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# COMMERCIAL BANK LOAN LOSS PROVISION DISCRETION: SIGNALS AND SIGNAL-JAMMING

By

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## ABSTRACT

COMMERCIAL BANK LOAN LOSS PROVISION DISCRETION:
SIGNALS AND SIGNAL-JAMMING

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In contrast to common notions of the information content of financial disclosures and accounting variables, this dissertation provides theory and empirical evidence suggesting that accounting discretion can result in *disinformative* signals to equity traders. A *disinformative* signal is defined as a signal that results in equity traders revising their distributions over some pricing-relevant variable such that their expectations become less precise. A hypothesis is developed, based on Scharfstein and Stein's (1990) herd behavior model—and, more generally, on learning, herd behavior, and noise trading models in the information and financial economics literatures—that discretionary disclosures can be disinformative to equity traders under certain conditions. Empirical evidence consistent with this hypothesis is presented in simultaneous long- and short-window associations between bank loan loss provision components, equity return variance, and share volume. Accordingly, this study presents both theory and empirical evidence suggesting that discretionary accounting disclosures can be disinformative under certain conditions. ■

To Diane, Andrew, and Stewart

For helping me understand why it all was, is, and will be meaningful.

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| Abbreviation | Description |
|---|---|
| $dper$ | Equal to one if $\hat{ur}_{it}^2$ and $\hat{uv}_{it}$ fall within 11 day disclosure period; else zero. |
| $\hat{E}_{t-1}nco_{it}$ | Expected net loan charge-offs for firm $i$, time $t$ estimated at time $t-1$ (as proxy for nondiscretionary $nco$). |
| $\hat{E}_{t-1}\Delta lla_{it}$ | Expected loan loss allowance change for firm $i$, time $t$ estimated at $t-1$ (as proxy for nondiscretionary $\Delta lla$). |
| $lla$ | Loan loss allowance; defined by the identity $-lla_t = -lla_{t-1} + nco_t - llp_t$. |
| $\Delta lla$ | Change in loan loss allowance; defined as $\Delta lla_t = -lla_t - (-lla_{t-1})$. |
| $llp$ | Loan loss provision; decomposed as $llp = nco + \Delta lla$. |
| $nco$ | Net loan charge-offs. |
| $npl$ | Non-performing loans. |
| $\Delta npl$ | Change in non-performing loans; defined as $\Delta npl_t = npl_t - npl_{t-1}$. |
| $plle$ | Pre-loan loss earnings defined by $plle = net\ income + llp$. |
| $\hat{u}_{nco,it}$ | Unexpected net loan charge-offs for firm $i$, time $t$ (as proxy for discretionary $nco$); defined as $\hat{u}_{nco,it} = nco_{it} - \hat{E}_t nco_{it}$. |
| $\hat{u}_{\Delta lla,it}$ | Unexpected loan loss allowance change for firm $i$, time $t$ estimated at time $t-1$ (as proxy for discretionary $\Delta lla$); defined as $\hat{u}_{\Delta lla,it} = lla_{it} - \hat{E}_t lla_{it}$. |
| $\hat{ur}_{it}^2$ | Squared unexpected (residual) equity return for firm $i$, time $t$. |
| $\hat{uv}_{it}$ | Unexpected (residual) equity share volume for firm $i$, time $t$. |
| $\rho$ | Parameter of AR(1) residual process: $u_t = \rho \cdot u_{t-1} + e_t$; $e_t \sim N(0, \sigma^2)$. |

# CHAPTER 1

# INTRODUCTION

A prevalent view in the financial accounting literature is that accounting variables can be either *informative* or *noninformative* to equity traders: rational traders and informationally efficient equity markets presumably ensure that *disinformative* signals in the form of financial reporting and disclosure manipulations are not impounded in equity prices (cf. Beaver, 1981; and Verrecchia, 1979). The term *disinformation* is used in the following sense: a disinformative disclosure results in equity traders revising their distributions over some pricing-relevant variable such that their expectations become less precise.[1] As an example, a disinformative disclosure decreases the ability of equity traders to make precise inferences about exogenous factors that influence expected profits. In this connection Beaver (1968, p. 69n.8) states: "It should be apparent that in a dynamic situation . . . a decision maker may be more uncertain about a given event after receiving a message about the event than he was before he received the message." Based generally on herd behavior and learning models developed in the financial and information economics literatures, this

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[1] In the finance literature, the term *disinformation* as used in this study would generally be referred to simply as *noise*. Similarly, in the accounting literature the term *disinformation* as used here would be referred to alternatively as *noise* (cf. Collins and Kothari, 1989), *increases in the uncertainty* of information contained in an accounting signal (cf. Kim and Verrecchia, 1994), or *reporting bias* (cf. Fischer and Verrecchia, 1998). Thus, the notion of disinformation used in this study subsumes two different types of noise: white noise with expectation $\mathrm{E}(u_t) = \mathrm{E}(u_t \mid x_t) = 0, \forall t$; and non-white "noise" with unconditional expectation $\mathrm{E}(u_t) = 0$ and conditional expectation, $\mathrm{E}(u_t \mid x_t) \neq 0, \forall t$.

study develops the hypothesis that under certain conditions managers use accounting discretion to generate disinformative disclosures which "jam" inferences of equity traders.

A sample of commercial banks is selected for testing the hypothesis that discretionary accounting disclosures can result in disinformative signals to equity traders since the economic conditions faced by banks are analogous to those required for the optimality of "signal-jamming" derived in Scharfstein and Stein (1990).[2] Since loan loss provisions represent one of the primary discretionary components of commercial bank earnings, this hypothesis is tested by examining the empirical association between: (a) unexpected equity return variance and the unexpected components of loan loss provisions; and, (b) unexpected equity share transaction volume and the unexpected components of loan loss provisions. Unexpected equity return variance and share transaction volume are selected as measures of pricing-relevant information available to the equity traders based primarily on theoretical models developed in Holthausen and Verrecchia (1988), and Kim and Verrecchia (1994), respectively.

Consistent with the signal-jamming hypothesis, characteristics of the empirical association between unexpected loan loss provision components, unexpected equity return variance, and unexpected share transaction volume suggest that discretion over loan loss provisions is used to emit disinformative signals to equity traders. This study contributes to the accounting literature by: (1) providing theory and empirical evidence suggesting

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[2] Although Scharfstein and Stein (1990) model *herd behavior* in a managerial labor market setting, such behavior results in *jamming labor market inferences* about managerial ability. Hence the term *signal-jamming* introduced to the economics literature in Fudenberg and Tirole (1986) is used in this study.

that discretionary accounting signals can be disinformative to equity traders; (2) introducing an alternative explanation for the use of accounting discretion; and (3) providing additional evidence with respect to existing explanations of the widely documented anomalous positive association between equity returns and unexpected loan loss provision components.[3]

The remainder of this dissertation is organized as follows: Chapter 2, Commercial Bank Institutional Characteristics; Chapter 3, Related Research; Chapter 4, Hypotheses; Chapter 5, Research Design; Chapter 6, Empirical Results; and Chapter 7, Summary and Conclusions. ■

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[3] This association is anomalous in several senses: increases in loan loss provisions are generally thought to be associated with decreases in future, expected returns of loan principal and interest; and, unexpected earnings has been shown to be positively associated with equity returns in the empirical accounting literature. Further, since bank managers have discretion over loan loss provisions, and since such unexpected loan loss provisions have been shown to be positively associated with (future) expected earnings before loan losses, this association has been attributed to "signaling" behavior by bank managers. However, it is difficult to test hypotheses of signaling behavior since the underlying theory predicts that under certain conditions it is optimal for agents to reveal their private, ex ante (and ex post) unobservable information. Indeed, Milgrom and Roberts (1987) note in their discussion of asymmetric information game theory that "the central object in the theory [i.e., private information] is, by its very nature, unobservable" (p. 191). Accordingly, studies of the information content and pricing of the unexpected component of loan loss provisions generally represent relatively indirect tests of hypotheses based on signaling theory.

# CHAPTER 2

# COMMERCIAL BANK INSTITUTIONAL CHARACTERISTICS

The commercial banking industry was selected for this study due to the unique informational characteristics of the asset portfolios held by most larger commercial banks. In particular, commercial and industrial loans, among other loan classes, that usually contain unobservable, heterogeneous credit (loan default) risk characteristics often comprise a substantial portion of a commercial banks assets. This characteristic, in combination with the uncertainty over the economic factors that influence commercial loan loss realizations and bank managers' ability to renegotiate loan contracts, reasonably results in a high level of managerial discretion over accounting recognition of loan losses. This chapter examines how these characteristics result in persistent information asymmetries between bank managers, auditors, regulators, and equity traders, and why it may be optimal for bank managers to take actions that tend to maintain or increase such information asymmetries.

## 2.1 Financial intermediation and information asymmetry

Commercial banks deal primarily in financial instruments: assets comprised primarily of loans and investment securities, and liabilities comprised primarily of deposit contracts and other financial obligations. The valuation of financial instruments is highly dependent on information (e.g., information about credit risk, interest rate environment, etc.). Since that information is costly to acquire or is unobservable, information asymmetries exist between borrowers and lenders that create economic opportunities for financial intermediation (Greenbaum and Thakor, 1995). Indeed, Greenbaum and Thakor (1995) suggest that persistent information asymmetries between net buyers (e.g., commercial borrowers) and net sellers (e.g., bank depositors) of funds is necessary for the existence of financial intermediaries in their information processing and asset transformation role.

With respect to accounting-related information asymmetries, Stigum and Branch (1983) suggest that bank managers use accounting discretion over the timing and realization of securities gains and losses to effect smooth, increasing earnings trends to influence bank analysts' perceptions of risk while noting that analysts are aware of this manipulation. They further suggest that commercial banks generally "stick with the herd" with respect to investment, financing and accounting policies in order to maintain perceived risk profiles consistent with their peer group (see, e.g., p. 183). This suggestion is consistent with the pervasive use of comparative peer group bank analysis by regulators and analysts discussed in many bank financial management texts (e.g., Hempel and Simonson, 1991).

These institutional characteristics suggest that financial reporting and related disclosures represent the primary source of information available to the money, debt and equity markets with respect to the risk–return characteristics of commercial bank assets.

Thus, these characteristics provide incentives for bank managers to exercise accounting discretion to influence risk–return inferences made by the capital markets.[4]

Greenbaum and Thakor (1995), and Stigum and Branch (1983), characterize banks as constrained profit-maximizers and note that the primary risks banks must effectively

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[4] This study assumes that—for the selected sample of commercial banks—managers primarily use accounting discretion for the purpose of influencing equity trader risk perceptions rather than for (short-run) manipulation of manager compensation and performance contracting variables. According to positive agency theory, "maximizing agents minimize the agency costs in any contracting relationship" in the long-run, and relatedly, "the organizational form, [represented by] its contracts, will be those that minimize the agency costs" (Jensen, 1983, p. 331). Under this maintained hypothesis, the coexisting expected profit-maximizing and agency explanations of managers' use of discretion over loan loss disclosures essentially reduce to one of expected profit maximization conditional on whether a bank is not failed or failing, or likely to be involved in a corporate control transaction.

In the context of this study, a reasonable assumption following from this maintained hypothesis is that banks which have not failed or been involved in a corporate control transaction (negotiation) are those whose managers are likely maximizing an expected utility function with bank profits as its primary argument (i.e., manager–shareholder incentives are aligned), ceteris paribus. These conditions are approximated in this study by using only bank–year observations from banks existing during the three years ended 12/31/96 that survive through 12/31/97 (see Chapter 5, Section 5.1, Population, sample, and data set).

manage on a day-to-day basis are *credit risk*, *liquidity risk* and *interest rate risk*.[5] Further, they note that these three sources of risk are necessarily interrelated and, accordingly, banks' decisions with respect to these risks are made jointly. Stigum and Branch (1983) provide a number of examples of large commercial banks where unfavorable credit risk information has resulted in increased liquidity risk (i.e., increased difficulty in obtaining adequate funding) and a related increase in interest costs as a result of the informational characteristics of financial intermediaries. This suggests the use of loan loss disclosure-related accounting discretion to influence the market's perception of the nature and level of risk over a bank's expected loan losses.

**2.2 Commercial bank loan loss disclosures**

Loan loss provisions represent one of the primary sources of earnings-based accounting discretion and are only one of several disclosures related to loan losses. Loan loss disclosures not given accounting recognition consist primarily of "non-performing" loan (*npl*) disclosures originally required under Regulation S-X of the Securities and Exchange Commission. Loan loss disclosures given accounting recognition consist of loan loss allowances (*lla*), loan loss provisions (*llp*), and net loan charge-offs (*nco*) and can be summarized in the following accounting identity at time *t*:

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[5] Credit risk is the risk of failure to fully realize the principal and interest payments due from a borrower under the terms of a lending contract. Liquidity risk is the risk that a bank will be unable to meet its contractual obligations on a timely basis. Interest rate risk is the risk that changes in the level or term structure of interest rates over time will result in changes in the value of its assets and liabilities.

$$-lla_t \equiv -lla_{t-1} - llp_t + nco_t \qquad [1]$$

where $-lla_{t-1}$ denotes the exogenous component of $-lla_t$.[6] Note that an absolute increase in any variable in equation [1] represents an increase in either expected or actual loan loss realizations since, under existing accounting standards, *lla* represents the amount necessary to state loans at their expected net realizable value and *nco* represents loan loss realizations. Thus, *llp* is an accounting construct that combines both actual loan loss realizations and managers' expectations of future loan loss realizations. To see this more clearly, define $\Delta lla_t \equiv -lla_t - (-lla_{t-1})$, substitute this term into equation (1), and rearrange to obtain:

$$llp_t = nco_t + \Delta lla_t \qquad [2]$$

where *nco* denotes current loan loss realizations, and $\Delta lla$ denotes changes in estimated unrealized loan losses, respectively. Equation [2] was introduced to the commercial bank accounting literature by Moyer (1990) and segregates the more discretionary component ($\Delta lla$) from the less discretionary component (*nco*) of recognized loan losses (*llp*). This decomposition is further suggested by Beatty, Chamberlain, and Magliolo (1995), and Collins, Shackelford, and Wahlen (1995) which both provide evidence suggesting bank managers simultaneously exercise discretion over both *llp* and *nco*.

Net loan charge-offs, *nco*, are less discretionary since economic events associated with loan loss realizations are observable to a bank's independent auditors and regulators

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[6] A summary of notation used in this paper is presented on p. xi, List of Abbreviations.

during the financial reporting process. The change in loan loss allowance, $\Delta lla$, is more discretionary since the combination of uncertainty over expected loan losses and inherent information asymmetries between bank managers, independent auditors, and regulators reasonably allows a wide range of discretion over this component of recognized loan losses (cf. AICPA, 1986).

### 2.3 Implications of commercial bank institutional characteristics

As financial intermediaries, commercial banks obtain economic profits primarily from transforming pools of loans and other financial assets with heterogeneous, unobservable risks into relatively low- and homogenous-risk financial instruments that are sold to depositors, shareholders, and others. Since buyers of these financial instruments must primarily use information contained in the financial disclosures of commercial banks to make inferences about these risks, managers have incentives to influence the inferences of the money, debt and equity markets.

The risk characteristics of commercial bank loan asset portfolios, in conjunction with loan loss accounting and disclosure requirements, suggest that bank managers have substantial discretion over loan loss provisions. Moreover, the commercial bank institutional literature suggests that accounting and financial discretion is often used to maintain a bank's risk–return profile such that it is similar to other banks, thereby, influencing risk–return inferences made by the capital markets. ■

# CHAPTER 3

# RELATED RESEARCH

This chapter discusses three literatures relevant to this study: the commercial bank accounting literature, the signal-jamming literature via a discussion of Scharfstein and Stein's (1990) herd behavior model, and the disclosure–equity market response literature. This discussion focuses on existing theory and empirical evidence relating to how and why bank managers exercise accounting discretion over loan loss recognition. In particular, this discussion introduces signal-jamming to the accounting literature as a plausible use of discretion over loan loss provisions (in equilibrium). Finally, the accounting disclosure–equity market response literature is discussed in relation to noise trading models in the financial economics literature, and the joint implications of these literatures with respect to this study are discussed.

## 3.1 Commercial bank accounting literature

The commercial bank accounting literature has focused primarily on two areas of inquiry: the pricing of expected and unexpected components of loan loss provisions, and the determinants of loan loss provision levels. Although several empirical regularities have been demonstrated by these studies (e.g., a positive association between increases in recognized loan losses and equity returns), this literature has shown that empirical associations between loan loss provisions and equity market data are highly conditional. In this connection, this section concludes by summarizing the implications of the commercial bank accounting literature with respect to how and why bank managers exercise accounting discretion over loan loss provisions.

### 3.1.1 *Loan loss disclosure pricing studies*

In general, the empirical results of loan loss disclosure pricing studies suggest that *llp* components contain pricing-relevant information, but that this information content is (perhaps highly) conditional on many firm-exogenous and firm-endogenous variables. Madura and McDaniel (1989) and Elliott, Hanna, and Shaw (1991) find a positive association between short-window unexpected equity returns and $\Delta lla$ announcements for large money center banks; however, Elliott, Hanna, and Shaw (1991) find that this association does not hold for non-money center banks and is not robust to further conditioning on loan and *lla* level disclosures for certain classes of risky loans, regulatory capital ratios, and market-to-book ratios.

In longer-window studies, Beaver and Engel (1996) find that there is a greater negative association between equity prices and expected *lla* components than for unexpected *lla* components. Liu and Ryan (1995) find that the information content of *llp* is preempted by nonperforming loan disclosures of banks with loan portfolios predominated by loan types which are more frequently negotiated, but not by such disclosures of other banks. Beaver, Eger, Ryan, and Wilson (1989) find a positive association between equity prices and *lla* levels, and negative associations between equity prices and *npl* levels and loan maturity disclosures; however, this study also finds that the association between prices and *lla* levels is not robust to conditioning on earnings-to-book ratios, book equity growth rates, and CAPM beta.

Other recent studies have shown that lagged unexpected *llp* components (as proxies for discretionary components) are positively associated with both pre-loan-loss earnings (*plle*) and equity returns, and therefore suggest that discretionary *llp* components represent pricing-relevant informative signals (Wahlen, 1994; and Liu, Ryan, and Wahlen, 1997).

### 3.1.2 *Loan loss disclosure discretion studies*

Empirical results of loan loss disclosure discretion studies generally suggest that bank managers exercise discretion over *llp* components jointly with other discretionary accounting variables to achieve multiple financial reporting objectives. Greenawalt and Sinkey (1988) find evidence consistent with the hypothesis that only non-money-center banks exercise discretion over *llp* levels to smooth earnings to both time-series and cross-sectional means. Moyer (1990) finds evidence consistent with the hypothesis that banks exercise discretion over *llp*, *nco*, and securities gains and losses to increase regulatory capital to minimum required levels and, thereby, reduce regulatory costs. Beatty, Chamberlain, and Magliolo (1995) find evidence consistent with the hypothesis that banks exercise discretion simultaneously over *llp*, *nco* and financing transactions to manage regulatory capital ratios. Collins, Shackelford, and Wahlen (1995) find evidence consistent with the hypothesis that bank managers exercise discretion over *llp* to smooth earnings to a time-series mean, and over *nco* to increase regulatory capital ratios.

### 3.1.3 *Implications of loan loss disclosure studies*

Loan loss disclosure pricing studies provide evidence that the unique pricing-relevant information of loan loss disclosures is contained in the unexpected components of such variables. However, results of these studies also suggest that such information contained in *llp* is highly conditional: Beaver, Eger, et. al (1989) find the price–*lla* association nonrobust to conditioning on more fundamental variables; Elliott, Hanna, and Shaw (1991) find the equity return–Δ*lla* association similarly nonrobust; Wahlen (1994) finds the return–unexpected *llp* association nonrobust to omission of the upper and lower 1% of loan loss disclosure sample distributions; and Liu, Ryan, and Wahlen (1997) show that the sign of the return–unexpected *llp* association is conditional on regulatory capital levels and interim-versus-year end reporting environment.

The loan loss disclosure discretion studies collectively provide evidence that bank managers exercise discretion over loan loss disclosures (in certain cases, jointly with other discretionary variables) in order to reduce intertemporal and cross-sectional variation in reported earnings, and to manage regulatory capital ratios. However, this stream of literature has focused largely on identifying determinants of loan loss provision levels and is generally silent on how bank managers may use accounting discretion to influence equity trader risk–return inferences.

These results, in combination, suggest that the existing commercial bank accounting literature has not converged to a *general* explanation of how and why bank managers use accounting discretion over *llp*, and of how and why equity traders respond to discretionary *llp* components.

### 3.2 Signal-jamming equilibrium

Scharfstein and Stein (1990) investigate conditions that can lead to herd behavior in a model characterized by multilateral uncertainty over both expected states of nature and managers' ability to predict investment outcomes, and by multilateral information asymmetry over the quality of the information set (i.e., informative versus purely noisy signals) available to each manager. In their model, the labor market can learn about a manager's ability by observing realizations of ex ante uncertain investment outcomes, and whether that manager's investment decision was similar to decisions of other managers. It is shown that herd behavior optimally arises in this context only when managers' prediction errors are at least partially correlated with each other. In this setting, this condition can lead managers to optimally "jam" the labor market's inferences with respect to their (perhaps poor) prediction ability through matching the investment decisions of other managers regardless of their respective beliefs about expected investment outcomes.

To see Scharfstein and Stein's (1990) result more clearly, consider the basic assumptions of their model:

(1) Multilateral uncertainty over expected states of nature and manager investment outcome prediction ability implies that investment outcomes and managers' abilities of predicting those outcomes are uncertain and neither (individual) managers nor the labor market has superior information about these sources of uncertainty.

(2) Multilateral information asymmetry over managers' information set quality implies that neither managers themselves nor the labor market know whether the information sets used in making investment decisions provides individual managers with informative or purely noisy signals of expected outcomes.

(3) Partially-correlated prediction errors imply that managers' predictions of investment outcomes tend to be related and that managers' information sets have a common component leading them to similar, incorrect inferences.

Intuitively, multilateral information asymmetry is necessary for Scharfstein and Stein's (1990) result since under perfect information managers' actions become observable to the labor market. Similarly, without multilateral uncertainty over states of nature and manager prediction ability, the labor market's inference problem degenerates to a perfect information setting for at least one manager thus allowing the labor market to observe or infer managers' (suboptimal) actions. Partially-correlated manager prediction errors are necessary for Scharfstein and Stein's (1990) result since without this condition prediction errors become orthogonal; thus allowing the labor market to correctly infer individual managers' actions over time.

It is not clear whether the conditions for the optimality of signal-jamming identified by Scharfstein and Stein (1990) hold—on average—in the commercial bank loan loss provision setting considered in this study. However, the basic assumptions central to their result (discussed above) represent conditions that seem sufficiently analogous to this setting to suggest that disinformative signals emitted by bank managers cannot be immediately observed with certainty by equity traders.

Importantly, Scharfstein and Stein (1990) derive conditions under which discretionary actions can result in disinformative signals that persist in a general equilibrium. In the context of this study, their model simply suggests that under certain conditions equity traders are unable to determine whether a signal emitted by a single firm in a single time period represents an informative "non-jamming" signal, or a disinformative "jamming" signal. The market may, however, learn over time that signal-jamming is occurring—*on average*—by observing signals and subsequent realizations for a number of firms. As a result of these inferences, equity prices for *all* such firms are discounted by traders since they are only able to infer average signal-jamming behavior using this information, not whether a single observed signal represents a non-jamming or a jamming signal.[7]

It can be seen that notions of equilibrium herd behavior and signal-jamming underlying Scharfstein and Stein (1990)—where it becomes optimal for managers to choose otherwise suboptimal actions, and the managerial labor market to price managerial labor based on average, expected suboptimal actions of managers—are similar to notions of equilibrium "price protection" in Jensen and Meckling (1976) where traders optimally set a firm's equity price based on the average, expected unobservable agency costs, and managers optimally impose such unobservable agency costs on the firm.

### 3.3 Disclosure and equity market responses

A number of theoretical models have been developed in the accounting literature that examine the relationship between accounting disclosure characteristics and equity market responses. Holthausen and Verrecchia (1988) develop a two-period, multi-asset model of the relationship between equity prices and sequential disclosures. It is shown under general assumptions that increases in the variance of sequential, pricing-relevant disclosures result in nonincreasing equity return variance *over periods spanning sequential disclosure dates*. Kim and Verrecchia (1994) develop an atemporal, single-asset model of equity market responses to financial accounting disclosures which carry unique

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[7] A simple model of incomplete learning is presented in Appendix 3 that shows a set of sufficient conditions for noninformative and disinformative discretionary accounting signals to persist indefinitely over time. Further, Appendix 5 presents a brief discussion of the financial economics and accounting literature suggesting that disinformative signals are impounded in data generated by otherwise informationally efficient capital markets.

information to traders and are subject to varying interpretations with respect to firms' financial performance (i.e., unique but noisy signals). This model shows that information processing activities of equity traders with respect to such disclosures result in increased trader information asymmetries which can lead to increased equity return variance and trading volume *around disclosure dates*.[8]

Holthausen and Verrecchia (1990) develop an atemporal model of informative disclosures and rational equity trader responses, and show that trader *informedness* and *consensus* occur jointly as a result of such disclosures.[9] They further show that:

(1) equity return variance and share volume are *increasing* in trader information precision since trader belief revisions are generally greater when information is more precise and such belief revisions result in increased trading activity;

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[8] Sequential increases in the variance of disclosures and, assuming rational expectations, related increases in information asymmetry both correspond to the notion of a disinformative signal. Information releases in Holthausen and Verrecchia (1988) represent noisy signals of (future) liquidating dividends which are analogous to accounting disclosures examined in this study: loan loss provisions as signals of changes in expected loan principal realizations. In Kim and Verrecchia (1994), higher levels of variance in accounting signals similarly represents less informative disclosures.

[9] In Holthausen and Verrecchia (1990), *informedness* refers to the level of precision (i.e., inverse variance) in a trader's probability distribution over some pricing-relevant disclosure; *consensus* refers to the level of trader agreement (i.e., the level of correlation of traders beliefs) over some pricing-relevant disclosure.

(2) equity return variance is *increasing* in trader belief correlation levels since "less uncertainty [is] resolved through the market [information] aggregation process" (p. 203) when traders beliefs are more highly correlated; and

(3) equity share volume is *decreasing* in trader belief correlation levels since similarity in trader beliefs results in similarity between their valuations.

Holthausen and Verrecchia's (1990) results on changes in trader belief heterogeneity are not of primary importance to this study since only the (dis)informativeness of discretionary accounting variables is examined. The empirical propositions underlying the main hypotheses developed in this study are derived primarily from Holthausen and Verrecchia (1988) and Kim and Verrecchia (1994). Rather, the positive relationship Holthausen and Verrecchia (1990) demonstrate between the variance of trader belief distributions and trader belief heterogeneity is used here to develop the maintained hypothesis—consistent with the empirical results of Barron (1995)—that an increase in the variance of an accounting signal is negatively related to equity share volume over disclosure-spanning time periods.

Empirical evidence is generally consistent with the referenced, theoretical accounting literature on disclosure and equity market response in suggesting that informative pricing-relevant disclosures result in increased equity return variance (e.g., Beaver, Clarke, and Wright, 1979; McNichols and Manegold, 1983; and, Morse and Ushman, 1983) and increased share transaction volume around disclosure dates (e.g., Beaver, 1968). Several recent empirical studies however find that equity share transaction volume is negatively related to the convergence of analyst beliefs in both short- and long-windows (Ziebart, 1990; and Barron, 1995) suggesting that higher levels of accounting signal information content result in decreased information asymmetries among traders and decreased share volume.[10]

Based on Holthausen and Verrecchia's (1990) framework of the relationships between informedness, consensus, and equity market responses, Table 1 summarizes the referenced accounting literature on disclosure and equity market response using *increased signal variance* and *increased trader belief diversity* as inversions of informedness and consensus.

Interestingly, although the theoretical results of Holthausen and Verrecchia (1988, 1990), and Kim and Verrecchia (1994), are derived under the assumption of rational trader expectations, these results are not inconsistent with noise trading models developed in the financial economics literature which relax the rational trader expectations assumption. Black (1986) characterizes "noise traders" as traders who revise beliefs and trade on the basis of noise *as if* they were acting on information, while "information traders" trade only on the basis of information (although due to the inherent limitations of econometric methods in the presence of nonstationary stochastic processes, among other

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[10] Barron and Karpoff (1998) present a theoretical model showing that increases in the precision of accounting signals can lead to this result under conditions of nonzero market transaction costs. That study suggests that these conditions can lead to problematic inference in accounting studies based on samples which include substantial numbers of firms with thinly-traded securities. Sensitivity tests (discussed in Chapter 6) suggest that thinly-traded firm year observations do not drive the results presented in this study.

factors, equity traders often do not know whether they are trading on information or noise). While the models developed in Holthausen and Verrecchia (1988, 1990), and Kim and Verrecchia (1994), permit accounting signals to be more and less informative, their underlying assumption of rational trader expectations implicitly constrains equity traders to unbiasedly, but imperfectly, observe pricing-relevant factors which map through a firm's accounting system. Alternatively stated, the rational expectations assumption requires traders to form beliefs and act only on the basis of informative signals in the sense that traders observe only signals drawn from actual conditional probability distributions: traders beliefs are consistent with actual conditional probability distributions.

Thus, under conditions where the rational expectations assumption holds, equity traders are able to observe and distinguish between informative, noninformative, and disinformative accounting signals. However, herd behavior and noise trading models referenced in this study suggest conditions under which this assumption does not hold in the sense that equity prices do not fully aggregate all available pricing-relevant information.

Kyle (1985) presents a model where an informed trader trades with noise traders (who may also trade among themselves) such that expected profits are maximized and "private information is incorporated into prices gradually" (p. 1316). Although exogenous in Kyle's model, the existence of noise trading activity both allows the informed trader to profit from having private information and prevents market makers from observing information trading. In turn, this allows the informed trader to choose an optimal price path over time conditional on the demand of noise traders such that returns to private information are maximized. Since the informed trader's private information becomes impounded in price in the limit, price revisions and trading volume *resulting from information trading* must also converge to zero in the limit.

Shleifer and Summers (1990) discuss a setting consisting of both information and noise traders where information traders do not drive equity prices to their rational values due to the absence of riskless arbitrage opportunities. Moreover, the notion is presented that systematic overreactions by noise traders to information—which tend to persist since noise traders obtain a higher return from an implicitly higher risk portfolio strategy—makes it optimal for information traders to condition their trading strategies on noise trading strategies. This suggests that under certain conditions it becomes optimal for information traders to manipulate trading activity and prices; temporarily driving prices further from their rational values and increasing share transaction volume.

The results of Kyle (1985), and Shleifer and Summers (1990), suggest that the combination of both information and noise trading activity tends to result in (1) increased equity return variance and share volume in shorter time periods around (information and disinformation) disclosure dates where the effects of noise trading strategies likely dominate market data, and (2) decreased equity return variance and share volume in longer time periods spanning disclosure dates where the effects of information trading strategies likely dominate market data.

It can be seen that the accounting disclosure–equity market response literature and noise trading literature discussed here are consistent and jointly suggest that noisy accounting signals generally lead to: (1) increased equity return variance and share volume in short-windows around disclosure dates where such data is largely generated by the actions of noise traders (who trade on noise as if it were information); and, (2) decreased equity return variance and share volume in long-windows spanning disclosure dates where such data is—on average—largely generated by the actions of information traders (who do not revise beliefs or trade on noise).

### 3.4 Implications of related research

Although considerable empirical research has been conducted on commercial bank loan loss provisions in the accounting literature, the highly-conditional empirical results suggest that the accounting literature has not converged to a robust explanation of how and why bank managers exercise accounting discretion over loan loss recognition. Consequently, it is not clear whether equity traders price information contained in loan loss disclosures about future loan loss realizations per se, or whether they price other factors associated with such disclosures. For example, it is not clear whether the widely-documented positive association between equity returns and unexpected loan loss provisions is due to information about the credit risk inherent in banks' loan portfolios and expected loan loss realizations, or is due to information about some other factor influencing banks' risk or expected returns.

To provide a theoretical framework for developing hypotheses that might provide a more adequate explanation of how and why commercial bank managers use discretion over loan loss provisions, and so gain insights into the equity pricing and information content of loan loss disclosures, Scharfstein and Stein's (1990) herd behavior model and several noise trading models are discussed. Consistent with the commercial bank institutional literature (discussed in Chapter 2, Section 2.1), the results of Scharfstein and Stein (1990) suggest that it is optimal for commercial banks to use accounting discretion to jam otherwise pricing-relevant information contained in loan loss disclosures.

Moreover, noise trading models developed in the financial economics literature suggest that traders with private information (including managers) have incentives to exploit information asymmetries between themselves and noise traders. Therefore, both the commercial bank institutional literature and financial economics literature suggest that the discretionary components of commercial bank loan loss provisions can be either *noninformative* or *disinformative*. Finally, the referenced accounting literature on disclosure and equity market response suggests observable equity market-based measures of the (dis)information content of discretionary accounting signals. ■

# CHAPTER 4

# HYPOTHESES

## 4.1 Informational characteristics of discretionary accounting signals

This study characterizes alternative explanations of the use of accounting discretion over *llp* within a fundamental framework providing a link to theory developed in the financial and information economics literatures. Consistent with notions of information in Beaver (1968, p. 69n.8), Lev (1969), and Theil (1967), it can be shown under reasonable assumptions that accounting signals can either be *informative*, *noninformative*, or *disinformative* (see Appendix 3). Table 2 presents definitions of these three possible accounting signal types as well as definitions of *signaling* and *signal-jamming* based on the information economics literature. Signaling and signal-jamming behavior represent two prominent uses of discretionary diclosure in the information and financial economics literature.

The framework spanned by the signaling and signal-jamming uses of discretionary disclosure has important theoretical properties. As shown in Table 3, these two types of discretionary disclosure behavior result in accounting signals with observable informational characteristics that are both mutually-exclusive and exhaustive with respect to accounting signal types. Further, Table 3 summarizes the necessary conditions for observing signaling and signal-jamming behavior in equity market data conditional on the assumption that the accounting variable (component) is discretionary.

It is also evident from Table 3 that the hypotheses developed in this study effectively contrast the signaling and signal-jamming uses of discretion over commercial bank loan loss provisions: A positive empirical association between capital market-based measures of accounting signal informational characteristics and the discretionary components of *llp* is consistent (only) with signaling behavior, while a negative association is consistent (only) with signal-jamming behavior. It should be noted that there are two characterizations of *signal-jamming* in the information economics literature: in one case, signal-jamming results solely in the addition of white-noise to signals (i.e., garbling) (see, e.g., Creane, 1995); more commonly in the literature, signal-jamming results in the distortion of other signals (i.e., belief manipulation) (see, e.g., Holmstrom 1982). If bank managers use *llp* discretion to engage in white-noise signal-jamming, then it is reasonable that no (measurable) association between measures of information content and discretionary *llp* components would exist in equity markets dominated by information traders.[11] However, while this study does not attempt to distinguish conditions under which white-noise signal-jamming occurs from conditions under which belief-manipulation signal-jamming occurs, it is generally assumed that bank managers use *llp* discretion to manipulate equity trader inferences.

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[11] This implies that inferences made in this study are dependent on the assumption of the relative proportion of information traders to noise traders. Consistent with Kyle (1985), inferences in this study are based on the maintained hypothesis that equity market data generated in longer, disclosure-spanning time periods is dominated by information trader activity, while such data generated in shorter periods around disclosure dates is dominated by noise trader activity.

### 4.2 Informative loan loss provisions signals

Recent loan loss disclosure pricing studies examining the associations between discretionary *llp* components, pre-loan-loss earnings (*plle*), and equity returns (Wahlen, 1994; and Liu, Ryan, and Wahlen, 1997) do not explicitly examine the mechanism by which *llp* and *plle* are related; nor are these studies entirely clear as to why equity traders would interpret discretionary components of *llp* as being predictive of *plle*. While *nco* represents charge-offs of interest-bearing loan assets and is a relatively unambiguous predictor of *decreases* in future loan interest revenue (a component of *plle*), $\Delta lla$ represents managers' beliefs over the changing credit risks inherent in bank loan portfolios—many of which may not be realized in losses of loan principal or decreases in loan interest revenues for at least several years—and is consequently substantially more ambiguous in its relationship to *plle* than is *nco*.

In this connection, two associations which could provide explanations of the observed association between lagged discretionary *llp* components and both *plle* and equity returns are: (1) a positive association between lagged discretionary *llp* components and loan interest revenue; and (2) a negative association between lagged discretionary *llp* components and *nco* (or *llp* in general). However, any positive association between lagged discretionary *llp* components and loan interest revenue is likely spurious since net interest revenue is decreasing in actual loan loss realizations *nco*, and is only related to

$\Delta lla$ indirectly through expected *nco*.[12] Consequently, a negative association between lagged discretionary *llp* components and *nco* is a more plausible explanation of the anomalous positive association between such *llp* components and equity returns.

This discussion suggests that it is necessary to test for any (non-zero) association between lagged discretionary *llp* components and both *plle* and *nco* since such an association would provide (1) evidence of the inadequacy of the *llp* components expectations model used in this study, and (2) evidence complementary to formal tests of the disinformation content of discretionary *llp* components (Hypotheses 2.1–2.4). Accordingly, since this study hypothesizes that bank managers generally use accounting discretion over *llp* components to jam otherwise pricing-relevant signals, it is hypothesized (in alternative form) that such *llp* components are not informative with respect to expected *nco*:

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[12] To see this more clearly, let loan interest revenue, $y$, for a given time period be defined as a linear function of daily-weighted-average loan interest yield $r$ and daily weighted-average loan principal balance outstanding $\bar{x}$: $y(r,\bar{x}) \equiv r \cdot \bar{x}$. Decomposing the end-of-period balance for loan principal outstanding using its basic accounting identity and finding the daily weighted-average of those components results in: $\overline{x_{end}} = \overline{x_{beg}} + \overline{adv} - \overline{col} - \overline{nco}$ where *adv*, *col*, and *nco* denote loan principal advances, collections, and net charge-offs for the period, respectively; and $x_{beg}$ denotes the exogenous component of ending loan principal. Using this decomposition of loan principal outstanding, the loan interest revenue function can be written as $y\left(r, \overline{adv}, \overline{col}, \overline{nco}; \overline{x_{beg}}\right) = r \cdot \left(\overline{x_{beg}} + \overline{adv} - \overline{col} - \overline{nco}\right)$. Noting that in general $r > 0$, it follows that loan interest revenue is decreasing in *nco* since $\partial y(.)/\partial \overline{nco} = -r < 0$ for all $\overline{nco} > 0$.

**$H_1$:** Lagged discretionary *nco* and lagged discretionary *Δlla* are *not* associated with net loan charge-offs conditional on other loan loss disclosure information available at time $t-1$.

Although the actual lag structure of any relationship between lagged discretionary *llp* components and *nco* is unknown, a rejection of this hypothesis in its null form would suggest that discretionary *llp* components are not informative with respect to the loan loss realization expectations of either bank managers or equity traders *as proxied for by the* llp *expectations model used in this study.*

**4.3 Disinformative loan loss provision signals**

Since the assumptions and conditions studied in Scharfstein and Stein's (1990) model closely correspond to those of the commercial bank institutional setting, it is reasonable that bank managers use loan loss disclosure discretion to jam pricing-relevant signals of expected earnings and expected loan loss realizations, ceteris paribus. Moreover, this proposition is reasonable since it also corresponds well with the suggestion in the institutional literature that banks generally exhibit herd behavior with respect to investment, financing and accounting policy.

Thus, both the signal-jamming and commercial bank institutional literatures suggest that bank managers facing uncertainty (over credit-, interest-, and liquidity-risk) use accounting discretion to influence the perceptions of investors with respect to managers predictive abilities and the credit risk inherent in banks' loan portfolios; and, thereby, to maintain or increase information asymmetries between themselves and suppliers of funds such that profits are maximized.[13] This suggests that bank managers use accounting discretion over *llp* components to emit disinformative disclosures.

In particular, it is reasonable to hypothesize bank managers emit signal-jamming disclosures with the objective of minimizing or reducing capital costs since bank financial statements are used largely by investors in evaluating the risk-return characteristics of bank debt and equity securities.[14,15] Based on the disclosure and equity market response

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[13] There exist striking historical examples of financial *disintermediation* in the commercial banking industry resulting from the collapse of information asymmetries between net sellers and net buyers of funds; e.g., the recent growth of the "junk bond" market and diversified investment funds which allow investors to diversify firm-idiosyncratic information risk has reduced the need for net sellers to place their funds with commercial banks in their role as information-processors and asset risk transformers. This suggests that banks derive economic rents precisely as a result of such information asymmetries.

[14] Here, investors includes all funding sources (including interbank placements) except for depositors insured by the FDIC. Although, a bank's cost of capital includes interest costs on deposits, commercial paper, and other debt securities, it is assumed that these capital costs are effectively impounded in cost of equity capital.

literature, if discretionary *llp* components represent disinformative, signal-jamming disclosures by bank managers, then those signals would result in a decrease in information (i.e., an increase in the uncertainty of a signal) available to equity traders, and would be observable: (1) as an increase in unexpected equity return variance and unexpected share transaction volume in a short-window around a disclosure date, and (2) as a decrease in unexpected equity return variance and unexpected share transaction volume in a longer, sequential disclosure date spanning period. However, given the likely differences in the

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[15] Signal-jamming in its most general form involves the addition of mean-zero noise to an existing signal (cf. Creane, 1995). Accordingly, if bank managers' discretionary *llp* disclosures result in the addition of mean-zero noise, then it follows that only the variance of pricing-relevant signals will change as a result. Beaver, Kettler, and Scholes (1970) and Beaver and Manegold (1975) find a positive association between accounting earnings volatility and equity market-based measures of (systematic and nonsystematic) risk.

These findings, in conjunction with the results of Scharfstein and Stein (1990), suggest that bank managers may also use *llp* discretion to manipulate accounting-based measures of systematic and nonsystematic risk to match a risk profile similar to other "peer group" banks. In so doing, signal-jamming banks would realize lower capital costs relative to non-signal-jamming banks since the market would be unable to determine whether any differential loan loss or earnings volatility observed in an individual bank is due to differences in actual risk or to differences in signal-jamming behavior. If excess loan loss or earnings volatility is interpreted as differences in actual risk, a bank would then be "trapped" into engaging in signal-jamming behavior in order to avoid potentially emitting (perhaps false) signals of inferior managerial ability and credit quality relative to other banks. This intuitive argument loosely follows the more formal equilibrium arguments in the signal-jamming literature including Fudenberg and Tirole (1986), and Holmstrom (1982).

relative levels of available discretion over *nco* and $\Delta lla$, it is not clear ex ante whether the discretionary components of either *nco* or $\Delta lla$ (or both) are likely to be informative, noninformative, or disinformative. Thus, more refined hypotheses addressing the relationships between discretionary components of *nco* and $\Delta lla$ , individually, and both unexpected equity return variance and unexpected share transaction volume are not presented here.[16] Accordingly, it is hypothesized (in alternative form) that:

<u>Equity return variance hypotheses</u>

$H_{2.1}$: Discretionary components of *nco* and $\Delta lla$ are ***negatively*** associated with unexpected equity return variance in longer time-windows spanning disclosure dates.

$H_{2.2}$: Discretionary components of *nco* and $\Delta lla$ are ***positively*** associated with unexpected equity return variance in short time-windows around disclosure dates.

<u>Equity share volume hypotheses</u>

$H_{3.1}$: Discretionary components of *nco* and $\Delta lla$ are ***negatively*** associated with unexpected share volume in a longer time-windows spanning disclosure dates.

$H_{3.2}$: Discretionary components of *nco* and $\Delta lla$ are ***positively*** associated with unexpected share volume in short time-windows around disclosure dates.

A rejection of these hypotheses in their null form would suggest that *llp* discretion is used to reduce pricing-relevant information available to equity traders. ■

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[16] However, this study explores empirically the relative informational characteristics of discretionary *llp* components by estimating and testing empirical models which decompose *llp* into nondiscretionary and discretionary *nco* and $\Delta lla$ components.

# CHAPTER 5

## RESEARCH DESIGN

This chapter describes the population, sample, and data set used in this study; presents the expectations models used in estimating the expected and unexpected components of dependent and independent variables; presents the empirical models used in testing the hypotheses developed in Chapter 4; and, formally restates those hypotheses in (statistical) terms relating to such empirical models.

### 5.1 Population, sample, and data set

This study uses equity market data available from the Center for Research on Securities Prices (CRSP) database, and financial reporting data available from the Standard & Poor's Compustat Disclosure database, for the three year period ended December 31, 1996 for all domestic U. S. commercial banks with over three billion dollars in total assets at that date. This initial sample is comprised of 104 commercial banks that represent a substantial portion of the total assets held in the U. S. commercial banking system (approximately 73%) at December 31, 1996. Certain data for eight banks in the initial sample were missing in either the CRSP or Compustat databases, thus reducing the sample to 96 banks. This remaining sample is assumed to be representative of the population of banks with sufficient equity market and money market access to exhibit the hypothesized discretionary disclosure behavior.

### 5.2 Unexpected return variance and share transaction volume

Consistent with the referenced accounting literature on disclosure and equity market response—and with Bernard's (1987) suggestion that cross-sectional correlations in capital market data can lead to inference problems in empirical accounting research—this study focuses on two forms of market response to discretionary *llp* components: unexpected daily equity return variance and unexpected daily share transaction volume. Unexpected components are derived from market models of returns and volume estimated using only data relating to the 96 commercial banks included in the sample. This method of estimating these unexpected components controls for common factors influencing equity returns and volume in the population of larger commercial banks, thus mitigating certain types of cross-sectional correlation problems in this study. In particular, this method provides estimates of firm-idiosyncratic equity returns and volume conditional on all common factors influencing average returns and volume in the sample of 96 commercial banks.

Formally, daily unexpected equity return variance is measured as the squared unexpected equity returns derived from the following model of daily equity returns for bank *i*, day *t* as a linear function of the equally-weighted, daily average market return for the 96 sample banks:

$$r_{it} = \beta_0 + \beta_1 \cdot \left( \tfrac{1}{n} \sum_{j=1}^{n} r_{jt} \right) + u_{it} \qquad n = 96;\; t = 1, \cdots, T \qquad [3]$$

where *t* is the index for the time period beginning on the first market trading day after October 14th and ending on the last market trading day before March 16th; a time period centered approximately on December 31 (the fiscal year end for all U. S. commercial banks). Consistent with the suggestion of Cohen, Hawawini, et. al (1980) that capital markets are generally characterized by trading frictions that result in serial correlations in returns and transaction volume, Prais–Winsten transformed FGLS parameter estimates are obtained for equation [3] to provide for consistent parameter estimation in the presence of AR(1) process serially-correlated error terms. (Although the actual structure of autoregressive processes in commercial bank equity returns and volume is unknown, most banks in the sample are actively traded suggesting that any trading frictions clear quickly and that the assumption of an AR(1) process is reasonable.) Residuals obtained from estimating equation [3] are then squared to obtain equity return variance for bank $i$, day $t$:

$$\hat{ur}_{it}^2 = \left[ r_{it} - \hat{\beta}_0 - \hat{\beta}_1 \cdot \left( \tfrac{1}{n} \sum_{j=1}^{n} r_{jt} \right) \right]^2 \qquad [4]$$

where $\hat{\beta}_0, \hat{\beta}_1$ denote the Prais–Winsten transformed FGLS parameter estimates.

Similarly, the second market response variable, unexpected daily equity share transaction volume ($\hat{uv}_{it}$), is measured as the unexpected equity share transaction volume derived from a model of daily equity share transaction volume $esv_{it}$ (scaled by outstanding shares) for bank $i$, day $t$ as a linear function of the equally-weighted, daily market average share transaction volume for the 96 sample banks:

$$\hat{uv}_{it} = esv_{it} - \hat{\gamma}_0 - \hat{\gamma}_1 \cdot \left( \tfrac{1}{n} \sum_{j=1}^{n} esv_{jt} \right) \quad n = 96;\ t = 1, \cdots, T \qquad [5]$$

where $(\hat{\gamma}_0, \hat{\gamma}_1)$ denote the Prais–Winsten transformed FGLS parameter estimates.

### 5.3 Unexpected loan loss provision components

Discretionary components of *llp* are modeled as the difference between observed *llp* for bank *i*, time *t* and the industry-expected *llp* derived from a pooled regression of *llp* amounts at time *t* on lagged loan and loan loss disclosure variables, and contemporaneous *plle* levels. The *llp* expectations model presented in equation [6] corresponds to a conditional expectation function where the three primary loan loss disclosures— $\Delta$*npl*, *nco* and $\Delta$*lla* —are assumed to be linear functions of the conditioning variables shown in their respective column vector in the matrix of independent variables. If there exist other variables on which bank managers' *nco* and $\Delta$*lla* choice is conditioned, then the resulting coefficient estimates obtained for such models will be biased and inconsistent.[17]

<u>Loan loss provision expectations.</u> The conditioning variables in [6] are approximately consistent with *llp* expectations models in the referenced loan loss disclosure *pricing* studies. The expectations model shown in [6] also incorporates findings of the referenced loan loss disclosure *discretion* studies which suggest that *llp* and *nco* are chosen jointly, conditional on *plle*. In this connection, the system of equations represented in [6] is estimated using SUR (seemingly unrelated regression) FGLS

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[17] With respect to the conditioning variables in equation [6], Sinkey and Greenawalt (1991) examine the determinants of commercial bank *nco* and finds that bank geographic region, loan portfolio growth and loan interest yield are associated with loan loss realizations. This suggests that both discretionary and nondiscretionary components of *nco* are influenced by these unmodeled factors. Further, to the extent that these factors are not already impounded in the other conditioning variables in equation [6], it is likely that equity traders' loan loss disclosure expectations differ from those represented here.

estimation which provides asymptotically-efficient parameter estimates in the presence of cross-equation correlation of dependent variables:

$$\begin{bmatrix} \Delta npl_{it} \\ nco_{it} \\ \Delta lla_{it} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ loans_{it-1} & loans_{it-1} & loans_{it-1} \\ lla_{it-1} & lla_{it-1} & lla_{it-1} \\ npl_{it-1} & npl_{it-1} & npl_{it-1} \\ 0 & nco_{it-1} & nco_{it-1} \\ 0 & \Delta lla_{it-1} & \Delta lla_{it-1} \\ 0 & plle_{it} & plle_{it} \end{bmatrix} \cdot \begin{bmatrix} \beta_{\Delta npl} \\ \beta_{nco} \\ \beta_{\Delta lla} \end{bmatrix} + \begin{bmatrix} u_{\Delta npl,it} \\ u_{nco,it} \\ u_{\Delta lla,it} \end{bmatrix} \qquad [6]$$

To partially mitigate potential estimation and inference problems resulting from heteroscedasticity, all loan loss-related variables at time *t* are scaled by total loans outstanding at that date. Similarly, total *loans* and *plle* for period *t* are scaled by total assets at that date resulting in total loans as a percent of total assets and pre-loan-loss return on assets, respectively.

Table 3 presents FGLS estimates and standard errors for the parameters of equation [6]. Although the results of this study are potentially sensitive to the loan loss expectations model shown in equation [6], sensitivity analyses discussed in Chapter 6 suggest that the results are robust to alternative specifications of this expectations model.

Discretionary loan loss provision components. Estimated unexpected *llp* components, which are used to proxy for discretionary *llp* components, are measured as the difference between bank *i*, year *t* reported *llp* components and the bank-specific conditional prediction obtained from estimating equation [6]:

$$\begin{bmatrix} \hat{u}_{nco,it} \\ \hat{u}_{\Delta lla,it} \end{bmatrix} = \begin{bmatrix} nco_{it} - \hat{E}nco_{it} \\ \Delta lla_{it} - \hat{E}\Delta lla_{it} \end{bmatrix} \qquad [7]$$

where the expected and unexpected components of $nco_{it}$ and $\Delta lla_{it}$ are denoted $\left(\hat{E}_{t-1}nco_{it}, \hat{E}_{t-1}\Delta lla_{it}\right)$ and $\left(\hat{u}_{nco,it-1}, \hat{u}_{\Delta lla,it-1}\right)$, respectively.

### 5.4 Empirical models and hypothesis tests

Hypothesis 1 states in alternative form that discretionary components of $nco_{it-1}$ and $\Delta lla_{it-1}$ do not contain signals with respect to future $nco_{it}$ levels controlling for other loan loss-related information available at time $t-1$. Based on the referenced commercial bank accounting literature and on the *llp* expectations model presented above, *nco* expectations are conditional on lagged loan and loan loss disclosure variables, and on contemporaneous $\Delta lla$ and *plle* levels. However, it is assumed that only expectations of *nco* and $\Delta lla$ for time $t$ (denoted $\hat{E}_{t-1}nco_{it}$ and $\hat{E}_{t-1}\Delta lla_{it}$, respectively) are available to the equity market at $t-1$. Accordingly, this expectation replaces the actual lagged observation of *nco* and $\Delta lla$. To test this hypothesis, the residuals from a regression of $nco_{it}$ on the conditioning variables shown in the bracketed terms of the right-hand side of equation [8] (which omit the unexpected components of $nco_{it-1}$ and $\Delta lla_{it-1}$) are obtained as:

$$\hat{e}_{nco,it} = nco_{it} - \left[ \begin{pmatrix} 1 \\ loans_{it-1} \\ lla_{it-1} \\ npl_{it-1} \\ \Delta npl_{it-1} \\ plle_{it-1} \\ plle_{it} \end{pmatrix}' \hat{\beta} + \begin{pmatrix} \hat{\mathrm{E}}_{it-1} nco_{it} \\ \hat{\mathrm{E}}_{it-1} \Delta lla_{it} \end{pmatrix}' \hat{\gamma} \right] \qquad [8]$$

where $(\hat{\beta},\hat{\gamma})$ denote Prais-Winsten transformed FGLS parameter estimates from a regression of $nco_{it-1}$ on the conditioning variables shown in the bracketed, right-hand side term. Then, using a Lagrange Multiplier test approach (Engle, 1982), the formal test of Hypothesis 1 can be stated in null form as: The elements of $\delta$ in equation [9] equal zero.

$$\hat{e}_{nco,it} = \begin{bmatrix} 1 \\ loans_{it-1} \\ lla_{it-1} \\ npl_{it-1} \\ \Delta npl_{it-1} \\ plle_{it-1} \\ plle_{it} \end{bmatrix}' \beta + \begin{bmatrix} \hat{\mathrm{E}}_{it-1} nco_{it} \\ \hat{\mathrm{E}}_{it-1} \Delta lla_{it} \end{bmatrix}' \gamma + \begin{bmatrix} \hat{u}_{nco,it-1} \\ \hat{u}_{\Delta lla,it-1} \end{bmatrix}' \delta + v_{it} \qquad [9]$$

A rejection of this hypothesis implies that the lagged discretionary components of *nco* and $\Delta lla$ $\left(\hat{u}_{\Delta lla,it-1}, \hat{u}_{nco,it-1}\right)$ are associated with the residuals obtained from estimating equation [6]. Since this result would imply that lagged discretionary *llp* components explain a significant amount of variation in $nco_{it}$ not explained by the *llp* expectations model shown in equation [6], a rejection of this hypothesis would be consistent with either the misspecification of equity trader expectations or the hypothesis that discretionary *llp* components are predictive of *nco*.

Equity return variance and share volume hypotheses. These hypotheses state in alternative form that the discretionary components of *nco* and $\Delta lla$ are negatively (positively) associated with both equity return variance and unexpected share volume in long-windows (short-windows). Similar to McNichols and Manegold (1983), and Morse and Ushman (1983), an 11 day event window centered on the disclosure date is used for the short-window hypotheses tests. The long-window tests correspond to time periods beginning on the first market trading day after October 14 and ending on the last market trading day before March 16 of each year (recalling that December 31 is the fiscal year end for all commercial banks). The formal tests of the equity return variance and share volume hypotheses can then be stated (in alternative form) with respect to both equations [10] and [11] as: The elements of $\gamma$ are less than zero; and, The elements of $\delta$ are greater than zero.

$$\hat{ur}_{it}^2 = \begin{bmatrix} 1 \\ dper_{it} \\ plle_{it} \\ plle_{it}^2 \\ \Delta npl_{it} \\ \Delta npl_{it}^2 \\ dper_{it} \cdot plle_{it} \\ dper_{it} \cdot plle_{it}^2 \\ dper_{it} \cdot \Delta npl_{it} \\ dper_{it} \cdot \Delta npl_{it}^2 \end{bmatrix}' \beta + \begin{bmatrix} \hat{u}_{nco,it} \\ \hat{u}_{nco,it}^2 \\ \hat{u}_{\Delta lla,it} \\ \hat{u}_{\Delta lla,it}^2 \end{bmatrix}' \gamma + \begin{bmatrix} dper_{it} \cdot \hat{u}_{\Delta lla,it} \\ dper_{it} \cdot \hat{u}_{\Delta lla,it}^2 \\ dper_{it} \cdot \hat{u}_{nco,it} \\ dper_{it} \cdot \hat{u}_{nco,it}^2 \end{bmatrix}' \delta + v_{it} \qquad [10]$$

$$\hat{uv}_{it} = \begin{bmatrix} 1 \\ dper_{it} \\ plle_{it} \\ plle_{it}^2 \\ \Delta npl_{it} \\ \Delta npl_{it}^2 \\ dper_{it} \cdot plle_{it} \\ dper_{it} \cdot plle_{it}^2 \\ dper_{it} \cdot \Delta npl_{it} \\ dper_{it} \cdot \Delta npl_{it}^2 \end{bmatrix}' \beta + \begin{bmatrix} \hat{u}_{nco,it} \\ \hat{u}_{nco,it}^2 \\ \hat{u}_{\Delta lla,it} \\ \hat{u}_{\Delta lla,it}^2 \end{bmatrix}' \gamma + \begin{bmatrix} dper_{it} \cdot \hat{u}_{\Delta lla,it} \\ dper_{it} \cdot \hat{u}_{\Delta lla,it}^2 \\ dper_{it} \cdot \hat{u}_{nco,it} \\ dper_{it} \cdot \hat{u}_{nco,it}^2 \end{bmatrix}' \delta + v_{it} \qquad [11]$$

Conditioning variables show in equations [10] and [11] are approximately consistent with recent loan loss disclosure pricing studies. The variable $dper_{it}$ is a binary indicator variable with a value of one if the observation of $\hat{ur}_{it}^2$ ($\hat{uv}_{it}$) falls within the 11 day disclosure period and zero otherwise. Ratio scale conditioning variables in equations [10] and [11] include quadratic terms of each such variable to control for nonlinearities in the data, and to give additional insights into the response surface characteristics of the associations between discretionary *llp* components and both unexpected equity return variance and unexpected share volume. ■

# CHAPTER 6

## EMPIRICAL RESULTS AND SENSITIVITY ANALYSES

This chapter discusses the empirical results of this study and the sensitivity of those results to various assumptions used in this study. In particular, this chapter discusses quantitative results in the form of parameter estimates and standard errors for models presented in Chapter 5; estimated marginal effects and the results of hypotheses tests; and, analyses of the sensitivity of results to estimation criterion, influential observations, and loan loss expectations model specification. This chapter further explores the convexity and concavity of nonlinearities found in the associations between estimated discretionary *llp* components and equity market responses and interprets them in the context of the hypotheses developed in this study.

Details of model parameter estimates and standard errors, hypotheses tests, and sensitivity analyses are presented primarily in Appendix 1, Tables 4–9.3. Descriptive statistics showing the basic distributional characteristics of the variables used in estimating equations [3]–[11] are presented in Table 10. Details underlying the qualitative discussion of the relationships between discretionary loan loss provision components and equity market responses are presented primarily in Appendix 2; such details being comprised of plots of equity return variance and unexpected share volume in the space of estimated marginal effects of loan loss provision discretion.

### 6.1 Informative loan loss provision discretion results

Fundamentally, Hypothesis 1 states that if discretionary *llp* components are informative to equity traders, then those components must be associated with future loan loss realizations—i.e., future net loan charge-offs (*nco*). Although the commercial bank accounting literature has often suggested that the informativeness of discretionary *llp* components results from bank managers *signaling* private information about future earnings, it is shown in Chapter 4 (fn. 11) that the empirical results of this literature are generally inconsistent with plausible explanations of the relationship between discretionary *llp* components and future *plle*. Further, the development of Hypotheses 2.1–3.2 suggests that any observed association between discretionary *llp* components and future *plle* is likely spurious. For these reasons, Hypothesis 1 is developed as a more direct test of the informativeness of discretionary *llp* components, and—consistent with a plausible explanation of the widely-documented positive empirical association between discretionary *llp* components and *equity returns*—states in alternative form that discretionary *llp* components are negatively associated with future *nco*. This implies that if discretionary *llp* components are informative to equity traders, then those components are predictive of future decreases in *nco* on average.

Full sample results. Results for the full sample of banks, shown in Table 5.1, indicate no significant association between either of the two estimated discretionary *llp* components $\left(\hat{u}_{nco,it-1}, \hat{u}_{\Delta lla,it-1}\right)$ and future loan loss realizations $nco_t$. Although inconsistent with Hypothesis 1 *per se*, this result is generally consistent with Hypotheses 2.1–3.2 which state that discretionary *llp* components are either noninformative or disinformative to equity traders on average. Thus, this result provides additional evidence consistent with the results of the tests of Hypotheses 2.1–3.2 discussed below.

Reduced sample results. Results for a reduced sample based on observations for the central 95% of the $\hat{u}_{nco,it-1}$ and $\hat{u}_{\Delta lla,it-1}$ sample distributions, shown in Table 5.2, indicate that of the two discretionary *llp* components only the less discretionary $\hat{u}_{nco,it-1}$ is significantly associated with $nco_t$. The *positive* association found between $\hat{u}_{nco,it-1}$ and $nco_t$ in the reduced sample suggests that the estimated discretionary component of *nco* is predictive of increases future loan loss realizations, and is therefore inconsistent with Hypothesis 1. Interestingly, however, this result also is inconsistent with results of other loan loss disclosure pricing studies showing that estimated discretionary *llp* components are positively associated with equity returns: If estimated discretionary components of *nco* are predictive of *increases* future loan loss realizations (and discretionary components of $\Delta lla$ are *not* predictive of loan loss realizations), then it is plausible that the observed positive association between equity returns and discretionary *llp* components results from correlated, omitted variables rather than pricing-relevant information contained in such discretionary accounting variables per se.

Results shown in Table 5.2 are also consistent with the hypothesis that discretion over *nco* is substantially constrained relative to $\Delta lla$ such that it contains substantially more information with respect to future loan realizations than does $\Delta lla$. This evidence is consistent with the notion that the relatively more discretionary $\hat{u}_{\Delta lla,it-1}$ is less informative than is the relatively less discretionary $\hat{u}_{nco,it-1}$, and is therefore not inconsistent with the hypothesis that bank managers use available accounting discretion over *llp* to jam otherwise pricing-relevant signals (i.e., Hypotheses 2.1–3.2).

Table 5.2 shows that the error term of the *llp* expectations model represented by Equation [6] is serially-correlated for a subset of the observations in this study. This suggests that the *llp* expectations model used in this study may be misspecified for banks with certain characteristics. However, preliminary sensitivity analyses discussed later in this chapter suggest that this potential expectation model misspecification does not seriously alter the inferences drawn with respect to either the equity return variance hypotheses or the equity share volume hypotheses.

**6.2 Disinformative loan loss provision discretion results**

Hypotheses 2.1–3.2 are linear hypotheses in the sense that discretionary *llp* components are expected to be monotonically associated with equity return variance and unexpected share volume. This implies that all levels of discretionary *llp* components have qualitatively similar informational characteristics; e.g., all levels of discretionary $\Delta lla$ are disinformative. Although these hypotheses are consistent with underlying theory referenced in Chapter 3, intuition suggests that these hypotheses cannot hold in general empirical settings. To see this more clearly, consider an extreme case where a discretionary $\Delta lla$ *increase* was equal to 50% of a bank's outstanding loan portfolio at time *t*. Intuition suggests that equity traders would interpret this increase as indicative of severe credit quality problems which are likely to be realized as large loan losses (*nco*) in subsequent periods. Thus, intuition suggests that the linear hypotheses developed in this study reasonably hold only on average, and not under extreme conditions.

As is common in empirical accounting research, the incompleteness of existing theory to explain and predict empirical phenomena necessarily results in the estimation of models that do not conform precisely to underlying theory. In this study, this necessitates the use of empirical models that include quadratic terms to control for basic nonlinearities in the association between discretionary *llp* components and equity market responses. Consequently, the estimated marginal effects of discretionary *llp* components on equity return variance and unexpected share volume, and the inferences about the informational characteristics of those components, are necessarily conditional. Nonetheless, estimating and testing models that allow for nonlinearities provides valuable insights into the limits of the theory and hypotheses discussed in this study; and, as will be shown, allows the results of this study to be reconciled with existing commercial bank accounting literature.

It is necessary to specify conditions under which the linear hypotheses of this study are predicted to hold since the estimated relationships are not constrained to be monotonic or linear. Since most empirical accounting research and economic theory involves explanations and predictions of *central tendencies* of economic behavior, the empirical results relating to Hypotheses 2.1–3.2 are evaluated using the central 95% of the sampling distributions of the estimated discretionary *llp* components. Thus, the empirical results of this study can be interpreted as evidence pertaining to the central tendencies (e.g., mean, median, etc.) of the informational characteristics of discretionary *llp* components.

Parameter estimates and standard errors for both the equity return variance and unexpected share volume models shown in equations [10] and [11] are obtained using FGLS estimation with heteroscedasticity-robust standard errors. To evaluate the robustness of these results to alternative estimation criteria and potential violations of assumptions underlying FGLS estimation, least absolute deviation (LAD) estimates with bootstrap-resampling estimated standard errors, and Prais–Winsten transformation FGLS estimates, are also obtained and discussed in Section 6.5, "Sensitivity analyses."

### *6.2.1 Hypotheses 2.1 and 2.2: Equity return variance results*

Empirical results are generally consistent with Hypotheses 2.1 and 2.2 as evidenced by the signs and statistical significance of the estimated marginal effects of $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ on unexpected equity return variance ($\hat{ur}^2$) shown in the first column of Table 6.1. This table shows that the signs of the estimated joint marginal effects of $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ (for the central 95% of those sample distributions) on unexpected equity return variance are negative at conventional significance levels in long time-windows spanning disclosure dates suggesting that—on average—equity traders find these signals disinformative. The signs of the estimated joint marginal effect of these variables are positive but not significant at conventional levels in the short time-window around disclosure dates suggesting that—on average—equity traders find these signals noninformative. Importantly, the pattern of statistical significance of the estimated marginal effects is also consistent with several intuitively plausible interpretations:

(1) Bank managers have relatively less discretion over *nco* than over $\Delta lla$, and equity traders consequently respond to pricing-relevant signals contained in *nco* as if these signals are less ambiguous than those contained in $\Delta lla$ (since the higher levels of statistical significance of the *nco* marginal effects suggest that more of the variance in equity trader responses is explained by *nco*); and,

(2) Increased levels of both noise trading activity and information trading activity around disclosure dates results in a noisier data environment that

partially obscures inferences of equity traders (and potentially tests of statistical significance in this study).

Thus, both the long- and short-window results are not inconsistent with the signal-jamming hypothesis developed in this study since jamming signals can result in either noninformative or disinformative signals (see Table 3). Moreover, these results suggest that equity traders do not find discretionary *llp* components to be informative—on average. Sensitivity analyses (discussed below) corroborate these results.

### *6.2.2 Hypotheses 3.1 and 3.2: Equity share volume results*

Although more ambiguous than results for the equity return variance hypotheses (2.1 and 2.2), empirical results are also generally consistent with Hypotheses 3.1 and 3.2 as evidenced by the signs of the estimated marginal effects of $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ on unexpected share volume ($\hat{uv}$) shown in the first column of Table 7.1. This table shows that only a marginally significant, positive association between $\hat{u}_{nco}$ and $\hat{uv}$ is evident in the data set and model used in this study. Similar to the nonsignificant short-window, equity return variance results discussed above, the results presented in Table 7.1 are not inconsistent with the signal-jamming hypothesis and suggest that equity traders do not find discretionary *llp* components to be informative—on average. The similarity between the signs of the estimated marginal effects, and their relative statistical significance, in both the equity return variance and equity share volume hypotheses tests are suggestive of mean-zero noise obscuring inference on Hypotheses 3.1 and 3.2. Alternatively stated, when (marginally) statistically significant, the results of the equity share volume tests are consistent with the equity return variance hypotheses test results.

Also similar to the equity return variance results, the equity share volume statistical results are consistent with several intuitively plausible interpretations:

(1) Inference on Hypotheses 3.1 and 3.2 is obscured since equity share volume is a noisier measure of information content than is equity return variance because it is influenced by a number of random factors other than pricing-relevant information (consider, e.g., liquidity trading); and

(2) Marginally-significant results are obtained (only) for *nco* in Hypothesis 3.2 since (as discussed previously) equity traders respond to pricing-relevant signals contained in *nco* as if these signals are less ambiguous than those contained in $\Delta lla$ due to differences in levels of available accounting discretion.

Again, although the empirical results on Hypotheses 3.1 and 3.2 are somewhat ambiguous, they are not inconsistent with the hypothesis that discretionary *llp* components are used to jam equity trader inferences—on average. Sensitivity analyses (discussed below) also corroborate these equity share volume results.

**6.5 Sensitivity analyses**

The empirical results of this study were analyzed for robustness to estimation criterion, error term assumption violations, influential observations, and alternative expectation model specification. These analyses suggest that the results of this study are not substantively influenced by econometric problems. A general discussion of non-significant results is included in Section 6.6, "Qualitative analysis of observed associations."

Estimation criterion. A well-known property of least squares estimation methods is that estimates are heavily influenced by observations which are substantially distant from sample means of dependent variables and independent variables; alternatively referred to as influential observations, extreme observations, or outlying observations depending on the particular location of the observations relative to the multivariate sample mean. Since this study focuses on (robust) central tendencies of the relationship between discretionary *llp* components and equity market responses, it is meaningful to consider whether *mean* marginal effects found using FGLS estimation are substantively similar to *median* marginal effects found using least absolute deviation (LAD) estimation.

Median effects are considered since the sample median is a robust estimator of central tendency for a number of families of probability distributions (DeGroot, 1986). Thus, equations [10] and [11] were estimated and tested using LAD (median) estimation with bootstrap-estimated standard errors to analyze the robustness of results to potential econometric problems caused by heavy-tailed and heteroscedastic, among other, error term structures. The results of these sensitivity analyses are shown primarily in Tables 6.2 and 7.2 where long- and short-window LAD estimated marginal effects and related hypotheses tests are presented.

The full data set results under LAD estimation, when statistically significant, were qualitatively similar to the primary FGLS marginal effects and hypotheses test results presented in Tables 6.1 and 7.1. Only one difference between *significant* full data set results under both FGLS and LAD estimation was found:

> The short period marginal effect of $\hat{u}_{\Delta lla}$ on $\hat{ur}^2$ (Tables 6.1 and 6.2) found to be nonsignificant and monotonic under FGLS estimation was found to

be significant ($p \cong .028$) and nonmonotonic under LAD estimation. This differing result suggests that influential observations obscure estimation and inference under FGLS with respect to a nonlinearity between $\hat{u}_{\Delta lla}$ on $\hat{ur}^2$. This type of nonlinearity is plausible since inspection of the concavity of this marginal effect (shown geometrically in Figures 1.2 and 1.4) suggests that the more extreme values of $\hat{u}_{\Delta lla}$ are more disinformative to equity traders consistent with the hypothesized signal-jamming use of accounting discretion over *llp* components.

Error term structure. The suggestion of Cohen, Hawawini, et. al (1980) that capital markets are generally characterized by trading frictions resulting in serial correlations in returns and transaction volume implies the possibility that the results of this study are sensitive to assumptions about the autoregressive structure of the error terms in equations [10] and [11]. In particular, noise added to the equity pricing information environment by discretionary *llp* components potentially results in lengthened equity trader response times. To test the sensitivity of the results under FGLS estimation to potential AR(1) process error terms, Prais–Winsten AR(1) transformed FGLS parameter estimates and standard errors are obtained for equations [10] and [11]. (Although higher-order AR processes error terms could be considered, the lack of any clear theoretical guidance in the accounting literature with respect to the length of time required for capital markets to adjust to new information would preclude meaningful inference in such an analysis.)

The results of this error term structure sensitivity analysis are shown primarily in Tables 6.3 and 7.3 where long- and short-window Prais–Winsten FGLS estimated marginal effects and related hypotheses tests are presented. The results under Prais–Winsten FGLS estimation were qualitatively similar to the primary FGLS marginal effects and hypotheses test results presented in Tables 6.1 and 7.1, and no differences were found between *significant* results under FGLS and Prais–Winsten FGLS estimation. Thus, these sensitivity analyses suggest that the results of this study are not sensitive to assumptions about the structure of the error terms in equations [10] and [11].

Influential dependent variable observations. The commercial bank accounting literature has shown that associations between *llp* components and equity returns are sensitive to omission of influential (i.e., extreme or outlying) observations. As an example, Wahlen (1994) finds that a positive association between unexpected *llp* and equity returns is not robust to the omission of the upper and lower 1% of the unexpected *llp* sample distribution. These findings suggest that results of this study are potentially sensitive to influential observations which are distant from the multivariate sample mean.

However, theory underlying this study suggests that more extreme independent variable observations are associated with the hypothesized signal-jamming behavior. To see this, recall that higher levels of discretion over *llp* components are necessary to generate such extreme observations—assuming adequacy of the loan loss expectations model in equation [6]. Turning to optimal disclosure behavior, the institutional characteristics of commercial banks including uncertainty over both exogenous factors influencing loan loss realizations and credit risk characteristics of bank loan portfolios, result in incentives for bank managers to maintain or increase information asymmetries (i.e., signal-jamming). Thus, higher levels of *llp* discretion associated with more extreme observations in the sample data set are reasonably more ambiguous and, in a dynamic setting, disinformative. It follows that the more extreme observations in the data set used in this study are encompassed by that theory and the resultant hypotheses. Accordingly, the full data set results are considered to be most informative with respect to the hypotheses of this study.

Notwithstanding the foregoing discussion, sensitivity of results to influential observations are analyzed through reestimation and testing of marginal effects tested omitting separately the upper and lower 2.5% of the sample distributions of dependent variables ( $\hat{ur}^2$ and $\hat{uv}$ ), and of independent variables ( $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ ). These analyses are primarily conducted to gain additional insights into the robustness and generalizability of results in this study. Accordingly, FGLS, LAD, and Prais–Winsten FGLS estimation are again used to reestimate equations [10] and [11] using the reduced data sets.

Reduced data set analyses based on omission of upper and lower 2.5% of *dependent* variable sample distributions are presented in the *second* columns of Tables 6.1 through 7.3; similar analyses based on omission of upper and lower 2.5% of *independent* variable sample distributions are presented in the *third* columns of Tables 6.1 through 7.3.

As shown in Tables 6.1 through 7.3, the omission of larger *dependent* variable observations generally results in either nonmonotonic estimated marginal effects of discretionary *llp* components, or increased statistical significance of those marginal effects. The tests of the significance of marginal effects take the form of (non-directional) Wald *F*-tests which indicate whether estimated marginal effects explain a significant portion of the variation in the dependent variables ( $\hat{ur}^2$ and $\hat{uv}$ ). Consequently, it is not surprising that omitting more extreme dependent variable observations often results in increased statistical significance of the estimated marginal effects. It follows that exploration of estimated nonmonotonicity, and convexity/concavity, of significant marginal effects when larger dependent variable observations are omitted is of greater relevance to assessing the robustness and generalizability of results in this study than statistical significance *per se*.

In the exploration of nonmonotonicity the association between discretionary *llp* components and equity market responses, the convexity and concavity of that association can be interpreted in terms of the hypotheses of this study. Specifically, given the hypothesis development in Chapter 4, the following signs of partial derivatives of the associations estimated in equations [10] and [11] are consistent with the hypotheses that discretionary *llp* components are *disinformative in longer, disclosure-spanning periods*:

$$\left(\frac{\partial^2 \hat{u}r^2(.)}{\partial \hat{u}_{nco}\partial \hat{u}_{nco}}, \frac{\partial^2 \hat{u}r^2(.)}{\partial \hat{u}_{\Delta lla}\partial \hat{u}_{\Delta lla}}\right) < 0 \quad \Leftrightarrow \quad \hat{u}r^2 \text{ is concave in } (\hat{u}_{nco}, \hat{u}_{\Delta lla}).$$

$$\left(\frac{\partial^2 \hat{u}v(.)}{\partial \hat{u}_{nco}\partial \hat{u}_{nco}}, \frac{\partial^2 \hat{u}v(.)}{\partial \hat{u}_{\Delta lla}\partial \hat{u}_{\Delta lla}}\right) < 0 \quad \Leftrightarrow \quad \hat{u}v \text{ is concave in } (\hat{u}_{nco}, \hat{u}_{\Delta lla}).$$

Similarly, the following signs of partial derivatives of these associations are consistent with the hypotheses that discretionary *llp* components are *disinformative in shorter periods around disclosure dates*:

$$\left(\frac{\partial^3 \hat{u}r^2(.)}{\partial dper \partial^2 \hat{u}_{nco}}, \frac{\partial^3 \hat{u}r^2(.)}{\partial dper \partial^2 \hat{u}_{\Delta lla}}\right) > 0 \quad \Leftrightarrow \quad \hat{u}r^2 \text{ is convex in } (\hat{u}_{nco}, \hat{u}_{\Delta lla}).$$

$$\left(\frac{\partial^3 \hat{u}v(.)}{\partial dper \partial^2 \hat{u}_{nco}}, \frac{\partial^3 \hat{u}v(.)}{\partial dper \partial^2 \hat{u}_{\Delta lla}}\right) > 0 \quad \Leftrightarrow \quad \hat{u}v \text{ is convex in } (\hat{u}_{nco}, \hat{u}_{\Delta lla}).$$

These derivatives are not shown explicitly here or in the appendices since the highest order terms included in equations [10] and [11] are quadratic; thus, convexity (concavity) can be easily seen geometrically as positive (negative) slopes in plots of marginal effects shown in Figures 1.1 through 2.6.

Differences between full data set results and significant marginal effects estimated using a reduced data set of the central 95% of sample dependent variable observations are:

(1) The *long-window* nonmonotonic marginal effect of $\hat{u}_{\Delta lla}$ on unexpected share volume becomes significant when reestimated using a reduced dependent variable observation data set as shown in Table 7.1. Consistent with the signal-jamming hypothesis, Figure 2.1 shows that unexpected share volume is *concave* in $\hat{u}_{\Delta lla}$ suggesting that the more extreme the discretion exercised over $\Delta lla$ components, the more disinformative such signals are to equity traders; in particular, to information traders which likely dominate market activity over longer periods; and

(2) Similarly, the *short-window* nonmonotonic marginal effect of $\hat{u}_{\Delta lla}$ on unexpected share volume becomes significant when reestimated using a reduced dependent variable observation data set as shown in Table 7.1. Again consistent with the signal-jamming hypothesis, Figure 2.2 shows that unexpected share volume is *convex* in $\hat{u}_{\Delta lla}$ suggesting that the more extreme the discretion exercised over $\Delta lla$ components, the more disinformative such signals are to equity traders since noise traders, which

likely dominate market activity in shorter periods around disclosure dates, react to disinformative signals *as if* they were informative.

As shown in Figures 1.1 through 2.6, in certain cases the convexity or concavity of associations between discretionary *llp* components and equity market responses under LAD (median) estimation is inconsistent with the hypotheses developed in this study. As an example, Figure 2.3 shows that unexpected share volume is *convex* in $\hat{u}_{\Delta lla}$ in a longer disclosure-spanning period suggesting that the more extreme the discretion exercised over $\Delta lla$ components, the more *informative* such signals are to equity traders in longer disclosure-spanning periods. However, this interpretation relies on the assumption that market activity is dominated by information traders in these longer periods. If noise trader activity generates sufficiently extreme observations, then this result potentially represents the measurement of signal disinformativeness under FGLS estimation.

Given the implicit linearity of theory underlying the hypotheses of this study, the implications of these alternative results under LAD estimation are not clear and should be explored in future extensions of this study. In some respects, this is an epistemological issue. In contrast to the *mean marginal effects* of discretionary *llp* components on equity market responses estimated under FGLS estimation, measures of central tendency under LAD estimation are *median effects*. Since both measures of marginal effects are "correct," the appropriate measure of central tendency for marginal effects is necessarily contextual. Because this study seeks to contribute to the financial accounting literature, FGLS estimation of mean marginal effects is considered most appropriate since this criterion is most common in the accounting literature. In this connection, results under

LAD estimation are perhaps most appropriately interpreted simply as tests of robustness and generalizability.

Influential independent variable observations. Similar to the discussion of potential influential dependent variable observations, loan loss disclosure pricing studies in the commercial bank accounting literature (e.g., Wahlen, 1994) suggest that the general full sample results of this study are potentially not robust to the omission of larger *independent* variable observations. Reduced data set analyses based on omission of upper and lower 2.5% of independent variable sample distributions are presented in the *third* columns of Tables 6.1 through 7.3.

As shown in Tables 6.1 through 7.3, the omission of larger independent variable observations often results in large (positive and negative) changes in the significance levels of marginal effects, and often from nonsignificant monotonic marginal effects to significant nonmonotonic marginal effects. These general results suggest that the essentially linear theory and hypotheses of this study potentially represent an inadequate explanation of use of accounting discretion over *llp* components.

Specific differences between full sample results and *significant* results obtained when larger independent variable observations are omitted are:

(1) The *long-window* marginal effect of $\hat{u}_{nco}$ on equity return variance becomes nonmonotonic when reestimated using a reduced independent variable observation data set as shown in Table 6.1. Consistent with the notion that pricing-relevant signals contained in *nco* are less ambiguous since bank managers have relatively less accounting discretion over *nco* than over $\Delta lla$, Figure 1.1 shows that unexpected share volume is *convex* in $\hat{u}_{nco}$

suggesting that more extreme *nco* observations in the reduced data set are informative to equity traders in long-windows.

Interestingly, since this result is derived from reestimating equation [11] using a reduced independent variable observation data set, it is also consistent with the signal-jamming hypothesis: Since the reestimated marginal effect of $\hat{u}_{nco}$ on equity return variance suggests that the remaining less discretionary observations of $\hat{u}_{nco}$ are generally more informative, this differing result suggests that the more discretionary (extreme) observations of $\hat{u}_{nco}$ are disinformative.

(2) The *long-window* marginal effect of $\hat{u}_{\Delta lla}$ on equity return variance becomes significant and nonmonotonic when reestimated using a reduced independent variable observation data set and LAD estimation as shown in Table 6.2. Consistent with the signal-jamming hypothesis, Figure 1.3 shows that equity return variance is *concave* in $\hat{u}_{\Delta lla}$ suggesting that more extreme $\Delta lla$ observations are disinformative to equity traders in long-windows (also consistent with the notion that higher levels of available discretion over *lla* result in more ambiguous pricing-relevant signals).

(3) The *short-window* marginal effect of $\hat{u}_{nco}$ on equity return variance becomes nonmonotonic when reestimated using a reduced independent variable observation data set and LAD estimation as shown in Table 6.2. Figure 1.4 shows that equity return variance is *concave* in $\hat{u}_{nco}$ suggesting that more extreme *nco* observations in the reduced data set are disinformative to

equity traders in short-windows. Viewed in relation to the nonsignificant full sample result, this result suggests that these more extreme *nco* observations are for some reason more ambiguous to equity traders.

(4) The *long-window* marginal effect of $\hat{u}_{nco}$ on unexpected share volume becomes nonmonotonic when reestimated using a reduced independent variable observation data set and LAD estimation as shown in Table 7.2. Figure 2.3 shows that equity return variance is *convex* in $\hat{u}_{nco}$ suggesting that more extreme *nco* observations in the reduced data set are more informative to equity traders in long-windows. Viewed in relation to the monotonic full sample result, this result suggests that these more extreme *nco* observations are for some reason less ambiguous to equity traders.

Although the differing results obtained under LAD estimation using the reduced data set omitting observations with larger values of $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ are not entirely consistent with the hypotheses developed in this study, the appropriate interpretation of these results is not entirely clear.

As discussed, results under LAD estimation are perhaps most appropriately interpreted as tests of robustness and generalizability. In this regard, these sensitivity analyses suggest that the primary results of this study are not entirely robust, similar to the findings of other studies in the commercial bank accounting literature. However, as also discussed, the more extreme observations of $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ are encompassed by the theory underlying the hypotheses of this study. Accordingly, the full data set results under

FGLS estimation are considered most informative with respect to the hypotheses of this study.

Loan loss provision expectations model specification. The commercial bank accounting literature has shown that associations between loan loss disclosures and equity market responses is often highly conditional (e.g., Beaver, Eger, Ryan, and Wilson, 1989; Elliott, Hanna, and Shaw, 1991; Liu and Ryan, 1995; and Liu, Ryan and Wahlen, 1997) suggesting that the results of this study are potentially sensitive to expectations model specification. To test the sensitivity of results to alternative expectations model specifications, equations [10] and [11] are reestimated with additional conditioning on the expected *nco* and *Δlla* components ($\hat{\mathrm{E}}nco$ and $\hat{\mathrm{E}}\Delta lla$).

Results shown in Tables 10.1–11.2 suggest that the empirical results with respect to Hypotheses 2.1–3.2 are robust to potential misspecifications (i.e., alternative partitionings of expected and unexpected components) of the *llp* expectations model shown in equation [6]. Specifically, where significant the results shown in Tables 10.1 and 10.2 are entirely similar to the results obtained when equations [10] and [11] are estimated without additional conditioning on $\hat{\mathrm{E}}nco$ and $\hat{\mathrm{E}}\Delta lla$; differing only in the levels of significance of the estimated marginal effects.

Sensitivity analyses summary. In aggregate, sensitivity analyses suggest that econometric problems do not substantively influence estimation or inference in this study. In particular, these analyses show that the empirical results are quite robust in the sense that the hypothesized signal-jamming use of accounting discretion over *llp* components is *not rejected* under: (1) an alternative estimation criterion, (2) an alternative error term structure assumption, (3) omission of potential influential observations in the extreme 2.5% of the sample distributions of dependent and independent variables in equations [10] and [11], and (4) alternative partitionings of *llp* into expected and unexpected components. Moreover, these analyses provide evidence corroborating the primary results of this study showing that discretionary *llp* components are generally disinformative to equity traders consistent with the hypothesized signal-jamming use of accounting discretion in commercial banks. ■

# CHAPTER 7

## SUMMARY AND CONCLUSIONS

This study provides both theory and evidence suggesting that discretionary earnings components can contain *disinformative signals* that result in systematic changes in equity return variability and share volume. In contrast to prior loan loss disclosure pricing studies, this study provides evidence consistent with the hypothesis that the discretionary components of commercial bank loan loss provisions do not contain pricing-relevant information on average. Moreover, some evidence is presented suggesting that greater use of accounting discretion over *llp* components results in more disinformative pricing-relevant signals to equity traders.

This study makes several contributions to the financial accounting literature. The notion of a disinformative accounting signal is developed and linked with existing theoretical models in the accounting and economics literatures. An alternative explanation for the use of accounting discretion and, relatedly, herd behavior and noise trading models from the financial economics literature are introduced. Empirical evidence consistent with the hypothesized signal-jamming use of discretion over accounting variables subject to uncertainty and information asymmetry is presented, and the second-order informational characteristics of discretionary accounting variables are explored. In particular, results obtained from the exploration of nonlinearities, including convexity and concavity of associations between discretionary *llp* components and equity market responses, emphasize the limitations of the implicitly linear theory underlying this and other financial accounting studies. In aggregate, these contributions suggest that use of theoretical models to guide empirical research, and the estimation of higher-order associations, can lead to meaningful, new insights into the relationships between accounting variables and equity market data.

With respect to identified nonlinearities, estimated parameters for the quadratic terms in equations [10] and [11] and shown in Tables 6.1 and 7.1 suggests that the second-order informational characteristics of discretionary *llp* components (i.e., convexity/concavity in equity return variance and share volume) differ under certain conditions. This, and the nonsignificant short-window and equity share volume results, suggest that more refined hypotheses and empirical tests would be necessary to obtain a more complete understanding of the conditions under which discretionary *llp* components are disinformative.

Future extensions of this study appear worthwhile since theory that explains and predicts when discretionary accounting variables and other disclosures are noninformative or disinformative has important implications. Specifically, the notion that accounting signals can be disinformative, and the conditions under which accounting signals are noninformative or disinformative, has clear implications for accounting education, financial analysts, portfolio managers, and accounting standard-setters. Future extensions of this study should examine potential sources of nonlinearities in the relationship between discretionary *llp* components and equity market responses including constrained discretion over *llp* components and the related effects on equity trader inferences, equity return variance and share volume to gain further insights into the conditions under which discretionary *llp* components are noninformative or disinformative. ■

# APPENDICES

## APPENDIX 1

**Table 1 Disclosure and equity market response**

| | Equity market response | |
|---|---|---|
| | Return variance | Share volume |
| ***In long-windows spanning disclosure dates*** | | |
| Increased signal variance | **Negative**[A] | |
| Increased trader belief heterogeneity | | **Negative**[D] |
| ***In short-windows around disclosure dates*** | | |
| Increased signal variance | **Positive**[B] | **Positive**[B] |
| Increased trader belief heterogeneity | **Positive**[B] | **Positive**[B,C] |

[A] Theoretical result of Holthausen and Verrecchia (1988).

[B] Theoretical result of Kim and Verrecchia (1994).

[C] Empirical result of Ziebart (1990).

[D] Empirical result of Barron (1995).

**<u>Table 2</u> Definitions of signal types**

| Term | Definition |
|---|---|
| *Informative signal* | Any data resulting in the revision of decision-makers' beliefs over the distribution of some information variable such that expectations with respect to that variable become *more precise* (cf. Theil, 1967; Hirshleifer, 1973; Holthausen and Verrecchia, 1988; and, Kim and Verrecchia, 1994). |
| *Noninformative signal* | Any data *not* resulting in a revision of decision-makers' beliefs over the distribution of some information variable (cf. Theil, 1967; and Hirshleifer, 1973). |
| *Disinformative signal* | Any data resulting in the revision of decision-makers' beliefs over the distribution of some information variable such that expectations with respect to that variable become *less precise* (cf. Theil, 1967; Holthausen and Verrecchia, 1988; and, Kim and Verrecchia, 1994). |
| *Signaling* | An observable, discretionary *informative signal* emitted by an agent with private information for the purpose of conveying such information where that signal cannot reasonably be imitated by other agents due to their higher cost of emitting that signal (cf. Spence, 1974; Rothschild and Stiglitz, 1976; Beaver, 1981). |
| *Signal-jamming* | An unobservable, discretionary *noninformative* or *disinformative signal* emitted by an agent resulting in a decrease in the level of information contained in some other signal (cf. Holmstrom, 1982; Fudenberg and Tirole, 1986; Stein, 1989; and Creane, 1995). |

**Table 3** **Necessary conditions for disclosure type observability**

| **Disclosure type**[b] | **Observable signal type**[a] | | |
|---|---|---|---|
| | ***Informative*** | ***Noninformative*** | ***Disinformative*** |
| Nondiscretionary ....... | Increased equity return variance or share transaction volume, *and* **observable nondiscretion.** | Nonincreased and nondecreased equity return variance and share transaction volume, *and* **observable nondiscretion.** | Decreased equity return variance or share transaction volume, *and* **observable nondiscretion.** |
| Discretionary: | | | |
| *Signaling* ............... | Informative signal conditions (above), *and* **observable discretion and private information.** | (*Not applicable by definition.*) | (*Not applicable by definition.*) |
| *Signal-jamming* ..... | (*Not applicable by definition.*) | Noninformative signal conditions (above) *and* **observable discretion.** | Disinformative signal conditions (above) *and* **observable discretion.** |

[a] Signal type is observable since under an assumption of semi-strong form informationally efficient equity markets, the type of market response *defines* signal type.

[b] In general, disclosure type is unobservable for various reasons; see Wilson (1996) and DeAngelo (1988) for discussions of the problems associated with observing discretionary accounting-related behavior.

**Table 4 Loan loss expectations model SUR estimation results**

| Independent and lagged dependent variables | Dependent variables: Change in nonperforming loans $\Delta npl_t$ — Parameter estimate | Standard error | Net loan charge-offs $nco_t$ — Parameter estimate | Standard error | Change in loan loss allowance $\Delta lla_t$ — Parameter estimate | Standard error |
|---|---|---|---|---|---|---|
| Intercept | .0020 | .0021 | -.0058 | .0016*** | .0036 | .0007*** |
| $loans_{t-1}$ | –.0024 | .0028 | .0022 | .0022 | –.0025 | .0010** |
| $lla_{t-1}$ | .0669 | .0410 | .0150 | .0315 | –.1150 | .0146*** |
| $npl_{t-1}$ | –.4115 | .0321*** | .1290 | .0260*** | –.0312 | .0120*** |
| $plle_t$ | | | .4097 | .0587*** | .0134 | .0271 |
| $nco_{t-1}$ | | | .0489 | .0502 | .1650 | .0232*** |
| $\Delta lla_{t-1}$ | | | .2443 | .0608*** | .0897 | .0281*** |
| | $n = 281$ | | $n = 281$ | | $n = 281$ | |
| | $\hat{R}^2 = .4929$*** | | $\hat{R}^2 = .3253$*** | | $\hat{R}^2 = .4560$*** | |

***, **, * denote significantly different from zero (two-tail test for parameter coefficients) at $p \leq .01$, $p \leq .05$, and $p \leq .10$, respectively.

$\hat{R}^2$ denotes asymptotically-consistent estimates of individual equation $R^2$ statistics.

**Table 5.1 Expectations model residual regression results and hypothesis test of lagged loan loss provision residuals (Full data set)**

| Independent and lagged dependent variables | Dependent variable: Net loan charge-offs $nco_{it}$ [5.1.1] Parameter estimate[a] | Standard error | Residuals from [5.1.1] estimation $\hat{e}_{nco,it}$ [5.1.2] Parameter estimate[b] | Standard error | Net loan charge-offs $nco_{it}$ [5.1.3] Parameter estimate[a] | Standard error |
|---|---|---|---|---|---|---|
| $\rho(e_{t-1})$ | .0769 | .0731 | | | –.0100 | .0733 |
| Intercept | –.0115 | .0037*** | –.0012 | .0040 | –.0127 | .0040*** |
| $plle_t$ | .4130 | .0855*** | –.0121 | .0866 | .3992 | .0865*** |
| $plle_{t-1}$ | .0549 | .1697 | .0268 | .1727 | .0805 | .1723 |
| $loans_{t-1}$ | .0070 | .0033** | .0013 | .0035 | .0082 | .0035** |
| $lla_{t-1}$ | .1327 | .0660** | .0217 | .0727 | .1533 | .0727** |
| $npl_{t-1}$ | .2507 | .0617*** | .0058 | .0621 | .2558 | .0620*** |
| $\Delta npl_{t-1}$ | .0277 | .0676 | –.0134 | .0696 | .0155 | .0694 |
| $\hat{\mathrm{E}}_{t-1}nco_{it}$ | –.3042 | .3763 | –.0768 | .3882 | –.3749 | .3874 |
| $\hat{\mathrm{E}}_{t-1}\Delta lla_{it}$ | 1.3107 | .4324*** | .1359 | .4617 | 1.4391 | .4611*** |
| $\hat{u}_{nco,it-1}$ | | | .0072 | .0719 | .0074 | .0718 |
| $\hat{u}_{\Delta lla,it-1}$ | | | –.1642 | .1776 | –.1615 | .1775 |
| | $n = 188$ | | $n = 188$ | | $n = 188$ | |
| | $R^2 = .3863$*** | | $R^2 = .0055$ | | $R^2 = .3882$*** | |

***Residual regression* [5.1.2] *Lagrange Multiplier test of* $\hat{u}_{nco,it-1}$ *and* $\hat{u}_{\Delta lla,it-1}$**

$$\mathrm{P}[\chi^2_{df=2} > (\chi^2_{df=2} = nR^2 = 188 \cdot .0055_{df=2})] \cong .5963$$

[a], [b] Prais-Winsten FGLS and OLS parameter estimates, respectively.

***, **, * denote significantly different from zero (two-tail test for parameter estimates) at $p \leq .01$, $p \leq .05$, and $p \leq .10$, respectively.

**Table 5.2 Expectations model residual regression results and hypothesis test of lagged loan loss provision residuals (Reduced data set)**

| Independent and lagged dependent variables | Dependent variable: Net loan charge-offs $nco_{it}$ [5.2.1] Parameter estimate[a] | Standard error | Residuals from [5.2.1] estimation $\hat{e}_{nco,it}$ [5.2.2] Parameter estimate[b] | Standard error | Net loan charge-offs $nco_{it}$ [5.2.3] Parameter estimate[a] | Standard error |
|---|---|---|---|---|---|---|
| $\rho(\hat{e}_{t-1})$ | −.0067 | .0816 | | | .1511 | .0816** |
| Intercept | −.0152 | .0033*** | .0133 | .0025*** | −.0008 | .0023 |
| $plle_t$ | .1959 | .0485*** | −.0983 | .0340*** | .1071 | .0335*** |
| $plle_{t-1}$ | .5954 | .1750*** | −.5365 | .1244*** | .0146 | .1160 |
| $loans_{t-1}$ | .0067 | .0024*** | −.0055 | .0017*** | .0003 | .0016 |
| $lla_{t-1}$ | .2895 | .0629*** | −.2390 | .0490*** | .0367 | .0471 |
| $npl_{t-1}$ | .2178 | .0601*** | −.2328 | .0446*** | −.0191 | .0423 |
| $\Delta npl_{t-1}$ | −.1544 | .0673** | .1011 | .0460** | −.0471 | .0438 |
| $\hat{E}_{t-1}nco_{it}$ | −1.4377 | .3790*** | 1.9590 | .2970*** | .5816 | .2742** |
| $\hat{E}_{t-1}\Delta lla_{it}$ | 1.3319 | .4000*** | −1.2131 | .2981*** | .0724 | .2890 |
| $\hat{u}_{nco,it-1}$ | | | .9004 | .0766*** | .8929 | .0755*** |
| $\hat{u}_{\Delta lla,it-1}$ | | | .0286 | .0980 | .0088 | .0988 |
| | $n = 153$ | | $n = 153$ | | $n = 153$ | |
| | $R^2 = .3465$*** | | $R^2 = .5530$*** | | $R^2 = .7174$*** | |

***Residual regression* [5.1.2] *Lagrange Multiplier test of* $\hat{u}_{nco,it-1}$ *and* $\hat{u}_{\Delta lla,it-1}$**

$$P[\chi^2_{df=2} > (\chi^2_{df=2} = nR^2 = 153 \cdot .5530_{df=2})] \cong .000$$

a, b Prais-Winsten FGLS and OLS parameter estimates, respectively.

***, **, * denote significantly different from zero (two-tail test for parameter estimates) at $p \leq .01$, $p \leq .05$, and $p \leq .10$, respectively.

**Table 6.1 Equity return variance ($\hat{ur}_{it}^2$) hypotheses tests: FGLS estimated marginal effects and related significance tests**

| Marginal effect | Sign of estimated marginal effect[1,2] based on parameter estimates from: Full data set | Reduced data set based on central 95% of *dependent variable* sample distribution | Reduced data set based on central 95% of *independent variable* sample distributions |
|---|---|---|---|
| **Hypothesis 2.1: Full period marginal effect on equity return variance < 0** | | | |
| $\frac{\partial \hat{ur}^2}{\partial \hat{u}_{nco}}$ | $<0$<br>$P > F(1,28866) \cong .000$ | $<0$<br>$P > F(1,27692) \cong .000$ | **Nonmonotonic**<br>$P > F(1,26570) \cong .000$ |
| $\frac{\partial \hat{ur}^2}{\partial \hat{u}_{\Delta lla}}$ | $<0$<br>$P > F(1,28866) \cong .024$ | $<0$<br>$P > F(1,27692) \cong .023$ | $<0$<br>$P > F(1,26570) \cong .991$ |
| **Hypothesis 2.2: Disclosure period marginal effect on equity return variance > 0** | | | |
| $\frac{\partial^2 \hat{ur}^2}{\partial \hat{u}_{nco} \partial dper}$ | $>0$<br>$P > F(1,28866) \cong .109$ | $<0$<br>$P > F(1,27692) \cong .234$ | **Nonmonotonic**<br>$P > F(1,26570) \cong .181$ |
| $\frac{\partial^2 \hat{ur}^2}{\partial \hat{u}_{\Delta lla} \partial dper}$ | $>0$<br>$P > F(1,28866) \cong .801$ | **Nonmonotonic**<br>$P > F(1,27692) \cong .229$ | $>0$<br>$P > F(1,26570) \cong .876$ |

(1) Tests of the significance of marginal effects, e.g., $\gamma_{\hat{u}_{nco}} + \gamma_{\hat{u}^2_{nco}} = 0$, $\delta_{dper \cdot \hat{u}_{nco}} + \delta_{dper \cdot \hat{u}^2_{nco}} = 0$ based on the notation in equations [10] and [11], take the form of a Wald $F$-test: $P(F_{1,n-k} > F^{obs}_{1,n-k})$.

(2) Sign of estimated marginal effect based on applicable parameter estimates in Table 8.1 for equation [10] evaluated on central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions: $\hat{u}_{nco,mid95\%} \cong [-.0059, .0053]$ and $\hat{u}_{\Delta lla,mid95\%} \cong [-.0031, .0032]$. "Nonmonotonic" denotes nonmonotonic estimated marginal effect evaluated using the central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions; e.g., $\partial \hat{ur}^2 / \partial \hat{u}_{nco} > 0$ for some $\hat{u}_{nco,mid95\%}$.

**Table 6.2 Equity return variance ($\hat{ur}_{it}^2$) hypotheses tests: LAD estimated marginal effects and related significance tests**

| Marginal effect | Sign of estimated marginal effect[1,2] based on parameter estimates from: Full data set | Reduced data set based on central 95% of *dependent variable* sample distribution | Reduced data set based on central 95% of *independent variable* sample distributions |
|---|---|---|---|
| **Hypothesis 2.1: Full period marginal effect on equity return variance < 0** | | | |
| $\frac{\partial \hat{ur}^2}{\partial \hat{u}_{nco}}$ | $< 0$<br>$P > F(1{,}28866) \cong .000$ | $< 0$<br>$P > F(1{,}27692) \cong .042$ | **Nonmonotonic**<br>$P > F(1{,}26570) \cong .030$ |
| $\frac{\partial \hat{ur}^2}{\partial \hat{u}_{\Delta lla}}$ | $< 0$<br>$P > F(1{,}28866) \cong .535$ | $< 0$<br>$P > F(1{,}27692) \cong .346$ | **Nonmonotonic**<br>$P > F(1{,}26570) \cong .003$ |
| **Hypothesis 2.2: Disclosure period marginal effect on equity return variance > 0** | | | |
| $\frac{\partial^2 \hat{ur}^2}{\partial \hat{u}_{nco} \partial dper}$ | $< 0$<br>$P > F(1{,}28866) \cong .488$ | **Nonmonotonic**<br>$P > F(1{,}27692) \cong .193$ | **Nonmonotonic**<br>$P > F(1{,}26570) \cong .002$ |
| $\frac{\partial^2 \hat{ur}^2}{\partial \hat{u}_{\Delta lla} \partial dper}$ | **Nonmonotonic**<br>$P > F(1{,}28866) \cong .028$ | **Nonmonotonic**<br>$P > F(1{,}27692) \cong .135$ | **Nonmonotonic**<br>$P > F(1{,}26570) \cong .591$ |

(1) Tests of the significance of marginal effects, e.g., $\gamma_{\hat{u}_{nco}} + \gamma_{\hat{u}_{nco}^2} = 0$, $\delta_{dper \cdot \hat{u}_{nco}} + \delta_{dper \cdot \hat{u}_{nco}^2} = 0$ based on the notation in equations [10] and [11], take the form of a Wald $F$-test: $\mathrm{P}(F_{1,n-k} > F_{1,n-k}^{obs})$.

(2) Sign of estimated marginal effect based on applicable parameter estimates in Table 8.2 for equation [10] evaluated on central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions: $\hat{u}_{nco,mid95\%} \cong [-.0059, .0053]$ and $\hat{u}_{\Delta lla,mid95\%} \cong [-.0031, .0032]$. "Nonmonotonic" denotes nonmonotonic estimated marginal effect evaluated using the central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions; e.g., $\partial \hat{ur}^2 / \partial \hat{u}_{nco} > 0$ for some $\hat{u}_{nco,mid95\%}$.

**Table 6.3 Equity return variance ($\hat{ur}_{it}^2$) hypotheses tests:**
**Prais-Winsten estimated marginal effects and related significance tests**

| Marginal effect | Sign of estimated marginal effect[1,2] based on parameter estimates from | | |
|---|---|---|---|
| | Full data set | Reduced data set based on central 95% of *dependent variable* sample distribution | Reduced data set based on central 95% of *independent variable* sample distributions |
| **Hypothesis 2.1: Full period marginal effect on equity return variance < 0** | | | |
| $\frac{\partial \hat{ur}^2}{\partial \hat{u}_{nco}}$ | $<0$<br>$P > F(1{,}28866) \cong .000$ | $<0$<br>$P > F(1{,}27692) \cong .000$ | **Nonmonotonic**<br>$P > F(1{,}26570) \cong .000$ |
| $\frac{\partial \hat{ur}^2}{\partial \hat{u}_{\Delta lla}}$ | $<0$<br>$P > F(1{,}28866) \cong .128$ | $<0$<br>$P > F(1{,}27692) \cong .020$ | $<0$<br>$P > F(1{,}26570) \cong .995$ |
| **Hypothesis 2.2: Disclosure period marginal effect on equity return variance > 0** | | | |
| $\frac{\partial^2 \hat{ur}^2}{\partial \hat{u}_{nco} \partial dper}$ | $>0$<br>$P > F(1{,}28866) \cong .231$ | $<0$<br>$P > F(1{,}27692) \cong .153$ | **Nonmonotonic**<br>$P > F(1{,}26570) \cong .316$ |
| $\frac{\partial^2 \hat{ur}^2}{\partial \hat{u}_{\Delta lla} \partial dper}$ | $>0$<br>$P > F(1{,}28866) \cong .901$ | **Nonmonotonic**<br>$P > F(1{,}27692) \cong .284$ | $>0$<br>$P > F(1{,}26570) \cong .928$ |

(1) Tests of the significance of marginal effects, e.g., $\gamma_{\hat{u}_{nco}} + \gamma_{\hat{u}^2_{nco}} = 0$, $\delta_{dper\cdot\hat{u}_{nco}} + \delta_{dper\cdot\hat{u}^2_{nco}} = 0$ based on the notation in equations [10] and [11], take the form of a Wald $F$-test: $P(F_{1,n-k} > F^{obs}_{1,n-k})$.

(2) Sign of estimated marginal effect based on applicable parameter estimates in Table 8.3 for equation [10] evaluated on central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions: $\hat{u}_{nco,mid95\%} \cong [-.0059, .0053]$ and $\hat{u}_{\Delta lla,mid95\%} \cong [-.0031, .0032]$. "Nonmonotonic" denotes nonmonotonic estimated marginal effect evaluated using the central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions; e.g., $\partial \hat{ur}^2 / \partial \hat{u}_{nco} > 0$ for some $\hat{u}_{nco,mid95\%}$.

**Table 7.1 Equity share volume ($\hat{uv}_{it}$) hypotheses tests: FGLS estimated marginal effects and related significance tests**

| Marginal effect | Sign of estimated marginal effect[1,2] based on parameter estimates from: Full data set | Reduced data set based on central 95% of *dependent variable* sample distribution | Reduced data set based on central 95% of *independent variable* sample distributions |
|---|---|---|---|
| **Hypothesis 3.1: Full period marginal effect on unexpected share volume < 0** | | | |
| $\frac{\partial \hat{uv}}{\partial \hat{u}_{nco}}$ | $< 0$<br>$P > F(1{,}29066) \cong .618$ | $< 0$<br>$P > F(1{,}27692) \cong .123$ | **Nonmonotonic**<br>$P > F(1{,}26753) \cong .936$ |
| $\frac{\partial \hat{uv}}{\partial \hat{u}_{\Delta lla}}$ | **Nonmonotonic**<br>$P > F(1{,}29066) \cong .576$ | **Nonmonotonic**<br>$P > F(1{,}27692) \cong .001$ | **Nonmonotonic**<br>$P > F(1{,}26753) \cong .987$ |
| **Hypothesis 3.2: Disclosure period marginal effect on unexpected share volume > 0** | | | |
| $\frac{\partial^2 \hat{uv}}{\partial \hat{u}_{nco} \partial dper}$ | $> 0$<br>$P > F(1{,}29066) \cong .106$ | $> 0$<br>$P > F(1{,}27692) \cong .122$ | **Nonmonotonic**<br>$P > F(1{,}26753) \cong .788$ |
| $\frac{\partial^2 \hat{uv}}{\partial \hat{u}_{\Delta lla} \partial dper}$ | **Nonmonotonic**<br>$P > F(1{,}29066) \cong .176$ | **Nonmonotonic**<br>$P > F(1{,}27692) \cong .075$ | **Nonmonotonic**<br>$P > F(1{,}26753) \cong .830$ |

(1) Tests of the significance of marginal effects, e.g., $\gamma_{\hat{u}_{nco}} + \gamma_{\hat{u}^2_{nco}} = 0$, $\delta_{dper \cdot \hat{u}_{nco}} + \delta_{dper \cdot \hat{u}^2_{nco}} = 0$ based on the notation in equations [10] and [11], take the form of a Wald $F$-test: $\mathrm{P}(F_{1,n-k} > F^{obs}_{1,n-k})$.

(2) Sign of estimated marginal effect based on applicable parameter estimates in Table 9.1 for equation [11] evaluated on central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions: $\hat{u}_{nco,mid95\%} \cong [-.0059, .0053]$ and $\hat{u}_{\Delta lla,mid95\%} \cong [-.0031, .0032]$. "Nonmonotonic" denotes nonmonotonic estimated marginal effect evaluated using the central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions; e.g., $\partial \hat{uv} / \partial \hat{u}_{nco} > 0$ for some $\hat{u}_{nco,mid95\%}$.

**Table 7.2 Equity share volume ($\hat{uv}_{it}$) hypotheses tests: LAD estimated marginal effects and related significance tests**

| Marginal effect | Sign of estimated marginal effect[1,2] based on parameter estimates from | | |
|---|---|---|---|
| | Full data set | Reduced data set based on central 95% of *dependent variable* sample distribution | Reduced data set based on central 95% of *independent variable* sample distributions |
| **Hypothesis 3.1: Full period marginal effect on unexpected share volume < 0** | | | |
| $\frac{\partial \hat{uv}}{\partial \hat{u}_{nco}}$ | $<0$<br>$P > F(1,29066) \cong .000$ | $<0$<br>$P > F(1,27692) \cong .000$ | **Nonmonotonic**<br>$P > F(1,26753) \cong .010$ |
| $\frac{\partial \hat{uv}}{\partial \hat{u}_{\Delta lla}}$ | **Nonmonotonic**<br>$P > F(1,29066) \cong .006$ | **Nonmonotonic**<br>$P > F(1,27692) \cong .000$ | **Nonmonotonic**<br>$P > F(1,26753) \cong .322$ |
| **Hypothesis 3.2: Disclosure period marginal effect on unexpected share volume > 0** | | | |
| $\frac{\partial^2 \hat{uv}}{\partial \hat{u}_{nco} \partial dper}$ | $>0$<br>$P > F(1,29066) \cong .236$ | $>0$<br>$P > F(1,27692) \cong .106$ | **Nonmonotonic**<br>$P > F(1,26753) \cong .416$ |
| $\frac{\partial^2 \hat{uv}}{\partial \hat{u}_{\Delta lla} \partial dper}$ | $>0$<br>$P > F(1,29066) \cong .801$ | **Nonmonotonic**<br>$P > F(1,27692) \cong .000$ | **Nonmonotonic**<br>$P > F(1,26753) \cong .425$ |

(1) Tests of the significance of marginal effects, e.g., $\gamma_{\hat{u}_{nco}} + \gamma_{\hat{u}^2_{nco}} = 0$, $\delta_{dper \cdot \hat{u}_{nco}} + \delta_{dper \cdot \hat{u}^2_{nco}} = 0$ based on the notation in equations [10] and [11], take the form of a Wald $F$-test: $P(F_{1,n-k} > F^{obs}_{1,n-k})$.

(2) Sign of estimated marginal effect based on applicable parameter estimates in Table 9.2 for equation [11] evaluated on central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions: $\hat{u}_{nco,mid95\%} \cong [-.0059, .0053]$ and $\hat{u}_{\Delta lla,mid95\%} \cong [-.0031, .0032]$. "Nonmonotonic" denotes nonmonotonic estimated marginal effect evaluated using the central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions; e.g., $\partial \hat{uv} / \partial \hat{u}_{nco} > 0$ for some $\hat{u}_{nco,mid95\%}$.

**Table 7.3 Equity share volume ($\hat{uv}_{it}$) hypotheses tests:**
**Prais-Winsten estimated marginal effects and related significance tests**

| Marginal effect | Sign of estimated marginal effect[1,2] based on parameter estimates from | | |
|---|---|---|---|
| | Full data set | Reduced data set based on central 95% of *dependent variable* sample distribution | Reduced data set based on central 95% of *independent variable* sample distributions |
| **Hypothesis 3.1: Full period marginal effect on unexpected share volume < 0** | | | |
| $\frac{\partial \hat{uv}}{\partial \hat{u}_{nco}}$ | $<0$ <br> $P > F(1{,}29066) \cong .652$ | $<0$ <br> $P > F(1{,}27692) \cong .154$ | **Nonmonotonic** <br> $P > F(1{,}26753) \cong .913$ |
| $\frac{\partial \hat{uv}}{\partial \hat{u}_{\Delta lla}}$ | **Nonmonotonic** <br> $P > F(1{,}29066) \cong .398$ | **Nonmonotonic** <br> $P > F(1{,}27692) \cong .000$ | **Nonmonotonic** <br> $P > F(1{,}26753) \cong .984$ |
| **Hypothesis 3.2: Disclosure period marginal effect on unexpected share volume > 0** | | | |
| $\frac{\partial^2 \hat{uv}}{\partial \hat{u}_{nco} \partial dper}$ | $>0$ <br> $P > F(1{,}29066) \cong .131$ | $>0$ <br> $P > F(1{,}27692) \cong .139$ | **Nonmonotonic** <br> $P > F(1{,}26753) \cong .768$ |
| $\frac{\partial^2 \hat{uv}}{\partial \hat{u}_{\Delta lla} \partial dper}$ | **Nonmonotonic** <br> $P > F(1{,}29066) \cong .020$ | **Nonmonotonic** <br> $P > F(1{,}27692) \cong .009$ | **Nonmonotonic** <br> $P > F(1{,}26753) \cong .846$ |

(1) Tests of the significance of marginal effects, e.g., $\gamma_{\hat{u}_{nco}} + \gamma_{\hat{u}^2_{nco}} = 0$, $\delta_{dper \cdot \hat{u}_{nco}} + \delta_{dper \cdot \hat{u}^2_{nco}} = 0$ based on the notation in equations [10] and [11], take the form of a Wald $F$-test: $\mathrm{P}(F_{1,n-k} > F^{obs}_{1,n-k})$.

(2) Sign of estimated marginal effect based on applicable parameter estimates in Table 9.3 for equation [11] evaluated on central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions: $\hat{u}_{nco,mid95\%} \cong [-.0059, .0053]$ and $\hat{u}_{\Delta lla,mid95\%} \cong [-.0031, .0032]$. "Nonmonotonic" denotes nonmonotonic estimated marginal effect evaluated using the central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions; e.g., $\partial \hat{uv} / \partial \hat{u}_{nco} > 0$ for some $\hat{u}_{nco,mid95\%}$.

**Table 8.1 Equity return variance ($\hat{ur}_{it}^2$) model FGLS estimation results**

| Independent variable | Full data set: Parameter estimate | Full data set: Standard error | Reduced data set based on central 95% of *dependent variable* sample distribution: Parameter estimate | Reduced data set based on central 95% of *dependent variable* sample distribution: Standard error | Reduced data set based on central 95% of *independent variable* sample distributions: Parameter estimate | Reduced data set based on central 95% of *independent variable* sample distributions: Standard error |
|---|---|---|---|---|---|---|
| Intercept | .0003 | .0000*** | .0002 | .0000*** | .0006 | .0000*** |
| *plle* | –.0094 | .0012*** | –.0027 | .0006*** | –.0400 | .0037*** |
| $plle^2$ | .1530 | .0400** | .0963 | .0172*** | .8733 | .0862*** |
| $\Delta npl$ | .0071 | .0025*** | .0006 | .0004* | .0101 | .0033*** |
| $\Delta npl^2$ | .1191 | .0566*** | .0233 | .0093** | .3333 | .1436** |
| $\hat{u}_{nco}$ | –.0189 | .0021*** | –.0050 | .0007*** | –.0287 | .0040*** |
| $\hat{u}^2_{nco}$ | .6102 | .0650*** | .1490 | .0209*** | 5.7503 | 1.1571*** |
| $\hat{u}_{\Delta lla}$ | –.0098 | .0023*** | –.0029 | .0009*** | –.0043 | .0038 |
| $\hat{u}^2_{\Delta lla}$ | –.7664 | .3435** | –.3079 | .1362** | .0360 | 2.6527 |
| *dper* | –.0000 | .0000 | .0000 | .0000* | –.0000 | .0001 |
| $dper \cdot plle$ | –.0005 | .0037 | –.0014 | .0016 | –.0020 | .0110 |
| $dper \cdot plle^2$ | .1531 | .1371 | .0142 | .0508 | .1936 | .3016 |
| $dper \cdot \Delta npl$ | –.0058 | .0036 | .0006 | .0013 | –.0069 | .0043 |
| $dper \cdot \Delta npl^2$ | –.0561 | .0751 | .0288 | .0328 | .0357 | .2161 |
| $dper \cdot \hat{u}_{nco}$ | .0069 | .0055 | –.0012 | .0019 | .0185 | .0086** |
| $dper \cdot \hat{u}^2_{nco}$ | –.2473 | .1548 | .0764 | .0645 | –3.6591 | 2.7223 |
| $dper \cdot \hat{u}_{\Delta lla}$ | .0064 | .0055 | .0013 | .0026 | .0093 | .0087 |
| $dper \cdot \hat{u}^2_{\Delta lla}$ | –.2028 | .7788 | –.4360 | .3603 | –.9962 | 6.3419 |
| | $n$ = 28884 | | $n$ = 27710 | | $n$ = 26588 | |
| | $R^2$ = .0044*** | | $R^2$ = .0073*** | | $R^2$ = .0073*** | |

***, **, * Significantly different from zero at $p \leq .01$, $p \leq .05$, $p \leq .10$, respectively. Parameter tests are two-tailed and based on heteroscedasticity-robust standard errors.

**Table 8.2 Equity return variance ($\hat{ur}_{it}^2$) model LAD regression estimation results**

| Independent variables | Full data set: Parameter estimates | Full data set: Standard errors | Reduced data set based on central 95% of *dependent variable* sample distribution: Parameter estimates | Reduced data set based on central 95% of *dependent variable* sample distribution: Standard errors | Reduced data set based on central 95% of *independent variable* sample distributions: Parameter estimates | Reduced data set based on central 95% of *independent variable* sample distributions: Standard errors |
|---|---|---|---|---|---|---|
| Intercept | .0001 | .0000*** | .0001 | .0000*** | .0001 | .0000*** |
| *plle* | −.0015 | .0006*** | −.0009 | .0005* | −.0084 | .0015*** |
| $plle^2$ | .0583 | .0180** | .0461 | .0172*** | .2390 | .0434*** |
| $\Delta npl$ | .0007 | .0003** | .0003 | .0004 | .0007 | .0002*** |
| $\Delta npl^2$ | .0219 | .0077*** | .0110 | .0080 | .0443 | .0129*** |
| $\hat{u}_{nco}$ | −.0026 | .0006*** | −.0015 | .0004*** | −.0015 | .0009* |
| $\hat{u}_{nco}^2$ | .1199 | .0274*** | .0520 | .0250** | .3706 | .1707** |
| $\hat{u}_{\Delta lla}$ | −.0015 | .0006** | −.0011 | .0005** | .0005 | .0009 |
| $\hat{u}_{\Delta lla}^2$ | −.0720 | .1184 | −.0973 | .1043 | −1.3480 | .4607*** |
| *dper* | .0000 | .0000 | .0000 | .0000 | .0001 | .0000* |
| $dper \cdot plle$ | −.0019 | .0020 | −.0019 | .0019 | −.0062 | .0038 |
| $dper \cdot plle^2$ | .0365 | .0688 | .0265 | .0552 | .1915 | .1204 |
| $dper \cdot \Delta npl$ | −.0013 | .0010 | −.0006 | .0008 | −.0009 | .0011 |
| $dper \cdot \Delta npl^2$ | .0033 | .0434 | .0098 | .0285 | .1151 | .0682* |
| $dper \cdot \hat{u}_{nco}$ | −.0008 | .0014 | −.0013 | .0013 | .0003 | .0014 |
| $dper \cdot \hat{u}_{nco}^2$ | .0733 | .1054 | .1370 | .1046 | −1.5136 | .4881*** |
| $dper \cdot \hat{u}_{\Delta lla}$ | .0000 | .0029 | −.0001 | .0015 | .0017 | .0022 |
| $dper \cdot \hat{u}_{\Delta lla}^2$ | −.5198 | .2363** | −.3734 | .2506 | −.7745 | 1.4391 |
| | $n = 28884$ | | $n = 27710$ | | $n = 26588$ | |
| | Pseudo-$R^2$ = .0018 | | Pseudo-$R^2$ = .0018 | | Pseudo-$R^2$ = .0023 | |

***, **, * Significantly different from zero at $p \leq .01$, $p \leq .05$, $p \leq .10$, respectively. Parameter tests are two-tailed and based on bootstrap-resampling estimated standard errors.

**Table 8.3 Equity return variance ($\hat{ur}_{it}^2$) model Prais-Winsten estimation results**

| Independent variables | Full data set: Parameter estimates | Full data set: Standard errors | Reduced data set based on central 95% of *dependent variable* sample distribution: Parameter estimates | Reduced data set based on central 95% of *dependent variable* sample distribution: Standard errors | Reduced data set based on central 95% of *independent variable* sample distributions: Parameter estimates | Reduced data set based on central 95% of *independent variable* sample distributions: Standard errors |
|---|---|---|---|---|---|---|
| $\rho$ | .0020 | .0059 | .0337 | .0060*** | .0078 | .0061 |
| Intercept | .0003 | .0000*** | .0002 | .0000*** | .0006 | .0000*** |
| *plle* | –.0094 | .0021*** | –.0027 | .0005*** | –.0401 | .0046*** |
| $plle^2$ | .1528 | .0597** | .0952 | .0150*** | .8756 | .1192*** |
| $\Delta npl$ | .0071 | .0013*** | .0006 | .0003* | .0100 | .0015*** |
| $\Delta npl^2$ | .1191 | .0338*** | .0223 | .0085*** | .3330 | .0717*** |
| $\hat{u}_{nco}$ | –.0189 | .0023*** | –.0050 | .0006*** | –.0288 | .0036*** |
| $\hat{u}_{nco}^2$ | .6101 | .0670*** | .1497 | .0172*** | 5.7840 | 1.2083*** |
| $\hat{u}_{\Delta lla}$ | –.0098 | .0034*** | –.0029 | .0008*** | –.0043 | .0055 |
| $\hat{u}_{\Delta lla}^2$ | –.7657 | .5082 | –.2968 | .1284*** | –.0163 | 3.0841 |
| *dper* | –.0000 | .0001 | .0000 | .0000* | –.0000 | .0001 |
| $dper \cdot plle$ | –.0005 | .0065 | –.0015 | .0016 | –.0020 | .0143 |
| $dper \cdot plle^2$ | .1533 | .1843 | .0167 | .0461 | .1963 | .3677 |
| $dper \cdot \Delta npl$ | –.0058 | .0041 | .0006 | .0010 | –.0069 | .0046 |
| $dper \cdot \Delta npl^2$ | –.0564 | .1043 | .0300 | .0259 | .0373 | .2203 |
| $dper \cdot \hat{u}_{nco}$ | .0069 | .0072 | –.0011 | .0018 | .0183 | .0111** |
| $dper \cdot \hat{u}_{nco}^2$ | –.2484 | .2072 | .0743 | .0527 | –3.7474 | 3.7208 |
| $dper \cdot \hat{u}_{\Delta lla}$ | .0064 | .0105 | .0014 | .0026 | .0095 | .0171 |
| $dper \cdot \hat{u}_{\Delta lla}^2$ | –.2031 | 1.5708 | –.4265 | .3960 | –.8731 | 9.5099 |
| | $n = 28884$ | | $n = 27710$ | | $n = 26588$ | |
| | $R^2 = 0.0044$*** | | $R^2 = 0.0072$*** | | $R^2 = 0.0073$*** | |

***, **, * Significantly different from zero at $p \leq .01$, $p \leq .05$, $p \leq .10$, respectively. Parameter tests are two-tailed and based on Prais-Winsten FGLS estimated standard errors.

**Table 9.1** **Equity share volume ($\hat{u}v_{it}$) model FGLS estimation results**

| Independent variable | Full data set: Parameter estimate | Full data set: Standard error | Reduced data set based on central 95% of *dependent variable* sample distribution: Parameter estimate | Reduced data set based on central 95% of *dependent variable* sample distribution: Standard error | Reduced data set based on central 95% of *independent variable* sample distributions: Parameter estimate | Reduced data set based on central 95% of *independent variable* sample distributions: Standard error |
|---|---|---|---|---|---|---|
| Intercept | .0512 | .0709 | –.2974 | .0500*** | .0850 | .1741 |
| *plle* | –5.5551 | 6.9402 | 9.6933 | 5.2664* | –9.0050 | 18.5798 |
| $plle^2$ | 109.5146 | 172.4685 | –58.4197 | 138.5031 | 195.0603 | 432.4086 |
| $\Delta npl$ | –.8225 | 5.6415 | –3.9126 | 2.5512 | –1.8990 | 7.2402 |
| $\Delta npl^2$ | –6.1293 | 136.9504 | –86.8973 | 67.4794 | –133.9542 | 346.1376 |
| $\hat{u}_{nco}$ | –3.6542 | 7.0077 | –5.3851 | 4.5863 | 1.6930 | 8.2981 |
| $\hat{u}^2_{nco}$ | 83.3542 | 166.4177 | 169.9128 | 111.0722 | –328.0400 | 4052.2540 |
| $\hat{u}_{\Delta lla}$ | –3.8446 | 11.0495 | –1.9402 | 7.2029 | .5172 | 11.9282 |
| $\hat{u}^2_{\Delta lla}$ | –1141.084 | 2045.599 | –4283.212 | 1288.579*** | –131.5254 | 8054.2790 |
| *dper* | –.4995 | .1773** | –.2328 | .1446 | –.8597 | .3944** |
| $dper \cdot plle$ | 52.2018 | 17.2061** | 35.5323 | 15.0489** | 89.0850 | 41.2717** |
| $dper \cdot plle^2$ | –1015.576 | 447.0096** | –995.4857 | 386.0642*** | –1923.771 | 967.0371** |
| $dper \cdot \Delta npl$ | –1.5925 | 11.0119 | 13.7927 | 8.3836* | 4.3338 | 12.2374 |
| $dper \cdot \Delta npl^2$ | –153.6676 | 255.7221 | 173.4291 | 200.4841 | 637.0107 | 652.1034 |
| $dper \cdot \hat{u}_{nco}$ | 36.3998 | 21.6999** | 29.1025 | 14.5982** | –15.0889 | 29.0713 |
| $dper \cdot \hat{u}^2_{nco}$ | –828.9889 | 512.1087 | –551.1934 | 351.9137 | 2720.4700 | 10077.77 |
| $dper \cdot \hat{u}_{\Delta lla}$ | 28.4797 | 40.4329 | 12.6574 | 21.3302 | –6.5728 | 33.8381 |
| $dper \cdot \hat{u}^2_{\Delta lla}$ | 9425.5860 | 6965.6750 | 7083.0460 | 3990.972* | 4545.9330 | 21199.16 |
| | $n = 29084$ | | $n = 27710$ | | $n = 26771$ | |
| | $R^2 = .0006$ | | $R^2 = .0030$*** | | $R^2 = .0004$ | |

***, **, * Significantly different from zero at $p \leq .01$, $p \leq .05$, $p \leq .10$, respectively. Parameter tests are two-tailed and based on heteroscedasticity-robust standard errors.

**Table 9.2 Equity share volume ($\hat{uv}_{it}$) model LAD regression estimation results**

| Independent variables | Full data set: Parameter estimates | Full data set: Standard errors | Reduced data set based on central 95% of *dependent variable* sample distribution: Parameter estimates | Reduced data set based on central 95% of *dependent variable* sample distribution: Standard errors | Reduced data set based on central 95% of *independent variable* sample distributions: Parameter estimates | Reduced data set based on central 95% of *independent variable* sample distributions: Standard errors |
|---|---|---|---|---|---|---|
| Intercept | –.4049 | .0442*** | –.4482 | .0430*** | –.4359 | .0569*** |
| *plle* | 13.8479 | 5.2815*** | 15.1617 | 4.6539*** | 15.3013 | 6.4549** |
| $plle^2$ | –238.7819 | 148.5350 | –248.7474 | 126.0201** | –299.7498 | 183.7157 |
| $\Delta npl$ | 4.9128 | 2.1297** | 3.2777 | 2.2774 | –1.3307 | 2.4008 |
| $\Delta npl^2$ | 43.5951 | 5.8461 | 6.2695 | 70.3514 | –592.8600 | 156.5212*** |
| $\hat{u}_{nco}$ | –13.8917 | 1.3104*** | –14.7730 | 2.2484*** | –23.7757 | 4.8231*** |
| $\hat{u}^2_{nco}$ | 410.1298 | 40.1045*** | 427.3518 | 56.8285*** | 3564.555 | 1329.451*** |
| $\hat{u}_{\Delta lla}$ | –3.0494 | 4.3403 | –2.2821 | 6.6906 | –9.4921 | 7.6849 |
| $\hat{u}^2_{\Delta lla}$ | –3589.942 | 1292.74*** | –4507.475 | 1191.052** | 4475.782 | 3562.089 |
| *dper* | –.1990 | .0805** | –.1821 | .1142 | –.2932 | .3276 |
| $dper \cdot plle$ | 29.2582 | 9.4877*** | 28.4503 | 9.7359*** | 38.1042 | 31.4534 |
| $dper \cdot plle^2$ | –910.7148 | 406.774** | –888.8962 | 349.1630** | –1091.865 | 852.8507 |
| $dper \cdot \Delta npl$ | 4.5174 | 6.8527 | 6.1078 | 6.1998 | 15.0654 | 21.6215 |
| $dper \cdot \Delta npl^2$ | 14.7956 | 174.256 | 67.1311 | 158.9010 | 1391.620 | 880.9906 |
| $dper \cdot \hat{u}_{nco}$ | 16.0926 | 12.5537 | 20.7500 | 30.3331 | –3.9819 | 47.4513 |
| $dper \cdot \hat{u}^2_{nco}$ | –287.7700 | 324.7623 | –390.7037 | 697.495 | 3865.241 | 18607.17 |
| $dper \cdot \hat{u}_{\Delta lla}$ | 14.2585 | 25.6545 | 22.4755 | 38.5729 | –1.6383 | 29.4970 |
| $dper \cdot \hat{u}^2_{\Delta lla}$ | 1066.624 | 6112.594 | 1393.776 | 6388.413 | –10202.82 | 24714.97 |
| | $n = 29084$ | | $n = 27710$ | | $n = 26771$ | |
| | Pseudo-$R^2$ = 0.0027 | | Pseudo-$R^2$ = 0.0036 | | Pseudo-$R^2$ = 0.0031 | |

***, **, * Significantly different from zero at $p \leq .01$, $p \leq .05$, $p \leq .10$, respectively. Parameter tests are two-tailed and based on bootstrap-resampling estimated standard errors.

**Table 9.3 Equity share volume ($\hat{u}v_{it}$) model Prais-Winsten estimation results**

| Independent variables | Full data set: Parameter estimates | Full data set: Standard errors | Reduced data set based on central 95% of *dependent variable* sample distribution: Parameter estimates | Reduced data set based on central 95% of *dependent variable* sample distribution: Standard errors | Reduced data set based on central 95% of *independent variable* sample distributions: Parameter estimates | Reduced data set based on central 95% of *independent variable* sample distributions: Standard errors |
|---|---|---|---|---|---|---|
| $\rho$ | −.0184 | .0059$^{***}$ | −.0008 | .0060 | −.0042 | .0061 |
| Intercept | .0514 | .0533 | −.2974 | .0357$^{***}$ | .0854 | .1042 |
| $plle$ | −5.5903 | 5.4481 | 9.6973 | 3.6390$^{***}$ | −9.0414 | 11.3662 |
| $plle^2$ | 110.1214 | 154.2623 | −58.5648 | 102.9188 | 195.6442 | 292.7288 |
| $\Delta npl$ | −.7370 | 3.3943 | −3.9160 | 2.2730$^{*}$ | −1.9198 | 3.6794 |
| $\Delta npl^2$ | −6.1549 | 87.3798 | −87.0204 | 58.3305 | −134.8521 | 175.8357 |
| $\hat{u}_{nco}$ | −3.6280 | 5.9901 | −5.3871 | 4.0209 | 1.6710 | 8.8808 |
| $\hat{u}^2_{nco}$ | 79.6817 | 173.3257 | 170.0085 | 118.4645 | −326.3606 | 2967.233 |
| $\hat{u}_{\Delta lla}$ | −3.6836 | 8.7615 | −1.9470 | 5.8207 | .5540 | 13.5279 |
| $\hat{u}^2_{\Delta lla}$ | −1107.425 | 1312.320 | −4283.602 | 881.7140$^{***}$ | −156.0391 | 7577.348 |
| $dper$ | −.5032 | .1653$^{***}$ | −.2330 | .1084$^{**}$ | −.8588 | .3227$^{***}$ |
| $dper \cdot plle$ | 52.6157 | 16.9157$^{***}$ | 35.5301 | 11.0482$^{***}$ | 88.9916 | 35.2024$^{**}$ |
| $dper \cdot plle^2$ | −1026.236 | 478.0977$^{**}$ | −995.2702 | 316.7511$^{***}$ | −1921.675 | 905.6496$^{**}$ |
| $dper \cdot \Delta npl$ | −1.8321 | 10.5197 | 13.7892 | 7.0062$^{**}$ | 4.4381 | 11.4000 |
| $dper \cdot \Delta npl^2$ | −157.8316 | 270.3536 | 173.5742 | 177.9597 | 640.6496 | 542.8893 |
| $dper \cdot \hat{u}_{nco}$ | 36.1458 | 18.5783$^{*}$ | 29.1131 | 12.4322$^{**}$ | −14.9894 | 27.3658 |
| $dper \cdot \hat{u}^2_{nco}$ | −825.6404 | 537.2879 | −551.1440 | 362.4471 | 2712.945 | 9167.700 |
| $dper \cdot \hat{u}_{\Delta lla}$ | 28.3577 | 27.1862 | 12.6662 | 18.0006 | −6.3437 | 41.9472 |
| $dper \cdot \hat{u}^2_{\Delta lla}$ | 9501.947 | 4071.591$^{**}$ | 7080.305 | 2718.483$^{***}$ | 4555.929 | 23420.18 |
| | $n = 29084$ | | $n = 27710$ | | $n = 26771$ | |
| | $R^2 = .0006$ | | $R^2 = 0.0030^{***}$ | | $R^2 = 0.0004$ | |

$^{***}$, $^{**}$, $^{*}$ Significantly different from zero at $p \leq .01$, $p \leq .05$, $p \leq .10$, respectively. Parameter tests are two-tailed and based on Prais-Winsten FGLS estimated standard errors.

**Table 10.1 Expectations model sensitivity analysis of $\hat{ur}_{it}^2$ hypotheses tests: FGLS estimated marginal effects and related significance tests**

| Marginal effect | Sign of estimated marginal effect[1,2] based on parameter estimates from | | |
|---|---|---|---|
| | Full data set | Reduced data set based on central 95% of *dependent variable* sample distribution | Reduced data set based on central 95% of *independent variable* sample distributions |
| **Hypothesis 2.1: Full period marginal effect on equity return variance < 0** | | | |
| $\frac{\partial \hat{ur}^2}{\partial \hat{u}_{nco}}$ | $< 0$<br>$P > F(1,28858) \cong .000$ | $< 0$<br>$P > F(1,27684) \cong .000$ | **Nonmonotonic**<br>$P > F(1,26562) \cong .000$ |
| $\frac{\partial \hat{ur}^2}{\partial \hat{u}_{\Delta lla}}$ | $< 0$<br>$P > F(1,28858) \cong .034$ | **Nonmonotonic**<br>$P > F(1,27684) \cong .022$ | $< 0$<br>$P > F(1,26562) \cong .778$ |
| **Hypothesis 2.2: Disclosure period marginal effect on equity return variance > 0** | | | |
| $\frac{\partial^2 \hat{ur}^2}{\partial \hat{u}_{nco} \partial dper}$ | $> 0$<br>$P > F(1,28858) \cong .029$ | $< 0$<br>$P > F(1,27684) \cong .357$ | **Nonmonotonic**<br>$P > F(1,26562) \cong .362$ |
| $\frac{\partial^2 \hat{ur}^2}{\partial \hat{u}_{\Delta lla} \partial dper}$ | $> 0$<br>$P > F(1,28858) \cong .325$ | **Nonmonotonic**<br>$P > F(1,27684) \cong .500$ | **Nonmonotonic**<br>$P > F(1,26562) \cong .742$ |

(1) Tests of the significance of marginal effects, e.g., $\gamma_{\hat{u}_{nco}} + \gamma_{\hat{u}^2_{nco}} = 0$, $\delta_{dper \cdot \hat{u}_{nco}} + \delta_{dper \cdot \hat{u}^2_{nco}} = 0$ based on the notation in equations [10] and [11], take the form of a Wald $F$-test: $P(F_{1,n-k} > F^{obs}_{1,n-k})$.

(2) Sign of estimated marginal effect based on applicable parameter estimates in Table 8.1 for equation [10] evaluated on central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions: $\hat{u}_{nco,mid95\%} \cong [-.0059, .0053]$ and $\hat{u}_{\Delta lla,mid95\%} \cong [-.0031, .0032]$. "Nonmonotonic" denotes nonmonotonic estimated marginal effect evaluated using the central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions; e.g., $\partial \hat{ur}^2 / \partial \hat{u}_{nco} > 0$ for some $\hat{u}_{nco,mid95\%}$.

**Table 10.2 Expectations model sensitivity analysis of $\hat{uv}_{it}$ hypotheses tests: FGLS estimated marginal effects and related significance tests**

| Marginal effect | Sign of estimated marginal effect[1,2] based on parameter estimates from | | |
|---|---|---|---|
| | Full data set | Reduced data set based on central 95% of *dependent variable* sample distribution | Reduced data set based on central 95% of *independent variable* sample distributions |
| **Hypothesis 3.1: Full period marginal effect on unexpected share volume < 0** | | | |
| $\dfrac{\partial \hat{ur}^2}{\partial \hat{u}_{nco}}$ | $<0$<br>$P > F(1{,}29058) \cong .805$ | $<0$<br>$P > F(1{,}27684) \cong .118$ | **Nonmonotonic**<br>$P > F(1{,}26745) \cong .932$ |
| $\dfrac{\partial \hat{ur}^2}{\partial \hat{u}_{\Delta lla}}$ | $<0$<br>$P > F(1{,}29058) \cong .939$ | **Nonmonotonic**<br>$P > F(1{,}27684) \cong .110$ | **Nonmonotonic**<br>$P > F(1{,}26745) \cong .931$ |
| **Hypothesis 3.2: Disclosure period marginal effect on unexpected share volume > 0** | | | |
| $\dfrac{\partial^2 \hat{ur}^2}{\partial \hat{u}_{nco} \partial dper}$ | $>0$<br>$P > F(1{,}29058) \cong .320$ | $>0$<br>$P > F(1{,}27684) \cong .214$ | **Nonmonotonic**<br>$P > F(1{,}26745) \cong .823$ |
| $\dfrac{\partial^2 \hat{ur}^2}{\partial \hat{u}_{\Delta lla} \partial dper}$ | $>0$<br>$P > F(1{,}29058) \cong .781$ | **Nonmonotonic**<br>$P > F(1{,}27684) \cong .523$ | **Nonmonotonic**<br>$P > F(1{,}26745) \cong .939$ |

(1) Tests of the significance of marginal effects, e.g., $\gamma_{\hat{u}_{nco}} + \gamma_{\hat{u}^2_{nco}} = 0$, $\delta_{dper \cdot \hat{u}_{nco}} + \delta_{dper \cdot \hat{u}^2_{nco}} = 0$ based on the notation in equations [10] and [11], take the form of a Wald $F$-test: $P(F_{1,n-k} > F^{obs}_{1,n-k})$.

(2) Sign of estimated marginal effect based on applicable parameter estimates in Table 8.1 for equation [10] evaluated on central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions: $\hat{u}_{nco,mid95\%} \cong [-.0059, .0053]$ and $\hat{u}_{\Delta lla,mid95\%} \cong [-.0031, .0032]$. "Nonmonotonic" denotes nonmonotonic estimated marginal effect evaluated using the central 95% of the $\hat{u}_{nco}$ and $\hat{u}_{\Delta lla}$ sample distributions; e.g., $\partial \hat{ur}^2 / \partial \hat{u}_{nco} > 0$ for some $\hat{u}_{nco,mid95\%}$.

**Table 11.1 Equity return variance ($\hat{ur}_{it}^2$) model FGLS estimation results with additional conditioning on expected *llp* components ($\hat{E}nco$ and $\hat{E}\Delta lla$)**

| Independent variable | Full data set: Parameter estimate | Full data set: Standard error | Reduced data set based on central 95% of *dependent variable* sample distribution: Parameter estimate | Reduced data set based on central 95% of *dependent variable* sample distribution: Standard error | Reduced data set based on central 95% of *independent variable* sample distributions: Parameter estimate | Reduced data set based on central 95% of *independent variable* sample distributions: Standard error |
|---|---|---|---|---|---|---|
| Intercept | .0003 | .0000*** | .0001 | .0000*** | .0006 | .0001*** |
| *plle* | –.0002 | .0041 | .0004 | .0012 | –.0335 | .0081*** |
| $plle^2$ | –.5153 | .1352*** | –.0985 | .0397** | .3220 | .2471 |
| $\Delta npl$ | .0091 | .0028*** | .0010 | .0004*** | .0140 | .0032*** |
| $\Delta npl^2$ | .0323 | .0492 | –.0001 | .0101 | .3822 | .1333*** |
| $\hat{u}_{nco}$ | –.0154 | .0025*** | –.0037 | .0007*** | –.0274 | .0040*** |
| $\hat{u}_{nco}^2$ | .4797 | .0769*** | .1063 | .0224*** | 4.9156 | 1.1929*** |
| $\hat{u}_{\Delta lla}$ | -.0084 | .0024*** | –.0021 | .0009** | –.0079 | .0037** |
| $\hat{u}_{\Delta lla}^2$ | –1.2228 | .5803** | –.3879 | .1698** | .7728 | 2.7098 |
| *dper* | –.0001 | .0001 | .0000 | .0000 | –.0001 | .0001 |
| $dper \cdot plle$ | .0062 | .0084 | .0002 | .0034 | .0137 | .0210 |
| $dper \cdot plle^2$ | –.1613 | .3425 | –.0334 | .1204 | –.3138 | .6815 |
| $dper \cdot \Delta npl$ | –.0070 | .0036* | .0005 | .0013 | –.0082 | .0049* |
| $dper \cdot \Delta npl^2$ | –.0639 | .0790 | .0275 | .0325 | .1149 | .2569 |
| $dper \cdot \hat{u}_{nco}$ | .0122 | .0057** | –.0008 | .0020 | .0152 | .0088* |
| $dper \cdot \hat{u}_{nco}^2$ | –.3848 | .1761** | .0633 | .0693 | –2.6656 | 2.9090 |
| $dper \cdot \hat{u}_{\Delta lla}$ | .0116 | .0058** | .0018 | .0027 | .0123 | .0088 |
| $dper \cdot \hat{u}_{\Delta lla}^2$ | 1.0916 | 1.1195 | –.3294 | .4843 | 2.1289 | 6.5122 |
| | $n = 28884$ | | $n = 27710$ | | $n = 26588$ | |
| | $R^2 = .0007$*** | | $R^2 = .0108$*** | | $R^2 = .0095$*** | |

***, **, * Significantly different from zero at $p \leq .01$, $p \leq .05$, $p \leq .10$, respectively. Parameter tests are two-tailed and based on heteroscedasticity-robust standard errors. (Parameter estimates and standard errors for $\hat{E}nco$ and $\hat{E}\Delta lla$ are not shown.)

**Table 11.2 Equity share volume ($\hat{ur}_{it}^2$) model FGLS estimation results with additional conditioning on expected *llp* components ($\hat{E}nco$ and $\hat{E}\Delta lla$)**

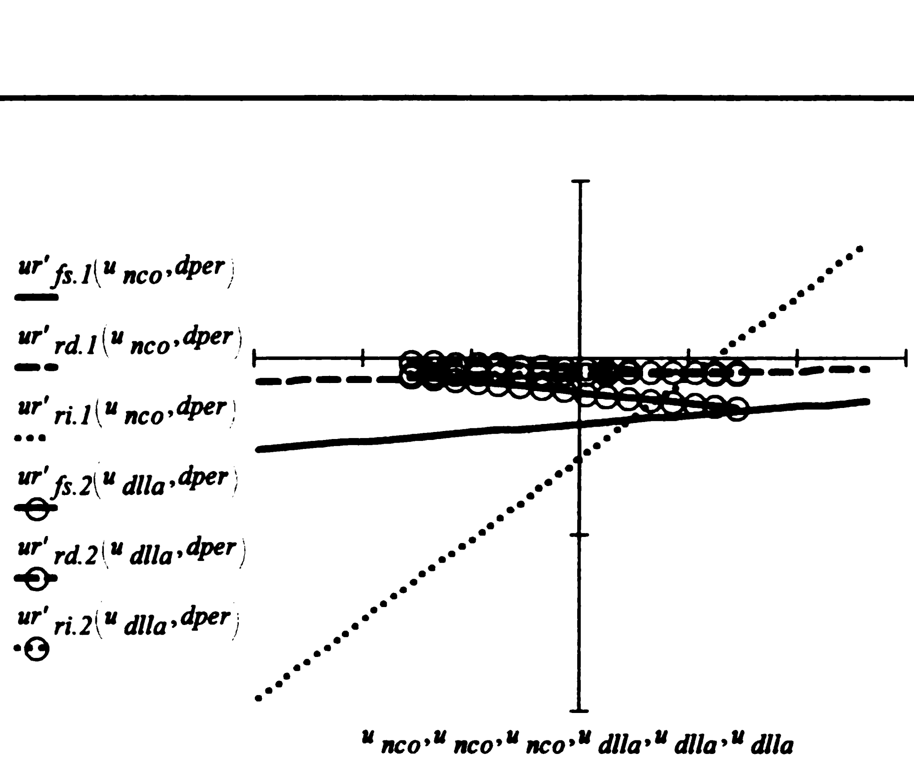
| | Full data set | | Reduced data set based on central 95% of *dependent variable* sample distribution | | Reduced data set based on central 95% of *independent variable* sample distributions | |
|---|---|---|---|---|---|---|
| Independent variable | Parameter estimate | Standard error | Parameter estimate | Standard error | Parameter estimate | Standard error |
| Intercept | .0565 | .0997 | −.2847 | .0640*** | .1373 | .2592 |
| *plle* | −6.1603 | 13.5333 | 5.1439 | 9.0966 | −17.4095 | 35.1819 |
| $plle^2$ | 102.0267 | 392.6803 | 278.5092 | 289.6346 | 353.5080 | 933.6975 |
| $\Delta npl$ | −1.4989 | 6.2752 | −6.1860 | 2.6654** | −1.3329 | 6.0090 |
| $\Delta npl^2$ | 9.8526 | 122.6756 | −11.2330 | 70.0853 | −99.8478 | 341.0789 |
| $\hat{u}_{nco}$ | −2.2474 | 7.6890 | −5.0651 | 4.8766 | 2.2543 | 8.4760 |
| $\hat{u}_{nco}^2$ | 46.4738 | 186.6758 | 184.4598 | 119.4560 | −356.1642 | 4146.3760 |
| $\hat{u}_{\Delta lla}$ | −2.6205 | 11.4947 | −.6074 | 7.4249 | .4864 | 12.3686 |
| $\hat{u}_{\Delta lla}^2$ | −195.5291 | 2577.084 | −2393.429 | 1494.7060 | 666.2982 | 7687.4240 |
| *dper* | −.6114 | .2910** | −.3641 | .1992* | −1.4105 | .6172** |
| $dper \cdot plle$ | 69.5015 | 42.3954 | 57.7359 | 29.1805** | 183.6198 | 85.1982** |
| $dper \cdot plle^2$ | −1271.775 | 1132.62 | −1543.834 | 899.1143* | −3690.436 | 2341.3670 |
| $dper \cdot \Delta npl$ | 4.4447 | 12.2316 | 18.1346 | 9.0818** | 5.1767 | 13.5263 |
| $dper \cdot \Delta npl^2$ | −278.1751 | 274.5694 | 77.0140 | 215.6372 | 860.4665 | 1176.7520 |
| $dper \cdot \hat{u}_{nco}$ | 26.2479 | 24.1597 | 25.4303 | 15.6783 | −24.4201 | 29.4760 |
| $dper \cdot \hat{u}_{nco}^2$ | −578.8285 | 579.0215 | −479.9551 | 380.8089 | 2336.752 | 10343.730 |
| $dper \cdot \hat{u}_{\Delta lla}$ | 19.4398 | 41.9075 | 8.7763 | 21.6655 | −7.4441 | 34.8962 |
| $dper \cdot \hat{u}_{\Delta lla}^2$ | 2204.881 | 7963.404 | 2884.027 | 4532.6740 | −1617.991 | 21081.060 |
| | $n = 29084$ | | $n = 27710$ | | $n = 26771$ | |
| | $R^2 = .0012$ | | $R^2 = .0042$*** | | $R^2 = .0007$ | |

***, **, * Significantly different from zero at $p \leq .01$, $p \leq .05$, $p \leq .10$, respectively. Parameter tests are two-tailed and based on heteroscedasticity-robust standard errors. (Estimated parameters and standard errors for $\hat{E}nco$ and $\hat{E}\Delta lla$ are not shown.)

## Table 12 Descriptive statistics

| Variable | Count | Minimum | Percentiles 2.5% | 50% | 97.5% | Maximum | Mean | Standard deviation |
|---|---|---|---|---|---|---|---|---|
| $\Delta lla$ | 29821 | −.0206 | −.0058 | .0003 | .0033 | .0100 | .0001 | .0025 |
| $\Delta npl$ | 29401 | −.0537 | −.0250 | −.0017 | .0048 | .0231 | −.0035 | .0075 |
| $lla$ | 29821 | .0102 | .0117 | .0170 | .0488 | .1002 | .0199 | .0099 |
| $llp$ | 29821 | −.0256 | −.0021 | .0030 | .0121 | .0598 | .0034 | .0051 |
| $loan$ | 29821 | .1215 | .1495 | .6573 | .7561 | .8284 | .6203 | .1267 |
| $nco$ | 29821 | −.0152 | −.0014 | .0026 | .0110 | .0592 | .0034 | .0048 |
| $npl$ | 29401 | .0000 | .0025 | .0077 | .0306 | .1141 | .0101 | .0105 |
| $plle$ | 29821 | −.0190 | .0069 | .0135 | .0211 | .0388 | .0138 | .0047 |
| $r_{it}$ | 30018 | −.1630 | −.0308 | .0000 | .0341 | .3091 | .0010 | .0162 |
| $r_{mt}$ | 30332 | −.0280 | −.0131 | .0012 | .0131 | .0193 | .0010 | .0061 |
| $\hat{u}_{\Delta lla}$ | 29506 | −.0117 | −.0031 | −.0001 | .0032 | .0082 | .0000 | .0018 |
| $\hat{u}_{nco}$ | 29506 | -.0148 | −.0059 | -.0003 | .0053 | .0473 | .0000 | .0039 |
| $\hat{ur}_{it}$ | 29824 | −.1571 | −.0274 | −.0004 | .0300 | .2992 | .0000 | .0145 |
| $\hat{ur}_{it}^2$ | 29824 | .0000 | .0000 | .0001 | .0013 | .0896 | .0002 | .0008 |
| $\hat{uv}_{it}$ | 30031 | −14.4101 | −2.7098 | −.2785 | 4.5887 | 76.7362 | −.0002 | 2.1432 |

## APPENDIX 2




$$ur'_{fs.1}(u_{nco}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco}} = -.0189 + 1.2204 \cdot \hat{u}_{nco} + .0069 \cdot dper - .4946 \cdot dper \cdot \hat{u}_{nco}$$

$$ur'_{rd.1}(u_{nco}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco}} = -.0050 + .2980 \cdot \hat{u}_{nco} - .0012 \cdot dper + .1528 \cdot dper \cdot \hat{u}_{nco}$$

$$ur'_{ri.1}(u_{nco}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco}} = -.0287 + 11.5006 \cdot \hat{u}_{nco} + .0185 \cdot dper - 7.3182 \cdot dper \cdot \hat{u}_{nco}$$

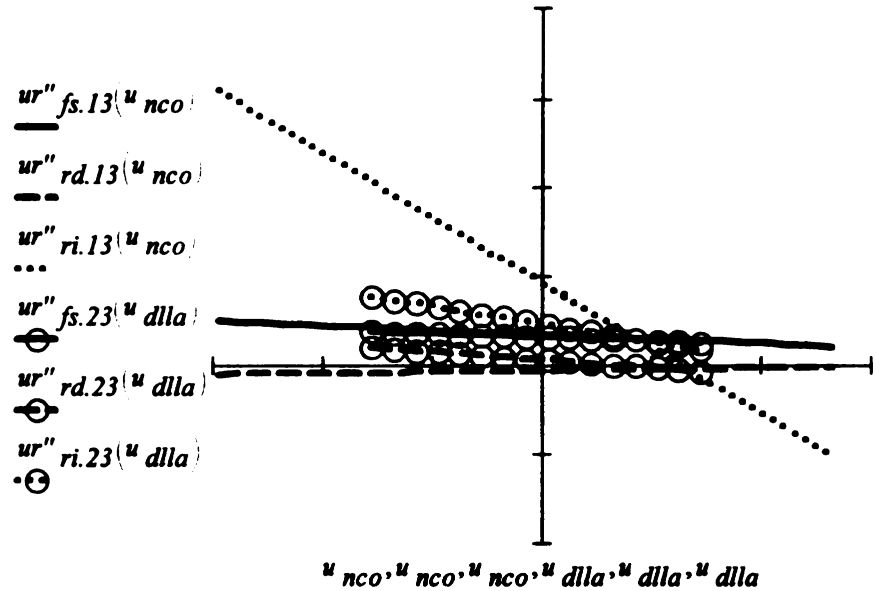
$$ur'_{fs.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla}} = -.0098 - 1.5328 \cdot \hat{u}_{\Delta lla} + .0064 \cdot dper - .4056 \cdot dper \cdot \hat{u}_{\Delta lla}$$

$$ur'_{rd.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla}} = -.0029 - .6158 \cdot \hat{u}_{\Delta lla} + .0013 \cdot dper - .8720 \cdot dper \cdot \hat{u}_{\Delta lla}$$

$$ur'_{ri.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla}} = -.0043 + .0072 \cdot \hat{u}_{\Delta lla} + .0093 \cdot dper - 1.9924 \cdot dper \cdot \hat{u}_{\Delta lla}$$

*fs, rd, ri* denotes marginal effect based on parameter estimates of equity return variance model using full data set, central 95% of *dependent* variable sample distribution, and central 95% of *independent* variable sample distribution, respectively.

**Figure 1.1** **Plot of FGLS estimated long-window marginal effects of loan loss provision discretion ($\hat{u}_{nco}$, $\hat{u}_{\Delta lla}$) on equity return variance ($\hat{ur}^2$).**




$$ur''_{fs.13}(u_{nco}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco} \partial\, dper} = .0069 - .4946 \cdot \hat{u}_{nco}$$

$$ur''_{rd.13}(u_{nco}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco} \partial\, dper} = -.0012 + .1528 \cdot \hat{u}_{nco}$$

$$ur''_{ri.13}(u_{nco}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco} \partial\, dper} = .0185 - 7.3182 \cdot \hat{u}_{nco}$$

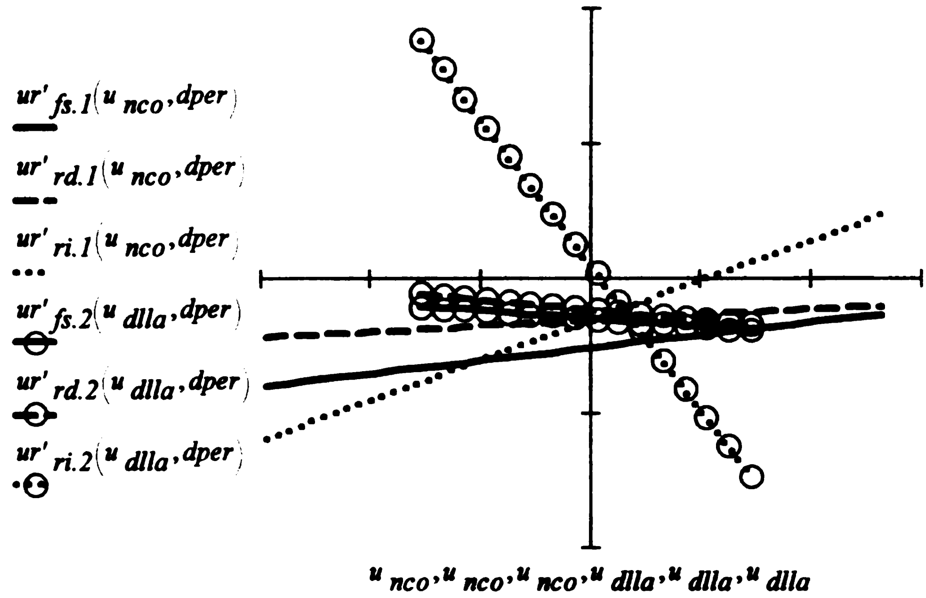
$$ur''_{fs.23}(u_{dlla}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla} \partial\, dper} = .0064 - .4056 \cdot \hat{u}_{\Delta lla}$$

$$ur''_{rd.23}(u_{dlla}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla} \partial\, dper} = .0013 - .8720 \cdot \hat{u}_{\Delta lla}$$

$$ur''_{ri.23}(u_{dlla}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla} \partial\, dper} = .0093 - 1.9924 \cdot \hat{u}_{\Delta lla}$$

*fs, rd, ri* denotes marginal effect based on parameter estimates of equity return variance model using full data set, central 95% of *dependent* variable sample distribution, and central 95% of *independent* variable sample distribution, respectively.

**Figure 1.2** **Plot of FGLS estimated short-window marginal effects of loan loss provision discretion ($\hat{u}_{nco}$, $\hat{u}_{\Delta lla}$) on equity return variance ($\hat{ur}^2$).**




$$ur'_{fs.1}(u_{nco}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco}} = -.0026 + .2398 \cdot \hat{u}_{nco} - .0008 \cdot dper + .1466 \cdot dper \cdot \hat{u}_{nco}$$

$$ur'_{rd.1}(u_{nco}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco}} = -.0015 + .1040 \cdot \hat{u}_{nco} - .0013 \cdot dper + .2740 \cdot dper \cdot \hat{u}_{nco}$$

$$ur'_{ri.1}(u_{nco}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco}} = -.0015 + .7412 \cdot \hat{u}_{nco} + .0003 \cdot dper - 3.0272 \cdot dper \cdot \hat{u}_{nco}$$

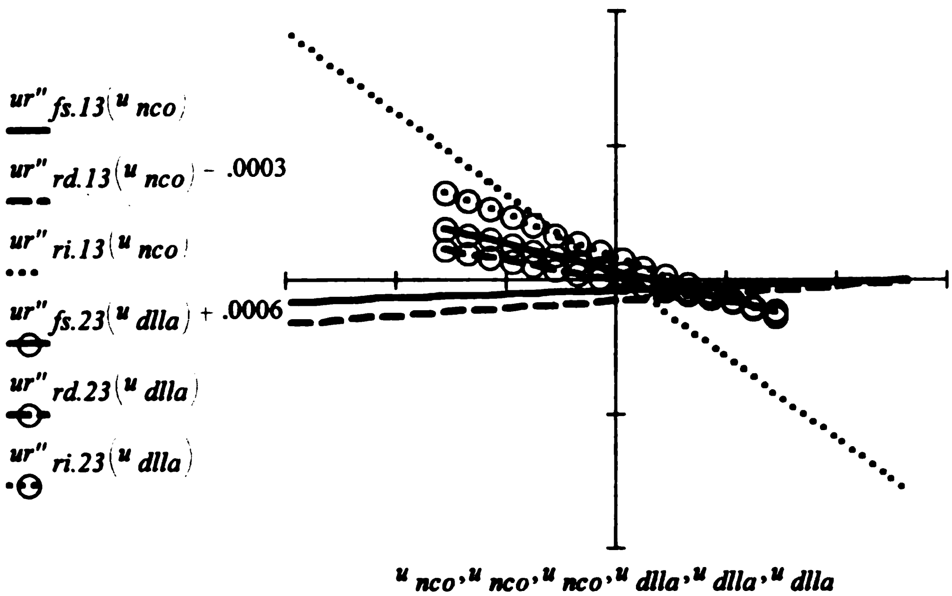
$$ur'_{fs.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla}} = -.0015 - .1440 \cdot \hat{u}_{\Delta lla} - 1.0396 \cdot dper \cdot \hat{u}_{\Delta lla}$$

$$ur'_{rd.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla}} = -.0011 - .1946 \cdot \hat{u}_{\Delta lla} - .0001 \cdot dper - .7468 \cdot dper \cdot \hat{u}_{\Delta lla}$$

$$ur'_{ri.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla}} = .0005 - 2.696 \cdot \hat{u}_{\Delta lla} + .0017 \cdot dper - 1.549 \cdot dper \cdot \hat{u}_{\Delta lla}$$

*fs, rd, ri* denotes marginal effect based on parameter estimates of equity return variance model using full data set, central 95% of *dependent* variable sample distribution, and central 95% of *independent* variable sample distribution, respectively.

**Figure 1.3 Plot of LAD estimated long-window marginal effects of loan loss provision discretion ($\hat{u}_{nco}$, $\hat{u}_{\Delta lla}$) on equity return variance ($\hat{ur}^2$).**




$$ur''_{fs.13}(u_{nco}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco} \partial \, dper} = -.0008 + .1466 \cdot \hat{u}_{nco}$$

$$ur''_{rd.13}(u_{nco}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco} \partial \, dper} = -.0013 + .2740 \cdot \hat{u}_{nco}$$

$$ur''_{ri.13}(u_{nco}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco} \partial \, dper} = .0003 - 3.0272 \cdot \hat{u}_{nco}$$

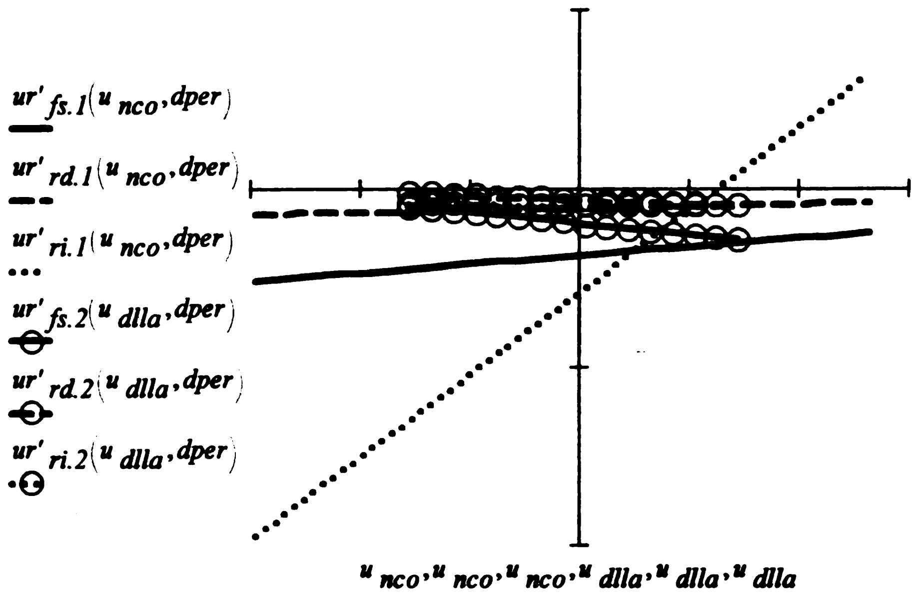
$$ur''_{fs.23}(u_{dlla}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla} \partial \, dper} = -1.0396 \cdot \hat{u}_{\Delta lla}$$

$$ur''_{rd.23}(u_{dlla}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla} \partial \, dper} = -.0001 - .7468 \cdot \hat{u}_{\Delta lla}$$

$$ur''_{ri.23}(u_{dlla}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla} \partial \, dper} = .0017 - 1.549 \cdot \hat{u}_{\Delta lla}$$

*fs, rd, ri* denotes marginal effect based on parameter estimates of equity return variance model using full data set, central 95% of *dependent* variable sample distribution, and central 95% of *independent* variable sample distribution, respectively.

**Figure 1.4 Plot of LAD estimated short-window marginal effects of loan loss provision discretion ($\hat{u}_{nco}$, $\hat{u}_{\Delta lla}$) on equity return variance ($\hat{ur}^2$).**




$$ur'_{fs.1}(u_{nco}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco}} = -.0189 + 1.2202 \cdot \hat{u}_{nco} + .0069 \cdot dper - .4968 \cdot dper \cdot \hat{u}_{nco}$$

$$ur'_{rd.1}(u_{nco}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco}} = -.0050 + .2994 \cdot \hat{u}_{nco} - .0011 \cdot dper + .1486 \cdot dper \cdot \hat{u}_{nco}$$

$$ur'_{ri.1}(u_{nco}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco}} = -.0288 + 11.568 \cdot \hat{u}_{nco} + .0183 \cdot dper - 7.4948 \cdot dper \cdot \hat{u}_{nco}$$

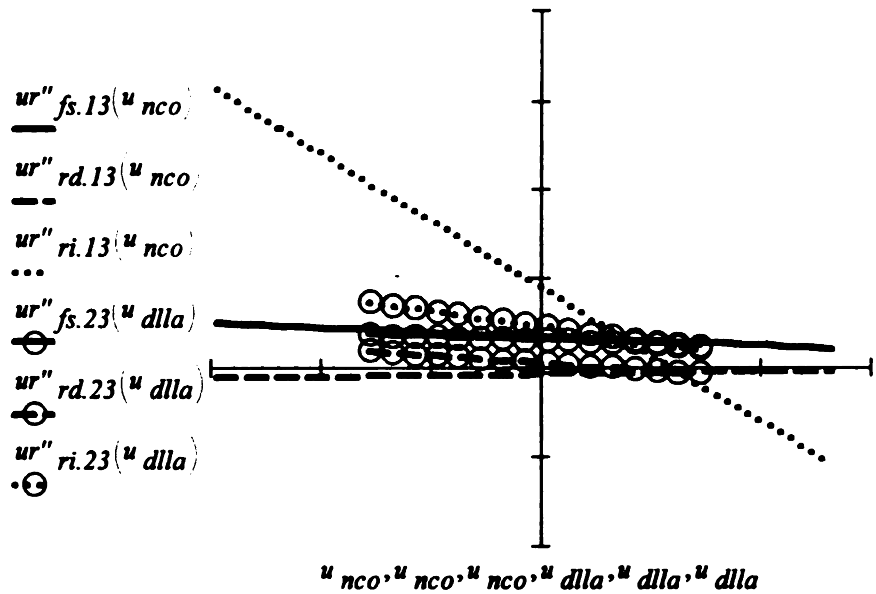
$$ur'_{fs.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla}} = -.0098 - 1.5314 \cdot \hat{u}_{\Delta lla} + .0064 \cdot dper - .4062 \cdot dper \cdot \hat{u}_{\Delta lla}$$

$$ur'_{rd.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla}} = -.0029 - .5936 \cdot \hat{u}_{\Delta lla} + .0014 \cdot dper - .8530 \cdot dper \cdot \hat{u}_{\Delta lla}$$

$$ur'_{ri.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla}} = -.0043 - .0326 \cdot \hat{u}_{\Delta lla} + .0095 \cdot dper - 1.7462 \cdot dper \cdot \hat{u}_{\Delta lla}$$

*fs, rd, ri* denotes marginal effect based on parameter estimates of equity return variance model using full data set, central 95% of *dependent* variable sample distribution, and central 95% of *independent* variable sample distribution, respectively.

**Figure 1.5 Plot of Prais-Winsten estimated long-window marginal effects of loan loss provision discretion ($\hat{u}_{nco}$, $\hat{u}_{\Delta lla}$) on equity return variance ($\hat{ur}^2$).**




$$ur''_{fs.13}(u_{nco}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco} \partial dper} = .0069 - .4968 \cdot \hat{u}_{nco}$$

$$ur''_{rd.13}(u_{nco}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco} \partial dper} = -.0011 + .1486 \cdot \hat{u}_{nco}$$

$$ur''_{ri.13}(u_{nco}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{nco} \partial dper} = .0183 - 7.4948 \cdot \hat{u}_{nco}$$

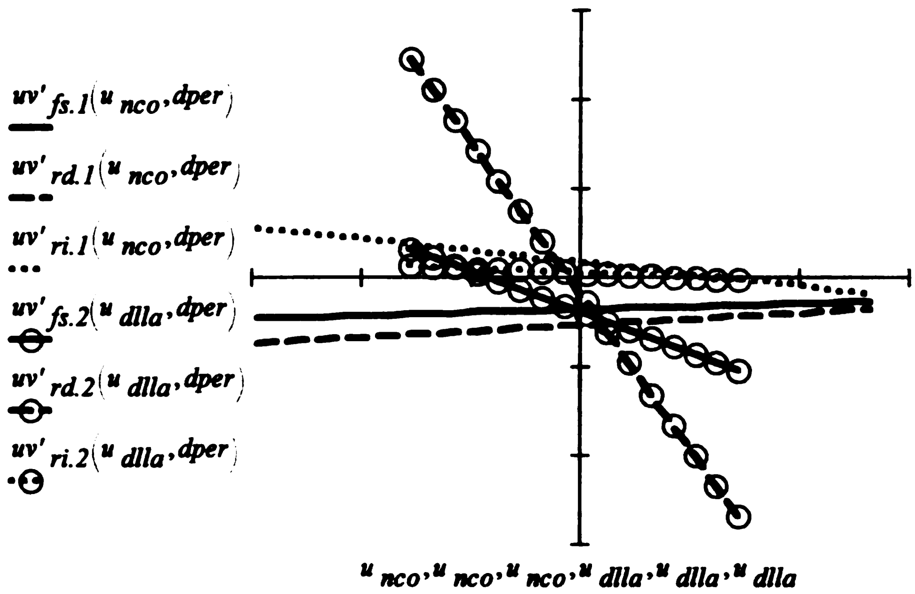
$$ur''_{fs.23}(u_{dlla}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla} \partial dper} = .0064 - .4062 \cdot \hat{u}_{\Delta lla}$$

$$ur''_{rd.23}(u_{dlla}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla} \partial dper} = .0014 - .8530 \cdot \hat{u}_{\Delta lla}$$

$$ur''_{ri.23}(u_{dlla}) \equiv \frac{\partial \hat{ur}^2(.)}{\partial \hat{u}_{\Delta lla} \partial dper} = .0095 - 1.7462 \cdot \hat{u}_{\Delta lla}$$

*fs, rd, ri* denotes marginal effect based on parameter estimates of equity return variance model using full data set, central 95% of *dependent* variable sample distribution, and central 95% of *independent* variable sample distribution, respectively.

**Figure 1.6 Plot of Prais-Winsten estimated short-window marginal effects of loan loss provision discretion ($\hat{u}_{nco}$, $\hat{u}_{\Delta lla}$) on equity return variance ($\hat{ur}^2$).**




$$uv'_{fs.1}(u_{nco}, dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{nco}} = -3.654 + 166.708 \cdot \hat{u}_{nco} + 36.400 \cdot dper - 1657.978 \cdot dper \cdot \hat{u}_{nco}$$

$$uv'_{rd.1}(u_{nco}, dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{nco}} = -5.385 + 339.826 \cdot \hat{u}_{nco} + 29.103 \cdot dper - 1102.387 \cdot dper \cdot \hat{u}_{nco}$$

$$uv'_{ri.1}(u_{nco}, dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{nco}} = 1.693 - 656.080 \cdot \hat{u}_{nco} - 15.089 \cdot dper + 5440.940 \cdot dper \cdot \hat{u}_{nco}$$

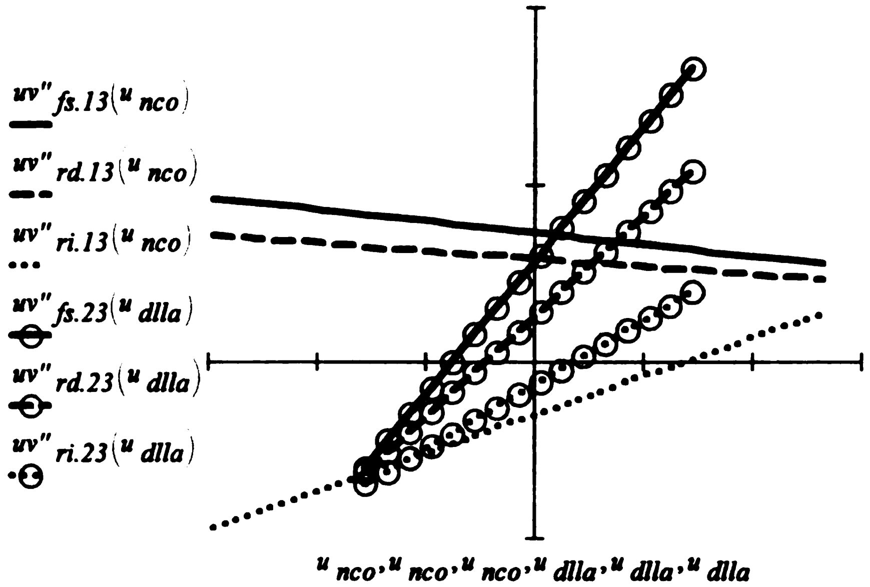
$$uv'_{fs.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla}} = -3.845 - 2282.168 \cdot \hat{u}_{\Delta lla} + 28.480 \cdot dper + 18851.17 \cdot dper \cdot \hat{u}_{\Delta lla}$$

$$uv'_{rd.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla}} = -1.940 - 8566.424 \cdot \hat{u}_{\Delta lla} + 12.657 \cdot dper + 14166.09 \cdot dper \cdot \hat{u}_{\Delta lla}$$

$$uv'_{ri.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla}} = .517 - 263.051 \cdot \hat{u}_{\Delta lla} - 6.573 \cdot dper + 9091.866 \cdot dper \cdot \hat{u}_{\Delta lla}$$

*fs, rd, ri* denotes marginal effect based on parameter estimates of equity return variance model using full data set, central 95% of *dependent* variable sample distribution, and central 95% of *independent* variable sample distribution, respectively.

**Figure 2.1** **Plot of FGLS estimated long-window marginal effects of loan loss provision discretion ($\hat{u}_{nco}$, $\hat{u}_{\Delta lla}$) on unexpected share volume ($\hat{uv}$).**




$$uv''_{fs.13}(u_{nco}) \equiv \frac{\partial uv''(.)}{\partial \hat{u}_{nco} \partial\, dper} = 36.400 - 1657.978 \cdot \hat{u}_{nco}$$

$$uv''_{rd.13}(u_{nco}) \equiv \frac{\partial uv''(.)}{\partial \hat{u}_{nco} \partial\, dper} = 29.103 - 1102.387 \cdot \hat{u}_{nco}$$

$$uv''_{ri.13}(u_{nco}) \equiv \frac{\partial uv''(.)}{\partial \hat{u}_{nco} \partial\, dper} = -15.089 + 5440.940 \cdot \hat{u}_{nco}$$

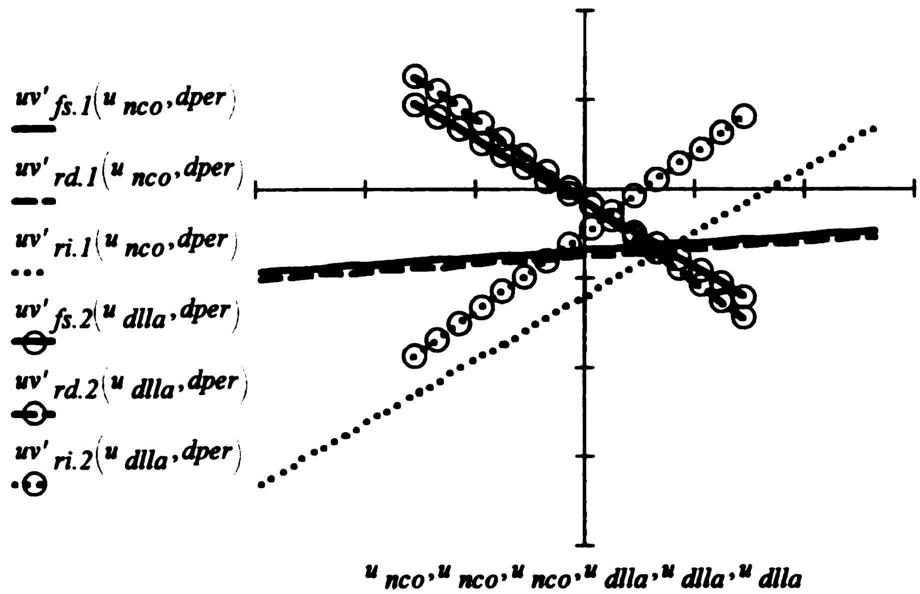
$$uv''_{fs.23}(u_{dlla}) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla} \partial\, dper} = 28.480 + 18851.17 \cdot \hat{u}_{\Delta lla}$$

$$uv''_{rd.23}(u_{dlla}) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla} \partial\, dper} = 12.657 + 14166.09 \cdot \hat{u}_{\Delta lla}$$

$$uv''_{ri.23}(u_{dlla}) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla} \partial\, dper} = -6.573 + 9091.866 \cdot \hat{u}_{\Delta lla}$$

*fs, rd, ri* denotes marginal effect based on parameter estimates of equity return variance model using full data set, central 95% of *dependent* variable sample distribution, and central 95% of *independent* variable sample distribution, respectively.

**Figure 2.2 Plot of FGLS estimated short-window marginal effects of loan loss provision discretion ($\hat{u}_{nco}$, $\hat{u}_{\Delta lla}$) on unexpected share volume ($\hat{uv}$).**




$$uv'_{fs.1}(u_{nco}, dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{nco}} = -13.892 + 820.260 \cdot \hat{u}_{nco} + 16.093 \cdot dper - 575.540 \cdot dper \cdot \hat{u}_{nco}$$

$$uv'_{rd.1}(u_{nco}, dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{nco}} = -14.773 + 854.704 \cdot \hat{u}_{nco} + 12.554 \cdot dper + 649.525 \cdot dper \cdot \hat{u}_{nco}$$

$$uv'_{ri.1}(u_{nco}, dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{nco}} = -23.776 + 7129.110 \cdot \hat{u}_{nco} - 3.982 \cdot dper + 7730.482 \cdot dper \cdot \hat{u}_{nco}$$

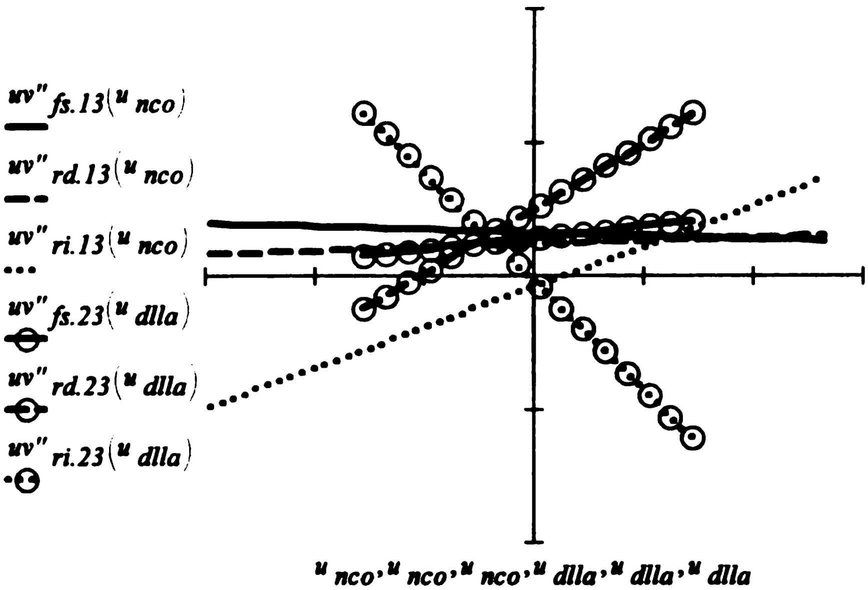
$$uv'_{fs.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla}} = -3.049 - 7179.88 \cdot \hat{u}_{\Delta lla} + 14.259 \cdot dper + 2133.248 \cdot dper \cdot \hat{u}_{\Delta lla}$$

$$uv'_{rd.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla}} = -2.282 - 9014.95 \cdot \hat{u}_{\Delta lla} + 25.655 \cdot dper + 12225.19 \cdot dper \cdot \hat{u}_{\Delta lla}$$

$$uv'_{ri.2}(u_{dlla}, dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla}} = -9.492 + 8951.56 \cdot \hat{u}_{\Delta lla} - 1.638 \cdot dper - 20405.64 \cdot dper \cdot \hat{u}_{\Delta lla}$$

*fs, rd, ri* **denotes marginal effect based on parameter estimates of equity return variance model using full data set, central 95% of *dependent* variable sample distribution, and central 95% of *independent* variable sample distribution, respectively.**

**Figure 2.3 Plot of LAD estimated long-window marginal effects of loan loss provision discretion ($\hat{u}_{nco}$, $\hat{u}_{\Delta lla}$) on unexpected share volume ($\hat{uv}$).**




$$uv''_{fs.13}(u_{nco}) \equiv \frac{\partial uv''(.)}{\partial \hat{u}_{nco} \partial\, dper} = 16.093 - 575.540 \cdot \hat{u}_{nco}$$

$$uv''_{rd.13}(u_{nco}) \equiv \frac{\partial uv''(.)}{\partial \hat{u}_{nco} \partial\, dper} = 12.554 + 649.525 \cdot \hat{u}_{nco}$$

$$uv''_{ri.13}(u_{nco}) \equiv \frac{\partial uv''(.)}{\partial \hat{u}_{nco} \partial\, dper} = -3.9819 + 7730.482 \cdot \hat{u}_{nco}$$

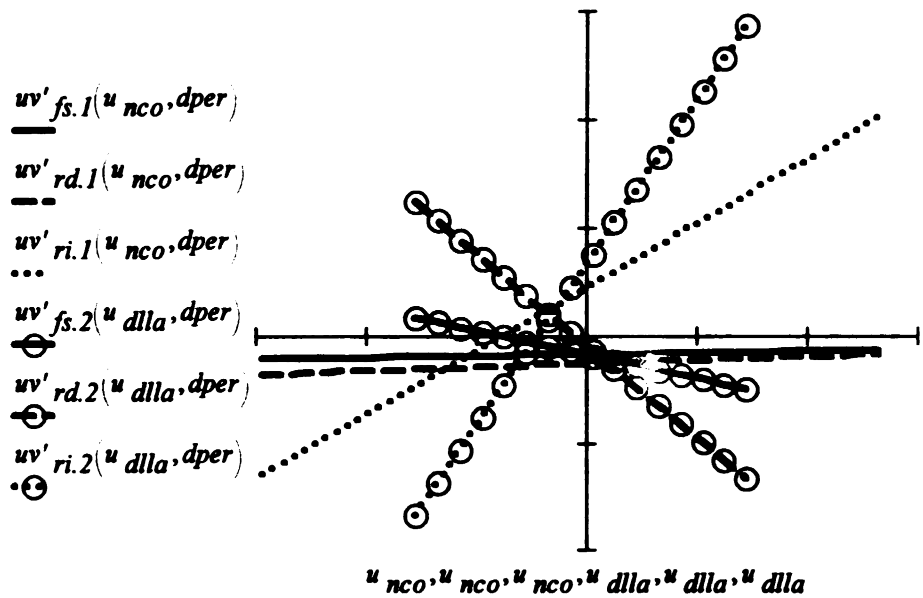
$$uv''_{fs.23}(u_{dlla}) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla} \partial\, dper} = 14.259 + 2133.248 \cdot \hat{u}_{\Delta lla}$$

$$uv''_{rd.23}(u_{dlla}) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla} \partial\, dper} = 25.655 + 12225.19 \cdot \hat{u}_{\Delta lla}$$

$$uv''_{ri.23}(u_{dlla}) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla} \partial\, dper} = -1.638 - 20405.64 \cdot \hat{u}_{\Delta lla}$$

*fs, rd, ri* denotes marginal effect based on parameter estimates of equity return variance model using full data set, central 95% of *dependent* variable sample distribution, and central 95% of *independent* variable sample distribution, respectively.

**Figure 2.4** **Plot of LAD estimated short-window marginal effects of loan loss provision discretion ($\hat{u}_{nco}$, $\hat{u}_{\Delta lla}$) on unexpected share volume ($\hat{uv}$).**




$$uv'_{fs.1}(u_{nco},dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{nco}} = -3.628 + 36.146 \cdot dper + 159.363 \cdot \hat{u}_{nco} - 1651.281 \cdot dper \cdot \hat{u}_{nco}$$

$$uv'_{rd.1}(u_{nco},dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{nco}} = -5.387 + 29.113 \cdot dper + 340.017 \cdot \hat{u}_{nco} - 1102.288 \cdot dper \cdot \hat{u}_{nco}$$

$$uv'i_{ri.1}(u_{nco},dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{nco}} = 8.881 + 27.366 \cdot dper + 5934.466 \cdot \hat{u}_{nco} + 18335.40 \cdot dper \cdot \hat{u}_{nco}$$

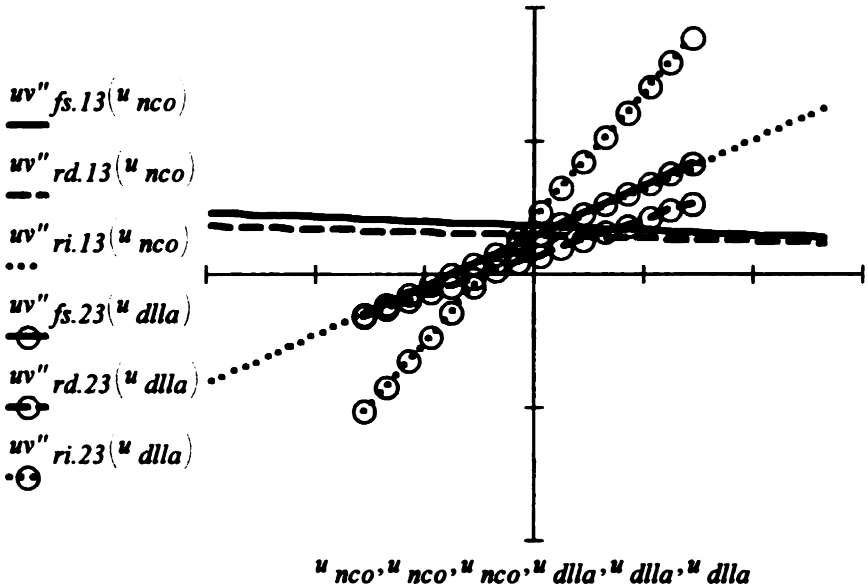
$$uv'_{fs.2}(u_{dlla},dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla}} = -3.684 + 28.358 \cdot dper - 2214.850 \cdot \hat{u}_{\Delta lla} + 19003.89 \cdot dper \cdot \hat{u}_{\Delta lla}$$

$$uv'_{rd.2}(u_{dlla},dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla}} = -1.947 + 12.666 \cdot dper - 8567.204 \cdot \hat{u}_{\Delta lla} + 14160.61 \cdot dper \cdot \hat{u}_{\Delta lla}$$

$$uv'_{ri.2}(u_{dlla},dper) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla}} = 13.528 + 41.947 \cdot dper + 15154.70 \cdot \hat{u}_{\Delta lla} + 46840.36 \cdot dper \cdot \hat{u}_{\Delta lla}$$

*fs, rd, ri* denotes marginal effect based on parameter estimates of equity return variance model using full data set, central 95% of *dependent* variable sample distribution, and central 95% of *independent* variable sample distribution, respectively.

**<u>Figure 2.5</u> Plot of Prais-Winsten estimated long-window marginal effects of loan loss provision discretion ($\hat{u}_{nco}$, $\hat{u}_{\Delta lla}$) on unexpected share volume ($\hat{uv}$).**




$$uv''_{fs.13}(u_{nco}) \equiv \frac{\partial uv''(.)}{\partial \hat{u}_{nco} \partial dper} = 36.146 - 1651.281 \cdot \hat{u}_{nco}$$

$$uv''_{rd.13}(u_{nco}) \equiv \frac{\partial uv''(.)}{\partial \hat{u}_{nco} \partial dper} = 12.554 - 1102.288 \cdot \hat{u}_{nco}$$

$$uv''_{ri.13}(u_{nco}) \equiv \frac{\partial uv''(.)}{\partial \hat{u}_{nco} \partial dper} = 27.366 + 18335.40 \cdot \hat{u}_{nco}$$

$$uv''_{fs.23}(u_{dlla}) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla} \partial dper} = 28.358 + 19003.89 \cdot \hat{u}_{\Delta lla}$$

$$uv''_{rd.23}(u_{dlla}) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla} \partial dper} = 12.666 + 14160.61 \cdot \hat{u}_{\Delta lla}$$

$$uv''_{ri.23}(u_{dlla}) \equiv \frac{\partial \hat{uv}(.)}{\partial \hat{u}_{\Delta lla} \partial dper} = 41.947 + 46840.36 \cdot \hat{u}_{\Delta lla}$$

*fs, rd, ri* denotes marginal effect based on parameter estimates of equity return variance model using full data set, central 95% of *dependent* variable sample distribution, and central 95% of *independent* variable sample distribution, respectively.

**Figure 2.6** **Plot of Prais-Winsten estimated short-window marginal effects of loan loss provision discretion ($\hat{u}_{nco}$, $\hat{u}_{\Delta lla}$) on unexpected share volume ($\hat{uv}$).**

# APPENDIX 3

## Informative, noninformative, and disinformative signals

The notions of informative and noninformative signals are well-developed in the accounting literature. However, since the notion of disinformative signals is not as common in the accounting literature,[1] it is useful to compare notions of information content found in the accounting literature with the formal foundations of the information content of signals developed in the economics literature. While this discussion focuses on a definition for disinformative signals and the conditions under which such signals *exist*, the conditions under which disinformative signals can be impounded in prices set in informationally efficient markets are considered in Appendices 3 and 4.

Information content in the accounting literature. In the financial accounting literature, an accounting signal is generally said to have pricing-relevant information content if that signal results in a change in the beliefs of traders such that they engage in observable equity market activity on the basis of that signal (cf. Beaver, 1968).[2] As an

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[1] No references to "disinformation" or "disinformative" were found in a keyword search of major accounting research journals for the period 1970 through 1995.

[2] With respect to other definitions of information content, Beaver (1968) comments that "*reduction of uncertainty* was not one of the definitions chosen" (p. 69, fn. 8) in his study of the information content of accounting earnings. However, given the operational definition of information content commonly used in financial accounting research, it is difficult to distinguish between trading activity resulting from changes in traders' assessments of uncertainty over expectations, and that resulting from changes in traders' expectations per se. Presumably, the "reduction of uncertainty" definition referred to by

example, a common maintained hypothesis in financial accounting research is that changes in aggregate market beliefs resulting from some accounting disclosure are observed when there exists a *significant association* between unexpected equity returns and the relevant unexpected accounting signal; alternatively stated, an accounting signal is said to have information content if there exists a significant association between unexpected equity returns and the unexpected component of that accounting signal. Formally, this test of information content commonly takes the form of a hypothesis test of a parameter in a regression equation such as:

$$\hat{ur}_{it} = \beta_0 + \beta_1 \cdot \hat{ux}_{it} + \mathbf{z}_{it} \cdot \boldsymbol{\beta}_z + u_{it} \qquad \text{[A1]}$$

where

$$\hat{ur}_{it} \equiv r_{it} - (\hat{\gamma}_{0,i} + \hat{\gamma}_{1,i} \cdot r_{mt}) \qquad \text{[A2]}$$

$$\hat{ux}_{it} \equiv x_{0,it} - \mathbf{x}_{it}\hat{\boldsymbol{\delta}}_i, \quad \mathbf{x}'_{it} = (1, x_{1,it}, x_{2,it}, \cdots, x_{k,it}) \qquad \text{[A3]}$$

$\hat{ur}_{it}$ the unexpected return for firm $i$, time $t$

$\hat{ux}_{it}$ the unexpected component of the accounting signal

$\hat{\gamma}_{k,i}$ return expectation model parameter estimates

$r_{mt}$ the actual return for the (equity) market, time $t$

$x_{0,it}$ the observed value of the accounting variable under study

$\mathbf{z}_{it}, \mathbf{x}_{it}$ vectors of various other conditioning variables

$\hat{\boldsymbol{\delta}}_i$ accounting variable expectation model parameter estimates

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Beaver (1968) was not considered relevant since there existed few theoretical models of equity market responses to noisy accounting signals at that time. Holthausen and Verrecchia (1988) presents such a model. Consider the following statement made in Kim and Verrecchia (1994, pp. 57-58): "The *informativeness* of price at the time of an earnings announcement can be measured by *the reduction of uncertainty* due to the price" [emphasis added].

Given the foregoing notation, if the null hypothesis, $H_0$: $\beta_1 = 0$, is rejected, then it is usually concluded that the accounting variable or signal has significant information content. Importantly, inferences drawn from such hypotheses tests are usually framed such that the measure of information content is effectively binary. Specifically, the information content (*ic*) of the unexpected component of an accounting variable, denoted $\hat{ux}$ in equation [A3], is usually measured as:

$$ic(\hat{ux}) = \begin{cases} \textit{exists} \text{ if } \beta_1 \neq 0. \\ \textit{does not exist} \text{ otherwise.} \end{cases} \qquad [A4]$$

Inferences drawn from other somewhat less common measures of information content in the accounting literature, share transaction volume, equity return variance, and bid-ask spreads, are generally framed in a similar manner. Therefore, under operational definitions of information content commonly used in the financial accounting literature, an accounting disclosure may either be informative or noninformative: a significant association between unexpected returns and accounting variables either exists ($\beta_1 \neq 0$) or does not exist ($\beta_1 = 0$) with some probability.

Information content in the economics literature. In a summary of the economic theory of information, Hirshleifer (1973, p. 31) states:

> The microeconomics of information . . . is an outgrowth of the economic theory of uncertainty. *Uncertainty* is summarized by the dispersion of individuals' subjective probability (or belief) distributions over possible states of the world. *Information*, for our purposes, consists of events tending to change these probability distributions . . . it is *changes* in belief distributions—a process not a condition—that constitutes here the essense of information.

This characterization implies that *any* event resulting in a change in an economic agent's belief distribution is informative. Thus, Hirshleifer's (1973) notion of information is closely analogous to the notion of information content in the financial accounting literature.

Underlying Hirshleifer's (1973) characterization of information and uncertainty is the assumption of "rational expectations" that underlies many theoretical models in the economics literature, as well as many theoretical models in the accounting literature; in particular, Holthausen and Verrecchia (1988), and Kim and Verrecchia (1994), referenced in this study. This assumption, often termed the *rational expectations hypothesis*, generally states that the beliefs (and belief distributions) of economic agents are equivalent to the actual probability distributions over the random variables on which economic decisions are made; less formally, agents' beliefs about decision variables correspond to the actual realizations of those variables on average. Thus, in a rational expectations world all events (signals) are either informative or noninformative since they must, by assumption, represent observations of either actual changes in the economic environment, or actual realizations from a stationary economic environment.

At least three related classes of theoretical models in the economics literature relax, in a certain sense, the rational expectations assumption in order to explain market efficiency anomalies and explicitly model learning processes of agents with incorrect prior beliefs: learning models (e.g., Holmstrom, 1982), herd behavior models (e.g., Scharfstein and Stein, 1990), and noise trading models (e.g., Kyle, 1985). Similarly, this study relaxes the rational expectations assumption in order to examine how accounting discretion affects the ability of equity traders to make inferences over time. If equity traders do not have (fully) rational expectations, then a definition of information content that explicitly allows for accounting signals to influence equity traders' learning processes is necessary.

In the econometrics literature, Theil (1967, p. 3) defines information content of a "*definite* and *reliable* message" that some event *i* has occurred in a manner equivalent to:

$$h(x_i) \equiv \ln\left(\frac{1}{x_i}\right) = \ln(1) - \ln(x_i) \qquad \text{[A5]}$$

where $x_i$ is the ex ante probability of event *i* occurring, and therefore $0 < x_i \leq 1$. Equation [A5] can be seen to represent the *ex post* change in the probability assessment of event *i* occurring given the message. Here the meaning of Theil's reference to a "*definite* and *reliable* message" is that the message represents event *i* with probability equal to one (i.e., it is a perfect signal).

Similar to Hirshleifer's (1973) characterization of information and uncertainty, this definition of information content shown in equation [A5] corresponds closely to the general notion of the information content in the empirical financial accounting literature. This can been seen by observing that equation [A5] is always non-negative for all ex ante probability assessments, implying that the information content of a *perfect signal* is always non-negative. Thus, under both the common operational definition of information content in the financial accounting literature, and under the definition of the information content of a *perfect signal* in the economics literature presented in equation [A5], signals must always have non-negative information content.

The information content of imperfect signals. The concept of information content corresponding to accounting signals as "perfect" signals (i.e., equation [A5]) is inadequate in the context of discretionary accounting variables representing estimates such as *lla* and *llp* since such variables do not generally represent noiseless or unbiased signals of realized facts. That is, equation [A5] is not an appropriate definition of information content for discretionary accounting variables since such variables do not in general represent signals of a realized event with a probability equal to one.

This can be seen more clearly following Theil (1967) defining $y_i$ as the probability that signal *i* noiselessly and unbiasedly represents some event *I*; then, substituting $y_i$ into equation [A5] to obtain:

$$h(y_i, x_i) \equiv \ln(y_i) - \ln(x_i) \qquad \text{[A6]}$$

it can be seen that equation [A6] is equivalent to equation [A5] when $y_i = 1$. However, in general accounting signals do not noiselessly and unbiasedly represent economic events, implying that, in general, $y_i \neq 1$.[3] Now considering the three exhaustive general cases of the relationship between the current signal $y_i$ versus the prior signal $x_i$, it can be shown that

$$\begin{aligned} y_i > x_i &\Leftrightarrow h(y_i, x_i) > 0 \\ y_i = x_i &\Leftrightarrow h(y_i, x_i) = 0 \\ y_i < x_i &\Leftrightarrow h(y_i, x_i) < 0 \end{aligned} \qquad \text{[A7]}$$

It follows from the more general definition of information content in equation [A6], and the relations shown in [A7], that an accounting signal may result in either an increase, no

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[3] Equation [6] is equivalent to the *general* definition of the information content of a signal presented in Theil (1967) and introduced to the accounting literature by Lev (1969).

change, or a decrease in information available to decision-makers. Thus, in general, accounting signals may be either *informative*, *noninformative*, or *disinformative*.

Persistence of noninformative and disinformative signals. It is not immediately clear from the preceding discussion whether noninformative and disinformative signals can persist in information environments similar to that of bank loan loss provisions. For example, a common argument in the financial accounting literature states that rational equity traders can infer the disinformative or noninformative component of an accounting variable and are thus able to adjust for that component in their decision-making processes.

To explore the notion that rational equity traders can infer whether a signal is noninformative or disinformative, it is necessary to examine how equity traders learn from observing time series of pricing relevant variables. The model considered here is closely analogous to the incomplete learning model presented in Holmstrom (1982). Let $n\tilde{c}o_{it}^{*}$ denote bank $i$, time $t$ reported net loan charge-offs, and $ll_i^{*}$ denote the exogenous economic factors influencing actual loan losses for bank $i$. Here the asterisk " $^{*}$ " denotes that these variables are observable by both bank managers and equity traders. Assume that the conditional expectation of $n\tilde{c}o_{it}^{*}$ for bank $i$, time $t$ is:

$$\mathrm{E}(n\tilde{c}o_{it}^{*} \mid ll_i^{*}, \tilde{u}_i) = ll_i^{*} + \tilde{u}_i \qquad \text{[A8]}$$

where $ll_i^{*}$ is nonrandom, and $\tilde{u}_i$ represents unobservable accounting discretion exercised over $n\tilde{c}o_{it}^{*}$ by the bank manager with expectation $\mathrm{E}(\tilde{u}_i) = \mu_{u_i}$. Equation [A8] says that the expectation of observable net loan charge-offs ($n\tilde{c}o_{it}^{*}$) is conditional on both an observable factor ($ll_i^{*}$) and on the manager's unobservable accounting discretion ($\tilde{u}_i$).

In order to examine a rational learning process, it is assumed that equity traders know the form of this conditional expectation function [A8] and are interested in estimating its parameters. The equity trader's problem of inference reduces to estimating $\widetilde{u}_i$ since $ll_i^*$ is nonrandom and stationary; with the objective of rationally inferring and pricing both the nondiscretionary and discretionary components of $n\widetilde{c}o_{it}^*$. Note that, by assumption, $\widetilde{u}_i$ is not conditional on time; that is, $\mathrm{E}(\widetilde{u}_i) = \mathrm{E}(\widetilde{u}_i \mid t)$ for all $t$. Thus, [A8] implies that in choosing $\widetilde{u}_i$ the bank manager responds to a large number of unrelated random factors each period, but that these factors are unpredictable and independent of $\widetilde{u}_i$. This assumption can be made without loss of generality since it is unnecessary to use (in this case, stronger) assumptions of nonstationary or nonindependent accounting discretion to obtain the result presented here.

Consider how an equity trader might estimate $\widetilde{u}_i$ from observing a time series of $n\widetilde{c}o_{it}^*$ and $ll_i^*$. Equation [A8] can be rewritten in estimation form as:

$$n\widetilde{c}o_{it}^* = ll_i^* + \widetilde{u}_i + \widetilde{e}_{it}\,; \quad \mathrm{E}(\widetilde{e}_{it} \mid t) = \mathrm{E}(\widetilde{e}_i) = 0 \qquad \text{[A9]}$$

which says that $n\widetilde{c}o_{it}^*$ is comprised of a nonrandom component, a random discretionary component, and another independent random source of mean-zero noise. Given the simple, stationary form of the conditional expectation function [A8], the sample mean based on a series of $n$ observations over time can be used to estimate of [A9]. Moreover, it can be shown that for the conditional expectation function considered here, the sample mean is an unbiased estimator of the population mean, suggesting that a rational equity trader would use this method to estimate the mean of $\tilde{u}_i$. Thus, the estimate of the mean of $\tilde{u}_i$ denoted $\hat{u}_i$ can be found (omitting ~) as:

$$\overline{nco^{*}_{i.}} \equiv \tfrac{1}{n}\sum_{t=1}^{n} nco^{*}_{it} = \tfrac{1}{n}\sum_{t=1}^{n}\left(ll^{*} + u_i + e_{it}\right) = ll^{*} + \overline{u_{i.}} + \overline{e_{i.}}$$

$$\hat{u}_i = \overline{nco^{*}_{i.}} - ll^{*} - \overline{e_{i.}}$$

$$\operatorname*{plim}_{t\to\infty}\ \hat{u}_i = \overline{nco^{*}_{i.}} - ll^{*} \qquad \text{[A10]}$$

This result says that given [A9], equity traders' inferences about accounting discretion are limited to observing (only) the *average accounting discretion exercised by managers over time*. That is, equity traders' learning over accounting discretion $\tilde{u}_i$ is incomplete—even asymptotically. Thus, this result suggests that equity traders cannot infer the discretionary component of accounting variables with certainty and, therefore, that noninformative and disinformative signals often cannot be observed by equity traders. ■

# APPENDIX 4

## Discretionary and nondiscretionary accounting disclosure

The three possible signal types shown in [A7] represent an exhaustive listing of possible states resulting from accounting disclosures. However, since the focus of this study is the empirical examination of pricing-relevant signals contained in *discretionary* accounting disclosures, it is necessary to refine this framework. Accounting disclosure can be decomposed along at least two dimensions: (1) discretionary versus nondiscretionary disclosure; and (2) observable versus nonobservable disclosure *behavior*. It is difficult to observe these categories of accounting disclosure for at least two reasons. Many accounting variables effectively have both a discretionary and a nondiscretionary component, and discretionary accounting behavior is in general unobservable since accounting variables subject to discretion are often based on the unobservable expectations of managers. In particular, loan loss provision (*llp*) can be decomposed into a relatively less discretionary component, net loan charge-offs (*nco*), which is based on observable events suggesting declines in the net realizable value of loans, and a relatively more discretionary component, change in loan loss allowance ($\Delta lla$), based largely on managers unobservable expectations over future loan loss realizations where:

$$llp_t = nco_t + \Delta lla_t = nco_t - (lla_t - lla_{t-1})$$

Based on definitions presented in Table 1, a cross-tabulation of accounting disclosure and signal types is presented in Table 2 to explicate the necessary conditions for the observability of disclosure types. The observability of informative, noninformative, and disinformative signals is essentially tautological: these signal types are operationally defined by their respective equity market response. Necessary conditions for the observability of disclosure type shown in Table 2 which are *substantially unobservable* are shown in bold and relate to managers' private information and disclosure behavior. As suggested by Table 2, disclosure type (nondiscretionary versus discretionary) is fundamentally unobservable since both managers' private information and, therefore, disclosure actions are unobservable. To see this more clearly, consider the alternative extreme case where a manager's private information is perfectly observable: if equity traders can perfectly observe the manager's private information, then it is straightforward that traders can observe whether the public disclosure is equivalent to the manager's private information and whether the manager has exercised accounting discretion.

Although disclosure type (i.e., nondiscretionary versus discretionary disclosure) is substantially unobservable, signaling disclosure behavior must result in informative signals, and signal-jamming disclosure behavior must either result in noninformative or disinformative signals, by definition (see Table 1). Thus, conditional on the assumption that an accounting variable (or component of an accounting variable) is discretionary, it follows that informative signals are consistent with signaling disclosure behavior, and noninformative and disinformative signals are consistent with signal-jamming disclosure behavior. ■

# APPENDIX 5

## Disinformative signals, noise traders, and equity prices

The notion that disinformation (or disinformative signals) can be impounded in equity prices set in otherwise informationally efficient markets is not new to either the financial economics or accounting literatures. In a discussion of the relative roles of information and noise in financial markets, Black (1986) summarizes a number of theoretical studies suggesting that the existence of "noise traders" who revise beliefs on the basis of noise *as if* they were acting on information is necessary for the existence of liquid capital markets. This implies that, in general, "noise" is impounded in equity prices set in liquid capital markets such as the NYSE, AMEX, and NASDAQ markets commonly used in examining the information content of accounting variables. Grossman and Stiglitz (1980) show under general assumptions that markets cannot be completely informationally efficient (in the conventional sense) in equilibrium when information is costly. Verrecchia (1980) defines market efficiency as the condition where the market price of a security is equal to that price set in a market where every trader has the same information as that represented by the union of all traders' information sets. Under this "consensus belief" price definition of market efficiency, Verrecchia (1980) shows that an informationally efficient equilibrium price can result under conditions of costly information acquisition and heterogeneous beliefs over risk-return distributions. Importantly, these models of market information efficiency ***do not preclude*** the existence of equilibrium prices set based on incomplete information (e.g., prices set under persistent information asymmetry between managers and equity traders). This suggests that the manager-trader information asymmetries implicit in disinformative accounting signals allow such signals to be impounded in equilibrium equity prices set in otherwise informationally efficient markets.

From another perspective, it is intuitive that a sufficient condition for disinformative signals to be impounded in equity prices is that managers with superior, private information relative to those disinformative disclosures maximize their wealth by not trading on that information. It is reasonable that since managers in a dynamic setting often have an incentive to maximize the price of their respective firm's equity without simultaneously trading on their private information (e.g., SEC law and regulation prohibit managers and other insiders from trading on "insider"—i.e., private—information), it is plausible that disinformative disclosures emitted by managers can be impounded in equity prices set in informationally efficient capital markets; particularly over time periods ordinarily spanned by periodic financial and accounting disclosures. In this connection, Kyle (1985) presents a model where an informed trader trades with noise traders such that expected profits are maximized and "private information is incorporated into prices gradually" (p. 1316). Relatedly, Fischer and Verrecchia (1998) presents an equilibrium model in an incomplete information setting where rational traders are unable to adjust perfectly for manager induced biases in financial reporting (i.e., disinformative signals). ■

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