy to control for any differences in managerial behavior in the fourth quarter relative to other quarters.

[23] Our inferences remain unchanged if we instead employ analyst fixed effects.

*Derivatives*Ineffective* (β_3) would indicate the relation between hedging and earnings predictability for firms that hold ineffective hedges.

A major criticism levelled against SFAS 133 is that stringent hedge accounting rules make earnings potentially more volatile and less predictable than if there were no hedging at all. To further explore this issue, as an additional test, we also focus on a subsample of firms for which derivative disclosures reveal that all of their hedging derivatives are either effective (as captured by setting the variable *AllIneffective* = *0*) or ineffective (*AllIneffective* = *1*). We re-estimate model (2) by replacing the variable *Ineffective* with the variable *Allineffective* to yield a more stringent test of H2. A comparison of firms that hold *only* effective and *only* ineffective hedges respectively would provide a clear picture of the impact of hedge ineffectiveness on earnings predictability, as shown in model 3.

$$\begin{aligned} Accuracy(Dispersion) = {} & \beta_0 + \beta_1 {*} Derivatives + \beta_2 {*} AllIneffective \\ & + \beta_3 {*} Derivatives {*} AllIneffective + \beta_4 {*} Analysts \\ & + \beta_5 {*} Size + \beta_6 {*} Intangible + \beta_7 {*} Volatility + \beta_8 {*} MB \\ & + \beta_9 {*} Issue + \beta_{10} {*} Turnover + \beta_{11} {*} Return + \beta_{12} {*} ROA \\ & + \beta_{13} {*} Foreign + \beta_{14} {*} M\&A + \beta_{15} {*} DA \\ & + \ \beta_{16} {*} Num\_firm + \beta_{17} {*} Num\_ind \\ & + \beta_{18} {*} Brokerage\_size + \beta_{19} {*} Forecast\_\mathrm{exp} \\ & + \beta_{20} {*} Forecast\_freq + \beta_{21} {*} Horizon \\ & + \gamma {*} Time\ Fixed\ Effects + \delta {*} Brokerage\ Fixed\ Effects \\ & + \varepsilon. \end{aligned} \tag{3}$$

As in the previous model, a negative (positive) β_3 with *Accuracy* (Dispersion) as the dependent variable would be consistent with H2. Moreover, despite the economic effect if, as critics claim, accounting effect of hedge ineffectiveness makes earnings even less predictable than if there were no hedging, then the sum of coefficients on $\beta_1 + \beta_3$ too would be negative (positive) with *Accuracy* (Dispersion) as the dependent variable .

4 Main results

4.1 Descriptive statistics

Table 1 reports descriptive statistics for oil-and-gas firms in Panel A and airlines in Panel B. For the former firms (Panel A of Table 1), the mean value of *Derivatives* is 0.445, which indicates that they use derivative contracts to hedge 44.5% of production on average. In other words, the extent of derivative usage is economically material in this industry to study derivative usage (Guay and Kothari 2003). The average oil-and-gas firm is followed by 26 analysts (*Analysts*). About 7% of sample firms issue equity

Table 1 Descriptive Statistics

Variable	Mean	Median	Standard Deviation	10th Percentile	90th Percentile	N
Panel A: Oil-and-Gas Exploration-and-Production Industry						
Accuracy	−0.315	−0.143	1.363	−0.616	−0.022	10,318
Dispersion	0.215	0.164	0.293	0.066	0.369	9,974
Derivatives	0.445	0.401	0.311	0.033	0.847	10,318
Analysts	25.630	27.000	7.459	16.000	34.000	10,318
Size	9.284	9.402	1.163	7.924	10.742	10,318
Intangible	0.039	0.014	0.053	0.000	0.125	10,318
Volatility	0.101	0.090	0.039	0.064	0.167	10,318
MB	1.755	1.604	2.217	0.913	2.939	10,318
Issue	0.071	0.000	0.257	0.000	0.000	10,318
Turnover	0.741	0.642	0.371	0.383	1.143	10,318
Return	−0.001	−0.001	0.165	−0.193	0.205	10,318
ROA	0.007	0.013	0.037	−0.015	0.034	10,318
Foreign	0.788	1.000	0.409	0.000	1.000	10,318
M&A	0.162	0.000	0.368	0.000	1.000	10,318
DA	0.105	0.109	0.040	0.050	0.147	10,318
Num_firm	16.445	16.000	7.829	7.000	26.000	10,318
Num_ind	1.721	2.000	0.924	1.000	2.000	10,318
Brokerage_size	34.068	23.000	28.617	6.000	79.000	10,318
Forecast_exp	14.905	11.000	13.523	2.000	35.000	10,318
Forecast_freq	2.690	2.000	2.054	1.000	4.000	10,318
Horizon	35.100	22.000	39.392	7.000	84.000	10,318
Ineffective	0.849	1.000	0.358	0.000	1.000	10,318
AllIneffective	0.523	1.000	0.499	0.000	1.000	10,318
Panel B: Airline Industry						
Accuracy	−0.800	−0.188	3.551	−1.384	−0.017	3,296
Dispersion	0.683	0.202	2.910	0.062	1.212	3,077
Derivatives	0.425	0.440	0.302	0.000	0.900	3,296
Analysts	10.774	11.000	3.651	5.000	15.000	3,296
Size	8.580	8.675	1.364	6.738	10.573	3,296
Intangible	0.058	0.009	0.094	0.000	0.214	3,296
Volatility	0.126	0.105	0.068	0.070	0.213	3,296
MB	2.061	1.695	18.105	0.562	4.859	3,296
Issue	0.029	0.000	0.166	0.000	0.000	3,296
Turnover	1.030	0.870	0.746	0.377	1.764	3,296
Return	0.212	−0.011	3.341	−0.246	0.322	3,296
ROA	0.009	0.009	0.027	−0.010	0.031	3,296
Foreign	0.035	0.000	0.185	0.000	0.000	3,296
M&A	0.024	0.000	0.154	0.000	0.000	3,296
DA	0.034	0.027	0.038	0.005	0.064	3,296
Num_firm	12.188	11.000	5.179	7.000	18.000	3,296

Table 1 (continued)

Variable	Mean	Median	Standard Deviation	10th Percentile	90th Percentile	N
Num_ind	1.935	1.000	1.542	1.000	4.000	3,296
Brokerage_size	32.830	18.000	29.215	6.000	82.000	3,296
Forecast_exp	14.557	11.000	12.477	2.000	33.000	3,296
Forecast_freq	1.944	2.000	0.928	1.000	3.000	3,296
Horizon	37.133	22.000	31.673	7.000	90.000	3,296
Ineffective	0.575	1.000	0.494	0.000	1.000	3,296
AllIneffective	0.203	0.000	0.402	0.000	1.000	3,296

This table presents the descriptive statistics of the variables used in regression models. The sample period is from 2001 to 2017. All variables are defined in Appendix E

(*Issue*), 79% report foreign income (*Foreign*), and 16% engage in mergers and acquisitions (*M&A*). The average analyst in our oil-and-gas sample follows 16 firms (*Num_firm*) and 1.7 industries (*Num_ind*) and works in a brokerage with 34 analysts (*Brokerage_size*). On average, our sample analysts generate 2.7 earnings forecasts per quarter per firm (*Forecast_freq*).

Derivative usage is also economically significant in the airline industry sample. As seen in Panel B of Table 1, the mean value of *Derivatives* is 0.425, indicating that, on average, airlines in our sample hedge 42.5% of their jet fuel consumption. Airlines are on average smaller than oil-and-gas firms.[24] On average, 11 analysts follow an airline in our sample (*Analysts*), while 3% of firms issue equity (*Issue*) and 2.4% engage in mergers and acquisitions (*M&A*). Average analyst covering the airline industry follows 12 firms (*Num_firm*) and 1.9 industries (*Num_ind*) and works in a brokerage with 32.8 analysts (*Brokerage_size*). Analysts in our airline sample generate 1.9 earnings forecasts per quarter per firm (*Forecast_freq*).

4.2 H1: Extent of hedging and forecasting properties

4.2.1 Analyses in levels

Table 2 reports results for Hypothesis H1, which addresses the relation between derivative usage and analyst forecast accuracy and dispersion. As previously noted, many firms hold both effective and ineffective hedges. If the economic effect of hedging dominates the accounting effect associated with the holding of ineffective hedges, then, on average, hedging should be associated with greater forecast accuracy and lower dispersion. The reverse would be true if the accounting effect were to dominate the economic effect, and/or if, as claimed by some research, analysts routinely misjudge earnings implications of hedging. Results for the oil-and-gas and airline industries are reported in Panels A and B of Table 2, respectively. In each panel, Column 1 reports results for regression model (1) with *Accuracy* as the dependent variable, and Column 2 reports results with *Dispersion* as the dependent variable. The coefficient of interest is β_1 (the coefficient on *Derivatives*).

[24] Natural log of total assets (*Size*) for oil-and-gas firms and airlines is 9.284 and 8.580 respectively.

Table 2 Relation between Derivative Usage and Analysts' Earnings Forecast Accuracy and Dispersion

		Dependent Variable			
		Accuracy		Dispersion	
		Coefficient	*p* value	Coefficient	*p* value
Panel A: Oil-and-Gas Exploration-and-Production Industry					
Intercept	β_0	−0.129	0.619	0.446	0.000
Derivatives	$\boldsymbol{\beta_1}$	**0.192**	**0.000**	**−0.052**	**0.009**
Analysts	β_2	0.007	0.001	−0.007	0.000
Size	β_3	0.191	0.000	−0.043	0.006
Intangible	β_4	−0.461	0.137	0.319	0.000
Volatility	β_5	−2.070	0.000	0.607	0.000
MB	β_6	0.032	0.000	−0.016	0.000
Issue	β_7	0.033	0.449	−0.041	0.000
Turnover	β_8	0.383	0.000	0.055	0.010
Return	β_9	−0.091	0.407	−0.133	0.000
ROA	β_{10}	9.849	0.001	−0.927	0.000
Foreign	β_{11}	−0.204	0.002	0.111	0.000
M&A	β_{12}	−0.030	0.171	−0.008	0.190
DA	β_{13}	−2.822	0.012	0.719	0.030
Num_firm	β_{14}	−0.005	0.119	0.001	0.224
Num_ind	β_{15}	−0.043	0.023	0.008	0.131
Brokerage_size	β_{16}	0.001	0.139	−0.000	0.078
Forecast_exp	β_{17}	0.000	0.874	0.000	0.362
Forecast_freq	β_{18}	−0.000	0.979	0.006	0.111
Horizon	β_{19}	−0.004	0.006	0.001	0.000
Time fixed effects?		Yes		Yes	
Brokerage fixed effects?		Yes		Yes	
Adj. R^2		0.237		0.331	
N		10,318		9,974	
Panel B: Airline Industry					
Intercept	β_0	−1.773	0.079	−0.013	0.987
Derivatives	$\boldsymbol{\beta_1}$	**1.062**	**0.002**	**−1.212**	**0.004**
Analysts	β_2	0.145	0.000	−0.076	0.001
Size	β_3	0.021	0.735	−0.036	0.647
Intangible	β_4	−0.249	0.698	0.352	0.494
Volatility	β_5	−5.971	0.001	7.100	0.000
MB	β_6	0.005	0.010	−0.004	0.020
Issue	β_7	0.514	0.002	−0.539	0.020
Turnover	β_8	−0.327	0.041	0.455	0.001
Return	β_9	0.009	0.098	−0.015	0.002
ROA	β_{10}	31.484	0.000	−30.200	0.003
Foreign	β_{11}	−0.138	0.375	0.124	0.425

Table 2 (continued)

		Dependent Variable			
		Accuracy		Dispersion	
		Coefficient	*p* value	Coefficient	*p* value
M&A	β_{12}	0.377	0.049	−0.185	0.324
DA	β_{13}	1.547	0.454	−1.523	0.336
Num_firm	β_{14}	0.032	0.401	0.014	0.405
Num_ind	β_{15}	−0.044	0.454	−0.031	0.401
Brokerage_size	β_{16}	−0.000	0.954	−0.008	0.207
Forecast_exp	β_{17}	−0.003	0.566	0.004	0.322
Forecast_freq	β_{18}	−0.052	0.554	0.037	0.266
Horizon	β_{19}	−0.015	0.007	0.009	0.002
Time fixed effects?		Yes		Yes	
Brokerage fixed effects?		Yes		Yes	
Adj. R^2		0.340		0.247	
N		3,296		3,077	

This table shows the OLS estimates for the following model:

Accuracy (Dispersion) = β_0 + β_1**Derivatives* + β_2**Analysts* + β_3**Size* + β_4**Intangible* + β_5**Volatility* + β_6 **MB* + β_7**Issue* + β_8**Turnover* + β_9**Return* + β_{10}**ROA* + β_{11}**Foreign* + β_{12}**M&A* + β_{13}**DA* + β_{14}* *Num_firm* + β_{15}* *Num_ind* + β_{16}* *Brokerage_size* + β_{17}* *Forecast_exp* + β_{18}* *Forecast_freq* + β_{19}* *Horizon* + γ**Time Fixed Effects* + δ**Brokerage Fixed Effects* + ε

All results are based on standard errors clustered simultaneously by firm and by analyst. All *p* values are based on two-tailed t-tests. The sample period is from 2001 to 2017. All variables are defined in Appendix E

Panel A of Table 2 (oil-and-gas industry) reports a positive and significant coefficient on *Derivatives* in Column 1 ($\beta_1 = 0.192$, *p* value<0.001), indicating that analysts' forecast accuracy increases along with derivative usage. In Column 2, the coefficient on *Derivatives* is negative and significant ($\beta_1 = -0.052$, *p* value = 0.009), suggesting that analysts' forecast dispersion decreases as derivative usage increases. In terms of economic significance, these results indicate that hedging 10% of output with derivatives improves analysts' forecast accuracy by 6.10%[25] and reduces forecast dispersion by 2.42%,[26] when compared to variable means.

Inferences from the airline industry are similar (Panel B of Table 2). In Column 1, the coefficient on *Derivatives* is reliably positive ($\beta_1 = 1.062$, *p* value = 0.002), indicating that greater usage of derivatives is associated with more accurate analysts' forecasts in the airline industry as well. Moreover, the coefficient on *Derivatives* is negative in Column 2 of Table 2, Panel B ($\beta_1 = -1.212$, *p* value = 0.004), suggesting that greater derivative usage is associated with lower forecast dispersion. With respect to economic significance, we observe that hedging 10% of jet fuel consumption improves analysts'

[25] 0.192*10%/0.315 = 6.10% (0.192 is the coefficient on *Derivatives* when *Accuracy* is the dependent variable, and 0.315 is the absolute value of mean of *Accuracy*).

[26] 0.052*10%/0.215 = 2.42% (0.052 is the absolute value of coefficient on *Derivatives* when *Dispersion* is the dependent variable, and 0.215 is the mean value of *Dispersion*).

forecast accuracy by 13.28%,[27] and reduces forecast dispersion by 17.75%,[28] when compared to variable means.

The findings from both industries strongly support the argument that, on average, it is the economic effect of hedging that dictates the association between hedging and earnings predictability and not the accounting effect.

4.2.2 Analyses in changes

The results reported above indicate that higher derivative usage is associated with more accurate and less-dispersed analyst forecasts. To further strengthen identification and establish causality, we also conduct a changes analysis by regressing the *change* in analyst forecast accuracy and dispersion ($\Delta Accuracy$ and $\Delta Dispersion$) on the *change* in derivative usage ($\Delta Derivatives$). Here, the idea is that, if, as indicated by our levels analyses, the economic effect of hedging dominates the accounting effect associated with ineffective hedges, increases in derivative usage should then be associated with *increases* in forecast accuracy and *decreases* in forecast dispersion. We also include all control variables in terms of changes. We do not include analyst-level variables in the change model, because analyst attributes are largely time-invariant and incorporating them causes unnecessary sample attrition.[29]

Table 3 presents the results. Panel A (Panel B) of Table 3 reports results for the oil-and-gas (airline) industry. In each panel, Column 1 reports results with $\Delta Accuracy$ as the dependent variable, while Column 2 reports results with $\Delta Dispersion$ as the dependent variable.

The inferences from our changes analyses are consistent with those from the levels analyses reported in Table 2. In Column 1, Panel A of Table 3 (oil-and-gas industry), we find the coefficient on $\Delta Derivatives$ (β_1) to be positive and significant with $\Delta Accuracy$ as the dependent variable ($\beta_1 = 0.018$, p value = 0.084). That is, increases in derivative usage in the oil-and-gas industry are associated with increases in analysts' forecast accuracy. Moreover, as reported in Column 2, β_1 is negative and significant when $\Delta Dispersion$ is the dependent variable ($\beta_1 = -0.014$, p value = 0.003), suggesting increases in derivative usage are associated with decreases in forecast dispersion.

The airline industry results reported in Panel B of Table 3 are similar, indicating that increases in jet fuel hedging are associated with increases in analysts' forecast accuracy; the coefficient on $\Delta Derivatives$ (β_1) is positive in Column 1 ($\beta_1 = 0.752$, p value = 0.006). In Column 2, we find the coefficient on $\Delta Derivatives$ (β_1) to be negative ($\beta_1 = -0.585$, p value = 0.005), suggesting increases in jet fuel hedging are associated with decreases in forecast dispersion.

In sum, the results reported in Table 3 further supports the notion that, on average, when firms hold a mix of effective and ineffective hedges, the economic effect of hedging dominates the countervailing accounting effects of ineffective hedges and analysts indeed are able to incorporate income volatility reducing effect of hedging into their earnings forecasts.

[27] 1.062*10%/0.800 = 13.28% (1.062 is the coefficient on *Derivatives* when *Accuracy* is the dependent variable, and 0.800 is the absolute value of mean of *Accuracy*).

[28] 1.212*10%/0.683 = 17.75% (1.212 is the absolute value of the coefficient on *Derivatives* when *Dispersion* is the dependent variable, and 0.683 is the mean value of *Dispersion*).

[29] Including these additional control variables reduces the size of our samples by about 40%.

Table 3 Relation between Change in Derivative Usage and Change in Analysts' Earnings Forecast Accuracy and Dispersion

		Dependent Variable			
		ΔAccuracy		ΔDispersion	
		Coefficient	*p* value	Coefficient	*p* value
Panel A: Oil-and-Gas Exploration-and-Production Industry					
Intercept	β_0	0.001	0.592	0.004	0.000
ΔDerivatives	$\boldsymbol{\beta_1}$	**0.018**	**0.084**	**−0.014**	**0.003**
ΔAnalysts	β_2	0.000	0.711	−0.003	0.000
ΔSize	β_3	−0.085	0.000	0.018	0.051
ΔIntangible	β_4	−0.220	0.125	−0.125	0.048
ΔVolatility	β_5	−0.162	0.012	−0.009	0.702
ΔMB	β_6	−0.011	0.000	0.002	0.068
ΔIssue	β_7	−0.014	0.001	−0.004	0.077
ΔTurnover	β_8	−0.041	0.000	0.072	0.000
ΔReturn	β_9	0.001	0.879	−0.001	0.805
ΔROA	β_{10}	−0.019	0.825	−0.063	0.043
ΔForeign	β_{11}	−0.013	0.590	0.012	0.355
ΔM&A	β_{12}	−0.000	0.950	0.005	0.000
ΔDA	β_{13}	0.052	0.566	0.062	0.059
Adj. R^2		0.010		0.058	
N		11,975		11,797	
Panel B: Airline Industry					
Intercept	β_0	−0.283	0.000	0.137	0.004
ΔDerivatives	$\boldsymbol{\beta_1}$	**0.752**	**0.006**	**−0.585**	**0.005**
ΔAnalysts	β_2	−0.097	0.144	0.025	0.450
ΔSize	β_3	3.542	0.000	−0.769	0.153
ΔIntangible	β_4	−12.094	0.004	1.406	0.569
ΔVolatility	β_5	−8.867	0.036	8.117	0.000
ΔMB	β_6	−0.018	0.034	0.010	0.018
ΔIssue	β_7	0.423	0.001	−0.069	0.505
ΔTurnover	β_8	−1.173	0.014	0.051	0.823
ΔReturn	β_9	−0.003	0.732	−0.010	0.014
ΔROA	β_{10}	12.362	0.000	−3.506	0.027
ΔM&A	β_{12}	−0.145	0.583	−0.032	0.829
ΔDA	β_{13}	−6.069	0.002	0.514	0.685
Adj. R^2		0.049		0.028	
N		3,943		3,406	

This table shows the OLS estimates for the following model:

$\Delta Accuracy\ (\Delta Dispersion) = \beta_0 + \beta_1{*}\ \Delta Derivatives + \beta_2{*}\ \Delta Analysts + \beta_3{*}\ \Delta Size + \beta_4{*}\ \Delta Intangible + \beta_5{*}\ \Delta Volatility + \beta_6{*}\Delta MB + \beta_7{*}\ \Delta Issue + \beta_8{*}\ \Delta Turnover + \beta_9{*}\ \Delta Return + \beta_{10}{*}\ \Delta ROA + \beta_{11}{*}\ \Delta Foreign + \beta_{12}{*}\ \Delta M\&A + \beta_{13}{*}\ \Delta DA + \varepsilon$

All results are based on standard errors clustered simultaneously by firm and by analyst. All p values are based on two-tailed t-tests. The sample period is from 2001 to 2017. All variables are defined in Appendix E. In Panel B, the control variable *ΔForeign* is omitted, due to the absence of variation in data

4.3 H2: The role of hedge ineffectiveness

4.3.1 Holding of ineffective hedges

In H2 we examine how the presence of hedges that do not qualify for hedge accounting (ineffective hedges) affects the relation between hedging and analyst forecast properties. Because ineffective hedges have a volatility increasing accounting effect on earnings, we predict their presence to have an incrementally negative (positive) effect on the association between analyst forecast accuracy (dispersion) and the extent of derivative usage. Table 4 presents the results. Panel A (Panel B) presents the results for the oil-and-gas (airline) industry. Column 1 of each panel presents results with *Accuracy* as the dependent variable, and Column 2 presents the results with *Dispersion* as the dependent variable.

In Table 4, Panel A, we find the coefficient on *Derivatives* to be positive with *Accuracy* as the dependent variable ($\beta_1 = 0.412$, p value $= 0.025$) and negative with *Dispersion* as the dependent variable ($\beta_1 = -0.199$, p value $= 0.016$). These results indicate that in the absence of ineffective hedges hedging is associated with more accurate and less dispersed analyst forecasts. Our coefficient of interest is that on the interaction term *Derivatives*Ineffective* (β_3). As predicted in hypothesis H2, we find β_3 to be reliably negative with *Accuracy* as the dependent variable ($\beta_3 = -0.363$, p value $=$ 0.040) and positive with *Dispersion* as the dependent variable ($\beta_3 = 0.187$, p value $=$ 0.015). In other words, we find that ineffective hedges significantly dampen the improvement of analysts' forecast properties associated with hedging. As an additional test, we also examine the sum of coefficients on *Derivatives* and *Derivatives*Ineffective* ($\beta_1 + \beta_3$). This sum remains positive with *Accuracy* as the dependent variable ($\beta_1 + \beta_3 = 0.049$, p value $= 0.105$) and negative with *Dispersion* as the dependent variable ($\beta_1 + \beta_3 = -0.012$, p value $= 0.433$), but neither of these are statistically significant at conventional levels. In other words, we fail to find a significant association between hedging and earnings predictability for oil-and-gas firms that hold ineffective hedges.

Results for the airline industry are reported in Panel B of Table 4. These results are quite similar to our findings for oil-and-gas industry. The coefficient on *Derivatives* continues to be positive with *Accuracy* as the dependent variable ($\beta_1 = 0.344$, p value<0.001) and negative with *Dispersion* as the dependent variable ($\beta_1 = -0.172$, p value $= 0.002$). More importantly, as shown in Panel B of Table 4, the coefficient of interest, that on the interaction term *Derivatives*Ineffective* continues to be significantly negative with *Accuracy* as the dependent variable ($\beta_3 = -0.428$, p value<0.001) and positive with *Dispersion* as the dependent variable ($\beta_3 = 0.148$, p value $= 0.026$). Moreover, the sum of coefficients on *Derivatives* and *Derivatives*Ineffective* ($\beta_1 + \beta_3$) continues to be statistically indistinguishable from zero in both columns of Table 4, Panel B (Column 1: $\beta_1 + \beta_3 = -0.084$, p value $= 0.267$; Column 2: $\beta_1 + \beta_3 = -0.024$, p value $= 0.685$). That is, for airlines with ineffective hedges, we do not observe derivative usage to significantly impact analysts' forecast accuracy or dispersion.

4.3.2 Firms that hold only effective or ineffective hedges

In this section, we examine firms that only hold either effective or ineffective hedges. This design allows us to provide a starker test of the effect of failure to qualify for

Table 4 The Effect of Failure to Qualify for Hedge Accounting on the Relation between Derivative Usage and Analysts' Earnings Forecast Accuracy and Dispersion

		Dependent Variable			
		Accuracy		Dispersion	
		Coefficient	*p* value	Coefficient	*p* value
Panel A: Oil-and-Gas Exploration-and-Production Industry					
Intercept	β_0	−1.381	0.000	0.473	0.000
Derivatives	β_1	**0.412**	**0.025**	**−0.199**	**0.016**
Ineffective	β_2	0.318	0.000	−0.200	0.000
Derivatives*Ineffective	β_3	**−0.363**	**0.040**	**0.187**	**0.015**
Analysts	β_4	0.006	0.001	−0.005	0.000
Size	β_5	0.149	0.000	−0.048	0.003
Intangible	β_6	−0.785	0.001	0.531	0.000
Volatility	β_7	−1.941	0.000	0.387	0.004
MB	β_8	0.025	0.000	−0.013	0.000
Issue	β_9	0.035	0.036	−0.027	0.000
Turnover	β_{10}	0.254	0.004	0.058	0.005
Return	β_{11}	0.103	0.055	−0.130	0.000
ROA	β_{12}	5.874	0.010	−1.093	0.000
Foreign	β_{13}	−0.237	0.000	0.129	0.000
M&A	β_{14}	−0.047	0.008	−0.002	0.776
DA	β_{15}	−2.596	0.002	0.812	0.014
Num_firm	β_{16}	−0.003	0.043	0.001	0.059
Num_ind	β_{17}	−0.031	0.044	0.007	0.161
Brokerage_size	β_{18}	0.000	0.644	−0.001	0.045
Forecast_exp	β_{19}	0.001	0.461	0.000	0.616
Forecast_freq	β_{20}	−0.005	0.608	0.003	0.440
Horizon	β_{21}	−0.002	0.000	0.001	0.000
	$\beta_1 + \beta_3$	**0.049**	**0.105**	**−0.012**	**0.433**
Time fixed effects?		Yes		Yes	
Brokerage fixed effects?		Yes		Yes	
Adj. R^2		0.316		0.366	
N		10,010		9,679	
Panel B: Airline Industry					
		Coefficient	***p* value**	**Coefficient**	***p* value**
Intercept	β_0	0.061	0.824	−0.117	0.528
Derivatives	β_1	**0.344**	**0.000**	**−0.172**	**0.002**
Ineffective	β_2	0.159	0.003	−0.029	0.472
Derivatives*Ineffective	β_3	**−0.428**	**0.000**	**0.148**	**0.026**
Analysts	β_4	0.047	0.000	−0.022	0.000
Size	β_5	0.026	0.247	−0.018	0.140
Intangible	β_6	−1.177	0.000	1.255	0.000

Table 4 (continued)

		Dependent Variable			
		Accuracy		Dispersion	
		Coefficient	*p* value	Coefficient	*p* value
Volatility	β_7	−3.297	0.000	2.947	0.000
MB	β_8	0.000	0.384	−0.000	0.865
Issue	β_9	0.129	0.036	0.024	0.663
Turnover	β_{10}	−0.012	0.819	0.040	0.081
Return	β_{11}	0.006	0.014	−0.011	0.000
ROA	β_{12}	5.810	0.000	−4.195	0.000
M&A	β_{14}	−0.054	0.564	0.164	0.045
DA	β_{15}	−0.693	0.061	0.640	0.034
Num_firm	β_{16}	0.002	0.677	0.006	0.029
Num_ind	β_{17}	−0.005	0.762	−0.010	0.265
Brokerage_size	β_{18}	0.001	0.356	−0.000	0.798
Forecast_exp	β_{19}	−0.001	0.684	0.000	0.809
Forecast_freq	β_{20}	0.017	0.329	−0.011	0.366
Horizon	β_{21}	−0.003	0.000	0.001	0.001
	$\boldsymbol{\beta_1+\beta_3}$	**−0.084**	**0.267**	**−0.024**	**0.685**
Time fixed effects?		Yes		Yes	
Brokerage fixed effects?		Yes		Yes	
Adj. R^2		0.325		0.499	
N		2,820		2,596	

This table shows the OLS estimates for the following model:

Accuracy (Dispersion) = β_0 + β_1*Derivatives* + β_2*Ineffective* + β_3*Derivatives* **Ineffective* + β_4*Analysts* + β_5*Size* + β_6*Intangible* + β_7*Volatility* + β_8*MB* + β_9*Issue* + β_{10} **Turnover* + β_{11}*Return* + β_{12}*ROA* + β_{13}*Foreign* + β_{14}*M&A* + β_{15}*DA* + β_{16}* *Num_firm* + β_{17} * *Num_ind* + β_{18}* *Brokerage_size* + β_{19}* *Forecast_exp* + β_{20}* *Forecast_freq* + β_{21}* *Horizon* + γ*Time Fixed Effects* + δ*Brokerage Fixed Effects* + ε

All results are based on standard errors clustered simultaneously by firm and by analyst. All p values are based on two-tailed t-tests. The sample period is from 2001 to 2017. All variables are defined in Appendix E. In Panel B, the control variable *Foreign* is omitted due to the absence of variation in data

hedge accounting on analysts' forecast properties, as firms that hold both types of hedges are excluded from the analyses. The downside is the loss of sample size.[30]

Panels A and B of Table 5 report the descriptive statistics for observations that hold either only effective or only ineffective hedges in oil-and-gas and airline firms respectively. The last column of each panel reports *p* values for tests of differences in means. These tests reveal firms holding only ineffective hedges to have more accurate and less dispersed forecasts than those holding only effective hedges in both industries.

[30] For this analysis, the oil-and-gas sample consists of 5,975 observations with 5,107 (868) observations belonging to firms that hold only ineffective (only effective) hedges. The airline sample consists of 1,397 observations with 630 (767) observations belonging to firms that hold only ineffective (only effective) hedges.

Table 5 Analyses of firms holding only effective or ineffective hedges

Panel A: Descriptive Statistics – Oil-and-Gas Exploration-and-Production Industry

	All Effective			All Ineffective			Mean value difference H_0:$\mu_{All\_Eff} = \mu_{All\_Ineff}$
Variable	**Mean**	**Median**	**Std**	**Mean**	**Median**	**Std**	***p*-value**
Accuracy	-0.220	-0.159	0.203	-0.194	-0.128	0.188	0.000
Dispersion	0.216	0.212	0.099	0.168	0.146	0.100	0.000
Derivatives	0.298	0.245	0.201	0.532	0.504	0.313	0.000
Analysts	22.714	25.000	8.740	27.789	28.000	6.204	0.000
Size	8.976	9.427	1.182	9.564	9.544	0.895	0.000
Intangible	0.009	0.007	0.014	0.044	0.019	0.056	0.000
Volatility	0.105	0.082	0.038	0.103	0.093	0.035	0.045
MB	1.541	1.534	0.345	1.853	1.697	1.689	0.000
Issue	0.086	0.000	0.281	0.073	0.000	0.260	0.160
Turnover	0.654	0.616	0.271	0.811	0.689	0.404	0.000
Return	0.013	0.038	0.171	-0.005	-0.009	0.163	0.003
ROA	0.023	0.026	0.023	0.002	0.007	0.036	0.000
Foreign	0.874	1.000	0.332	0.728	1.000	0.445	0.000
M&A	0.185	0.000	0.389	0.115	0.000	0.319	0.000
DA	0.095	0.102	0.033	0.100	0.103	0.040	0.000
Num_firm	15.092	14.500	7.654	17.607	17.000	7.843	0.000
Num_ind	1.652	2.000	1.165	1.784	2.000	0.727	0.000
Brokerage_size	41.154	35.000	32.745	31.874	22.000	27.097	0.000
Forecast_exp	16.022	13.000	12.590	15.546	11.000	13.990	0.347
Forecast_freq	3.468	2.000	2.977	2.695	2.000	2.006	0.000
Horizon	41.211	24.000	46.739	32.181	21.000	36.830	0.000
N (tests of accuracy)	868			5,107			
N (tests of dispersion)	792			4,972			

Panel B: Descriptive Statistics – Airline Industry

	All Effective			All Ineffective			Mean value difference H_0:$\mu_{All\_Eff} = \mu_{All\_Ineff}$
Variable	**Mean**	**Median**	**Std**	**Mean**	**Median**	**Std**	***p*-value**
Accuracy	-0.476	-0.247	0.600	-0.390	-0.146	0.611	0.008
Dispersion	0.381	0.243	0.368	0.295	0.158	0.335	0.000
Derivatives	0.623	0.650	0.316	0.467	0.500	0.103	0.000
Analysts	7.931	7.000	3.617	10.103	10.000	2.488	0.000
Size	7.824	8.040	1.211	8.311	8.505	0.733	0.000
Intangible	0.033	0.008	0.069	0.054	0.009	0.089	0.000
Volatility	0.138	0.122	0.064	0.129	0.112	0.068	0.018
MB	1.440	1.235	2.212	1.976	1.548	1.759	0.000
Issue	0.020	0.000	0.139	0.056	0.000	0.229	0.000
Turnover	0.943	0.908	0.488	1.150	0.936	0.769	0.000
Return	0.014	-0.002	0.265	0.276	-0.013	2.950	0.015
ROA	0.009	0.006	0.021	0.011	0.012	0.023	0.169

Table 5 (continued)

M&A	0.052	0.000	0.222	0.017	0.000	0.131	0.001
DA	0.033	0.025	0.052	0.033	0.030	0.025	0.913
Num_firm	12.308	12.000	5.497	12.737	12.000	5.172	0.137
Num_ind	1.717	1.000	1.431	2.078	1.000	1.709	0.000
Brokerage_size	33.838	21.000	28.567	31.232	14.000	30.792	0.102
Forecast_exp	11.694	9.000	10.564	14.652	12.000	11.528	0.000
Forecast_freq	1.613	1.000	0.830	2.098	2.000	0.954	0.000
Horizon	48.222	41.000	34.075	32.635	20.000	28.830	0.000
N (tests of accuracy)	767			630			
N (tests of dispersion)	736			577			

Panel C: Test Results – Oil-and-Gas Exploration-and-Production Industry

		Dependent Variable			
		Accuracy		**Dispersion**	
		Coefficient	***p*-value**	**Coefficient**	***p*-value**
Intercept	β_0	0.049	0.779	0.097	0.182
Derivatives	β_1	**0.092**	**0.009**	**-0.081**	**0.000**
AllIneffective	β_2	0.163	0.000	-0.155	0.000
Derivatives*AllIneffective	β_3	**-0.131**	**0.000**	**0.119**	**0.000**
Analysts	β_4	0.004	0.000	-0.004	0.000
Size	β_5	-0.003	0.582	0.004	0.128
Intangible	β_6	-0.694	0.000	0.645	0.000
Volatility	β_7	-0.286	0.000	-0.031	0.364
MB	β_8	-0.004	0.012	0.001	0.241
Issue	β_9	0.007	0.471	-0.004	0.264
Turnover	β_{10}	-0.080	0.000	0.108	0.000
Return	β_{11}	-0.005	0.762	-0.015	0.019
ROA	β_{12}	0.509	0.000	-0.255	0.000
Foreign	β_{13}	-0.075	0.000	0.062	0.000
M&A	β_{14}	-0.000	0.951	-0.008	0.007
DA	β_{15}	0.306	0.000	-0.057	0.050
Num_firm	β_{16}	0.000	0.419	0.000	0.131
Num_ind	β_{17}	-0.003	0.495	-0.003	0.081
Brokerage_size	β_{18}	0.000	0.810	-0.000	0.082
Forecast_exp	β_{19}	-0.000	0.679	0.000	0.083
Forecast_freq	β_{20}	0.001	0.590	-0.003	0.000
Horizon	β_{21}	-0.000	0.000	0.000	0.000
	$\beta_1+\beta_3$	**-0.039**	**0.000**	**0.038**	**0.000**
Time fixed effects?		Yes		Yes	
Brokerage fixed effects?		Yes		Yes	
Adj. R^2		0.215		0.524	
N		5,975		5,764	

Table 5 (continued)

Panel D: Test Results – Airline Industry					
		Dependent Variable			
		Accuracy		**Dispersion**	
		Coefficient	***p*-value**	**Coefficient**	***p*-value**
Intercept	β_0	-0.070	0.926	0.379	0.389
Derivatives	β_1	**0.272**	**0.004**	**-0.280**	**0.000**
AllIneffective	β_2	0.369	0.004	-0.207	0.007
Derivatives*AllIneffective	β_3	**-0.731**	**0.006**	**0.330**	**0.039**
Analysts	β_4	0.037	0.000	-0.032	0.000
Size	β_5	0.078	0.005	-0.044	0.004
Intangible	β_6	-1.248	0.000	1.221	0.000
Volatility	β_7	-1.837	0.000	1.566	0.000
MB	β_8	-0.000	0.747	0.000	0.186
Issue	β_9	0.356	0.000	-0.092	0.064
Turnover	β_{10}	-0.032	0.311	0.050	0.022
Return	β_{11}	-0.002	0.800	-0.008	0.065
ROA	β_{12}	4.937	0.000	-2.258	0.000
M&A	β_{14}	0.147	0.107	-0.015	0.755
DA	β_{15}	-0.412	0.283	-0.036	0.864
Num_firm	β_{16}	-0.002	0.766	0.005	0.130
Num_ind	β_{17}	-0.004	0.850	-0.007	0.606
Brokerage_size	β_{18}	0.002	0.429	-0.000	0.680
Forecast_exp	β_{19}	-0.000	0.868	-0.001	0.571
Forecast_freq	β_{20}	0.066	0.004	-0.011	0.424
Horizon	β_{21}	-0.002	0.002	0.001	0.000
	$\beta_1+\beta_3$	**-0.460**	**0.058**	**0.051**	**0.718**
Time fixed effects?		Yes		Yes	
Brokerage fixed effects?		Yes		Yes	
Adj. R^2		0.294		0.417	
N		1,397		1,313	

Panels A and B of Table 5 provide descriptive statistics for observations with only effective and only ineffective hedges for oil-and-gas and airline firms respectively. Regression results are reported in Panels C and D. All results are based on standard errors clustered simultaneously by firm and by analyst. All p-values are based on two-tailed t-tests. The sample period is from 2001 to 2017. All variables are defined in Appendix E. In Panel D, the control variable *Foreign* is omitted, due to the absence of variation in data

Panels C and D of Table 5 show the OLS estimates for the following model: *Accuracy (Dispersion)* = β_0 + β_1**Derivatives* + β_2**AllIneffective* + β_3**Derivatives*AllIneffective* + β_4**Analysts* + β_5**Size* + β_6**Intangible* + β_7**Volatility* + β_8**MB* + β_9**Issue* + β_{10}**Turnover* + β_{11}**Return* + β_{12}**ROA* + β_{13}**Foreign* + β_{14}**M&A* + β_{15}**DA* + β_{16}** Num_firm* + β_{17}** Num_ind* + β_{18}** Brokerage_size* + β_{19}** Forecast_exp* + β_{20}** Forecast_freq* + β_{21}** Horizon* + γ**Time Fixed Effects* + δ**Brokerage Fixed Effects* + ε

Moreover, firms with only ineffective hedges are larger and are covered by more analysts. Together, these univariate differences are consistent with the well-established finding that larger firms are followed by more analysts and exhibit greater earnings predictability (e.g., Bhushan 1989; Alford and Berger 1999). These differences work against our prediction that holding only ineffective hedges would contribute to lower earnings predictability and underscores the importance of controlling for them in multivariate tests. In the oil-and-gas industry, firms holding only ineffective hedges tend to hedge more than firms holding only effective hedges, but the reverse is true for airlines. Note that, in the oil-and-gas industry, the number of observations with only ineffective hedges is much higher than that with only effective hedges.

A closer examination of the data (untabulated) reveals that over time many oil-and-gas firms elect to designate all their derivatives as ineffective. Many of their derivative portfolios tend to be quite complex because they hedge multiple output types (crude oil and natural gas) produced in multiple locations using a wide variety of derivatives. The increasing proclivity to elect to designate these hedges as ineffective is consistent with these firms finding the benefits of complying with onerous hedge accounting rules not worth the cost. In contrast, the fraction of airlines holding only effective versus only ineffective hedges is more balanced. Note that, because they are hedging the price risk of a single, homogenous input (jet fuel), their derivative portfolios tend to be much less complex than those held by oil-and-gas firms.

Panel C (D) of Table 5 reports results of regression model (3) for oil-and-gas firms (airlines). As in the previous Table, in Panel C of Table 5, we find the coefficient on *Derivatives* to be positive with *Accuracy* as the dependent variable ($\beta_1 = 0.092$, p value $= 0.009$) and negative with *Dispersion* as the dependent variable ($\beta_1 = -0.081$, p value<0.001). That is, for oil-and-gas firms holding only effective hedges, derivative usage is associated with greater forecast accuracy and lower dispersion. Similar to our findings on hypothesis H2, we find the coefficient on the interaction term to be reliably negative with *Accuracy* as the dependent variable ($\beta_3 = -0.131$, p value<0.001) and positive with *Dispersion* as the dependent variable ($\beta_3 = 0.119$, p value<0.001). The relationship between hedging and earnings predictability for firms that hold only ineffective hedges is reflected in the sum of coefficients *Derivatives* and *Derivatives*AllIneffective.* We find this sum to be reliably negative with *Accuracy* as the dependent variable ($\beta_1 + \beta_3 = -0.039$, p value<0.001) and positive with *Dispersion* as the dependent variable ($\beta_1 + \beta_3 = 0.038$, p value<0.001). That is, when oil-and-gas firms hold only ineffective hedges, hedging is associated with lower earnings predictability than if there were no hedging in the first place.

Results for the airline industry, as reported in Panel D of Table 5, are similar. The coefficient on *Derivatives* is positive with *Accuracy* as the dependent variable ($\beta_1 = 0.272$, p value $= 0.004$) and negative with *Dispersion* as the dependent variable ($\beta_1 = -0.280$, p value<0.001). The coefficient on the interaction term *Derivatives*AllIneffective* remains negative with *Accuracy* as the dependent variable ($\beta_3 = -0.731$, p value $= 0.006$) and positive with *Dispersion* as the dependent variable ($\beta_3 = 0.330$, p value $= 0.039$). Further, as with oil-and-gas firms, the sum of coefficients *Derivatives* and *Derivatives*AllIneffective* continues to be negative with *Accuracy* as the dependent variable ($\beta_1 + \beta_3 = -0.460$, p value $= 0.058$). The only difference between the results from oil-and-gas industry and airlines is that, even though this sum remains positive with *Dispersion* as the dependent variable, it is not statistically significant for airlines ($\beta_1 + \beta_3 = 0.051$, p value $= 0.718$).

Collectively, the results reported in Table 5 support the concerns raised by practitioners that failure to qualify for hedge accounting under stringent conditions imposed by SFAS 133 could create excess income statement volatility, even when derivative instruments are in place for hedging. That is, under prevailing hedge accounting rules, derivative hedging could cause earnings to be less predictable than if there were no hedging at all.

5 Additional analyses

Turning to the impact of derivative hedging on analysts' ability to predict earnings, Chang et al. (2016) document a negative association between the initiation of derivatives and analysts' earnings predictability and attribute this finding to analysts routinely misjudging the earnings implications of derivatives. Campbell et al. (2015) also draw similar inferences. If an analyst's ability is a primary driver of the association between derivative hedging and analysts' earnings predictability, we would expect analyst properties, such as experience, access to resources (proxied by brokerage size), and industry expertise, to moderate this relationship (Clement 1999; Jacob et al. 1999). Accordingly, we partition our sample based on these analyst properties and re-examine all of our hypotheses. However, in untabulated results, we fail to find consistent evidence to suggest that analysts with greater experience, those employed by large brokerages, or those who are industry specialists perform better in terms of forecasting earnings of firms that hedge, regardless of whether hedges qualify as effective. In other words, while the results reported in the previous section strongly suggest prevailing accounting treatment of derivative instruments to affect the association between hedging and earnings predictability, we fail to identify analyst ability as a significant determinant of this relationship.

6 Conclusion

Derivatives are inherently complex. Financial accounting standards require detailed and elaborate reporting with respect to derivatives to help financial statement users understand their earnings and valuation implications. When derivatives are used for hedging, it would seem that earnings and cash flow volatilities should decrease, improving their predictability by investors and financial analysts. Yet the impact of hedging on earnings volatility is unclear, due to the stringent hedge accounting rules imposed by SFAS 133. Moreover, some research suggests that even sophisticated financial statement users are unable to understand earnings implications of derivative hedging (Campbell 2015; Campbell et al. 2015; Chang et al. 2016). Therefore, whether hedging improves or impairs analysts' earnings forecasting efficacy is an empirical question.

We examine this issue in the context of two industries that extensively use derivatives to manage price risks: the oil-and-gas exploration-and-production and airlines. Firms in the former industry hedge to reduce output price risk, while those in the latter have a natural incentive to hedge against highly volatile input fuel prices. Our results establish that, when derivatives are used for hedging, overall they improve earnings predictability and the forecasting efficacy of financial analysts. However, we also find that extant reporting regulations pertaining to hedge accounting have a significant bearing on this outcome. Specifically, we show that derivatives that fail to qualify for hedge accounting significantly impair earnings predictability. Moreover, when all of firms' hedges fail to qualify for hedge accounting, hedging in fact makes earnings less predictable. This latter finding provides credence to the criticism that stringent hedge accounting requirements imposed by SFAS 133 induce artificial income volatility and supports attempts to simplify hedge accounting rules.

The intricacies of derivatives accounting rules raise many other interesting empirical questions. For example, per SFAS 133, the fair value changes of cash flow hedges that qualify for hedge accounting (effective hedges) are recognized in statements of other comprehensive income, while fair value changes of derivatives that do not qualify for hedge accounting (ineffective hedges) are recognized in income statements. While regulators prescribe such differential treatments, it would be interesting to examine whether the market values them differently. Another related issue is whether hedge ineffectiveness affects the value relevance of earnings. These are avenues for future research.

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Appendix A

Hedge accounting and hedge ineffectiveness under SFAS 133

Prior to the adoption of SFAS 133, hedging derivatives were kept off the balance sheet. Once the manager determines that a given derivative is used for hedging (as opposed to trading), its impact is recorded on the income statement in the same period in which the underlying hedged transaction is recognized. In the event the derivative is not a perfect hedge, the impact of the imperfection is also recognized in the same period that the hedged transaction is recognized. Hence, pre-SFAS 133, to the extent that the derivative provided *some* economic protection against the price volatility of the hedged item, the income statement was shielded from this volatility.

SFAS 133 significantly altered derivative accounting by requiring that all derivatives be recorded on the balance sheet at fair value. Under SFAS 133, only hedges that qualify as "effective hedges" for accounting purposes are allowed to be accounted under *hedge accounting*, in which changes in fair value are recorded in other comprehensive income (OCI) until the hedged item is recorded in earnings (at which time these changes are also released to earnings). Therefore, the income statement effect of cash flow hedges that qualify for hedge accounting under SFAS 133 is broadly similar to that of pre-SFAS 133 period.

SFAS 133 imposes stringent guidelines for derivatives to be deemed effective hedges and qualify for hedge accounting. Assessments of hedge effectiveness are required at the inception of the transaction, at least every three months thereafter, and whenever financial statements or earnings are reported (SFAS 133, ¶20b). While the standard does not prescribe a specific method of determining hedge effectiveness, most firms use the "80–125 dollar offset ratio standard," in which the dollar offset ratio is defined as the change in the value of the hedging instrument divided by the change in the value of the hedged item over the assessment period. In other words, while a hedging instrument the value of which changes 75 cents in the opposite direction for every one dollar change in the price of the hedged item would substantially (albeit imperfectly) offset the underlying price risk, it would not qualify as an effective hedge for hedge accounting purposes and would therefore be deemed ineffective. Moreover, even highly effective hedges might be disqualified from hedge accounting in the absence of formal documentation of the hedging relationship and the entity's risk management objectives and strategy (SFAS 133, ¶20a).

For hedges that do not qualify for hedge accounting (ineffective hedges), periodic fair value changes are reported directly in the income statement, regardless of when the hedged item is recognized in the income statement. This income statement recognition of interim changes in derivative fair values exposes the firm to potential earnings volatility (accounting effect), even though the economic objective of the hedge is to reduce cash flow volatility (economic effect).

At the end of this appendix, we provide a stylized illustration of how failure to qualify as effective hedges under SFAS 133 could provide economic and accounting outcomes that conflict with one another.

Many firms find it difficult to meet the high threshold of hedge effectiveness stipulated by SFAS 133 (i.e., the 80–125 dollar offset ratio or the 80%–125% negative correlation), due to factors such as differences between the basis of the hedging instrument and the hedged item as well as differences in certain terms of the hedging instrument and hedged item, such as maturities, quantity, location, or delivery dates. For example, an oil-and-gas firm might find it difficult to obtain derivatives that meet the hedge accounting standards, because the price reference location of highly liquid exchange-traded crude oil and natural gas derivatives may not fully correspond with their production location.[31] Similarly, since jet fuel derivatives are not exchange traded, many airlines use crude oil and heating oil contracts as economic substitutes. While these substitutes would significantly counter jet fuel price risks, they may fail to meet SFAS 133 effectiveness thresholds and hence may not qualify for hedge accounting. Moreover, as a practical matter, many firms hold a combination of both effective and ineffective hedges. Two illustrative disclosures relating to airlines using heating oil contracts as substitutes for jet fuel hedges and firms holding both effective and ineffective hedges are presented in Appendix B.

[31] For example, the prices of mostly liquid oil futures contracts traded on NYMEX are based on West Texas intermediate crude. An oil-and-gas firm that uses these instruments to hedge its production elsewhere might fail to qualify for hedge accounting.

As explained previously, critics contend that high effectiveness thresholds and onerous documentation requirements imposed by SFAS 133 to qualify for hedge accounting cause the potential unintended consequences of hedging derivatives creating artificial income volatility making earnings less predictable.

Illustration of Economic and Accounting Outcomes of Hedge Effectiveness

This illustration considers hedging outcomes for a hypothetical crude oil producer XYZ, wanting to hedge the sale of 10,000 barrels of crude oil taking place at the end of four reporting periods from now with forward contracts. We consider three scenarios.

a. Entire sale is hedged with a fully effective forward contract that qualifies for hedge accounting (Tables 6 and 7)
b. Entire sale is hedged with a contract that is an economic hedge but one that does not qualify for hedge accounting (Tables 8 and 9)
c. Half the sale is hedged with the contract in (a) above while the remaining half is hedged with the contract in (b) above (Table 10)

The following assumptions are made.

- Fixed price stipulated in forward contracts is $50 per barrel. Hence the expected value of the transaction is $500,000 (10,000 x $50).
- XYZ neither receives nor pays an upfront premium so that the fair value of the derivative at inception is zero.
- Time value of money is ignored in all fair value calculations.
- Spot price per barrel for the type of crude oil produced by XYZ turns out to be $44.00, $40.50, $39.30, and $38.10 at the end of periods one, two, three, and four respectively.

Scenario a: A fully effective hedge that qualifies for hedge accounting

Table 6 This table shows the crude oil spot price per barrel, fair value change during the period, and cumulative fair value change for both the derivative and the anticipated hedged transaction at the end of each period. Note that the periodic price changes in the derivative and underlying hedged transaction are perfect (i.e., −100%), implying a fully effective hedge

Period (1)	Derivative			Hedged Transaction		
	Spot price per barrel ($) (2)	Fair value change during the period ($) (3)	Cumulative Fair Value Change ($) (4)	Spot price per barrel ($) (5)	Fair value change during the period ($) (6)	Cumulative Fair Value Change ($) (7)
1	44.00	60,000	60,000	44.00	−60,000	−60,000
2	40.50	35,000	95,000	40.50	−35,000	−95,000
3	39.30	12,000	107,000	39.30	−12,000	−107,000
4	38.10	12,000	119,000	38.10	−12,000	−119,000

Table 7 This table shows the income statement, statement of other comprehensive income (OCI), and cash flow effects of the derivative and the hedged transaction at the end of each period

Period (1)	Net Income Increase/(Decrease)			OCI Increase/(Decrease)			Operating Cash Flow Increase/(Decrease)		
	Due to derivative ($) (2)	Due to hedged transaction ($) (3)	Total ($) (4)	Due to derivative ($) (5)	Due to hedged transaction ($) (6)	Total ($) (7)	Due to derivative ($) (8)	Due to hedged transaction ($) (9)	Total ($) (10)
1	–	–	–	60,000	–	60,000	–	–	–
2	–	–	–	35,000	–	35,000	–	–	–
3	–	–	–	12,000	–	12,000	–	–	–
4	119,000	381,000*	500,000	(107,000)	–	(107,000)	119,000	381,000*	500,000

*10,000 barrels x $38.10 per barrel

As can be seen in column (10) of Table 7, the net cash flow effect of derivative and the hedged transaction is a cash inflow of $500,000 at the end of period four, which secures an effective price of $50.00 per barrel. The income statement effect (column 4) is identical to the cash flow effect, because interim fair value changes of the derivative are recognized in other comprehensive income (OCI) and released back to the income statement when the hedged transaction occurs at the end of period four. With this forward contract, XYZ effectively eliminates price uncertainty of period four crude oil production from both cash flow and income statement standpoints. Thus, effective hedging dampens variations in *both* cash flows and earnings by offsetting fluctuations in output and factor prices.

Scenario b: An economic hedge that does not qualify for hedge accounting

Table 8 This table shows the crude oil spot price per barrel, fair value change during the period, and cumulative fair value change for both the derivative and the anticipated hedged transaction at the end of each period. Note that, unlike in Scenario a, even though fair value changes of the derivative instrument and the underlying hedged transaction are negatively correlated, they are not perfect. From a practical standpoint, this can be viewed as a case where the actual production location and the production location on which the forward contract is based on differ. The correlation between the fair value changes in the derivative and the underlying hedged transaction is −75%. Under extant hedge accounting rules this hedge would be deemed ineffective and would not qualify for hedge accounting.

Period (1)	Derivative			Hedged Transaction		
	Spot price per barrel ($) (2)	Fair value change during the period ($) (3)	Cumulative Fair Value Change ($) (4)	Spot price per barrel ($) (5)	Fair value change during the period ($) (6)	Cumulative Fair Value Change ($) (7)
1	44.00	60,000	60,000	44.00	−60,000	−60,000
2	42.00	20,000	80,000	40.50	−35,000	−95,000
3	38.50	35,000	115,000	39.30	−12,000	−107,000
4	37.50	10,000	125,000	38.10	−12,000	−119,000

Referring to column (10) of Table 9, the net cash flow effect of the derivative and hedged transaction is a cash inflow of $506,000 at the end of period four, which secures an effective price of $50.60 per barrel. In other words, the derivative has significantly (albeit imperfectly) shielded XYZ from price fluctuations in the crude oil market. However, because the derivative does not qualify for hedge accounting, interim changes in the fair value of the derivative are recognized not in OCI, but directly in the income statement. Thus, the effective price reported in period four when the hedged transaction takes place is $39.10 per barrel. Consequently, the income statement is exposed to fluctuations in crude oil prices and fails to reflect the fact that the price risk was substantially hedged. This illustrates that, while economic hedges can significantly reduce risks associated with price volatility, to the extent that they do not qualify for hedge accounting, such risk reductions are not reflected in the income statement.

Table 9 This table shows the income statement, statement of other comprehensive income (OCI), and cash flow effects of the derivative and the hedged transaction at the end of each period

Period (1)	Net Income Increase/(Decrease)			OCI Increase/(Decrease)			Operating Cash Flow Increase/(Decrease)		
	Due to derivative ($) (2)	Due to hedged transaction ($) (3)	Total ($) (4)	Due to derivative ($) (5)	Due to hedged t ransaction ($) (6)	Total ($) (7)	Due to derivative ($) (8)	Due to hedged transaction ($) (9)	Total ($) (10)
1	60,000	–	60,000	–	–	–	–	–	–
2	20,000	–	20,000	–	–	–	–	–	–
3	35,000	–	35,000	–	–	–	–	–	–
4	10,000	381,000*	391,000	–	–	–	125,000	381,000*	506,000

*10,000 barrels x $38.10 per barrel

Scenario c: A combination of the fully effective hedge that qualifies for hedge accounting and the economic hedge that does not qualify for hedge accounting

Table 10 This table shows the income statement, statement of other comprehensive income (OCI), and cash flow effects of the derivative and the hedged transaction at the end of each period under a scenario where half the sale is hedged with the contract in (a) above while the remaining half is hedged with the contract in (b) above. This can be thought of as the common situation of a firm holding both effective and ineffective hedges

Period (1)	Net Income Increase/(Decrease)			OCI Increase/(Decrease)			Operating Cash Flow Increase/(Decrease)		
	Due to derivative ($) (2)	Due to hedged transaction ($) (3)	Total ($) (4)	Due to derivative ($) (5)	Due to hedged transaction ($) (6)	Total ($) (7)	Due to derivative ($) (8)	Due to hedged transaction ($) (9)	Total ($) (10)
1	30,000	–	30,000	30,000	–	–	–	–	–
2	10,000	–	10,000	17,500	–	–	–	–	–
3	17,500	–	17,500	6000	–	–	–	–	–
4	64,500	381,000*	445,500	(53,500)	–	–	122,000	381,000*	503,000

*10,000 barrels x $38.10 per barrel

Under this scenario, interim fair value changes of the derivative that qualifies for hedge accounting do not impact the income statement and are recognized in OCI instead. On the other hand, interim fair value changes of the derivative that do not qualify for hedge accounting are directly recognized in the income statement. Column (10) of Table 10 reveals that the net cash flow effect of the derivative and hedged transaction is an inflow of $503,000 at the end of period four, which secures an effective price of $50.30 per barrel. The income statement impact lies in between scenario a. and b. above, resulting in an income of $445,500 in period four, reflecting an effective price of $44.55 per barrel. Holding both types of derivatives (ones that do and do not qualify for hedge accounting) provides some protection to the income statement against price risk in crude oil prices, but it is smaller when compared with the economic protection provided in terms of cash flows.

Appendix B

Examples of Hedge Ineffectiveness Disclosures

The following disclosure made by US Airways Group, Inc., in its 2007 10-K filling illustrates the issue of using heating oil contracts to hedge against jet fuel price risk and the consequent origination of hedge ineffectiveness.

> The Company utilizes financial derivative instruments primarily to manage its risk associated with changing jet fuel prices. The Company currently utilizes heating oil-based derivative instruments to hedge a portion of its exposure to jet fuel price increases. These instruments consist of costless collars. As of December 31, 2007, the Company has entered into costless collars to hedge approximately 22% of its 2008 projected mainline and Express jet fuel requirements. The Company does not purchase or hold any derivative financial instruments for trading purposes. (p. 79)
>
> In 2007, US Airways realized operating income of $524 million and income before income taxes of $485 million. Included in these results is $245 million of net gains associated with fuel hedging transactions. This includes $187 million of unrealized gains resulting from the application of mark-to-market accounting for changes in the fair value of fuel hedging instruments as well as $58 million of net realized gains on settled hedge transactions. US Airways is required to use mark-to-market accounting as our existing fuel hedging instruments do not meet the requirements for hedge accounting established by SFAS No. 133, "Accounting for Derivative Instruments and Hedging Activities." If these instruments had qualified for hedge accounting treatment, any unrealized gains or losses would have been deferred in other comprehensive income, a component of stockholder's equity, until the jet fuel is purchased and the underlying fuel hedging instrument is settled. (p. 44)
> -US Airways Group, Inc. 10-K, 2007

The following disclosure by Forest Oil Corp. in its 3Q 2001 10-Q filling provides a typical example of a firm employing a combination of both effective and ineffective hedges.

> (O)n January 1, 2001, the Company began accounting for the energy swaps and collars, in accordance with SFAS No. 133. All of Forest's energy swap and collar agreements and a portion of Forest's basis swaps in place at January 1, 2001 have been designated as cash flow hedges. As a result, changes in the fair value of the cash flow hedges are recognized in other comprehensive income until the hedged item is recognized in earnings, and any change in fair value resulting from ineffectiveness is recognized immediately in earnings. Changes in the fair value of basis swaps not designated as cash flow hedges are recognized in other income.[32] The increase in fair value of derivative financial instruments included in other comprehensive income during the third quarter and nine months ended September 30, 2001 was $14,308,000 and $30,774,000, respectively. … Included in other income during the third quarter and nine months ended September 30, 2001 are net gains (losses) of $(8,806,000) and $2,298,000, respectively, on basis swaps and other instruments not designated as cash flow hedges.
> -Forest Oil Corp 10-Q, 3Q-2001

Appendix C

A model of hedge accounting

In this appendix, we model the income statement effects of hedging by a firm in steady state to analytically demonstrate how hedge accounting affects earnings volatility.

Let $\widetilde{x}_u$ represent period-specific fluctuations (i.e., gain or loss) of a going concern's exposure to price risk of the underlying item in steady state. By definition, $E(\widetilde{x}_u) = 0$. Let $Var(\widetilde{x}_u) = \sigma^2$. Let a fraction θ $(0 < \theta < 1)$ of hedging positions closed every period because of the culmination of the underlying transaction. For a firm to be in steady state, we assume that new exposures of the same magnitude originate in each period so that the full extent of exposure remains unchanged from period to period.

The firm wishes to hedge this exposure with a derivative instrument. Let period-specific fluctuations in the market value of hedging derivative portfolio be represented by $\widetilde{x}_d$ with $E(\widetilde{x}_d) = 0$. Let $Var(\widetilde{x}_d) = \sigma^2$. We assume the same variance for the two random variables for analytical convenience but without loss of generality.[33]

Let $\mathrm{Cov}(\widetilde{x}_u, \widetilde{x}_d) = \rho_{ud}\sigma^2$, where ρ_{ud} is the standard Pearson correlation coefficient. For the derivative portfolio to be a hedge it must be that case that $\rho_{ud} < 0$. The net exposure in any period is then given by

[32] Forest Oil uses the term "not designated as cash flow hedges" to denote derivatives that are deemed ineffective and do not qualify for hedge accounting.

[33] Our analysis holds even when these variances are unequal as long as the difference is within a reasonable range.

$$\begin{aligned}\widetilde{\mathrm{x}}_{\mathrm{net}} &= \widetilde{\mathrm{x}}_{\mathrm{u}} + \widetilde{\mathrm{x}}_{\mathrm{d}}, \textit{with}\\ E\left(\widetilde{x}_{net}\right) &= 0, \textit{and}\\ Var\left(\widetilde{x}_{net}\right) &= Var\left(\widetilde{x}_{u}\right) + Var\left(\widetilde{x}_{d}\right) + 2Cov\left(\widetilde{x}_{u}, \widetilde{x}_{d}\right)\\ &= 2\sigma^2(1 + \rho_{\mathrm{ud}}).\end{aligned}$$

With this structure, observe that $Var\ (\widetilde{x}_{net}) = 0$ for $\rho_{\mathrm{ud}} = -1$, reflecting a *perfect* hedge. In general, for hedging to be economically beneficial, it must be the case that

$$\begin{aligned}&Var\left(\widetilde{x}_{net}\right) < Var\left(\widetilde{x}_{u}\right)\\ &\Leftrightarrow 2\sigma^2(1 + \rho_{\mathrm{ud}}) < \sigma^2\\ &\Leftrightarrow \rho_{\mathrm{ud}} < -\frac{1}{2}\end{aligned}$$

We will henceforth assume that all hedges satisfy this condition—otherwise there is no purpose in hedging.

We define what constitutes an ineffective hedge from an accounting perspective in reference to a threshold $\overline{\rho} \in (-1, -\frac{1}{2})$, to capture the essence of SFAS 133.

Definition 1 *Given a threshold* $\overline{\rho} \in (-1, -\frac{1}{2})$*, a hedging derivative is deemed ineffective from an accounting perspective if* $\rho_{ud} > \overline{\rho}$*; it is deemed effective otherwise;* i.e.*, if* $\rho_{ud} \leq \overline{\rho}$*.*

Thus hedging is *economically beneficial* but *ineffective* if $\rho_{\mathrm{ud}} \in \left(\overline{\rho}, -\frac{1}{2}\right)$. On the other hand, hedging is *economically* beneficial and *effective* if $\rho_{\mathrm{ud}} \in (-1, \overline{\rho}]$.

Note that, in practice, firms typically apply the negative 80% correlation threshold to determine whether a derivative qualifies as an effective hedge for accounting purposes. Therefore, in general, firms likely have some effective and some ineffective hedges. To motivate our hypotheses of how effective and ineffective hedges might affect income volatility, we next consider two extreme cases—when the entire hedging derivative portfolio is fully effective and when it is fully ineffective.

Case 1: Fully effective hedging derivative portfolio: $-1 < \rho_{\mathrm{ud}} \leq \overline{\rho}$

In this case, hedging will affect income statement volatility only when the underlying hedged item is "consummated" which happens for a fraction θ of the exposure every period.[34] Consequently, hedging will decrease income statement volatility if

$$\begin{aligned}&Var\left(\theta\widetilde{x}_{net}\right) < Var\left(\theta\widetilde{x}_{u}\right)\\ \Leftrightarrow\quad &Var\left(\widetilde{x}_{net}\right) < Var\left(\widetilde{x}_{u}\right)\end{aligned}$$

[34] Strictly speaking, under SFAS 133, fair value changes of ineffective portions of outstanding (unconsummated) hedges that even qualify for hedge accounting need to be immediately recognized in earnings. We ignore this for analytical parsimony.

This inequality is always satisfied when $\rho_{ud} < -\frac{1}{2}$. Moreover, because $\rho_{ud} \leq \overline{\rho} < -\frac{1}{2}$ for effective hedges, effective hedges always decrease income statement volatility.

Case 2: Fully ineffective hedging derivative portfolio: $\overline{\rho} < \rho_{ud} < -\frac{1}{2}$

In this case, the net income is also affected by immediate recognition of gains and losses associated with the ineffective hedging derivatives associated with the (1 - θ) fraction of hedged item that remain unconsummated at the end of the period. Accordingly, the net income effect in a period may be computed as

$$\widetilde{x}_{net} = \theta\left(\widetilde{x}_u + \widetilde{x}_d\right) + (1-\theta)\widetilde{x}_d.$$

It follows that

$$\begin{aligned} Var\left(\widetilde{x}_{net}\right) &= \theta^2 Var\left(\widetilde{x}_u + \widetilde{x}_d\right) + (1-\theta)^2 Var\left(\widetilde{x}_d\right) + 2\theta(1-\theta)Cov\left(\widetilde{x}_u + \widetilde{x}_d, \widetilde{x}_d\right) \\ &= 2\theta^2\sigma^2(1+\rho_{ud}) + (1-\theta)^2\sigma^2 + 2\theta(1-\theta)\left[Cov\left(\widetilde{x}_u, \widetilde{x}_d\right) + Var\left(\widetilde{x}_d\right)\right] \\ &= 2\theta^2\sigma^2(1+\rho_{ud}) + (1-\theta)^2\sigma^2 + 2\theta(1-\theta)\left[\rho_{ud}\sigma^2 + \sigma^2\right] \\ &= 2\theta\sigma^2(1+\rho_{ud}) + (1-\theta)^2\sigma^2 \end{aligned}$$

The income statement volatility will decrease relative to when there is no hedging if and only if

$$\begin{aligned} 2\theta\sigma^2(1+\rho_{ud}) + (1-\theta)^2\sigma^2 &< \theta^2\sigma^2 \\ \Leftrightarrow 2\theta\rho_{ud} + 1 &< 0 \\ \Leftrightarrow \theta\rho_{ud} &< -\frac{1}{2} \end{aligned}$$

Because $0 < \theta < 1$ and $\rho_{ud} < 0$, the larger the θ, the more negative the ρ_{ud}, or both, the more likely the above inequality holds. This condition implies that the economically beneficial effects of hedging will overwhelm the accounting effects of ineffective hedging when a larger fraction of derivative positions is closed every period, price fluctuations of hedging derivatives are more negatively correlated with the underlying hedged item, or both. Conversely, accounting effect will overwhelm the economic effect and increase earnings volatility when a large fraction of derivative positions remains open, when the negative correlation between price fluctuations of hedging derivatives and the underlying hedged item is relatively weak, or both.

We recognize that the parameter θ, which represents the fraction of exposure for which the underlying hedged item is "consummated" every period, cannot be empirically estimated from available data, especially given that it likely varies across firms and varies over time for the same firm. Our motivation in presenting this model is to simply establish that ineffective hedges need not always *increase* income volatility because of how they are accounted for under SFAS 133. The economic effect associated with these hedges could well outweigh the deleterious accounting effect and result in a decrease in income volatility.

Appendix D

Computation of Extent of Derivative Usage (*Derivatives*)

Oil-and-Gas Industry

This example illustrates the computation of derivatives measure (*Derivatives*) for Stone Energy Corp. for second quarter of 2004.

As reported in its first quarter 2004 10-Q fillings, Stone Energy had the following outstanding derivative contracts to cover its second quarter 2004 production (that is, derivative contracts that become exercisable during second quarter of 2004).

Crude oil

Put options – 682,500 Barrels (Bbls)

Natural Gas

Swaps – 1,365,000 thousands of cubic feet (MCF)

Put options – 8,190,000 Mcf

According to the second quarter 2004 10-Q fillings, Stone Energy's crude oil and natural gas production for the period were 1,552,000 Bbls and 14,443,000 Mcf respectively.

Therefore, for the second quarter of 2004, Stone Energy used derivative contracts to hedge 43.98% of its crude oil production (682,500/1,552,000) and 66.16% of its natural gas production [(1,365,000 + 8,190,000)/14,443,000].

The oil-and-gas industry uses a standard conversion rate of one Bbl of oil to six Mcf of gas to convert oil production into natural gas equivalent. Therefore 39.20% of Stone Energy's second quarter 2004 total production relates to crude oil [(1,552,000*6)/{(1,552,000*6) + 14,443,000}], and the remaining 60.80% relates to natural gas [(14,443,000)/{(1,552,000*6) + 14,443,000}].

Applying these relative production fractions to derivative hedging fractions of crude oil and natural gas, it can be seen that, for the second quarter of 2004, Stone Energy used derivative instruments to hedge 57.46% of its total production [(0.4398 × 0.3920) + (0.6616 × 0.6080) = 0.5746].

Hence, the variable *Derivatives* takes the value for 0.5746 for Stone Energy in the second quarter of 2004.

Airline Industry

The following excerpt from United Airlines' third quarter 2004 form 10-Q typifies the extent of hedging disclosures provided by most airlines.

"During the second quarter of 2004, we began to implement a strategy to hedge a portion of our price risk related to projected jet fuel requirements primarily through collar options. … Currently, we have hedged approximately 36% of our fourth quarter 2004 projected fuel requirements at an average price of $1.00 to $1.17 per gallon, excluding taxes."

The company clearly states that 36% of expected jet fuel consumption is covered by derivative contracts. Hence, for the fourth quarter of 2004, the variable *Derivative* for United Airlines would take the value of 0.36.

Appendix E

Variable Definitions

Variable name	Definition
Accuracy	Analyst forecast accuracy: The absolute value of the difference between the individual analyst earnings forecast and the actual earnings scaled by stock price at the end of the quarter t for firm i. The values are multiplied by −100, so that greater values indicate more accurate forecasts. Specifically, $\lvert CEF_{it} - EPS_{it}\rvert / P_{it} * (-100)$, where CEF_{it}, EPS_{it}, and P_{it} are the most recent individual analyst quarter earnings forecasts, actual earnings per share, and quarter-end price per share for firm i at period t, respectively.
Dispersion	Analyst forecast dispersion: The inter-analyst standard deviation of quarter earnings forecasts deflated by stock price at the end of quarter t for firm i. The value is multiplied by 100. Specifically, $[SD_{it}/P_{it}]*100$, where SD_{it} and P_{it} are the standard deviation of quarter earnings forecasts and quarter-end price per share for firm i at period t, respectively. Note that *Dispersion* changes as new analyst forecasts are issued.
Derivatives	The extent of derivative usage: For oil-and-gas industry, *Derivatives* is measured as the fraction of firm i, period t production covered by derivatives contracts. For airline industry, *Derivatives* is measured as the fraction of firm i, period t estimated jet fuel consumption covered by derivatives contracts.
Analysts	The total number of analysts following firm i at quarter t.
Size	Natural log of total assets of firm i at the beginning of quarter t.
Intangible	Intangible ratio: Ratio of intangible assets to total assets at beginning of year t.
Volatility	The standard deviation of monthly stock returns for firm i at year t-1.
MB	Market-to-book ratio: Market value of equity (prccq×cshoq) divided by book value of equity (atq-ltq-pstkl/4 + txditcq+dcvt/4).
Issue	An indicator variable taking the value of 1 if firm i issues equity greater than 5% of total assets at quarter t and 0 otherwise.
Turnover	Stock turnover: The ratio of the number of shares traded in quarter t to the average number of shares outstanding in quarter t.
Return	Market adjusted stock return: Quarterly stock return for firm i at quarter t-1, adjusted for contemporaneous quarterly market return.
ROA	Return on assets: Income before extraordinary items (ibq) divided by total assets (atq) at the beginning of quarter t.
Foreign	Foreign operations: An indicator variable taking the value of 1 if foreign income or loss (pifo) is not equal to 0 and 0 otherwise.
M&A	Mergers and acquisitions: An indicator variable taking the value of 1 if cash flow from mergers and acquisitions (aqcq) is not equal to 0 and 0 otherwise.
DA	Absolute value of discretionary accruals. The discretionary accruals is obtained using Jones (1991) accruals expectation model as modified by Dechow et al. (1995).
Ineffective	An indicator variable taking the value of 1 if firm i in quarter t have nonzero ineffective gain/loss and 0 otherwise.

AllIneffective	An indicator variable taking the value of 1 if none of the firms' hedges qualify for hedge accounting and 0 if all of the firms' hedges qualify for hedge accounting.
Num_firm	Number of firms analyst j follows in quarter t.
Num_ind	Number of industries analyst j follows in quarter t.
Brokerage_size	The size of brokerage that analyst j works in at quarter t, measured as the number of analysts working in the brokerage at quarter t.
Forecast_exp	Number of quarters analyst j has followed firm i.
Forecast_freq	Number of forecasts analyst j makes for firm i in quarter t.
Horizon	Number of days between forecast issuance date and actual earnings announcement date.

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