7-2023

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Citation

CAMPBELL, John L.; CAO, Sean Shun; CHANG, Hye Sun; and CHIOREAN, Raluca. The implications of firms' derivative usage on the frequency and usefulness of management earnings forecasts. (2023). *Contemporary Accounting Research*. 40, (4), 2409-2445.
Available at: https://ink.library.smu.edu.sg/soa_research/2030

Received: 13 April 2020 | Accepted: 31 May 2023

DOI: 10.1111/1911-3846.12883

ARTICLE

CAAA ACPC CONTEMPORARY ACCOUNTING RESEARCH | RECHERCHE COMPTABLE CONTEMPORAINE

The implications of firms' derivative usage on the frequency and usefulness of management earnings forecasts

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[Corrections made on August 11, 2023: The initial version was published erroneously without final edits and has been updated.]

Abstract

We investigate how firms' use of derivatives impacts voluntary disclosure and offer four main findings. First, we find that when firms begin using derivative instruments, they increase the frequency of management earnings forecasts. Second, using path analysis, we find a direct link between derivative usage and forecast frequency, as well as an indirect link through reduced earnings volatility. Third, we find that CEOs with more pronounced career concerns increase forecast frequency *only* when derivatives make earnings easier to forecast and find no evidence that investor demand drives the decision to provide a forecast. These results suggest that the primary mechanism for the association between derivative usage and forecast frequency is a reduction in the manager's costs of providing the forecasts. Finally, we find that the majority of derivative-induced forecasts are uninformative to capital market participants, especially after FAS 161 provided the necessary underlying data to understand how firms use derivatives. Overall, we provide the first empirical evidence that firms that use derivatives issue more management forecasts, but we also find that these incremental forecasts are largely uninformative and appear driven by managerial career concerns.

KEYWORDS

analyst forecasts, derivatives, management forecasts, risk management

Accepted by Hai Lu.

Les implications de l'utilisation de dérivés par les entreprises sur la fréquence et l'utilité des prévisions de résultats de la direction

Résumé

Les auteurs étudient l'impact de l'utilisation de dérivés par les entreprises sur la communication d'information facultative et formulent quatre conclusions principales. Premièrement, ils constatent que lorsque les entreprises commencent à utiliser des instruments dérivés, elles augmentent la fréquence des prévisions de résultats de la direction. Deuxièmement, en effectuant l'analyse de chemin, ils observent un lien direct entre l'utilisation de dérivés et la fréquence des prévisions, ainsi qu'un lien indirect par le biais d'une réduction de la volatilité des bénéfices. Troisièmement, ils notent que les PDG avec des préoccupations de carrière plus prononcées augmentent la fréquence des prévisions seulement lorsque les dérivés rendent les résultats plus faciles à prévoir et ils ne trouvent aucune donnée indiquant que la demande des investisseurs motive la décision d'établir une prévision. Ces résultats donnent à penser que le mécanisme principal de l'association entre l'utilisation de dérivés et la fréquence des prévisions est une réduction des couts encourus par le gestionnaire pour établir les prévisions. Enfin, les auteurs constatent que la majorité des prévisions induites par les dérivés sont peu informatives pour les participants du marché financier, notamment après que le FAS 161 ait fourni les données sous-jacentes nécessaires pour comprendre comment les entreprises utilisent les dérivés. Dans l'ensemble, cette étude révèle les premières données empiriques indiquant que les entreprises utilisant des dérivés publient plus de prévisions de la direction, mais que ces prévisions supplémentaires sont également largement peu informatives et semblent motivées par les préoccupations de carrière des gestionnaires.

MOTS-CLÉS

dérivés, gestion des risques, prévisions des analystes, prévisions de résultats

1 | INTRODUCTION

Firms' use of derivatives has increased exponentially over the last few decades, as the total notional amount of derivative contracts increased from $72 trillion in 1998 to $640 trillion in 2019, an increase of over 800% (BIS, 2019). Prior research focuses on why and how firms use derivatives, the implications of derivative usage on firm performance, as well as capital market participants' use of mandatory derivative disclosures. However, prior research has yet to examine whether derivative usage impacts a firm's voluntary disclosure (Campbell et al., 2019).

In this study, we examine whether the use of derivatives is associated with the frequency of a particular type of voluntary disclosure—management earnings forecasts—and, if so, whether this relation appears to be driven by an increase in managers' willingness to supply the disclosure or by an increase in investor demand for the disclosure. Specifically, we examine four research questions. First, is the use of derivatives positively associated with management earnings forecast frequency? Second, does the manner in which firms use derivatives (i.e., to hedge risks or to speculate on them) appear to drive this association? Third, does the association between derivatives and forecast frequency vary based on investor demand for the forecasts and/or managers' career concerns? Finally, do derivative-induced forecasts provide meaningful information to capital market participants?

Regulators have spent considerable effort over the last two decades increasing the transparency of firms' mandatory derivative disclosures (FASB, 1998, 2006, 2008, 2016). Understanding how derivative usage impacts voluntary disclosure helps to complete the picture of information available to market participants. Furthermore, we use the derivative setting to gain insights on a more fundamental question posed by Beyer et al. (2010) in their review of the disclosure literature—whether voluntary disclosure decisions appear to be driven by investor demand for the disclosure or by the manager's cost of providing that disclosure. Because derivatives are complex transactions and firms can use them either to reduce or increase their risk exposures, it is natural to assume that when firms use derivatives, investor demand for voluntary disclosure will increase. The question then becomes whether managers will voluntarily provide disclosure beyond what is mandatory to meet investor demand, even if it increases the possibility that their careers will be negatively affected.

Using a hand-collected sample of 28,851 derivative users and non-users, we start by examining the baseline relation between derivative usage and management forecast frequency. We next address omitted factors that correlate with both risk management and disclosure decisions using the quasi-experimental setting of derivative initiation (Chang et al., 2016). We find that a firm's use of derivatives is positively associated with the frequency of management earnings forecasts and that derivative initiation increases forecast frequency. Next, we perform a path analysis that suggests not only a direct link between derivative usage and increased forecasts, but also an indirect link as derivative usage reduces future earnings volatility. These initial results suggest that, on average, risk management activities improve management forecast frequency when they make future firm performance easier to predict and therefore reduce managers' career concerns related to inaccurate forecasts.

To further examine this relation, we perform two additional tests. First, we find that the positive association between the use of derivatives and management forecast frequency is present *only* when a firm uses derivatives to hedge market risks effectively and/or uses hedge accounting, making future firm performance easier to predict. We find no such result when a firm ineffectively hedges or speculates with derivatives or fails to use hedge accounting. Second, we find that managers with high career concerns, represented by young CEOs and those with short tenure, increase forecast frequency *only* when derivatives make it easier to forecast future earnings. We find no such difference for older CEOs and those with long tenure whose career and reputation are relatively stable. These results are inconsistent with heightened investor demand due to the complexity of derivatives increasing forecast frequency as, in that case, guidance frequency should increase regardless of managers' career concerns.

Finally, we examine whether derivative-induced forecasts provide useful information to capital market participants. Specifically, we examine whether these forecasts improve analyst forecast accuracy. We find that analyst forecast accuracy improves when firms issue more derivative-induced management forecasts, especially when the firm is using derivatives to speculate or is otherwise ineffectively hedging. Perhaps most importantly, we find that after FAS 161 improved derivative disclosures and allowed investors to better understand how firms use derivatives, this association is no longer present. In other words, our results suggest that the derivative-induced forecasts that analysts find to be most useful are in cases where managers are using derivatives to speculate rather than hedge, but after FAS 161 even those forecasts are not useful because analysts can get the information from mandatory disclosures.

Our main tests focus on management earnings forecasts because derivative usage is highly related to a firm's earnings.[1] However, in additional analyses, we examine the association between the use of derivative financial instruments and sales forecasts and find a positive association when derivative usage makes it easier to forecast future sales—that is, when firms use foreign exchange rate hedges rather than interest rate hedges. These results continue to support the idea that the decisions managers make regarding disclosures are driven at times by their disclosure cost instead of investor demand. To mitigate concerns of reverse causality and correlated omitted variables, we use difference-in-differences (DiD) analyses showing that *after* a firm *initiate*s (*terminates*) a derivative program, forecast frequency increases (decreases). Our results are robust to firm and/or manager fixed effects and the inclusion of potential time-varying omitted variables such as analyst forecast accuracy and financial statement complexity. Nevertheless, as with any archival study, we must caveat that our tests reflect associations for which we cannot definitively ascribe causality.

We make several contributions to the derivative and voluntary disclosure literatures. First, we find that derivative usage leads to increased voluntary disclosure through management forecasts and that at least one mechanism for this relation is reduced earnings volatility. Recent research provides evidence that derivative usage reduces earnings volatility in the oil-and-gas and airline industries and/or in post-FAS 161 time periods (Pierce, 2020; Ranasinghe et al., 2022). We validate these findings in our broader sample. More importantly, we also provide robust evidence linking earnings volatility to management forecasts. Overall, we answer the call for research on the relation between derivatives and voluntary disclosure by Campbell et al. (2019) and identify direct and indirect links between derivative usage and management earnings forecasts.

Second, our study provides insight into the factors that drive the management forecast decision, using settings that jointly examine more than one reason why managers might issue guidance. We do this using the derivative setting, where there are at least three reasons managers might provide forecasts: (1) an increase in investor demand for a forecast, (2) an increase in the manager's belief that a forecast would provide benefits to capital market participants, and (3) a decrease in the manager's perceived cost of providing a forecast. The totality of our evidence suggests that, at least in the derivative setting, the "cost-related" explanation appears to drive the forecast decision. Taken together with prior research, our results also suggest that not only do career concerns motivate managers to withhold disclosure of *bad news* (Baginski et al., 2018; Pae et al., 2016), they also appear to motivate managers to withhold the disclosure of information that is more *uncertain*.

Third, we contribute to the literature on the usefulness of management forecasts. Generally, prior literature finds that management forecasts improve analyst forecast accuracy, and thus conclude that management forecasts are useful to capital market participants (Beyer et al., 2010). We document a setting where management forecasts do not improve analyst forecasts, and yet managers provide them anyway. Specifically, our results suggest that the derivative-induced forecasts that analysts find to be most useful are in cases where managers

[1]Both management and analyst tracking services focus on "Street" measures of earnings, excluding a variety of expenses (e.g., special items and non-cash items) required under GAAP. Because derivatives can result in special and/or non-cash items (e.g., unrealized gains and losses), some analysts might exclude the effects of derivatives from their earnings forecasts (Chang et al., 2016). However, a firm's use of derivatives often affects what consists of "Street" earnings, such as sales revenue and cost of goods sold.

are using derivatives to speculate rather than hedge, but that after FAS 161 even those forecasts are not useful because analysts get the information from mandatory disclosures.

Finally, we contribute to the regulatory debate on how firms can improve disclosures to help investors understand the impact of derivatives on financial statements (Campbell, 2015; Campbell et al., 2015; Chang et al., 2016; Ernst & Young, 2010; FASB, 2016; SEC, 2008). Our results suggest that *mandatory* disclosure regulation appears to be the most effective way to get investors the information they need about the relation between derivative usage and future earnings. Specifically, regulators may wish to expand mandatory disclosures in cases where providing the disclosure could impact a manager's career concerns.

2 | LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 | Relevant prior literature on derivatives

A vast literature examines why firms use derivatives. Volatility in underlying rates or prices (e.g., interest rates, foreign currency exchange rates, or commodity prices) leads firms to experience higher volatility in their earnings and cash flows. Thus, firms exposed to these market risks are more likely to experience negative earnings and cash flow shocks. Negative earnings and cash flow shocks are particularly costly for firms facing financial distress and firms that need to raise capital, so these firms are more likely to use derivatives to smooth cash flows (Froot et al., 1993; Géczy et al., 1997; Smith & Stulz, 1985). Similarly, because firms pay taxes when their earnings are positive but do not receive money from the government for negative earnings, firms exposed to volatility in underlying rates or prices are more likely to use derivatives to smooth earnings and reduce their overall tax burdens (Donohoe, 2015; Smith & Stulz, 1985). Finally, negative earnings and cash flow shocks are costly for undiversified managers whose compensation and human capital are tied to the firm. Therefore, risk-averse managers as well as managers with lower levels of option compensation are more likely to use derivatives to hedge (Smith & Stulz, 1985; Spanò, 2007). To sum up, firms are more likely to use derivatives when they are sensitive to volatility in underlying rates or prices, face financial distress, external financing costs, and convex tax rates, and have more risk-averse managers (Campbell et al., 2019).

However, prior research also suggests that firms use derivatives to speculate or "take a view" and, thus, exacerbate earnings and cash flow volatility (Bodnar et al., 1998). In fact, these firms can benefit from such speculation if they have institutional knowledge on the underlying rate or price movements (Géczy et al., 2007). Similarly, if managers are compensated in ways that benefit them from volatility (i.e., option compensation), they will use fewer hedges or perhaps be willing to speculate with derivatives. Thus, firms also have incentives to use derivatives in a way that exacerbates earnings and cash flow volatility.

Prior research also examines the capital market consequences to the mandatory disclosure of derivatives. Although early work finds that mandatory derivative disclosures are priced by investors (Venkatachalam, 1996; Zhang, 2009), analysts and investors do not seem to impound derivative information fully at the disclosure date (Campbell, 2015; Campbell et al., 2015; Campbell, D'Adduzio, et al. 2021). However, FAS 161 appears to have improved the disclosure environment, as at least some of these inefficiencies improve after its issuance in 2008 (Campbell, Khan, & Pierce, 2021).

Despite the literature on the impact of mandatory disclosures of derivatives, prior research has yet to consider the link between derivative usage and voluntary disclosure (Campbell et al., 2019). We address this gap in the literature. We also consider whether changes in mandatory disclosure under FAS 161 impact the relation between derivative usage and voluntary disclosure.

2.2 | Relevant prior literature on voluntary disclosure

A long line of accounting research examines why firms voluntarily disclose financial information demanded by outsiders. Theory and empirical evidence suggest that voluntary disclosures can increase firm value by reducing information asymmetry and increasing stock liquidity (Easley & O'Hara, 2004; O. Kim & Verrecchia, 1994), by decreasing the cost of capital through lower estimation risk (Baginski & Hinson, 2016) or by increasing the precision and quantity of information (Easley & O'Hara, 2004).

These potential benefits increase the likelihood that managers will respond to investor demand for voluntary disclosures. For example, greater information demand increases managerial incentives to provide forecasts (Ajinkya et al., 2005). Managers are also more likely to issue forecasts when reported earnings are less informative (Wasley & Wu, 2006), when investors have inaccurate perceptions (Ajinkya & Gift, 1984; Balakrishnan et al., 2014), or when information asymmetry among investors is high (Coller & Yohn, 1997). In addition, Guay et al. (2016) find that financial statement complexity (measured as readability, length of firms' 10-K filing, and adoptions of FAS 133 and FAS 157) is positively related to management forecast frequency.

Also, managers' forecast decisions depend on the perceived benefits of providing a forecast. Managers provide more forecasts when they believe that their forecasts will be more informative to market participants, for example, when earnings volatility is lower (Waymire, 1985), during periods of low macroeconomic uncertainty (K. Kim et al., 2016), and when the firm's internal information environment is stronger (Feng et al., 2009).

Despite incentives to provide voluntary disclosures when investors demand them, it is costly for both firms and managers to provide such disclosures (Beyer et al., 2010). For example, firms may face litigation and proprietary costs (Francis et al., 1994; Verrecchia, 1983) or declines in market value when forecasts are inaccurate (Beyer, 2009). For managers themselves, voluntary disclosures impose *direct* costs, as they must expend time and effort to gather the requisite information to forecast earnings, as well as *indirect* costs if forecasts are inaccurate. Forecasting requires both managers' knowledge of the firm's business environment and their skill in forecasting the firm's performance. Inaccurate forecasts expose managers to the risk of loss in perceived ability, compromising forecasting reputation (Williams, 1996), increasing executive turnover (Lee et al., 2012), and decreasing managerial pay (Zamora, 2009).

Although numerous studies examine the effect of investor demand on management earnings forecast (MEF hereafter) frequency, surprisingly few studies examine the link between career concerns and disclosure choices (Beyer et al., 2010; T. Kim et al., 2023; Pae et al., 2016). Specifically, T. Kim et al. (2023) note that "studies examining the effects of career concerns on the attributes of earnings forecast are sparse, and that a more basic question regarding the effect on the decision whether to issue a forecast has been largely unaddressed." Among the few studies on this topic, Pae et al. (2016) show that CEOs with greater career concerns are more likely to provide downward earnings guidance upon bad news while Baginski et al. (2018) document that managers' career concerns are associated with a delay in bad news disclosure. Furthermore, theoretical and empirical research documents that managerial costs and investor demand are associated with providing forecasts in two separate research streams (Beyer et al., 2010). In this study, we jointly consider managerial costs and investor demand as the channels through which derivative usage influences management forecasts.

2.3 | Hypothesis development

Derivatives are highly complex financial contracts and affect major components of accounting earnings, such as, sales, COGS, interest expense, R&D expenditure, and unrealized holding gains/losses, among others. Despite their popularity, even sophisticated financial statement users such as sell-side analysts fail to fully comprehend the earnings implications of derivatives and hedge accounting (Campbell et al., 2015; Chang et al., 2016). The multiple iterations made to accounting for derivatives and hedge accounting over the past two decades further highlight the challenges financial statement users and ultimately regulators face in how to best account for them. For example, the FASB recognizes that GAAP for derivatives present some challenges as they "sometimes do not permit an entity to properly recognize the economic results of its hedging strategies in the financial statements" and financial statement users note that "the effect of hedge accounting on an entity's reported results often is difficult to understand and interpret" (FASB, 2017, p. 7). For this reason, it seems likely that investors would demand more voluntary disclosure when firms use derivatives. If so, we should find a positive association between derivative usage and management forecast frequency.

However, the extent to which managers provide forecasts is also likely to depend on the manner in which they use derivatives. If managers use derivatives to hedge risks associated with volatility in underlying rates or prices over which they have no control, their firm's cash flow and earnings volatility will decrease. Furthermore, when firms use hedge accounting, they often must demonstrate that the derivatives will hedge future purchases and sales, forcing managers to forecast purchase decisions and sales levels internally, as well as to pay closer attention to interest rate, foreign exchange, and commodity markets. The net effect of these impacts is that managers' disclosure costs will decline and their incentives to provide earnings guidance will increase. On the other hand, if managers use derivatives to speculate or "take a view" under the belief that they have an informational advantage relative to the market, earnings volatility will increase. This increased uncertainty in future earnings and cash flows would increase disclosure costs and decrease managers' incentives to provide guidance.

In sum, derivative instruments, with their inherent economic and accounting complexity, whether used for hedging or speculating, should unequivocally increase investor demand for voluntary disclosure, suggesting that derivative usage will increase management forecast activity. However, given the fact that the cost of providing the disclosure hinges on how managers use derivatives, the association between derivative usage and management forecast frequency is an empirical question. This leads to our first hypothesis:

> **Hypothesis 1 (H1).** Derivative usage is not associated with management forecast frequency.

As just discussed, if firms use derivatives to hedge risks associated with volatility in underlying rates or prices over which they have no control, cash flow and earnings volatility will decline, and future earnings will be easier to predict. Furthermore, the process of applying hedge accounting should increase managers' ability to forecast future performance. As a result, any association between derivative usage and management forecast frequency will be stronger when firms use derivatives to hedge.

On the other hand, if firms use derivatives to "take a view" and speculate, earnings volatility would increase, making it more difficult for managers to predict future earnings. Furthermore, managers might perceive that investor demand for forecasts will be greater if the derivatives make earnings harder to predict. Although prior research suggests that investors are unable ex ante to know whether firms use derivatives to hedge or to speculate (Chang et al., 2016), all that is necessary is that managers perceive that investor demand increases if they use derivatives to speculate. If managers respond to that perception, any association between derivative usage and management forecast frequency might be stronger when firms use derivatives to speculate. Our second hypothesis (stated in null form) follows:

Hypothesis 2 (H2). The association between derivative usage and management forecast frequency is unchanged if firms use derivatives to hedge, rather than to speculate about, underlying risk exposures.

Beyer et al. (2010) call for research to examine multiple reasons why managers issue forecasts, noting that prior literature fails to do so. The use of derivatives provides a setting in which to jointly examine multiple reasons why managers issue forecasts because (1) the complexity of derivatives leads to an increase in investor demand for a forecast (to which we refer as the "investor demand" explanation), (2) a derivative-induced reduction in earnings volatility increases the perceived benefit of providing a forecast to capital market participants (which Waymire, 1985 labels a "benefit-related" explanation), or (3) derivative usage decreases the cost of providing a forecast (which Waymire, 1985 labels a "cost-related" explanation).[2] As discussed earlier, because of the complexity of derivatives and the potential for managers to use and account for them in different ways, investor demand for forecasts should unequivocally increase when managers begin using derivatives. That is, if the relation is driven by the "investor demand" explanation, the expectation is unequivocal that derivative usage leads to increased guidance regardless of a manager's career concerns.

On the other hand, if the relation between derivative usage and guidance is driven by the "cost-related" explanation (i.e., managers' career concerns), we should find a positive relation between derivatives and forecast frequency for managers with high career concerns only when they use derivatives to hedge, or in a way that reduces earnings volatility and makes future earnings easier to predict. Hypothesis 3 (stated in null form) follows:

Hypothesis 3 (H3). For managers with high career concerns, the association between derivative usage and management forecast frequency is unchanged when managers use derivatives to hedge, rather than to speculate about, underlying risk exposures.

To further understand the reasons behind why derivatives might drive the decision to increase forecasts, we examine the capital market consequences of derivative-induced forecasts. If firms increase management forecast frequency due to "investor demand," then derivative-induced forecasts should unequivocally be informative to market participants. However, if firms increase management forecast frequency because the manager is using derivatives to reduce earnings volatility and perceives their forecasts will be more useful to capital markets (i.e., Waymire's "benefit-related" explanation), then such derivative-induced forecasts may be more informative to investors than those issued by the firms that use derivatives in a way that makes it harder to predict earnings.

If career concerns motivate managers to provide forecasts only when earnings are easy to forecast and they can easily meet/beat forecasts (i.e., Waymire's "cost-related" explanation), these forecasts may not be as useful to investors. Finally, derivative-induced forecasts may help analysts when derivative disclosures are voluntary and sparse, and those forecasts may be irrelevant after the adoption of FAS 161, which requires detailed derivative disclosures. Thus, a natural set of questions to ask is whether (1) derivative-induced forecasts are informative to professional analysts, (2) whether their usefulness depends on how the firm is using derivatives, and (3) whether their usefulness differs in time periods after FAS 161 when mandatory disclosures might have made derivative-induced management forecasts less useful. Our final set of hypotheses follow:

[2]Although a number of studies examine how a *firm* trades off the costs and benefits of voluntary disclosures, few studies examine this trade-off for the *manager* (a limitation noted by Healy & Palepu, 2001; Beyer et al., 2010; Pae et al., 2016; T. Kim et al., 2023).

Hypothesis 4a (H4a). Derivative-induced forecasts are associated with subsequent analyst forecast accuracy.

Hypothesis 4b (H4b). The association between derivative-induced forecasts and subsequent analyst forecast accuracy is unchanged when managers use derivatives to hedge, rather than to speculate about, underlying risk exposures.

Hypothesis 4c (H4c). The association between derivative-induced forecasts and subsequent analyst forecast accuracy is weaker after mandatory derivative disclosures improved with FAS 161.

3 | DATA AND SAMPLE SELECTION

We collect data from the intersection of the Compustat, CRSP, and I/B/E/S databases. Using the I/B/E/S guidance database, we first identify firms that issue at least one forecast between 1997 and 2019, resulting in 52,123 firm-year observations. We then retain observations with necessary stock market and accounting data available in Compustat, CRSP, and I/B/E/S. Our sample firms also meet the following criteria: (1) publicly traded, (2) domestically incorporated, (3) in a nonfinancial/nonregulated industry, and (4) a nonsubsidiary. Finally, we merge this filtered sample with data on corporate derivatives.

Following Manconi et al. (2018), we collect corporate derivative information from annual filings using a keyword search through the SeekEdgar database. Although we closely follow their data collection procedure, we significantly expand their list of keywords (Appendix 1 lists all keywords used). To identify derivative users (*User*), a firm must have 20 or more derivative-related keywords in their annual reports, otherwise, the firm is classified as a *Non-User*.

Among derivative users, we further distinguish among foreign exchange (FX), interest rate (IR), and commodity price (CP) users. We classify firms as FX, IR, or CP users if the filings contain at least three instances of keywords associated with FX, IR, or CP derivative instruments, respectively, based on the keywords in Appendix 1. Our final sample consists of 28,851 firm-year observations with 16,527 *User* and 12,324 *Non-User* firm-year observations. We also identify a sample of *New Users*. Consistent with prior research (Chang et al., 2016), a firm is a *New User* if it does *not* report a derivative position when it first appears in the sample but reports a position in a later year. Firms enter the *New User* sample only when derivatives are first observed (after first observing no usage).[3] The *New User* sample consists of 727 firms.

4 | EMPIRICAL RESULTS

4.1 | Descriptive statistics

Panel A of Table 1 reports the sample selection criteria described in Section 3. Panel B presents the temporal distribution of the sample. The number of *Non-Users* and *Users* is fairly stable over time, with a slight decrease (increase) in *Non-User* (*User*) observations over time. In contrast to the steady number of *Non-Users* and *Users*, the increase in *New Users* (103) in 2001

[3]To illustrate, consider a firm that did not use derivatives until 2003. From 1997 to 2002, observations for this firm are classified in the *Non-User* sample. In 2003, the observation is classified in the *New User* sample. *New User* designation only occurs the first time that derivative usage is observed (after initially observing *no* usage).

TABLE 1 Characteristics of *Non-Users*, *Users*, and *New Users*.

Panel A: Sample selection

	Obs.
Firms that issue at least one earnings forecast from 1997 to 2019 (3,275 firms)	52,123
Less:	
Observations with missing necessary information to calculate variables	6,203
Observations in financial and regulated industries (SIC 4400–4999 and 6000–6999)	14,261
Observations with missing corporate derivative information are defined by performing a keyword search through annual reports)	2,808
Final sample	28,851

Panel B: Temporal distribution of sample observations

	Non-Users		*Users*		*New Users*	
Year	**Obs.**	**%**	**Obs.**	**%**	**Obs. Obs.**	**%**
1997	484	4	399	2	0	0
1998	714	6	529	3	100	14
1999	830	7	589	4	52	7
2000	901	7	644	4	68	9
2001	716	6	787	5	103	14
2002	664	5	829	5	52	7
2003	687	6	843	5	46	6
2004	630	5	868	5	37	5
2005	615	5	846	5	33	5
2006	632	5	820	5	34	5
2007	606	5	792	5	33	5
2008	541	4	818	5	32	4
2009	470	4	832	5	22	3
2010	459	4	827	5	16	2
2011	448	4	802	5	17	2
2012	442	4	775	5	12	2
2013	406	3	752	5	15	2
2014	413	3	704	4	8	1
2015	385	3	671	4	14	2
2016	368	3	636	4	6	1
2017	336	3	619	4	12	2
2018	310	3	601	4	7	1
2019	267	2	544	3	8	1
Total	12,324		16,527		727	

Panel C: Industry distribution of sample observations

	Non-Users		*Users*		*New Users*	
Industry group	**Obs.**	**%**	**Obs.**	**%**	**Obs.**	**%**
Consumer non-durables	743	6	1525	9	59	8
Consumer durables	340	3	801	5	27	4
Manufacturing	1,023	8	2,944	18	86	12

TABLE 1 (Continued)

Panel C: Industry distribution of sample observations

	Non-Users		*Users*		*New Users*	
Industry group	**Obs.**	**%**	**Obs.**	**%**	**Obs.**	**%**
Energy and extraction	186	2	407	2	13	2
Chemicals and allied products	146	1	854	5	10	1
Business equipment	3,627	29	3,446	21	196	27
Telecommunications	182	1	228	1	7	1
Wholesale and retail	1,935	16	2,411	15	111	15
Healthcare	1,899	15	1,629	10	94	13
Constr., transport, and services	2,243	18	2,282	14	124	17
Total	12,324		16,527		727	

Note: This table presents characteristics of *Non-Users*, *Users*, and *New Users*. Panel A presents the sample selection procedure, Panel B reports the temporal distribution of sample observations, and Panel C reports the industry distribution of the sample. *Users* are identified by performing a keyword search in annual filings. A firm is a *New User* if it does *not* report a derivative position when it first appears in the sample but reports a position in a later year. Firms enter the *New User* sample only when derivatives are first observed (after first observing no use).

coincides with the enactment of FAS 133.[4] Panel C of Table 1 illustrates the industry distribution of *Non-Users*, *Users*, and *New Users*. We find a slightly greater proportion of *Users* and *New Users* relative to *Non-Users* in the manufacturing industry, and the opposite in the business equipment industry. To mitigate concerns with industry and time, we include industry and year fixed effects throughout our analyses.

Table 2 reports descriptive statistics for our sample. Panels A and B report that the mean frequency of management earnings forecasts (*FREQ*) is 1.876 and is significantly higher for *Users* (2.245) than *Non-Users* (1.380). Also, *Users* have higher institutional ownership and analyst following, and are larger than *Non-Users*. Panel C of Table 2 reports the Pearson and Spearman correlations. A positive pattern can be observed between *USER* and *FREQ* in both sets of correlations, providing univariate evidence that derivative users issue more forecasts.

To address endogeneity, we employ the focused setting of *New Users* and DiD design. We use propensity score matching (PSM) to identify a control group of *Non-Users*. Specifically, PSM matches observations from the treatment group (*New Users*) and the control group (*Non-Users*) on several dimensions (observed risk management incentives described in detail in the following section). If the covariates are balanced, differences in an outcome (MEF frequency) can be attributed to the treatment (derivative initiation) rather than other firm characteristics.

Table 3 reports the covariate balance between *New Users* and the matched *Non-User* control firms. We report the p-values from the tests of the differences in means (t-tests), medians (Wilcoxon rank-sum tests), and distributions (Kolmogorov–Smirnov test) of risk management incentives between *New Users* and *Non-Users*. PSM does *not* require matched firms to be identical across all covariates (Caliendo & Kopeinig, 2008). Of the 18 variables, only two are statistically dissimilar at the 90% confidence level ($\Delta CRISK$ and $\Delta PEVOL$). When all the covariates are considered together, the Hotelling's T^2 test ($p = 0.930$) indicates that *New Users* are not different from the matched *Non-User* control firms. Overall, Table 3 indicates that our matching process is successful.

[4] FAS 133 is effective for fiscal years beginning after June 15, 2000. To mitigate the possibility that changes in accounting standards make existing *Users* appear to be *New Users*, we test our hypotheses (unreported) after excluding *New Users* in the enactment year for FAS 133 (i.e., the year 2001). Inferences remain the same.

TABLE 2 Descriptive statistics.

Panel A: Summary statistics

	Mean	Std. dev.	Q1	Median	Q3
FREQ	1.876	2.442	0.000	0.000	4.000
INST	0.660	0.173	0.585	0.629	0.785
SIZE	6.894	2.006	5.664	6.883	8.168
FOL	9.698	8.772	3.000	7.000	14.000
BIGN	0.897	0.304	1.000	1.000	1.000
LITIGATION	0.367	0.482	0.000	0.000	1.000
MB	2.869	3.477	1.102	1.992	3.463
NEGNEWS	0.342	0.474	0.000	0.000	1.000
PEVOL	0.019	0.027	0.005	0.009	0.020
ABRETVOL	0.065	0.041	0.047	0.056	0.073
ABACC	−0.017	0.117	−0.068	−0.006	0.042
FCOMPLEXITY	2.747	0.823	2.947	2.985	3.020
AEFA	−2.434	34.321	−0.356	−0.100	−0.018

Panel B: Descriptive statistics partitioned by *Users* and *Non-Users*

	(1) *Users*		(2) *Non-Users*		
	Mean	Median	Mean	Median	*t*-stat [(1) − (2)]
FREQ	2.245	1.000	1.380	0.000	**31.18**
INST	0.682	0.585	0.631	0.585	**25.39**
SIZE	7.482	7.506	6.105	6.157	**62.11**
FOL	11.265	9.000	7.597	6.000	**37.06**
BIGN	0.935	1.000	0.846	1.000	**23.62**
LITIGATION	0.293	0.000	0.466	0.000	**−30.29**
MB	2.735	1.937	3.049	2.070	**−7.55**
NEGNEWS	0.315	0.000	0.379	0.000	**−11.21**
PEVOL	0.015	0.008	0.023	0.012	**−23.76**

TABLE 2 (Continued)

Panel B: Descriptive statistics partitioned by *Users* and *Non-Users*

	(1) *Users*		(2) *Non-Users*		
	Mean	**Median**	**Mean**	**Median**	***t*-stat [(1) – (2)]**
ABRETVOL	0.062	0.048	0.070	0.048	**−14.57**
ABACC	−0.015	−0.006	−0.019	−0.006	2.36
FCOMPLEXITY	2.725	2.986	2.775	2.984	**−5.21**
AEFA	−1.879	−0.087	−3.177	−0.118	**3.08**
Obs.	16,527		12,324		

Panel C: Pearson (above diagonal) and Spearman (below diagonal) correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	*USER*		**0.175**	**0.147**	**0.340**	**0.207**	**0.145**	**−0.178**	**−0.045**	**−0.066**	**−0.146**	**−0.088**	0.014	**−0.030**	**0.019**
(2)	*FREQ*	**0.166**		**0.500**	**0.352**	**0.366**	**0.105**	**−0.020**	**0.084**	**−0.352**	**−0.105**	**0.269**	−0.013	**0.085**	**0.033**
(3)	*INST*	**0.158**	**0.595**		**0.263**	**0.287**	**0.125**	**−0.016**	**0.039**	**−0.192**	**−0.097**	−0.008	**−0.015**	**0.031**	**0.032**
(4)	*SIZE*	**0.359**	**0.319**	**0.322**		**0.642**	**0.303**	**−0.058**	**0.305**	**−0.161**	**−0.123**	−0.012	**−0.057**	**0.252**	**0.069**
(5)	*FOL*	**0.205**	**0.396**	**0.348**	**0.668**		**0.209**	**0.085**	**0.181**	**−0.128**	**−0.093**	**0.067**	**−0.056**	**0.096**	**0.049**
(6)	*BIGN*	**0.145**	**0.087**	**0.108**	**0.278**	**0.205**		**−0.046**	**0.055**	−0.004	**−0.056**	0.010	**−0.026**	**0.138**	**0.024**
(7)	*LITIGATION*	**−0.178**	0.003	0.000	**−0.031**	**0.086**	**−0.026**		**0.083**	0.001	**0.107**	**0.118**	**−0.029**	**−0.056**	**−0.017**
(8)	*MB*	**−0.049**	**0.109**	**0.075**	**0.328**	**0.198**	**0.039**	**0.104**		**−0.089**	**0.036**	0.013	**−0.081**	**0.068**	**0.029**
(9)	*NEGNEWS*	**−0.066**	**−0.360**	**−0.227**	**−0.154**	**−0.135**	**−0.034**	−0.003	**−0.118**		**0.046**	**−0.094**	**−0.030**	**−0.046**	**−0.043**
(10)	*PEVOL*	**−0.138**	**−0.130**	**−0.110**	**−0.238**	**−0.110**	**−0.084**	**0.130**	**−0.036**	**0.077**		**0.082**	**−0.080**	**0.070**	**−0.126**
(11)	*ABRETVOL*	**−0.045**	**0.448**	**0.178**	**−0.043**	**0.123**	0.002	**0.137**	0.005	**−0.123**	**0.041**		**−0.027**	**0.081**	−0.004
(12)	*ABACC*	0.009	−0.014	**−0.015**	**−0.050**	**−0.045**	**−0.021**	**−0.027**	**−0.065**	**−0.035**	**−0.057**	**−0.024**		**−0.033**	**0.022**
(13)	*FCOMPLEXITY*	**0.017**	**0.040**	**0.018**	**0.038**	**0.062**	**0.036**	**0.065**	−0.015	−0.011	**−0.021**	**0.050**	**−0.030**		0.012
(14)	*AEFA*	**0.066**	**0.113**	**0.117**	**0.261**	**0.120**	**0.025**	**−0.017**	**0.189**	**−0.087**	**−0.219**	**−0.033**	−0.001	**−0.030**	

Note: This table reports descriptive statistics for *Users and Non-Users*. Panel A shows descriptive statistics for the entire sample, and Panel B reports summary statistics for *Users* and *Non-Users*, along with *t*-statistics for mean tests of differences between those two groups. Panel C presents the Pearson (above diagonal) and Spearman (below diagonal) correlations for the variables in the main analyses. Bold *t*-statistics denote statistical significance at the 1% level (two-tailed).

TABLE 3 Covariate balance for matched sample.

	New Users/Non-Users		
	Mean diff. **p-value**	**Median diff.** **p-value**	**Dist. diff.** **p-value**
Risk management incentives			
IRISK	0.339	0.990	0.747
FRISK	0.314	0.281	0.309
CRISK	0.174	0.255	0.161
Δ*IRISK*	0.513	0.542	0.410
Δ*FRISK*	0.486	0.480	0.703
Δ*CRISK*	0.000***	0.004***	0.013**
SIZE	0.624	0.486	0.580
ALTZ	0.166	0.109	0.144
USCORE	0.937	0.971	0.896
ECSENS	0.977	0.717	0.616
CETR	0.218	0.781	0.788
CDEBT	0.370	0.275	0.024
PSTOCK	0.432	0.110	0.989
ABACC	0.104	0.435	0.340
PCVOL	0.472	0.215	0.127
PEVOL	0.407	0.360	0.410
Δ*PCVOL*	0.500	0.596	0.572
Δ*PEVOL*	0.012**	0.020**	0.009***
Hotelling's T^2		0.930	

Note: This table presents the covariate balance between the 727 *New Users* and propensity score matched control firms (*Non-Users*) in the match year. Reported values are p-values for tests of differences in means (t-tests), medians (Wilcoxon rank-sum test), and distributions (Kolmogorov–Smirnov homogeneous distributions test) of risk management incentives. Hotelling's T^2 test is the multivariate equivalent of the two-sample t-test and considers whether the vector of all variable means differ between the two groups. Variables are defined in Appendix 2.

** and *** represent significance levels of 5% and 1%, respectively.

4.2 | Derivative usage and management earnings forecast frequency (H1)

We test H1 using the following negative binomial model:

$$FREQ_{it} = \psi_0 + \psi_1 USER_{it} + \sum_x \psi_x CTRL_{it}^x + \sum_k \psi_k IND_{it}^k + \sum_t \psi_t YR_{it}^t + \varepsilon_{it}, \tag{1}$$

where *FREQ* equals the number of annual earnings forecasts issued by firm i in year t and *USER* equals one if firm i reports a position in derivatives in year t (zero otherwise). Following prior studies (Ali et al., 2014), we control for institutional ownership (*INST*), the market value of equity (*SIZE*), analyst following (*FOL*), and the market-to-book ratio (*MB*). We also include audit firm size (*BIGN*) to capture whether a firm's disclosure policy is influenced by audit quality (Dunn & Mayhew, 2004). Prior research (Healy & Palepu, 2001; Skinner, 1994) suggests that litigation risk and negative news affect disclosure choices because firms generally increase their disclosures when facing litigation risks from delayed disclosure about negative news. Thus, we include litigation risk (*LITIGATION*) and negative news (*NEGNEWS*). We also control for past earnings volatility (*PEVOL*) and abnormal returns (*ABRETVOL*) because they are related to the cost and effort of issuing forecasts (Waymire, 1985).[5] In addition, we include abnormal accruals (*ABACC*) to account for the relation between disclosure frequency and earnings management (Jo & Kim, 2007). Finally, we control for financial reporting complexity (*FCOMPLEXITY*) and analyst earnings forecast accuracy (*AEFA*) as investors demand more information when financial reporting complexity is high and analysts issue inaccurate forecasts (Chang et al., 2016; Guay et al., 2016). If MEF frequency is higher (lower) for derivative users relative to non-users (i.e., H1), the coefficient on *USER* should be significantly positive (negative). Table 4, Panel A, presents the estimates of Equation (1) using our entire sample of *Users* and *Non-Users*. We find that the coefficient on *USER* is significantly positive (0.130; *p*-value <0.01).[6]

Next, we examine the relation between derivative usage and MEF frequency in the more focused setting of derivative initiation using a DiD design, which *controls* for variation in an outcome (MEF frequency) that is *not* the result of treatment exposure (derivative initiation) by comparing the treatment group to an untreated control group.[7] A firm belongs to the treatment group if it is a *New User* that initiates a derivative position at some point between 1997 and 2019. We then employ PSM to identify a control group of *Non-Users*, limiting control firms to those that do not use derivatives at any point during the sample period and then estimating the propensity of derivative initiation using a probit model. In this model, we include risk management incentives that explain corporate use of derivatives. These include exposures to interest rate (*IRISK*), foreign exchange rate (*FRISK*), and commodity price (*CRISK*) as well as changes in these exposures ($\Delta IRISK$; $\Delta FRISK$; $\Delta CRISK$) to account for concurrent shocks that can motivate derivative initiation.[8] By insulating firm value and cash flows from unfavorable changes in risk exposure, derivatives can mitigate financial distress (Mayers & Smith, 1982), harmonize financing and investment goals (Froot et al., 1993), and reduce agency conflicts (Smith & Stulz, 1985). We thus include the likelihood of financial distress (*ALTZ*), likelihood of underinvestment (*USCORE*), and the sensitivity of executive compensation to firm value (*ECSENS*) to capture these benefits. We also include the cash effective tax rate (*CETR*) to reflect the tax planning features of derivatives (Smith & Stulz, 1985). As derivative substitutes, we control for convertible debt (*CDEBT*), preferred stock (*PSTOCK*), and abnormal accruals (*ABACC*). Finally, the level and change of cash flow (*PCVOL*; $\Delta PCVOL$) and earnings volatility (*PEVOL*; $\Delta PEVOL$) capture other general incentives for derivative initiation (Zhang, 2009). By including risk management incentives, the absence of derivatives among the potential *Non-User* control firms reflects a choice not to use them, rather than a lack of incentives to do so. After matching *New Users* with *Non-Users*, we estimate the following negative binomial model:

$$\begin{aligned} FREQ_{it} = \varphi_0 + \varphi_1 NEWUSER_i + \varphi_2 POST_{it} + \varphi_3 NEWUSER \times POST_{it} + \sum_x \varphi_x CTRL^x_{it} \\ + \sum_k \varphi_k IND^k_{it} + \sum_t \varphi_t YR^t_{it} + \varepsilon_{it}, \end{aligned} \tag{2}$$

[5] Our argument is based on uncertainty regarding future earnings (i.e., forward earnings volatility). The variable *PEVOL* is based on the ex post realization of earnings. When we exclude *PEVOL* from our tests, the results are unchanged.

[6] To estimate the economic magnitude, we compare the coefficient of *USER* with that of *SIZE*. For this comparison, we convert *SIZE* into a binary variable that equals one (zero) for large (small) firm size based on the median value of *SIZE*. In the negative binomial model, we interpret the regression coefficient as the change in the natural log of expected counts of the response variable for a one-unit change in the predictor variable. The (unreported) results indicate that the coefficients on *USER* and *SIZE* are very similar, which implies that the effects of *USER* on the frequency of MEFs are economically large enough to be comparable with that of *SIZE*.

[7] Another way we address selection bias is by employing a Heckman two-stage selection model. This methodology does not affect our inferences.

[8] Our matching model includes risk management incentives since the determinants of MEFs are not directly related to firms' propensity to use derivatives. In unreported tests, we include all covariates in the matching model to match firms on as many relevant characteristics as possible, and the inferences from our study do not change.

TABLE 4 Derivative usage and management earnings forecast frequency.

Panel A: *User* sample	*FREQ* Coefficient (*p*-value)
USER	0.130***
	(0.000)
INST	2.069***
	(0.000)
SIZE	0.134***
	(0.000)
FOL	0.015***
	(0.000)
BIGN	−0.020
	(0.721)
LITIGATION	−0.111**
	(0.022)
MB	−0.004
	(0.268)
NEGNEWS	−0.945***
	(0.000)
PEVOL	−4.891***
	(0.000)
ABRETVOL	1.184***
	(0.000)
ABACC	0.030
	(0.656)
FCOMPLEXITY	0.019
	(0.487)
AEFA	0.001
	(0.176)
Industry FE	Yes
Year FE	Yes
Pseudo R^2	0.15
Observations	28,851

Panel B: *New User* sample	*FREQ* Coefficient (*p*-value)
NEWUSER	−0.068
	(0.372)
POST	0.029
	(0.682)
NEWUSER* × *POST	0.166**
	(0.045)

TABLE 4 (Continued)

Panel B: *New User* sample	***FREQ*** **Coefficient (*p*-value)**
INST	2.247***
	(0.000)
SIZE	0.223***
	(0.000)
FOL	−0.003
	(0.333)
BIGN	−0.014
	(0.866)
LITIGATION	−0.100
	(0.110)
MB	−0.008*
	(0.089)
NEGNEWS	−0.920***
	(0.000)
PEVOL	−3.767***
	(0.000)
ABRETVOL	1.237***
	(0.000)
ABACC	0.080
	(0.437)
FCOMPLEXITY	0.085***
	(0.003)
AEFA	−0.000
	(0.863)
Industry FE	Yes
Year FE	Yes
Pseudo R^2	0.16
Observations	17,867

Note: This table reports tests of whether firms' use of derivatives affects the frequency of management earnings forecast, where the dependent variable is *FREQ*. Panel A reports a test of whether being a derivative user is associated with a higher level of MEFs. *USER* equals one if firm *i* reports a position in derivatives in year *t* (zero otherwise). Panel B reports a test of whether derivative initiation increases the frequency of management earnings forecasts. *NEWUSER* equals one for *New User* firm observations and zero for matched control firm observations. *POST* equals one for periods after derivative initiation for *New Users* and corresponding control firms (zero otherwise). The coefficient on *NEWUSER* × *POST* reflects the DiD estimator of the effects of derivative initiation on the frequency of management earnings forecasts. Robust standard errors are clustered by firm. Variables are defined in Appendix 2. The variables of interest are in bold. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

where *NEWUSER* equals one for *New User* observations and zero for the control firm observations. *POST* is coded one for the post-treatment periods for *New Users* and the corresponding control firms (zero otherwise). The coefficient on *NEWUSER* captures the difference in MEF frequency between *New Users* and the control firms before derivative initiation, and the coefficient on *POST* reflects the change in MEF frequency between the pre- and post-initiation periods among the control firms. Thus, the coefficient on $NEWUSER \times POST$ captures the effect of derivative initiation on the frequency of management forecasts for *New Users* relative to *Non-User* control firms. If *New Users* increase (decrease) MEF frequency after derivative initiation (i.e., H1), the coefficient on $NEWUSER \times POST$ should be positive (negative).

Panel B of Table 4 presents estimates of Equation (2). The statistically insignificant coefficient for *New Users* suggests that there is no difference between *New Users* and a matched control group of *Non-Users* before derivative initiation. In addition, the insignificant coefficient for *POST* implies no change in MEF frequency among control firms during the sample period. However, the coefficient on $NEWUSER \times POST$ is significantly positive, providing further evidence for H1.[9] That is, relative to control firms, MEF frequency increases for *New Users* after initiation.

To gauge the economic magnitude of the effect of derivative initiation on the frequency of MEFs, we estimate the percentage change in *FREQ* for *New Users* after initiation by calculating the marginal effect of *POST* on *FREQ* for *New Users*. This marginal effect indicates how *FREQ* changes for *New Users* as *POST* changes from 0 to 1, holding other variables constant. The ratio of the marginal effect of *POST* to its pre-initiation value (i.e., $POST = 0$) estimates the relative percentage change in *FREQ* for *New Users* after initiation. The ratios indicate that, relative to *Non-User* control firms, *New Users* experience 19.67% increase in the frequency of MEFs (on average) after derivative initiation. The economic magnitude analysis indicates that our results are both statistically and economically significant. Overall, the results in Table 4 suggest that, on average, derivative users provide more MEFs than non-users, and that derivative initiation increases forecast frequency.

4.3 | Derivative usage to hedge or speculate about underlying risk exposures (H2)

We use three methods to test H2, which examines whether the way in which managers use derivatives explains the association between derivative usage and management forecast frequency. First, we use path analysis, which considers the existence and relative importance of indirect paths of influence that jointly create the overall effects (Bhattacharya et al., 2012). We use the KHB method developed by Karlson et al. (2013) to decompose the total effect into a direct and an indirect effect as this method can be used for regressions where the dependent variable is counts. Specifically, we decompose the relation between *USER* and *FREQ* into direct and indirect paths whereby derivative usage (*USER*), MEF frequency (*FREQ*), and forward earnings volatility (*FEVOL*) are ex ante designated as the source, outcome, and mediating variables, respectively (Figure 1). We first evaluate *total* effects of derivative usage on MEF frequency by estimating Equation (1) without the mediating variable (*FEVOL*). We then examine the *direct* effect of derivative usage on MEF frequency by including *FEVOL* in Equation (1). The estimated coefficient for *USER* represents the direct effect of derivative usage on MEF frequency (i.e., the solid arrow in Figure 1). Furthermore, the difference between the direct and total effects is the *indirect* effect, which captures the portion of the variation in *USER* that is related to *FEVOL* (i.e., the dashed arrow in Figure 1).[10]

Panel A of Table 5 presents the results of the path analysis test without control variables and fixed effects. Column 1 reports that the coefficient for *USER* (0.495) is significant and positive when we estimate Equation (1) without *FEVOL*. In Column 2, we estimate Equation (1) with *FEVOL* and the coefficient for *USER* (0.425) captures the direct effect of derivative usage

[9]We also find that MEF frequency decreases for firms that stopped using derivatives relative to a matched control sample after derivative termination. This finding (unreported) corroborates the evidence reported in Table 4.

[10]In untabulated analysis, we also regress *USER* on *FEVOL* and find that derivative usage is negatively associated with forward earnings volatility.

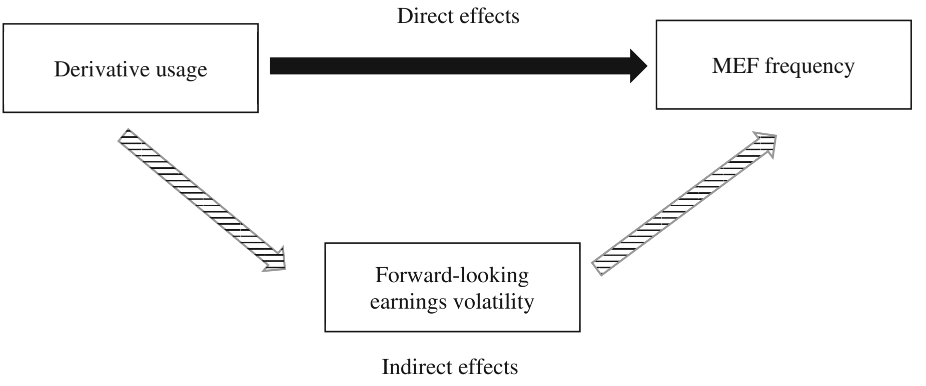

FIGURE 1 Path analysis diagram. This figure diagrams both direct (solid arrow) and indirect (dashed arrow) paths for the effects of a firm's derivative usage on MEF frequency. We measure forward-looking earnings volatility by taking the standard deviation of consecutive quarterly earnings in years $t+1$ and $t+2$.

on MEF frequency after controlling for forward earnings volatility. Furthermore, Column 3 presents the results on the indirect effect of derivative usage in conjunction with forward earnings volatility on MEF frequency. Specifically, we report that the ratio of the indirect effect to total effect is approximately 14%, indicating a substantial portion of the total effect that is incrementally explained by *FEVOL*.[11] The fact that the earnings volatility channel, while significant, accounts for 14% of the overall relation between derivative usage and MEF frequency shows that there exists a direct link between derivative usage and MEF frequency as well. Prior research suggests that this direct effect comes from derivative-induced improvements in the forecasting process itself. This argument is based on both theory (Hemmer & Labro, 2008) and survey evidence (Ittner & Michels, 2017). Hemmer and Labro (2008) identify an explicit theoretical link between internal information quality and the quality of the information reported externally. Also, Ittner and Michels (2017) find that more sophisticated risk-based forecasting and planning processes are associated with smaller earnings forecast errors and narrower forecast widths. They argue that risk-based forecasting improves managers' forecasting ability not just by reducing the volatility of firm performance but also by improving the forecasting process itself, providing managers with better information regarding upcoming earnings.

Panel B of Table 5 presents the results of path analysis with all control variables and fixed effects. We report the total (0.130) and direct (0.124) effect of derivative usage on MEF frequency in Columns 1 and 2, respectively. In Column 3, we report the portion of the variation in *USER* related to *FEVOL*. Specifically, we find that the coefficient for *USER* is 0.006 (z-stat = 3.68) and the proportion of the total effect that is explained by *FEVOL* is 5% after including all other control variables. In sum, the results in Panels A and B of Table 5 are reliable evidence of both a direct path from derivative usage to MEF frequency and an indirect path that is mediated by forward earnings volatility. Both channels imply that the positive

[11]To provide context and compare the effect size of *FEVOL* with that of other variables, we conduct a few additional tests. First, we use firm size (*SIZE*) as a mediating variable. Large firms face stronger incentives to hedge than small firms and corporate hedging exhibits significant economies of scale (Aretz & Bartram, 2010), and Baginski et al. (2004) consider firm size as the major determinant of management forecast decisions. Given that almost all variables are correlated with *SIZE*, we expect the indirect effect of *SIZE* to be economically significant. As predicted, we find that the indirect effect is approximately 44.6% when *SIZE* is a mediating variable and no other control variables are included. Second, we use financial reporting complexity (*FCOMPLEXITY*) as a meditating variable considering that investor demand for management forecasts is high when financial reporting complexity is high (Guay et al., 2016). The indirect effect of *FCOMPLEXITY* is statistically significant but its effect size is 2.6%. Compared to the effect of these variables, the indirect effect of future earnings volatility that we document (14%) is not negligible.

TABLE 5 Path analysis.

Panel A: Path analysis without control variables and fixed effects

	(1) *FREQ* Total effect Coefficient (*p*-value)	(2) *FREQ* Direct effect Coefficient (*p*-value)	(3) *FREQ* Indirect effect (within) Coefficient (*p*-value)	%
FEVOL		−11.485***		
		(0.000)		
USER	0.495***	0.425***	0.070***	14.1
	(0.000)	(0.000)	(0.000)	
Controls, Industry FE, Year FE	No	No	No	
Pseudo R^2	0.15	0.15	0.15	
Observations	28,851	28,851	28,851	

Panel B: Path analysis with control variables and fixed effects

	(1) *FREQ* Total effect Coefficient (*p*-value)	(2) *FREQ* Direct effect Coefficient (*p*-value)	(3) *FREQ* Indirect effect (within) Coefficient (*p*-value)	%
FEVOL		−3.925***		
		(0.000)		
USER	0.130***	0.124***	0.006***	4.6
	(0.000)	(0.000)	(0.000)	
Controls, Industry FE, Year FE	Yes	Yes	Yes	
Pseudo R^2	0.15	0.15	0.15	
Observations	28,851	28,851	28,851	

Note: This table reports the path analysis decomposing the relation between the variable of interest, *USER*, the causal variable, *FEVOL*, and outcome variable, *FREQ*, into direct and indirect paths (Figure 1). In Column 1, we estimate Equation (1) after excluding *FEVOL* to examine the total (direct and indirect) effect of *USER* on *FREQ*. In Column 2, we estimate Equation (1) including *FEVOL* so that the coefficient for *USER* captures the direct effect of *USER* on *FREQ* controlling for *FEVOL*. Column 3 reports the difference between the total and the direct effect, reflecting the incremental effect of each variable on *FREQ*. The indirect effect % is the absolute value of the indirect effect divided by the total effect. We use the KHB method to decompose the total effect into a direct and an indirect effect. Robust standard errors are clustered by firm. Variables are defined in Appendix 2. The variables of interest are in bold.
*** represents significance level of 1%.

association between derivative usage and management earnings forecasts is stronger when managers use derivatives in a way that makes future earnings easier to forecast.[12]

A second way to test H2 is to classify firms as hedging or speculating based on ex post outcomes from derivative usage. Following Zhang (2009), we first classify *New Users* as effective hedgers or ineffective hedgers/speculators. We designate a *New User* as an effective hedger (*EH*) if the actual risk exposure is less than expected after derivative initiation and as an ineffective hedger/speculator (*IS*) otherwise (Zhang, 2009).[13] We then estimate Equation (2) with two modifications. First, we replace *NEWUSER* with (1) *NEWUSER_EH*, an indicator variable equal to one for effective hedgers (zero otherwise) and (2) *NEWUSER_IS*, an indicator variable equal to one for ineffective hedgers/speculators (zero otherwise). Second, we interact these two

[12]Due to hedge accounting rules that require managers to forecast purchases and sales internally, this direct channel also plays a stronger role when managers use derivatives to hedge.
[13]See Appendix S1 in the Supporting Information for detailed classification procedures.

variables with *POST*. If the manner in which derivatives are used influences the decision to issue forecasts, the interaction coefficient on *NEWUSER_EH* × *POST* should be significantly different than the interaction coefficient on *NEWUSER_IS* × *POST*.

Panel A of Table 6 reports the association between the frequency of MEFs and *New Users* that are effective hedgers (*EH*) and ineffective hedgers/speculators (*IS*). Out of the 727 *New Users*, 528 (199) firms are classified as *EH* (*IS*) firms. The coefficient on *NEWUSER_EH* × *POST* (0.218) is significantly positive but the interaction coefficient for *NEWUSER_IS* × *POST* is insignificant. Furthermore, the coefficient on *NEWUSER_EH* × *POST* is statistically greater than the coefficient on *NEWUSER_IS* × *POST* ($\chi^2 = 4.46$). These findings suggest that managers *only* increase MEF frequency when future earnings are easier to forecast due to effective hedging.

To confirm our assumption that the cost of disclosure varies with how firms use derivatives, we examine whether effective hedgers realize earnings that are less volatile after derivative initiation relative to ineffective hedgers/speculators. We find that forward earnings volatility (*FEVOL*) is 0.015 for effective hedgers and 0.018 for ineffective hedgers and the mean difference is statistically significant ($t = 5.29$; unreported). To provide more direct evidence that forecasting earnings is costlier for firms that use derivatives ineffectively or for speculative purposes, we also test whether effective hedgers improve their forecast accuracy and precision while ineffective/speculative hedgers do not. Untabulated results confirm that the accuracy and precision of MEFs improve only for firms that use derivatives effectively after derivative initiation.

As a third and final way to test H2, we examine whether firms' accounting designation for derivatives is associated with MEF frequency. Recent research suggests that hedge accounting reduces earnings volatility (Pierce, 2020; Ranasinghe et al., 2022), which should make earnings easier to forecast. Specifically, we test whether hedge accounting users are more likely to issue forecasts than non-hedge users by replacing *USER* in Equation (1) with hedge accounting users (*HEDGE_USER*) and non-hedge users (*NONHEDGE_USER*). *HEDGE_USER* equals one for *User* observations with nonmissing and nonzero unrealized holding gains/losses from derivatives (zero otherwise), and *NONHEDGE_USER* equals one for *User* observations with missing or zero unrealized holding gains/losses from derivatives (zero otherwise).[14] Among 16,527 *User*s (firm-year obs.), 6,404 (10,123) are classified as hedge accounting users (non-hedge users). We test whether the coefficient on *HEDGE_USER* is significantly different than the coefficient on *NONHEDGE_USER*.

Panel B of Table 6 reports that the coefficient for *HEDGE_USER* (0.166) is significantly positive and a Wald test of the difference between the coefficients on *HEDGE_USER* and *NONHEDGE_USER* indicates that the coefficient for *HEDGE_USER* is significantly greater than that of *NONHEDGE_USER*.[15] Overall, the collective evidence in Tables 5 and 6 suggests that the positive relation between derivative usage and forecast frequency is driven, at least in part, by whether managers use derivatives to hedge, rather than to speculate about, underlying risk exposures.

4.4 | Managerial cost explanation (H3)

4.4.1 | Managers' career concerns

As previously discussed, investor demand for management forecasts should unequivocally increase when firms begin using derivatives as the complexities of derivatives plague investors when they assess firms' financial reports. That is, if the relation is driven by the "investor

[14]A firm can apply hedge accounting to a subset of its derivatives. We consider firms that do not designate any derivatives as accounting hedges as a *NONHEDGE_USER*, and classify firms that designate at least a part of their derivatives as accounting hedges as a *HEDGE_USER*. Excluding firms that designate some (but not all) derivatives as hedges does not change our inferences.

[15]We examine whether hedge accounting users realize earnings that are less volatile relative to non-hedge accounting users. We find that forward earnings volatility (*FEVOL*) is 0.014 for hedge accounting users and 0.018 for non-hedge accounting users and the mean difference is statistically significant ($t = 9.62$; unreported).

TABLE 6 Tests of managerial disclosure cost.

Panel A: Effective hedgers (*EH*) versus ineffective hedgers and speculators (*IS*)	***FREQ*** **Coefficient** **(*p*-value)**
NEWUSER_EH	−0.183*
	(0.051)
NEWUSER_IS	0.091
	(0.269)
POST	0.023
	(0.730)
NEWUSER_EH* × *POST Ψ_1	0.218**
	(0.034)
NEWUSER_IS* × *POST Ψ_2	0.003
	(0.969)
INST	2.267***
	(0.000)
SIZE	0.213***
	(0.000)
FOL	−0.004
	(0.247)
BIGN	−0.036
	(0.669)
LITIGATION	−0.075
	(0.218)
MB	−0.007
	(0.126)
NEGNEWS	−0.916***
	(0.000)
PEVOL	−3.886***
	(0.000)
ABRETVOL	1.070***
	(0.000)
ABACC	0.042
	(0.671)
FCOMPLEXITY	0.094***
	(0.002)
AEFA	0.000
	(0.732)
Industry FE, Year FE	Yes
Pseudo R^2	0.16
Observations	17,867
Wald χ^2: $\Psi_1 > \Psi_2$	4.46**

TABLE 6 (Continued)

Panel B: Hedge accounting choice	***FREQ*** **Coefficient (*p*-value)**
HEDGE_USER Ψ_1	0.166***
	(0.000)
NONHEDGE_USER Ψ_2	−0.012
	(0.710)
INST	2.069***
	(0.000)
SIZE	0.129***
	(0.000)
FOL	0.014***
	(0.000)
BIGN	−0.025
	(0.674)
LITIGATION	−0.108**
	(0.022)
MB	−0.004
	(0.233)
NEGNEWS	−0.943***
	(0.000)
PEVOL	−4.936***
	(0.000)
ABRETVOL	1.181***
	(0.000)
ABACC	0.038
	(0.627)
FCOMPLEXITY	0.019
	(0.502)
AEFA	0.001
	(0.153)
Industry FE, Year FE	Yes
Pseudo R^2	0.15
Observations	28,851
Wald χ^2: $\Psi_1 > \Psi_2$	10.53***

Panel C: Managerial disclosure cost based on CEO age	**(1)** ***FREQ*** **Young CEOs Coefficient (*p*-value)**	**(2)** ***FREQ*** **Older CEOs Coefficient (*p*-value)**
NEWUSER_EH × ***POST*** Ψ_1	0.348***	0.124*
	(0.000)	(0.069)

(Continues)

TABLE 6 (Continued)

Panel C: Managerial disclosure cost based on CEO age

	(1) ***FREQ*** **Young CEOs Coefficient (*p*-value)**	**(2)** ***FREQ*** **Older CEOs Coefficient (*p*-value)**
NEWUSER_IS × ***POST*** Ψ_2	0.025	0.119*
	(0.784)	(0.076)
CTRL	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Pseudo R^2	0.16	0.34
Observations	5,356	5,149
Wald χ^2: $\Psi_1 > \Psi_2$	9.27***	0.00

Panel D: Managerial disclosure cost based on CEO tenure

	(1) ***FREQ*** **CEOs with short tenure Coefficient (*p*-value)**	**(2)** ***FREQ*** **CEOs with long tenure Coefficient (*p*-value)**
NEWUSER_EH × ***POST*** Ψ_1	0.264**	0.135**
	(0.014)	(0.034)
NEWUSER_IS × ***POST*** Ψ_2	−0.043	0.131*
	(0.646)	(0.060)
CTRL	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Pseudo R^2	0.15	0.34
Observations	5,504	5,001
Wald χ^2: $\Psi_1 > \Psi_2$	7.23***	0.00

Note: This table reports a test of managerial disclosure costs based on a firm's hedge effectiveness, hedge accounting choice, CEO age, and CEO tenure. In Panels A and B, we test whether effective hedgers and hedge accounting users are more likely to issue earnings forecasts than ineffective hedgers or non-hedging users, respectively. Panels C and D report tests of how managers' career concerns play a role in determining management forecast decisions. We use the median value of CEO age and tenure length to create subsamples in Panels B and C, respectively. Career concerns are greater when managers are younger and have shorter tenure. Robust standard errors are clustered by firm. Variables are defined in Appendix 2. The variables of interest are in bold.
*, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

demand" explanation, derivative usage leads to increased guidance regardless of managers' career concerns. On the other hand, if the relation between derivative usage and guidance is driven by managers' career concerns, then managers with high career concerns will increase forecast frequency only when they use derivatives in a way that makes it easier to predict future earnings. In H3, we seek to disentangle these two potential reasons for the association between derivative usage and management forecast frequency.

Following prior research (Ali & Zhang, 2015; Baginski et al., 2018), we classify younger managers and/or those who have short tenure as managers with greater career concerns. Therefore, in Panels C and D of Table 6, we repeat the analysis in Panel A of Table 6 separately for the high and low career concern partitions where we use CEO age and CEO tenure as proxies for career concerns, respectively. If career concerns are driving the decision to issue forecasts, we expect the coefficient on *NEWUSER_EH* × *POST* to be greater than that of *NEWUSER_IS*×*POST* in the high career concern partition, but not in the low career concern partition (H3). Otherwise, we expect no difference. In Column 1 of Panel C, the significant and positive coefficient for *NEWUSER_EH* × *POST* (0.348) and the insignificant coefficient for *NEWUSER_IS* × *POST* (0.025) suggest that young managers increase MEF frequency *only* when firms effectively hedge their risks. On the contrary, we find both significant and positive coefficients for *NEWUSER_EH* × *POST* and *NEWUSER_IS* × *POST* in Column 2, implying older managers with lower career concerns increase MEF frequency following derivative initiation, regardless of the manner in which they use derivatives. We find similar results in Panel D when we use CEO tenure to proxy for career concerns rather than age. Taken together, these results are consistent with the notion that managers consider career concerns when issuing earnings forecasts (or Waymire's "cost-related" explanation).

4.4.2 | Evidence of at least some impact of "investor demand"?

Recall that in tests of H3, we find that the relation between derivative usage and forecast frequency varies with managers' career concerns. These results are inconsistent with the "investor demand" explanation as derivative usage should lead to increased guidance regardless of managers' career concerns if managers provide forecasts in response to heightened investor demand. Nevertheless, if investors do not know ex ante how managers will use derivatives (and investor uncertainty increases), they will likely price protect themselves unless the manager provides a forecast (Guay et al., 2016). Thus, in this section, we examine whether some portion of the forecast decision is a response to an increase in investor demand. That is, we examine whether managers appear to weigh investors' information demand against the disclosure cost they face when they issue forecasts.

Following prior research (Chang et al., 2016; Guay et al., 2016), we define investor demand as high (low) when financial reporting complexity is high (low). Specifically, we measure financial reporting complexity using Gunning Fog readability index for 10-Ks. We then classify observations into the high (low) investor demand sample if a firm's 10-K readability is above (below) the median value of the Fog index. We also measure managers' cost of providing forecasts using the *EH* (low cost) and *IS* (high cost) classification and create four partitions: low cost and low demand (Cell [1]), low cost and high demand (Cell [2]), high cost and low demand (Cell [3]), and high cost and high demand (Cell [4]).

In Panel A of Table 7, we estimate Equation (2) with indicator variables for low versus high disclosure cost in a subsample of low versus high demand firms. The coefficients of interest are Ψ_1 and Ψ_2 on the interaction terms *NEWUSER_EH* × *POST* and *NEWUSER_IS* × *POST*. These coefficients capture the change in the frequency of MEFs after derivative initiation for firms with low cost (*EH*) and firms with high cost (*IS*) to provide disclosures.[16] First, we find that the coefficient for *NEWUSER_EH* × *POST* is significantly positive, suggesting that effective hedgers increase the frequency of MEFs after derivative initiation. Second, we find a significant difference between the interaction coefficient on *NEWUSER_EH* × *POST* in the low and high demand samples (Cells [1] and [2]; $\chi^2 = 2.71$), indicating that managers respond to investor demand when their disclosure cost is low. Third, the coefficient on *NEWUSER_IS* × *POST* is

[16]An assumption in these tests is that investor demand is constant when managers use derivatives to speculate as compared to when they use derivatives to hedge. This assumption is supported by prior research showing that investors are unable to tell ex ante how managers use derivatives (e.g., Chang et al. 2016). Importantly, if this assumption does not hold, we would simply find the opposite of our predictions—that forecast activity would increase for speculating firms rather than hedging firms. As can be seen in our results, if anything, firms provide fewer forecasts when speculating in all cases, again suggesting that our results are driven by reduced costs to forecast rather than increased demand for forecasts.

insignificant in both low- and high-demand samples (Cells [3] and [4]), and the difference in the interaction coefficient across the low and high demand samples is insignificant (Cells [3] and [4]; $\chi^2 = 0.02$). Thus, when the disclosure cost is high, investor demand does not lead to an increase in MEF frequency. Overall, the results in Panel A of Table 7 suggest that managerial disclosure costs have a first-order effect on the decision to issue earnings forecasts.

4.5 | Consequences of derivative-induced management forecasts (H4)

A natural question that follows is whether investors benefit from management earnings forecasts if managers issue more forecasts when their disclosure cost is low. This inquiry helps to further identify the reasons behind why derivative usage might drive managers' decisions to issue a forecast. For example, if the reason for issuing a forecast is "investor demand" then the forecasts are likely to be useful. Similarly, if firms increase MEF frequency because managers are using derivatives to reduce earnings volatility and perceive their forecasts will be more useful to capital markets (i.e., Waymire's "benefit-related" explanation), then the forecasts issued by effective hedgers should be more informative than those issued by ineffective hedgers/speculators. However, if firms increase MEF frequency because managers are using derivatives to reduce earnings volatility and career concerns motivate them to provide forecasts they can meet/beat (i.e., Waymire's "cost-related" explanation), the forecasts issued by effective hedgers may not be particularly useful to investors. For the impact of issuing management forecasts on investors, we specifically focus on analyst forecast accuracy as prior research (Campbell et al., 2015; Chang et al., 2016) documents the degradation of analyst forecast accuracy for derivative users.

To investigate whether derivative-induced forecasts are, on average, informative to analysts (H4a), we create partitions based on whether firms increase (decrease/do not change) the frequency of management forecasts after derivative initiation. To test if the effect of derivative-induced forecasts on analyst forecast accuracy varies with how firms use derivatives (H4b), we include an indicator variable for effective hedgers (*NEWUSER_EH*) and ineffective hedgers/speculators (*NEWUSER_IS*) and interact them with *POST*. We then regress analyst earnings forecast accuracy (*AEFA*) on *NEWUSER_EH* × *POST* and *NEWUSER_IS* × *POST* together with the main effects (*NEWUSER_EH, NEWUSER_IS*, and *POST*) in each partition. In Panel B of Table 7, the generally positive coefficients on *NEWUSER_EH* × *POST* and *NEWUSER_IS* × *POST* in Column 1 provide preliminary evidence that derivative-induced forecasts are positively associated with analyst forecast accuracy, and that—consistent with H4a—these forecasts are useful for investors.[17] More importantly, Wald chi-square statistics that compare the interaction coefficients across columns are statistically significant. These Wald chi-square statistics suggest that analyst forecast accuracy improves both for effective and speculative derivative users when derivative-induced forecasts are provided. However, when we test H4b and consider the effects of how firms use derivatives, in Column 1, a significant and positive coefficient on *NEWUSER_IS* × *POST* (0.184) and an insignificant coefficient on *NEWUSER_EH* × *POST* suggest that derivative-induced forecasts are *more* informative when firms use derivatives to speculate.[18] These results

[17]We test whether management forecasts help analysts accurately forecast earnings especially when analysts do *not* anticipate the income statement impact of derivatives. In untabulated results, we find that analyst earnings forecast accuracy is significantly lower when the volatility of unrealized derivatives gains/losses (measured by the standard deviation of unrealized derivatives gains/losses deflated by total assets) is higher, making it harder for analysts to anticipate the impact of derivatives on earnings. We then create subsamples based on whether firms increase (decrease/do not change) the frequency of management forecasts after derivative initiation as we did for Panels B and C of Table 7. Next, we run analyst forecast accuracy on the volatility of unrealized derivatives gains/losses with control variables in each subsample. The above result holds only when firms decrease/do not change the frequency of management forecasts after derivative initiation suggesting that management forecasts help analysts predict earnings when there is higher uncertainty of the earnings impact of derivatives.

[18]Note that in Columns 1 and 2 of Panel B of Table 7, matched non-users are a control group. Although a significant Wald chi-square statistic (6.02) suggests that there is an improvement in analyst forecast accuracy for effective hedgers, such improvement in analyst forecast accuracy is not significantly different from the accuracy improvement for a control group.

are consistent with Waymire's (1985) "cost-related" explanation but inconsistent with his "benefit-related" explanation. Finally, the significant and negative coefficients for both *NEWUSER_EH* × *POST* and *NEWUSER_IS* × *POST* in Column 2 indicate that the Chang et al. (2016) findings that analyst forecast accuracy decreases for new derivative users after derivative initiation regardless of how they use derivatives are driven by firms that do not provide

TABLE 7 Managerial disclosure cost and investor demand.

Panel A: Trade-off between managerial disclosure cost and investor demand

			Investor demand: Low *FREQ* Coefficient *z*-stat (*p*-value)			Investor demand: High *FREQ* Coefficient *z*-stat (*p*-value)
Disclosure cost	Low	***NEWUSER_EH* × *POST*** Ψ_1	0.171**			0.667***
			(0.029)			(0.000)
		CTRL2	Included			Included
		Industry FE	Included			Included
		Year FE	Included			Included
		Pseudo R^2	0.15			0.17
		Observations	8,933	**(1)**	**(2)**	8,934
	High	***NEWUSER_IS* × *POST*** Ψ_2	−0.050	**(3)**	**(4)**	−0.014
			(0.490)			(0.620)
		CTRL2	Included			Included
		Industry FE	Included			Included
		Year FE	Included			Included
		Pseudo R^2	0.15			0.17
		Observations	8,933			8,934

Panel B: Impact of management forecasts on subsequent analyst forecast accuracy

	(1) ***AEFA*** **Increase in MEF freq.** **Coefficient** **(*p*-value)**		**(2)** ***AEFA*** **Decrease in MEF freq.** **Coefficient** **(*p*-value)**
NEWUSER_EH*×*POST Ψ_1	0.074		−0.406**
	(0.288)		(0.014)
NEWUSER_IS*×*POST Ψ_2	0.184**		−0.290*
	(0.032)		(0.060)
CTRL3	Yes		Yes
Industry FE	Yes		Yes
Year FE	Yes		Yes
Adjusted R^2	0.30		0.32
Observations	12,549		3,852
F-stat: $\Psi_1 = \Psi_2$	3.69*		0.45
Wald χ^2: $\Psi_1(1) = \Psi_1(2)$		6.02	
Wald χ^2: $\Psi_2(1) = \Psi_2(2)$		7.19	

(Continues)

TABLE 7 (Continued)

Panel C: Impact of management forecasts on subsequent analyst forecast accuracy pre- and post-FAS 161

	(1) Pre-FAS 161		**(2) Post-FAS 161**	
	AEFA **Increase in MEF freq. Coefficient (*p*-value)**	***AEFA*** **Decrease in MEF freq. Coefficient. (*p*-value)**	***AEFA*** **Increase in MEF freq. Coefficient (*p*-value)**	***AEFA*** **Decrease in MEF freq. Coefficient. (*p*-value)**
NEWUSER_EH* × *POST Ψ_1	0.062	−0.445*	0.059	−0.102
	(0.658)	(0.057)	(0.490)	(0.675)
NEWUSER_IS* × *POST Ψ_2	0.196**	−0.175*	0.090	−0.280
	(0.049)	(0.082)	(0.370)	(0.287)
CTRL3	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.29	0.34	0.31	0.28
Observations	7,695	2,251	4,854	1,601
F-stat: $\Psi_1 = \Psi_2$	2.25*	0.52	0.47	0.45

Note: This table reports tests of trade-offs managers face between their disclosure cost and investor demand when issuing earnings guidance (Panel A), the impact of management forecasts on analyst forecast accuracy (Panel B), and its impact on analyst forecast accuracy pre- and post-FAS 161 (Panel C). In Panel A, sample partitions are based on whether investors exhibit high or low information demand proxied by the natural log of the Gunning Fog readability index for 10-Ks and whether *New Users* have high or low disclosure costs based on their hedging results (effective hedging vs. speculating). *CTRL2* in Panel A include all control variables except for *FCOMPLEXITY* as we use this variable to partition the sample (High vs. Low investor demand). In Panel B, sample partitions are based on whether firms increase (or decrease/do not change) MEF frequency after derivative initiation. In Panel C, we repeat the same analysis as in Panel B for pre-FAS 161 and post-FAS 161 periods separately. *CTRL3* in Panels B and C include all control variables except for *AEFA* as we use *AEFA* as a dependent variable in these tests. Robust standard errors are clustered by firm. Variables are defined in Appendix 2. The variables of interest are in bold.
*, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

management forecasts frequently. In sum, the results in Panel B of Table 7 indicate that, on average, derivative-induced forecasts are useful for analysts and analyst forecast accuracy improves especially when the manager's cost of providing the forecast is high (because they are using derivatives to increase earnings volatility).[19]

Finally, to test H4c, we investigate whether enhanced derivative disclosures mandated by FAS 161 change the usefulness of management forecasts for analysts. As previously discussed, Campbell, Khan, and Pierce (2021) document that the enhanced mandatory derivative disclosures set forth in FAS 161 improve investors' understanding of firms' hedging activities, evidenced by more accurate analyst forecasts after FAS 161. If analysts find enhanced derivative disclosures to be useful, it is likely that the increase in MEF frequency may not be as useful after FAS 161 improved mandatory derivative disclosures. In Panel C of Table 7, we repeat the analysis in Panel B separately for pre- and post-FAS 161 periods. Consistent with the on average results in Panel B, we find that analyst forecast accuracy for ineffective hedgers/speculators appears to improve when managers increase the frequency of their forecasts in the *pre*-FAS 161 period. However, consistent with H4c, we find that the coefficients on both *NEWUSER_EH* × *POST* and *NEWUSER_IS* × *POST* are *insignificant* in the *post*-FAS

[19]We further examine if the results in Panel B of Table 7 vary with managerial career concerns. Consistent with the findings that management forecasts issued when the disclosure cost is high help analysts improve their forecasts the most, we find that the improvement in analyst forecast accuracy manifests mostly when managers increase the frequency of their forecasts despite a higher degree of career concerns (i.e., young CEOs and those with short tenure).

161 period, even when managers increase the frequency of their forecasts. These findings imply that the combination of managers' career concerns and improved mandatory disclosures results in derivative-induced forecasts providing no benefit to analysts. Taken together, these results further confirm that these forecasts are motivated by the manager's cost of providing them, rather than an increase in investor demand for them or any benefit investors might receive from them. That is, even though these forecasts are not necessary in the post-FAS 161 period, managers continue to provide them because the cost of providing them is low.

4.6 | Additional analyses

4.6.1 | Sales forecasts

Derivative usage can also influence the volatility of future sales. Thus, we further examine the association between derivative usage and sales forecasts. Foreign exchange hedgers are likely to have lower sales volatility relative to interest rate derivative users that hedge nonoperating items (e.g., interest expense) as the former often hedges sales prices of their inventory using FX derivatives. We therefore predict that foreign exchange hedgers are more likely to issue sales forecasts relative to interest rate hedgers. Panel A of Table 8 presents a positive association between foreign exchange hedgers (*FX_HEDGER*) and the frequency of management *sales* forecasts (*FREQ_SALES*) consistent with the important role of managerial disclosure costs in the decision to issue forecasts.

4.6.2 | Attributes of management earnings forecasts other than frequency

In our main tests, our dependent variable is MEF frequency. In Panel B of Table 8, we replicate our main analysis using two alternative attributes for guidance: (1) a firm's initiation of a forecasting policy (*INITIATE*, a binary variable equal to one if firms without MEFs in the previous 2 years start providing MEFs) and (2) the decision to issue MEFs (*ISSUE*, a binary variable equal to one if the firm issues earnings forecasts in a given year). Consistent with our main results, we find a positive relation between these measures of MEFs and derivative usage.

Similarly, in Panel C of Table 8, we consider whether derivative usage impacts forecast accuracy and precision. Consistent with our results related to frequency, we find a significantly positive association between the derivative usage and management forecast accuracy as well as precision. These results suggest that derivative users are not only more likely to issue guidance, but that guidance is more likely to have a tighter range and to be more accurate.

4.6.3 | Correlated omitted variables

As previously discussed, prior research argues that firms are most likely to use derivatives when they face volatility in an underlying rate or price. A natural question to ask, then, is whether our results are driven by underlying risk exposures or the act of using derivatives. To investigate this possibility, we create an indicator variable *HIRISKEXP* that equals one if a firm is in the upper quartile of interest rate risk (*IRISK*), foreign exchange rate risk (*FRISK*), or commodity price risk (*CRISK*) exposures. Under the argument that when firms face greater risk exposure (and thus higher earnings volatility) they are less likely to provide a forecast, we would expect the coefficient on *HIRISKEXP* to be

TABLE 8 Alternative measures for management earnings forecast frequency.

Panel A: Sales forecast frequency

	FREQ_SALES **Coefficient (*p*-value)**
FX_HEDGER	0.033*
	(0.080)
CTRL	Yes
Industry FE	Yes
Year FE	Yes
Pseudo R^2	0.04
Observations	18,670

Panel B: Decision to initiate or issue earnings forecasts

	(1) *INITIATE* Coefficient (*p*-value)	**(2) *ISSUE* (binary variable) Coefficient (*p*-value)**
USER	0.090**	0.160***
	(0.035)	(0.000)
CTRL	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Pseudo R^2	0.52	0.51
Observations	9,022	28,851

Panel C: Management earnings forecast accuracy and precision

	(1) *ACCURACY* Coefficient (*p*-value)	**(2) *PRECISON* Coefficient (*p*-value)**
USER	0.023***	0.003*
	(0.000)	(0.068)
CTRL	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	0.03	0.04
Observations	13,546	13,580

Note: This table reports additional tests using alternative measures for management earnings forecast frequency. Panel A reports a test of whether foreign exchange hedgers are more likely to issue sales forecasts. Panel B, Column 1 (Column 2) presents a test of whether derivative usage is associated with the decision to initiate (issue) earnings forecasts. Panel C reports tests of how firms' use of derivatives influences management earnings forecast accuracy (Column 1) and precision (Column 2). Robust standard errors are clustered by firm. Variables are defined in Appendix 2. The variables of interest are in bold.
*, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

negative and significant. We however fail to find a significant relation between *HIRISKEXP* and *FREQ* (untabulated), suggesting that underlying risk exposure is not driving our results.

In untabulated results, we also find that our inferences hold if we perform three other tests, namely: (1) if we examine derivative termination rather than initiation, (2) if we include manager fixed effects, and (3) if we include firm fixed effects.[20] Lastly, we confirm that including *changes* in analyst forecast accuracy and financial reporting complexity as additional controls and interacting them with *POST* and *NEWUSER* × *POST* in Panel B of Table 4 do not alter the main inferences.

5 | CONCLUSION

We examine whether and how firms' derivative usage impacts voluntary disclosure and offer four main findings. First, we find that derivative usage is positively associated with the frequency of management earnings forecasts, and that derivative initiation increases the forecast frequency. Second, using path analysis, we find a direct link between derivative usage and forecast frequency, as well as an indirect link through reduced earnings volatility. Third, we find that CEOs with more pronounced career concerns increase forecast frequency *only* when derivatives make earnings easier to forecast and find no evidence that investor demand for forecasts drives the decision to provide a forecast. These results suggest that the primary mechanism for the association between derivative usage and forecast frequency is a reduction in the manager's personal costs of providing the forecasts.

Finally, we find that the majority of these derivative-induced forecasts are largely uninformative to capital market participants, especially after FAS 161 provided the necessary underlying data to understand firms' derivative usage. Overall, we provide the first empirical evidence that firms that use derivatives issue more management forecasts, but also find that these incremental forecasts are uninformative and appear motivated by managers' career concerns. Future research may wish to examine what benefits (if any) managers receive by providing management forecasts with limited usefulness (i.e., whether these managers are less likely to be fired or receive higher compensation).

ACKNOWLEDGMENTS

The authors are especially grateful to Hai Lu (editor) and two anonymous reviewers for many helpful suggestions. In addition, the authors would like to thank Steve Baginski, Elizabeth Blankespoor, Qiang Cheng, Ted Christensen, Bryan Cloyd, John Core, Matt DeAngelis, Guojin Gong, Zhaoyang Gu, Frank Heflin, Ole-Kristian Hope, Steve Kachelmeier, Jungbae Kim, Yongtae Kim, Tamara Lambert, Zhejia Ling, Partha Mohanram, Robbie Moon, Suresh Nallareddy, Spencer Pierce, Grace Pownall, Tharindra Ranasinghe, Ewa Sletten, Theodore Sougiannis, Mohan Venkatachalam, Greg Waymire, Ben Whipple, Holly Yang, Eric Yeung, and Liandong Zhang for numerous constructive comments. The authors also thank participants at the SMU-NCCU Joint Accounting Conference, Singapore Management University (SMU) Accounting Symposium, European Accounting Association (EAA) Annual Meeting, Southeast Summer Accounting Research Conference (SESARC) at the University of Georgia, and American Accounting Association (AAA) Annual Meeting, and workshop participants at Georgia State University, Lehigh University, and Tsinghua University. John Campbell gratefully acknowledges support from a Terry Sanford Research Award from the Terry College of Business at the University of Georgia.

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[20]Firm fixed effects may not be appropriate in this setting as (1) we have firms with no variation in their user/non-user status over the sample period (firms that are pure non-users or firms that use derivatives in every period) and (2) firms that have no variation in user/non-user status (e.g., pure non-user) are dissimilar to firms with variation (firms that use derivatives from time to time). This can bias the coefficient for *USER* in either direction, affect standard errors, and cause Type I and II errors (deHaan, 2021). Nevertheless, in unreported results, we drop no variation firms and include firm fixed effects. Our inferences remain unchanged.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Campbell, J. L., Cao, S. S., Chang, H. S., & Chiorean, R. (2023). The implications of firms' derivative usage on the frequency and usefulness of management earnings forecasts. *Contemporary Accounting Research*, *40*(4), 2409–2445. https://doi.org/10.1111/1911-3846.12883

APPENDIX 1: FINANCIAL DERIVATIVE-RELATED KEYWORDS

Keywords to identify derivative users

Derivative contract, derivative instrument, derivative financial instrument, derivative position, derivative asset, derivative liability, change in fair value of derivative, derivative expense, derivative gain, derivative loss, gain on derivative, loss on derivative, hedge, designated as a hedge, designated as hedges, instruments are designated, contracts are designated, hedge of the net investment, net investment hedge, cash flow hedge, fair value hedge, ineffective portion, notional, embedded derivative, forward contract, futures contract, call option, call contract, put option, put contract, option contract, swap, swaption, cap agreement, lock agreement.[21]

Keywords to identify IR derivative users

Interest rate contract, interest rate derivative, interest rate instrument, interest rate forward, interest rate collar, interest rate swap, zero coupon swap, single currency basis swap, interest rate future, interest rate option, interest rate cap, interest rate floor, interest rate lock.

Keywords to identify FX derivative users

Forward rate agreement, forward rate contract, forward rate option, foreign exchange contract, foreign exchange rate contract, currency contract, currency rate contract, foreign exchange derivative, foreign exchange rate derivative, currency derivative, currency rate derivative, foreign exchange instrument, foreign exchange rate instrument, currency instrument, currency rate instruments, foreign exchange forward, foreign exchange rate forward, currency forward, currency rate forward, forward foreign exchange, foreign exchange future, foreign exchange rate future, currency future, currency rate future, foreign exchange swap, foreign exchange rate swap, currency rate swap, currency swap, foreign exchange option, foreign exchange rate option, currency option, currency rate option, foreign exchange cap, foreign exchange rate cap, currency cap, currency rate cap, foreign exchange floor, foreign exchange rate floor, currency floor, currency rate floor, foreign exchange collar, foreign exchange rate collar, currency collar, currency rate collar.

Keywords to identify CP derivative users

Commodity contract, commodity price contract, commodity derivative, commodity price derivative, commodity instrument, commodity price instrument, commodity forward, commodity price forward, commodity future, commodity price future, commodity option, commodity price option, commodity cap, commodity price cap, commodity floor, commodity price floor, commodity collar, commodity price collar, commodity swap, commodity price swap.

[21] We use the stemming option to include grammatical derivations of the keywords (e.g., hedge, a hedge, hedges, hedging). We also run a separate search for the key phrase "hedge fund" to adjust for instances where the keywords do not capture a firm's use of derivatives.

APPENDIX 2: VARIABLE DEFINITIONS

Variable	Definition
Dependent variables	
FREQ	MEF frequency, defined as the number of annual earnings forecasts issued by firm *i* in year *t*.
AEFA	Analyst earnings forecast accuracy, defined as the absolute value of the difference between the consensus annual earnings forecast and the actual earnings, scaled by stock price of year *t* for firm *i*. We multiply the result by −100 such that greater values indicate more accurate forecasts. See Chang et al. (2016) for details.
FREQ_SALES	Management sales forecast frequency, defined as the number of annual sales forecasts issued by firm *i* in year *t*.
INITIATE	Initiation of issuing earnings forecasts, defined as the first-year firm *i* issues earnings forecasts in I/B/E/S after 2 nonforecasting years.
ISSUE	Indicator variable equal to one if the firm issues earnings forecasts in fiscal year *t*, and zero otherwise.
ACCURACY	MEF accuracy, defined as the absolute value of the difference between actual earnings and the management forecast deflated by the median analyst forecast for firm *i* in year *t*. We multiply the result by −1 such that greater values indicate more accurate forecasts. See Karamanou and Vafeas (2005) for details.
PRECISION	MEF precision, defined as forecast width for firm *i* in year *t*. We multiply the result by −1 such that greater values indicate more precise forecasts.
Variables of interest	
USER	Indicator variable equal to one if the firm reports a position in derivatives in fiscal year *t*, and zero otherwise.
NEWUSER	Indicator variable equal to one for all *New User* firm observations and zero for all matched control firm observations.
FEVOL	Forward earnings volatility, defined as the standard deviation of quarterly earnings before extraordinary items (ibq) in years $t + 1$ and $t + 2$. See Ellahie and Peng (2021) for details.
EH	Indicator variable equal to one if the firm effectively hedges (reduces) its exposure to at least two risks: interest rate (*IRISK*), foreign exchange rate (*FRISK*), or commodity price (*CRISK*) risks relative to expectations after derivative initiation, and zero otherwise. See Zhang (2009) for details.
POST	Indicator variable equal to one for both *New User* and matched control firm observations in periods after derivative initiation, and zero otherwise.
HEDGE_USER	Indicator variable equal to one for *User* observations with nonmissing and nonzero unrealized holding gain/loss from derivatives, and zero otherwise.
NONHEDGE_USER	Indicator variable equal to one for *User* observations with missing or zero unrealized holding gain/loss from derivatives, and zero otherwise.
FX_HEDGER	Indicator variable equal to one for foreign exchange hedgers, and zero otherwise.
Disclosure determinants	
INST	Institutional ownership for firm *i* at end of year *t*.
SIZE	Log of equity market value (prcc_f × csho) at end of year *t*.
FOL	Number of analysts following firm *i* in year *t*.
BIGN	Indicator variable for Big N auditors.
LITIGATION	Indicator variable equal to one if the firm belongs to an industry with a high incidence of litigation, and zero otherwise. See Francis et al. (1994) for details.
MB	Market-to-book ratio, defined as equity market value (prcc_f × csho) divided by book value of equity (at − lt − pstkl + txditc + dcvt) at end of year *t*.

(Continues)

APPENDIX (Continued)

Variable	Definition
NEGNEWS	Indicator variable for negative earnings news for firm *i* in year *t*.
PEVOL	Past earnings volatility, defined as the standard deviation of quarterly earnings before extraordinary items (ibq) during the most recent 2 years.
ABRETVOL	Abnormal return volatility, defined as the standard deviation of monthly stock returns (adjusted for industry average) for firm *i* at year *t*.
ABACC	Abnormal accruals, based on the performance-matched modified Jones model.
FCOMPLEXITY	Log of Gunning Fog readability index for firm *i*'s 10-K in year *t* downloaded from SEC Analytics Suite.
Risk management incentives	
IRISK	Interest rate risk exposures, defined as the absolute value of the estimated coefficient from a regression of firms' monthly holding period stock returns on the monthly percentage change in the London Interbank Offered Rate for 24 months prior to fiscal year-end. See Guay (1999), Zhang (2009), and Chang et al. (2016).
FRISK	Foreign currency exchange rate risk exposures, defined as the absolute value of the estimated coefficient from a regression of firms' monthly holding period stock returns on the monthly percentage change in the Federal Reserve Board trade-weighted US dollar index for 24 months prior to fiscal year-end. See Guay (1999), Zhang (2009), and Chang et al. (2016).
CRISK	Commodity price risk exposures, defined as the absolute value of the estimated coefficient from a regression of firms' monthly holding period stock returns on the monthly percentage change in the Producer Price Index for 24 months prior to fiscal year-end. See Guay (1999), Zhang (2009), and Chang et al. (2016).
Δ*IRISK*	Change in interest rate risk exposures, defined as the difference between interest rate risk exposures in year *t* and year $t-1$.
Δ*FRISK*	Change in foreign currency exchange rate risk exposures, defined as the difference between foreign currency exchange rate risk exposures in year *t* and year $t-1$.
Δ*CRISK*	Change in commodity price risk exposures, defined as the difference between commodity price risk exposures in year *t* and year $t-1$.
ALTZ	Likelihood of entering financial distress, defined as the modified Altman *Z*-score based on parameter weights reported by Shumway (2001).
USCORE	Likelihood of underinvestment, defined by first ranking cash flow from operations (oancf), debt-to-assets ratio (lt/at), and scores from a factor analysis of four growth opportunity measures (prior investment activity, geometric growth in market value of assets, market-to-book ratio, and research and development into deciles by year and industry). Decile ranks for debt-to-asset ratios and growth opportunity factor scores are then added to the reverse decile rank for cash flows from operations, with the result scaled by 30 (total possible points). See Chang et al. (2016).
ECSENS	Sensitivity of executive compensation to firm value, defined by first computing the dollar change in value of CEO stock and option holdings that would result from a one percentage point increase in the stock price of the firm (0.01 × prcc_f × [shrown_tot + opt_unex_exer_num]). The result is then normalized by the sum of CEO salary and bonus (salary + bonus) to capture the share of total CEO compensation that would result from a one percentage point increase in firm value. Compensation data obtained from ExecuComp. See Bergstresser and Philippon (2006).
CETR	Cash effective tax rate (3 years), defined as the 3-year sum (t to $t+2$) of worldwide cash taxes paid (txpd) divided by the 3-year sum (t to $t+2$) of pre-tax book income (pi) less special items (spi). ETRs are reset to 1 (0) if greater (less) than one (zero). See Dyreng et al. (2008).
CDEBT	Convertible debt, defined as convertible debt (dcvt) divided by lagged total assets (at).
PSTOCK	Preferred stock, defined as preferred stock (pstk) divided by lagged total assets (at).

APPENDIX (Continued)

Variable	Definition
PCVOL	Cash flow volatility, defined as the standard deviation of quarterly operating cash flows (oancfy, adjusted to reflect quarterly data) during the most recent 2 years.
$\Delta PCVOL$	Change in cash flow volatility, defined as the difference in cash flow volatility year t and year $t-1$.
$\Delta PEVOL$	Change in earnings volatility, defined as the difference in earnings volatility year t and year $t-1$.

Note: Compustat mnemonics are in parentheses.