ACCOUNTING WORKSHOP

“How Often Do Managers Withhold Information?”

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How Often Do Managers Withhold Information?*

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Abstract

This paper structurally estimates the disclosure model of Dye (1985) and Jung and Kwon (1988) (DJK) using management forecasts of US large-cap firms. We find that managers withhold information about 13% of the time. Next, to assess the performance of the baseline model, we test it against two alternatives: a model in which managers do not disclose selectively and a model in which investors form their expectations naively. On a firm by firm basis, the model is rejected against one of these alternatives for about half of the firms in our sample. Nevertheless, compared to the alternatives, the baseline model is preferred (has greatest likelihood). Finally, we compare the model’s estimated precision of managerial expectations to the realized volatility of earnings, and show that expectations exhibit excess volatility for about one third of the sample firms, which we interpret as a sign of managerial overconfidence.

Keywords: voluntary disclosure, structural estimation
JEL Classification: D72, D82, D83, G20

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Confirmations should count only if they are the result of risky predictions [emphasis added]; that is to say, if, unenlightened by the theory in question, we should have expected an event which was incompatible with the theory...


1 Introduction

Disclosure theory is arguably the foundation of accounting thought. According to this theory, the release of information is a choice that responds to incentives and constraints. In its classic form, the theory conjectures that managers wish to increase market perceptions about future value and, to do so, withhold bad news. Confirming this empirical prediction is relatively easy, as an ample empirical literature suggests that managers selectively disclose (Beyer, Cohen, Lys and Walther, 2010). But, falsifying the model is more difficult, given that the theory relies on inputs that are not directly observable. Does classic disclosure theory achieve a satisfactory first-order approximation of data? This is the, risky, prediction that we set out to test, by structurally estimating a classic disclosure model and quantifying its performance using statistical tests.

To test the theory, we adapt the model of Dye (1985) and Jung and Kwon (1988), hereafter, the DJK model. In this model, a manager is privately informed about the value of a traded firm, and decides whether to disclose or withhold the information to maximize the current market value of the firm. Absent any friction, disclosure strategies unravel to full disclosure, because a manager with the best information among other withholding managers will always be better-off disclosing (Grossman and Hart, 1980; Milgrom, 1981; Grossman, 1981). To break unraveling, DJK assume that there is a random friction, unobservable to outsiders, which makes the manager either unable or unwilling to disclose information. As long as the probability of the friction is non-zero, even a manager that is not subject to the friction may selectively withhold some information.
The disclosure friction has many possible interpretations. In the conventional interpretation, the manager occasionally does not receive information and cannot credibly communicate the absence of information. Or, with no change to the model, managers might occasionally face prohibitive proprietary costs if they were to disclose early.

For our application, which relies on relatively short-term horizons (a forecast about earnings to be released in the next quarter), we prefer an alternative interpretation – uncertainty about managerial objectives – in the spirit of Fischer and Verrecchia (2000). When the DJK friction is present, the manager has a long-term focus and, having no utility for short-term price movements, does not disclose and, instead, waits for the news to arrive in the next quarter.\footnote{It can be shown that, if there is any arbitrary level of stickiness in the friction, a forward-looking manager with no utility for current stock price will, optimally, withhold. This is because a disclosure increases the perceived probability that the manager is not subject to the friction in future periods which, in DJK, reduces future prices.} Otherwise, the manager is subject to short-term price pressure and discloses to maximize the current stock price.\footnote{This interpretation seems to have received a fair amount of empirical support, as firms engaged in equity transactions or facing short-term incentives tend to disclose more information (Marquardt and Wiedman, 1998).}

We use quarterly management forecasts from US large-cap firms to structurally estimate the model. Management forecasts are ideal for a test of DJK, as they are voluntary and take the form of quantitative forecasts about future earnings. Most firms make their forecast about earnings in the following quarter (although they sometimes also provide longer horizons). Hence, most of the uncertainty is resolved at the earnings release date, thus leaving aside difficult issues relating to the optimal timing of information which is absent from the original DJK.\footnote{This feature allows us to estimate the model as a single-period prediction model rather than, as would be the case if we were considering long-term information that could be updated (e.g., a one-year forecast). Guttman, Kremer and Skrzypacz (2014) show that a manager will strategically time disclosures, when receiving information over time. They show that the market tends to reward a late disclosure information. The reason for this is that, since the late disclosure follows an initial inference from not observing an early disclosure, the market can make a more aggressive inference about a later disclosure.}

Lastly, management forecasts, when available, are one of the most important sources of information. For example, Beyer, Cohen, Lys and Walther (2010) measure that about 16% of quarterly stock return variance is explained...
by management forecasts, versus 2% for earnings announcements (see Table 1, p.300).

To make the theory amenable to empirical testing, we augment it with time-series autocorrelation in the friction, to capture the possibility of sticky disclosure policies. For example, if frictions are very persistent, the market will strongly expect the absence of a friction after a disclosure is made, implying that the manager will be very likely to disclose again in the next period.

We estimate the conjectured structure of the model by maximum likelihood, to recover both the probability and persistence of the friction, as well as the noise in managerial signals. For the model to match observed forecasts, we find that managers strategically withhold information infrequently, that is, about only 13% of the time on average. The reason for this is not that they face very large frictions: indeed, frictions occur on average only about once every two quarters but, rather, that market pressure, in the form of negative expectations conditional on withholding, induces managers to strategically withhold only very bad news. Stickiness is also a factor, and we show that a firm that discloses information in the past period is about two to three times less likely to face a friction in the period that follows.

We next test the null model against two alternative models: non-strategic and naive-investors. In the non-strategic model, managers are forthcoming and do not selectively withhold information; we could interpret this model, for example, as litigation costs disciplining managers not to manipulate the information flow (Francis, Philbrick and Schipper, 1994). Under the non-strategic model, time-series variation in disclosure is only driven by the friction and managers do not withhold bad news. Alternatively, in the naive-investors model, investors are subject to a form of the winner’s curse, a notable feature of many laboratory experiments (Bloomfield and O’Hara, 2000). In this model, investors price a non-disclosing firm by using the unconditional probability of the friction, rather than the probability conditional on no-disclosure. They thus fail to recognize that the absence of disclosure is correlated with the existence of the friction. For a given
process for the friction, the non-strategic model predicts more voluntary disclosure while the naive-investors model predicts less voluntary disclosure.

We conduct likelihood ratio tests for non-nested models (Lewis, Butler and Gilbert, 2011), using the DJK model as the null and either the non-strategic or naive-investors model as the alternative. On a firm by firm, the model is rejected at the 5% level for about half of the sample, predominantly against the non-strategic model. The null that the model applies to all firms is also rejected, at the 1% level. The cause of this global rejection is that about 10-20% of firms repeatedly report unfavorable news that would have been very unlikely if the model were true. Nevertheless, as to the selection of a model among DJK, the non-strategic model and the naive-investors model, DJK exhibits the highest Akaike information criterion. Furthermore, 52% of firms are best described by DJK, with the remaining firms equally explained by either of the two alternatives. We conclude that the model is imperfect, and fails the explain the entire cross-section of firm disclosures, but is, nevertheless, the best available model to explain managerial forecasts.

Our model estimates also allow us to test for managerial behavioral biases. According to standard statistics, the variance of a prediction (an expectation) cannot be greater than what it forecasts. The variance of managerial predictions is not directly observable because we only observe truncated predictions when disclosure is strategic. With our model, however, we recover from the estimation the location of the truncation and, therefore, the original variance of the manager’s expectations. If managers make their predictions rationally, this variance should be less than the variance of earnings. By contrast, if managers are overconfident in their signal (our leading behavioral explanation), the variance of the prediction may be higher. We cannot reject overconfidence about

4Indeed, this observation is noted by Skinner (1994); our approach also us to rigorously evaluate “how much” bad news disclosure is required to make the DJK model fail. This is particularly important as, a fact we shall cover in more detail later on, bad news disclosure are not impossible under the theoretical DJK model.

5This property is recently used in the context of analysts’ forecasts by Lundholm and Rogo (2014); these are easier to examine because they are less likely to exhibit a truncation. They show that, like for management forecasts, there is excess volatility of forecasts for about half of the firms.
one third of the time. Indeed, for about 10% of firms in the sample, forecasts seem to exhibit abnormal levels of excess volatility of about 3 to 5 times the volatility of reported earnings.

**Related literature.** Prior literature in the area of corporate finance has primarily focused on the structural estimation of real decisions, such as capital structure and investment choices (Hennessy and Whited, 2005). Our approach is more closely related to a number of recent studies, which focus on the estimation of biases in reported earnings e.g. Beyer, Guttman and Marinovic (2014) who estimate a dynamic misreporting model. In their model, the manager can bias a mandatory report for a cost (Goldman and Slezak, 2006; Kedia and Philippon, 2009; Acharya and Lambrecht, 2011) but the market cannot recover the true signal because of noise in the accounting system. Both Zakolyukina (2014) and Terry (2014) estimate structural models where agents consider the dynamic consequences of manipulation. Zakolyukina (2014) estimates her model using observed accounting violations, recovering current choice of manipulation as a trade-off between current benefits and an increase in the long-term probability of an accounting restatement. Terry (2014) focuses on the effect of misreporting on firm’s dynamic investment policy, measuring that reporting incentives appear to cause significant distortions to investment. Lastly, several studies focus on a structural model of reversals, that is over-reporting of earnings must reverse when cash flows occur, to identify misreporting.

Two examples in this strand are Gerakos and Kovrijnykh (2013) and Nikolaev (2014). The first paper shows that biases in reported earnings map into a second-order autocorrelation in accruals; as we do, they apply their methodology to the cross-section of firms to test for strategic manipulation. The second paper estimate a structural model of reversals from its moment conditions to recover the link between manipulation and observed reversals. In this prior literature, discretion takes the form of a bias to earnings. By contrast, our study focuses on disclosures that are entirely voluntary. To our knowledge, the only study that implements a test of a voluntary prediction model is Chen
and Jiang (2006); however, they focus on how analysts weight information when making forecasts.\footnote{There is also an existing and related literature using reduced-form approaches to study the the causes and consequences of discretionary withholding (or timing) of information – a partial list includes Lang and Lundholm (2000); Aboody and Kasznik (2000); Nagar, Nanda and Wysocki (2003); Kothari, Shu and Wysocki (2009); Hollander, Pronk and Roelofs (2010). To our knowledge however, we are the first study to structurally estimate the setting of management forecasts using an explicit model of strategic withholding of information.}

There is also an extensive theoretical literature on voluntary disclosure drawing on the original model of Dye (1985).\footnote{There is also a large literature providing empirical evidence about management forecasts. This approach can be much more comprehensive as to the factors that relate to forecasts, such as cross-sectional differences in litigation risk (Brown, Hillegeist and Lo, 2005) or shocks to stock prices (Sletten, 2012). By contrast, our purpose here is to identify and measure one first-order, unobservable, economic primitive of forecasts.} One of the robust predictions of this theory is the use of sanitization strategies, in which unfavorable information is withheld Shin (1994, 2003). The Dye model, which we estimate here, is one form of sanitization but the literature has shown that this can also be affected by various other factors. For example, in Hagerty and Fishman (1989) and Bushman (1991), the amount of information released is a function of the price discovery in the market. Fishman and Hagerty (1990) show that some mandatory disclosure will affect voluntary disclosure, in a model where the manager might cherry-pick across multiple dimensions of information. Dye and Sridhar (1995) and Acharya, Demarzo and Kremer (2011) show that, given correlation between firms’ information, firms’ disclosure can be positively correlated to other firms’ disclosures. While we have left these factors aside here, our methodology may, in the future, allow researchers to condition the estimation on other observable feature.

The remainder of the paper is organized as follows. We describe in Section 2 the modeling framework and estimation strategy. Section 3 reports the data and our main estimation results. Section 4 uses the estimations to form a test of managerial overconfidence. Finally Section 5 concludes.
2 Theoretical development

2.1 The model

We follow the setting and notation of Jung and Kwon (1988), using indices $i, t$ where $i$ is for each firm and $t$ is for each period (quarter). In each period, investors believe that there is a probability $p_{i,t}$ that the manager faces a disclosure friction; then, the manager cannot disclose. With probability $1 - p_{i,t}$, the manager is not subject to the friction and may either truthfully disclose a forecast $x_{i,t} = \mathbb{E}_t(v_{i,t+1})$ about next-quarter earnings $v_{i,t+1}$, or withhold that information. When not subject to the friction, the manager has short-term reporting motives and wishes to maximize the market price. The market does not know if withholding was due to the friction. The random variable $x_{i,t} \sim N(\mu_{i,t}, \sigma_i)$ is normally distributed with p.d.f. $f_{i,t}$ and c.d.f. $F_{i,t}$.

Hereafter, we assume that investors use the analyst consensus as their common prior and, then, we center each forecast by subtracting the analyst consensus and setting $\mu_{i,t} = 0$. In this model, $\sigma_i$ represents the dispersion in the managers’ posterior beliefs and can be interpreted as the quality of the manager’s private information.

In the absence of the friction, the manager discloses strategically to maximize the post-disclosure market price. This is intended to represent, for example, a manager who is willing to accelerate the effect of news before the next-quarter earnings announcement.

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8In theory, it would be possible to estimate the model non-parametrically, using the observed distribution of forecasts; indeed, perhaps the rejection the model may be due to the misspecification implied by the normal distribution. However, the number of observation here is too small for a reasonable non-parametric estimation (in general, about 10 to 20 forecasts). So, as in Gayle and Miller (2009), we anchor our structural estimates to normality.

9Due to time constraints, we estimated the model in this version using realized earnings as a noisy estimate of the prior. Using a few firms as test cases, it did not seem to make much difference as compared to the consensus. The final version of the estimation will use consensus only.

10We have assumed here that the manager that is not subject to the friction has a short-term, myopic focus to increase the current stock price, while (under our leading interpretation) the manager that is subject to the friction has no utility for the current stock price. Under these assumptions, we can solve the optimal disclosure in each period separately following DJK (which we test). Models with forward-looking motives can be very different from DJK because they require a set of assumptions about how the manager trades off current versus future stock prices, with and without the friction. As to proper science, we do not believe that it is appropriate to estimate such a complex dynamic theory, until we have established the performance of the benchmark model.
As shown by equation (7) in Jung and Kwon (1988), the manager will forecast if and only if \( x_{i,t} \geq y_{i,t} \) where \( y_{i,t} \) is a disclosure threshold given by

\[
P_{i,t}(\mathbb{E}_t(x_{i,t}) - y_{i,t}) = (1 - p_{i,t}) \int_{-\infty}^{y_{i,t}} F_{i,t}(x) \, dx. \tag{1}
\]

Using the standard properties of Normal distributions, equation (1) reduces to

\[
-\frac{p_{i,t}}{1 - p_{i,t}} (y_{i,t} - \mu_{i,t}) = \int_{-\infty}^{y_{i,t}} \Phi\left(\frac{x - \mu_{i,t}}{\sigma_{i,t}}\right) \, dx,
\]

where \( \Phi \) is the c.d.f. of the standard Normal. With a change of variables, this equation reduces to

\[
-\frac{p_{i,t}}{1 - p_{i,t}} z_{i,t} = \int_{-\infty}^{z_{i,t}} \Phi(x) \, dx \tag{2}
\]

where \( z_{i,t} \equiv \frac{y_{i,t} - \mu_{i,t}}{\sigma_{i,t}} \). Equation (2) defines an implicit function \( z_{i,t} = Z(p_{i,t}) \) that maps the probability of a friction \( p_{i,t} \) to a standardized disclosure threshold \( z_{i,t} \).

Note that the probability of observing a forecast in this period \( q_{i,t} \) is then given by

\[
q_{i,t} = (1 - p_{i,t}) (1 - F(y_{i,t})) = (1 - p_{i,t}) \Phi(-Z(p_{i,t})). \tag{3}
\]

Equation (3) forms the core of our empirical strategy, as it can be inverted to map the (observable) frequency of forecast into the probability of the friction. That is, it implicitly defines a function \( P(q_{i,t}) \) such that, for any \( q_{i,t} \), where \( p_{i,t} = P(q_{i,t}) \) would be a solution to the above equation. Conveniently, under normality, the function \( P(\cdot) \) does not require knowledge of \( \mu_{i,t} \) or \( \sigma_{t} \), and the next claim guarantees that \( p_{i,t} \) is identified.

**Claim 1** The function \( P(\cdot) \) is a strictly decreasing, continuous, invertible bijection on \([0, 1]\).

The mapping \( P(\cdot) \) is strictly decreasing. Given a higher frequency of disclosure,
the model predicts a higher probability of a friction. Furthermore, because of strategic disclosure, the probability of the friction is always strictly less than the probability of not observing a disclosure.

2.2 Intuition for the estimation strategy

We first explain the estimation strategy under the simplifying assumption that the probability of the friction is constant over time \( p_i \). This is not the case in the data, and we shall later on address this by modeling the time series process of the friction.

Assume that \( p_i \) is the investor prior about the friction for firm \( i \). Here we assume investors know \( p_i \), but in practice investors may condition their assessment of the probability of the friction based on the number of periods since the last forecast or, in theory, may condition their assessment on other sources of public information.

Suppose that we have access to \( n \) observations of which \( n' \leq n \) are forecasts, while \( n-n' \) are no-disclosure. Then, denote \( x \equiv \{x_i\}_{i=1}^{n'} \), as a vector of observed forecasts. The likelihood of the data is given by

\[
L(p, \sigma) = \begin{cases} 
0 & \text{if } \frac{\min(x)}{\sigma} < Z(p) \\
(p + (1-p) \Phi(-Z(p)))^{n-n'} (1-p)^{n'} \prod_{i=1}^{n'} f(x_i) & \text{if } \frac{\min(x)}{\sigma} \geq Z(p) .
\end{cases}
\]

Since \( Z(p) < 0 \), the model enforces a lower bound

\[
\sigma_i \geq \frac{\min(x)}{Z(p)}
\]

on the manager’s private information. This bound is key to understanding how the Dye model reconciles observations in which (unconditionally) bad news is voluntarily disclosed, that is, when \( \min(x) \) is very negative. In the model, the standardized forecast must always be above \( Z(p) \). So, for bad news to be disclosed, it must be that the manager signal (if any) is precise, which leads to great variability \( \sigma_i \) in his posterior assessment.
Intuitively, if the manager information is precise then the market will tend to sanction more a non-disclosure, implying that there are more unfavorable news that tend to be disclosed.

Naturally, a greater probability of a friction $p$ implies that the manager, overall, discloses fewer unfavorable news. Hence, as we have stated in claim 1, the increase in this bound is much greater when the frequency of disclosure is itself very low, because the low frequency indicated that this manager was unlikely to be informed. In summary, an occasional disclosure of bad news indicates a manager who is often subject to a friction but, when not, has very precise information to forecast.

The maximum likelihood estimator $(\hat{p}^{MLE}, \hat{\sigma}^{MLE})$ takes one of two forms. If equation (4) is not binding then, the likelihood function can be decomposed to estimate $\sigma^{MLE}$ and $p^{MLE}$ separately, as

\[
\hat{p}^{MLE} = \arg \max_p \left( p + (1-p) \Phi \left( -Z(p) \right) \right)^{n'-n} \left( 1 - p \right)^{n'},
\]

\[
\frac{\min (x)}{\hat{\sigma}^{MLE}} \geq Z(\hat{p}^{MLE}).
\]

Two remarks are in order. First, the MLE estimator is not identical to the moment estimator which would have the form $\hat{p} = P(\hat{q})$. The reason is that $p^{MLE}$ takes into account the noise in the observed frequency of disclosure. Second, while the observed forecasts are truncated, the MLE estimator $\sigma^{MLE}$ seemingly ignores it and uses the estimator of an untruncated normal, even though a truncated normal has lower variance. The truncation, in this model, is not a fixed number but depends on the variance, so that the estimation is different from that of a standard truncated normal.

Furthermore, proper consideration of the bound is critical when observing low fore-
casts. Suppose next that equation (4) binds, then the MLE estimator then is

\[
\sigma_{\text{MLE}} = \min_{x} \left( \frac{z}{(p^{\text{MLE}})} \right),
\]

\[
p^{\text{MLE}} = \arg \max_{p} \left( p + (1 - p) \Phi(z) \right)^{n-n'} (1 - p)^{n'} \frac{\min(x)}{z(p)} \prod_{i=1}^{n'} \Phi\left( \frac{\min(x)}{z(p)} x_i \right).
\]

When equation (4) is binding, the estimation can no longer be conducted as two separate problems for \( p^{\text{MLE}} \) and \( \sigma^{\text{MLE}} \). That is, to explain low forecasts, the model can either increase the manager’s precision, which can make small observed \( x_i \) unlikely, or decrease the manager’s probability of a friction, which can make frequent disclosures unlikely. The maximum likelihood meets the bound by balancing this trade-off.

### 2.3 Stickiness in forecasts

Management forecasts stickiness vary, which suggests one should use the number of periods since the last forecast as the relevant public information on which to condition the estimation, that is, estimate the probability of the friction separately for each history.\footnote{Both empirical (Houston, Lev and Tucker, 2010; Chen, Matsumoto and Rajgopal, 2011) and theoretical papers (Diamond and Verrecchia, 1991; Verrecchia, 2001; Grubb, 2011) have offered analysis to the causes and consequences of the commitment to a disclosure policy.}

Our data only involves 12 years of forecasts, with about 50 quarters per firm (Section 3 describes the data in more detail). Given that most firms issued forecasts less than half of the time and occasional forecasters have between 5 to 10 forecasts, this implies that the number of observations per history is very limited.

To address the issue, we augment the model by modeling the time series process for the friction. Formally, we assume that there is a friction \( \theta_{t,i} \in \{0,1\} \) where \( \theta_{t,i} = 1 \) indicates that the manager is subject to the friction. \( \theta_{t,i} \) follows a Markov chain with transition matrix:
\[
K = \begin{bmatrix}
    k_{1,i} & 1 - k_{1,i} \\
    k_{2,i} & 1 - k_{2,i}
\end{bmatrix}
\]

That is, if (not) subject to the friction at date \( t \), the manager is subject to the friction at date \( t + 1 \) with probability \( (k_{2,i}) k_{1,i} \). One problem is that the friction itself is not directly observable to investors, so that \( \theta_{t,i} \) is a hidden Markov chain. For example, conditional on no-disclosure at date \( t \), the investor does not know whether \( \theta_{t,i} = 1 \) or \( \theta_{t,i} = 0 \) but the manager strategically withheld information.

Investors update their beliefs about \( \theta_{t,i} \) dynamically according to Bayes rule. Conditional on observing a disclosure at date \( t \), investors immediately know that \( \theta_{t,i} = 0 \) (no friction), and update their belief for the next period to \( p_{t+1,i} = k_{2,i} \). Conditional on observing no disclosure at date \( t \), investors must update to:

\[
E_t(\theta_{t,i}|d_{t,i} = ND) = \frac{p_{t,i}}{(1 - p_{t,i})\Phi(Z(p_{t,i}))} = \alpha(p_{t,i})
\]

Denoting \( d_{t,i} \in \{x_t, ND\} \) where \( d_{t,i} = x_{t,i} \) indicates a forecast and \( d_{t,i} = ND \) indicates no-disclosure, the probability \( p_{t,i} \) is restricted to the following form:

\[
p_{t+1,i} = \begin{cases} 
    k_{2,i} & \text{if } d_{t,i} \neq ND \\
    \alpha(p_{t,i})k_{1,i} + (1 - \alpha(p_{t,i}))k_{2,i} & \text{if } d_{t,i} = ND
\end{cases}
\]

(5)

For the first observation in the sample, we use the steady state distribution of \( \theta_{t,i} \). Because the beliefs are reset at each new forecasts, this approximation only affects the estimates prior to the first forecast.\(^\text{12}\) As a special case, if \( k_{1,i} = k_{2,i} = k \), the probability of receiving information is iid, and the estimation procedure can be run as stated in the

\(^{12}\) We have chosen this approximation because it is computationally tractable. An alternative would be to obtain by simulation the true likelihood function of the observations prior to the first forecast in steady-state; however, this method is computationally infeasible, especially given that we heavily rely on parametric bootstrap. When estimating the model on simulated data, the steady-state approximation does not seem to play a major role.
previous section with a single state with \( p = k_1 = k_2 \).

With this assumption, we can pool the entire sequence of firm observations across all states into a single likelihood function

\[
L(k_{1,i}, k_{2,i}, \sigma_i) = \prod_{t=1}^{T} \left[ I_{d_t \neq ND} (1 - p_{t,i}) f(x_{t,i}) + I_{d_t = ND} (p_{t,i} + (1 - p_{t,i}) \Phi(Z(p_{t,i}))) \right]
\]

where \( p_{t,i} \) follows the process in (5).

One benefit of this estimation procedure is that we only estimate the two parameters \((k_{1,i}, k_{2,i})\) of this hidden Markov chain. Furthermore, these estimates have a direct interpretation in terms of the stickiness, \( k_{2,i} - k_{1,i} \) of the underlying friction; when \( k_{2,i} = k_{1,i} \) the friction is i.i.d.

### 2.4 Alternative hypotheses

Given that we want to test the model, we develop two simple alternatives to DJK that will be the basis for our statistical tests. The first is a model in which managers do not exert discretion when they are not subject to the friction and always disclose the information if they have a short-term focus. We refer to this as the non-strategic model. It closely maps to the likelihood function of the baseline model except that we set \( Z_a(p) = -\infty \). Let \( L_a(k_{1,i}, k_{2,i}, \sigma_i) \) denote the corresponding likelihood.

For the second alternative hypothesis, we assume that investors are subject to a behavioral bias, and do not perfectly perceive what withholding implies about the friction. This is the behavioral bias formulated in the original Dye (1985) (equation (1), p. 129) where the price conditional on withholding is distorted to

\[
P_{ND} = p_{i,t} \mathbb{E}(\tilde{x}_{i,t}) + (1 - p_{i,t}) \mathbb{E}(\tilde{x}_{i,t} | \tilde{x}_{i,t} < \sigma_i Z_b(p_{i,t})),
\]

where \( Z_b(p_{i,t}) \) is the standardized disclosure threshold.
In equilibrium, a firm with $\bar{x}_{i,t} = \sigma_i Z_b(p_{i,t})$ at the disclosure threshold must be expecting exactly $P_{ND} = \sigma_i Z_b(p_{i,t})$. Solving this equation, the disclosure threshold is defined by

$$Z_b(p_{i,t}) = -(1 - p_{i,t}) \frac{\Phi'(Z_b(p_{i,t}))}{\Phi(Z_b(p_{i,t}))}$$

We refer to this as the naive-investor model and it maps the likelihood function but using the alternative standardized threshold $Z_b(p_{i,t})$. The associated likelihood $L_b(k_{1,i}, k_{2,i}, \sigma_i)$. As to the dynamic updating of the beliefs $p_{i,t}$, we do not impose any persistent behavioral biases and assume that investors use the updating rule in equation (5).\(^{13}\)

To further motivate these two alternative models, let us denote $P_a(q)$ and $P_b(q)$ as the (unique) implicit solution to

$$q = (1 - P_b(q)) \Phi(-Z(P_b(q))).$$

That is, $P_a(q)$ is the friction that maps to an observed disclosure frequency $q$ in model “a” and $P_b(q)$ that map to an observed disclosure frequency in model “b”.

We also compute two parameters of special interest in the model. First, we define as $p_{i,\infty}$ as firm $i$’s steady-state probability of being subject to the friction, that is, $(p_{i,\infty}, 1 - p_{i,\infty}) = (p_{i,\infty}, 1 - p_{i,\infty})K$. This is a measure of the importance of the friction and lies in between $k_{1,i}$ and $k_{2,i}$. Second, we define $v_{i,\infty}$ as the steady-state probability of withholding information strategically. This parameter is slightly more difficult than $p_{i,\infty}$ because it is an expectation over all the distributions of steady-state histories. We compute it by Monte-Carlo integration using a long history of 1000 periods from the MLE estimates, recovering this probability as the frequency of strategic withholding in this history.

\(^{13}\)While we also considered behavioral biases with respect to the dynamic updating rule, it turns out that the behavioral model performs poorly under both specifications. We choose this one in particular because the effect of the error is conceptually simple and is not magnified over time.
2.5 Standard errors and test statistics

It is well-known that, under regularity conditions that hold in our model, the MLE estimator is consistent, asymptotically normal and attains the Cramér-Rao lower bound (Maddala and Lahiri, 1992). However, using the asymptotic properties of the estimator is problematic in our setting, because we have a limited sample size and the data is correlated. To address this, we estimate all standard errors by parametric bootstrap. Bootstrap is a method designed to perform well when using small samples such as ours.

**Standard errors.** Using the assumed parametric structure, we simulate data and generate a distribution of parameter estimates. Specifically, after estimating \((k_{1,i}^{MLE}, k_{2,i}^{MLE}, \sigma_i^{MLE})\), we simulate 120 random histories of 500 observations, and re-estimate the model with each history using the last 50 observations (if the original data had 50 periods). This generates a distribution of 120 set of parameters and we then estimate the standard-error of this vector of estimates.

**Tests.** To test the model, we compute the likelihood ratio test statistic, taking the DJK model as the null hypothesis \(H_0\) and either the non-strategic or naive-investor model the alternative hypothesis \(H_a\). That is, for \(j = a, b\), the test statistic is

\[
\Lambda_{i,j} = \frac{\mathcal{L}(k_{1,i}^{MLE}, k_{2,i}^{MLE}, \sigma_i^{MLE})}{\max_{k_1, k_2, \sigma} \mathcal{L}_j(k_1, k_2, \sigma)}.
\]

As a direct application of the Neyman-Pearson lemma, the likelihood ratio test has highest power across all test statistics. Since we use the test for non-nested models, however, the test statistic does not have a chi-square distribution; besides, we cannot rely on asymptotic theory given the nature of our data. Therefore, we use again parametric bootstrap to compute the distribution of the test statistic. For each of the random histories generated earlier, we compute the 120 test statistics and obtain the 1%, 5% and 10% critical value for the test statistic as the 1%, 5% and 10% quantiles of the
distribution. We also conduct a global test, testing \( H_0: \) “DJK holds for all firms” against \( H_i \) “Model \( i \) holds for all firms”. The test procedure is identical to the method above, except that we use the joint test statistic \( \prod_i \Lambda_{i,j} \).

3 Estimation

3.1 Data

The current analysis is based on a random draw of 100 firms from the sample of firms present in the S&P500 index every year between 1997 and 2013.\(^{14}\) These firms are by construction large, with large analyst coverage and high institutional ownership and, consequently, likely not to be sample-selected in terms of management forecast coverage from commercial vendors such as First Call – alleviating the primary concern of measurement error in both \( q_i \) and the reported management forecasts (Chuk, Matsumoto and Miller, 2013).

Panel A of Table 1 describes the data filtering steps used in processing First Call’s management forecasts. We begin with 6,229 forecasts from 95 firms. Next, we restrict analysis to fiscal years beginning in 1998 because of expanded coverage of First Call to reduce selection bias (5,961 remaining forecasts) (Anilowski, Feng and Skinner, 2007). We then focus on EPS forecasts made prior to the end of the fiscal period to distinguish from pre-announcements (2,018 remaining forecasts). We then focus on the first forecast if there was more than one and, finally, we restrict forecasts to point and range estimates, leaving us with a sample of 1,244 forecasts from 84 firms.\(^{15}\)

Panel B of Table 1 describes the raw sample of earnings announcements, also from First Call.\(^{16}\) We follow similar restrictions to the management forecasts - with the last

\(^{14}\)This is done, at the moment, for computational reasons related to our estimation procedure (each firm takes 30 minutes to estimate). In future versions of the manuscript, we plan to extend the procedure to all firms with management forecasts.

\(^{15}\)For range forecasts we use First Call’s normalized point estimate.

\(^{16}\)This choice was made because of comparability issue stemming from GAAP vs non-GAAP forecasts.
step being a filter on firms that have at least 20 earnings announcement and 2 voluntary forecasts in our entire sample period.\footnote{By construction we are excluding firms which almost never issue a forecast- though these firms are still rationalizable under Dye’s model e.g. as \( p \) approaches 1.} This final step results in a final sample of 71 firms making 1,198 earnings forecasts prior to 3,832 earnings announcements.

Panel A of Table 2 provides firm level summary statistics over the entire sampling period. The average firm experienced 54 reporting periods, with an average forecast frequency \((\hat{Q})\) of 31.3\%. The average realized earnings per share (split-adjusted) is 0.511, and greater than the average realized earnings conditional on no forecast 0.484. Also note that the mean forecast 0.574 is generally larger than the actual earnings 0.511, suggesting that the distribution of forecasts might be truncated. This is consistent with both DJK and the naive-investors model, but not with the non-strategic in which managers always report when they are not subject to the friction.

Two empirical choices are of importance, and worth discussing in more details. We use earnings per share, which is itself an issue of unresolved controversy among empiricists. Our approach would be severely affected by market noise if we were, say, dividing by market price and, to be fair to the institutional setting, managers forecasts earnings per share, not the price to earnings ratio. Cheong and Thomas (2011) show that earnings per share do not appear to show any variation with scale because, plausibly, firms manage their share price to ensure comparability. This is our implicit assumption when using earnings per share or, more accurately, the precision of the manager’s private information about earnings per share does not significantly vary during the sample period.

We also checked whether managers bias their forecasts in their sample, that is, exhibit systematic non-zero forecast errors. There is some debate in the literature as to whether management forecasts are biased; for example, in their review of the literature, Coller and Yohn (1998) conclude that forecasts do not appear biased while, with more recent data, Rogers and Stocken (2005) observe that forecasts appear biased.\footnote{It is difficult to settle this question empirically because biases are, on average, small and detecting} Across all firms

\footnote{And earnings across Compustat and First Call: see Barth et al. (2012) for more details.}
in our sample, we do not find evidence of a significant positive or negative bias, primarily because we focus on large firms. On a per-firm basis, evidence of a bias is mixed, with about one third of the firms with no significant bias, one third positive, and one third negative (Panel A Table 2). Unfortunately, adjusting for the bias, that is, subtracting the per-firm estimated bias is not without cost, because it relies on very noisy firm-level estimate of the bias and the implicit assumption that investors use future information to correct their bias. For this reason, we have chosen not to correct for bias; in most cases, the estimated firm-level is relatively small, perhaps because of our current focus on large firms.

Panel B of Table 2 provides industry-means of key summary statistics (first and second moments of realized earnings and forecasts, as well as the average pre-forecast analyst consensus) where industry is defined using the 2-digit Global Industry Classification Scheme. Note that our current sample of firms is concentrated in industrials (N=18), consumer discretionary (N=11), and information technology (N=10).

### 3.2 Empirical results - parameter estimates

Panel A of Table 3 reports the summary statistics of the estimated parameters for each of the three models (DJK, models non-strategic and naive-investors). In all models, the friction appears to be fairly sticky, with a range of $70\%-85\%$ probability ($k_1$) of an existing friction persisting to the next quarter, versus a probability ($k_2$) of $36\%-55\%$ of the friction appearing in the next quarter if it was not present. The overall levels of stickiness $k_1 - k_2$ predicted in all models are very similar.

The models predict different probabilities of being subject to the friction, with the DJK predicting that the manager is less frequently subject to the friction than mod-

---

18 Within the sample of biased firms however, there appears to be equal distribution across positive and negative biases.
els non-strategic and naive-investors. In the non-strategic model, the manager always discloses when not subject to the friction so that, to explain a certain pattern of non-disclosure, the friction must be frequent. In the naive-investors model, naive investors penalize the manager for not disclosing, also causing more disclosure relative to DJK. Having noted this, the parameter estimates are not very different across the three models.

There is much more variation in the estimated precision of the manager’s information. In the non-strategic model, no information is truncated and the precision of the manager’s information is the variability of the observed forecasts (recall that a well-informed forecaster has greater variability), or $\sigma = .29$. This is the model in which the manager is expected to have the least precise information. The DJK model predicts a precision of $\sigma = .36$, although it is noteworthy that this appears to be driven by above-median firms, since the median is very similar to the non-strategic model. In the DJK model, the reports are selected, so that observed forecasts are from a truncated normal distribution. A truncated normal distribution has lower variance than the original distribution, implying that, to explain the observed variance, the variance of the untruncated information must be greater. The naive-investors model exhibits significantly greater variance, at $\sigma = .49$. As we shall see later, the naive-investors model appears to have lower likelihood than the other two models, and thus some “implausible” observations are reconciled by appealing to more variance.

In Panel A, the last two numbers of worth some further discussion, in that they report the steady-state probability of the friction and of strategic withholding under the DJK model. The friction is relatively frequent, with a point estimate 49%. Within our leading explanation, therefore, managers do not frequently withhold information for strategic reasons but, frequently, they simply have no interest in moving the market price with news that will be reported next quarter. We find that strategic withholding is not that common in this sample, occurring only about 13% of the quarters. The reason for this is
tied to the DJK model: in this model any above-average information is always disclosed without a friction so that (with symmetric distribution) strategic withholding must occur strictly less than one minus the probability of the friction (.5 * 49% = 24.5). In fact, the actual number is even less given that the market’s skepticism induces some disclosure of unfavorable events.

In Panel B, we break down these results by industry groupings (2-digit GICS). We find, for example, that highly volatile or industries that rely on inputs that are hard to predict exhibit lower quality of managerial information, with energy and telecommunications featuring very low quality private information. On the other hand, as intuitively expected, utilities and industrial sectors feature greater quality. The case of the financial industry is somewhat interesting as well because (with telecommunications), it is the only industry for which we do not observe stickiness. The financial industry exhibits fairly precise managerial information, which may be driven by the role of accrual assumptions quarter over quarter.

As to the steady-state probability of withholding, we find some, moderate, differences across industries. Telecommunications and utilities are the most likely to withhold information, about one quarter out of five. By contrast, energy, healthcare and technology withhold information only about one quarter out of 10.

The last column presents the steady-state probability of experiencing a friction. The energy sector appears, by far, the most likely to exhibit a friction (79%), and information technology the least likely (27%). Our best conjecture for this result is that technology firms are the most likely to face short-term market pressure, as a result of stock compensation or their reliance on equity financing. But, then, we should also expect financial firms to be unlikely to have this friction; yet this is not the case (57%).

Figure 5 presents histograms for the four parameter estimates across firms, in the DJK model. Notice that the standardized disclosure threshold $z$ is by construction negative, reflecting the prediction of the model that the probability of disclosure must be greater

<table>
<thead>
<tr>
<th>Industry Grouping</th>
<th>Withholding Probability</th>
<th>Friction Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy</td>
<td>0.25</td>
<td>0.79</td>
</tr>
<tr>
<td>Utilities</td>
<td>0.25</td>
<td>0.79</td>
</tr>
<tr>
<td>Energy</td>
<td>0.25</td>
<td>0.79</td>
</tr>
<tr>
<td>Utilities</td>
<td>0.25</td>
<td>0.79</td>
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</tr>
<tr>
<td>Energy</td>
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<td>0.79</td>
</tr>
<tr>
<td>Utilities</td>
<td>0.25</td>
<td>0.79</td>
</tr>
</tbody>
</table>
than 50%. The histogram reveals a fair amount of variation at the firm level, especially for
the disclosure threshold and the steady-state probability of the friction. But, of interest,
the model predicts a fairly small range for the estimated probability of withholding.

We note two additional interesting facts. First, closer inspection of the threshold $z$
reveals that a large peak at a disclosure around $-3$, that is, (by and large) firms tend
to strategically withhold information that is about one standard deviation below mean.
Second, the histogram of $\sigma^2$ shows that a very significant proportion of firms appear to
have very low quality information (the mode of the distribution), essentially making a
forecast that is unchanging - and therefore, which carries very little information. In this
same histogram, we observe a few outliers, with seemingly “extreme” precision, equal to
multiple times the true standard error of reported earnings.

3.3 Empirical results - tests

We now turn to formally test the DJK model. In Panel A of Table 4, we test the
hypothesis that the friction is sticky on a per-firm basis.

$$H_0 : k_2 - k_1 = 0.$$ 

Interestingly, when applying this test on per-firm basis, we find that the absence of stick-
iness may only be rejected about 42% of the time (at 5%), thus indicating that stickiness
is perhaps not as prevalent than commonly thought. One benefit of our approach, to
test this question, is that we present a model that fully explains how stickiness maps into
observable forecasts. As an output, this test also delivers an empirical specification of
which firms are sticky based on a formal test (prior studies use a more ad-hoc approach).

We move next to the formal tests of the theory. In Panel B of the same table, we
report the (log) likelihood of the three models. Given that the models have the same
degrees of freedom, the (log) likelihood in this panel maps to the Akaike information
criterion (AIC) and strongly indicates that the DJK model is the preferred model against both the non-strategic and naive-investors models.

In Panels C and D, we apply a likelihood ratio test of DJK, against either of the two alternative model. The DJK model is rejected for 45% of the sample against the non-strategic model and for 53.5% of the sample against the naive-investors model. It is important to note that rejection does not mean that the non-strategic or naive-investors is a better model but, rather, indicates misspecification in the DJK model.\footnote{In fact, in un-tabulated results, the rejection rates are much greater if we use either non-strategic and naive-investors as the null against DJK.}

In Panel E, we conduct a global test to test whether the DJK can be universally applied to all firms in the sample. We report the critical value of the test statistics at 1%, 5% and 10% significance. Comparing these critical values to the difference between log likelihoods in Panel B, the DJK model is rejected at the 1% level. Note that this is hardly surprising, since this test essentially rejects the idea that we can blindly apply DJK to all firms in the sample.

4 Applications

4.1 A test of overconfidence

An extensive literature suggests that managerial overconfidence is fairly widespread (Malmendier, Tate and Yan, 2011); however, disentangling over-confidence from private information can be difficult. Management forecast are a well-suited setting to detect over-confidence because they are examples of actual forecasts about future earnings, based on what the manager believes to be true.

In our model, we define over-confidence as excessive reliance on one’s signal, whether positive or negative (this is different from optimism which is a positive bias). Absent
overconfidence, basic probability theory implies that

\[ \text{Var}(x_{i,t}) = \text{Var}(E_t(v_{i,t+1})) = \sigma^2_i < \text{Var}(v_{i,t+1}) = \sigma^2_{e,i} \]

That is, the variability in the manager’s expectation must be lower than the variability in earnings.\(^\text{21}\)

We test, for each firm, \(H_0: \sigma_i < \sigma^2_{e}\). To conduct this test, we simulate the distribution of \(\hat{\sigma}_i - \hat{\sigma}_e\) given our parameter estimates. Then, we reject \(H_0\) when \(\text{Prob}(\hat{\sigma}_i - \hat{\sigma}_e < 0) < 5\%\).

Before presenting the analysis, a fairly widespread level of overconfidence is suggested in earlier tables. Starting with the descriptive summary statistics in Panel A of Table 2. The standard deviation of realized earnings is about .3, only marginally different from the forecasts (.29). If these were equal, managers would have to be perfectly informed and not truncated (since truncating will reduce the standard error of the forecasts). Both of these implications appear to be violated in the data. The forecast error is about 10% of realized earnings and few managers predict their next quarter earnings perfectly. The average forecast is also greater, at .57, than the average earnings (in periods with and without forecasts), at .51, which indicates that there is some selection of forecasts. This is not due to bias, as we do not see a difference between means when restricting to periods with forecasts.

In Figure 5, we also obtain some heavily anomalous information precisions. These precisions are many times above the standard-error of earnings. Even if we omit these observations, many firms have a fairly high precision, around .3 – .4 which implies that they know most of the information in advance.

The results of the formal test are documented in Panel F of Table 4. Our test reject no overconfidence for as many as 64.79% of the sample, showing excess volatility of

\(^{21}\)Note that DJK remains applicable even with overconfidence, given that the input of the model is the manager’s subjective beliefs about how the market react.
forecasts. It is worth noting that the DJK model predicts much more over-confidence than in the non-strategic model, since in the latter model, the precision of the manager’s information is captured by the variance in observed forecasts. Indeed, given that the DJK is a preferred model over the non-strategic model, it probably offer a better test of overconfidence.

4.2 What is the friction?

In this section, we develop an exploratory analysis of what may underlie the friction. As we have seen, there are many possible reasons why a manager may not disclose for reasons not related to increase the short-term stock price. Our leading explanation has been, in this respect, the idea that some managers have a pure long-term and do not care to accelerate news by only a quarter. Here, we present some additional evidence that is suggestive of this explanation.

The conventional alternative explanation, stated explicitly in DJK, is that managers do not always receive information. This is slightly problematic for our setting, given that managers are always somewhat informed about the future quarter and, when they are badly informed, they may nevertheless issue a range forecast and a forecast with some clarifying language.

Having noted this, some empirical facts are also discordant with the conventional interpretation. In Figure 6, we plot the average beliefs as implied by the estimated DJK across fiscal reporting periods, for both above-median and below-median (in frequency) disclosers. We observe a very clear shock occurring between 2000 − q3 and 2001 − q4, coinciding with greater stock market pressure during a period of large corporate frauds. At the same moment, we see that many above median firms shifted to be less likely to bear the friction. We do not see this pattern for firms that were not disclosing frequently, possibly because the probability of the friction was low in the first place. We find this trend very suggestive that the occurrence of the friction is tied to market pressures, not
to changes to the manager’s information endowment.

As a second piece of evidence, we report in Table 5 the correlation between the estimated parameters of the DJK model. If the friction is related to the manager’s overall information endowment, we should expect that managers that are more likely to be endowed with information should (plausibly) have more precise information. That is, the steady-state probability of the friction $p_{i,\infty}$ should be negatively correlated to the $\sigma_i$. This is not the case, in fact, at the firm level, the probability of the friction is not associated to the quality of the information.

5 Conclusion

In this study, we develop a simple methodology to fit the parsimonious model of Dye (1985) and Jung and Kwon (1988), or DJK model, using management forecast data. We fail to reject DJK as the null for about half of the firms in the sample relative to two alternatives, but do reject it as universal model of forecasts. While flawed, we show nevertheless that DJK performs better, in likelihood term, over alternatives that ignore strategic disclosure or feature behavioral investor biases.

We hope to offer, here, a starting point to identify the failures of the disclosure theory and offer as much material for further research in empirical and theoretical research. The data appears to suggest that there are fundamental differences between how firms forecasts, with some following DJK while others disclosing information regardless of its price impact. Further work should, therefore, involve richer settings that build over the DJK approach. For theoretical research, we appear to find robust evidence that managers do not form rational expectations but, instead, feature some large levels of overconfidence. Lastly, our model is amenable to test richer theories to disclosure, by conditioning the probability of the friction on various determinants of disclosure.

We conclude with a brief note on what might be the most controversial, although
admittedly tangential, aspect of our analysis. It does not seem plausible, in our setting, that the nature of the friction may be that management is not informed. We could not find any element, in our setting, that would suggest that some managers do not receive information. Instead, much of our analysis appears to be consistent with a different interpretation which fits the model in the same manner. That is, it seems that, randomly, managers may or may not care about the current market price (have short-term motives). This alternative explanation appears to make considerable more sense to explain the data and is at the root of the many tests, in empirical work, of incentives affecting disclosure. Perhaps one should hope that our evidence will change the standard interpretation of DJK.
References


Lundholm, R. J. and Rogo, R. (2014). Do analysts forecasts vary too much? Available at SSRN.


Table 1. Sample Selection and Summary Statistics

Our initial firm sample is a random draw of 100 firms from the sample of firms who existed in the S&P500 index every year between 1997 and 2013. Panel A and B report our sample selection criterion of management forecasts and earnings announcements from the First Call database.

### Panel A: Management Forecasts

<table>
<thead>
<tr>
<th>Step</th>
<th>Rule</th>
<th>Obs</th>
<th>Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Raw sample</td>
<td>6,229</td>
<td>95</td>
</tr>
<tr>
<td>Restrict to:</td>
<td>1) 1998Q1-2011Q3 fiscal years</td>
<td>5,961</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2) Quarterly guidance on EPS</td>
<td>2,018</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3) Guidance date prior to end of fiscal period</td>
<td>1,747</td>
<td></td>
</tr>
<tr>
<td></td>
<td>4) First dated guidance per fiscal period</td>
<td>1,380</td>
<td></td>
</tr>
<tr>
<td></td>
<td>5) Point and range estimates</td>
<td>1,244</td>
<td>84</td>
</tr>
</tbody>
</table>

### Panel B: Earnings Announcements

<table>
<thead>
<tr>
<th>Step</th>
<th>Rule</th>
<th>Obs</th>
<th>Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Raw sample</td>
<td>13,136</td>
<td>100</td>
</tr>
<tr>
<td>Restrict to:</td>
<td>1) 1998Q1-2011Q3 fiscal years</td>
<td>6,172</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2) Original un-restated announcements</td>
<td>5,400</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3) Non data error firms (e.g. earning date prior to fiscal end date)</td>
<td>5,335</td>
<td></td>
</tr>
<tr>
<td></td>
<td>4) Firms with minimum of 20 earning announcements and 2 voluntary forecasts</td>
<td>3,832</td>
<td>71</td>
</tr>
</tbody>
</table>
Table 2. Summary Statistics of Raw Data

Panel A reports key summary statistics of our final sample of 71 firms. Management forecasts and realized earnings are both split-adjusted. The indicator variable “Reject Zero mgmt. forecast error” is one if we reject the null of zero forecast error for that firm in a simple t-test at the 5% level. The pre-forecast analyst consensus is defined as the average consensus (split-adjusted) of the most current (on an analyst by analyst basis) forecasts made in the 60 day calendar window prior to the date of management forecast disclosure. Panel B groups firms according to their historical 1998 two-digit Global Industry Classification Scheme (GICS) and reports the average of firm-level average earnings, forecasts, and their standard deviations across the groupings.

Panel A: Firm Level

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>P25</th>
<th>P50</th>
<th>P75</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of reporting periods</td>
<td>71</td>
<td>53.97</td>
<td>.17</td>
<td>54</td>
<td>54</td>
<td>54</td>
</tr>
<tr>
<td>Fraction of periods with forecasts ($\hat{Q}$)</td>
<td>71</td>
<td>.31</td>
<td>.24</td>
<td>.11</td>
<td>.26</td>
<td>.52</td>
</tr>
<tr>
<td>Average value of realized earnings</td>
<td>71</td>
<td>.51</td>
<td>.26</td>
<td>.34</td>
<td>.47</td>
<td>.63</td>
</tr>
<tr>
<td>Average value of realized earnings (no forecast)</td>
<td>71</td>
<td>.48</td>
<td>.27</td>
<td>.31</td>
<td>.44</td>
<td>.63</td>
</tr>
<tr>
<td>Standard deviation of realized earnings</td>
<td>71</td>
<td>.3</td>
<td>.27</td>
<td>.15</td>
<td>.24</td>
<td>.35</td>
</tr>
<tr>
<td>Average value of forecasts</td>
<td>71</td>
<td>.57</td>
<td>.31</td>
<td>.35</td>
<td>.52</td>
<td>.68</td>
</tr>
<tr>
<td>Standard deviation of forecasts</td>
<td>71</td>
<td>.29</td>
<td>.26</td>
<td>.13</td>
<td>.25</td>
<td>.34</td>
</tr>
<tr>
<td>Average mgmt. forecast error</td>
<td>71</td>
<td>.07</td>
<td>.22</td>
<td>-.01</td>
<td>.02</td>
<td>.11</td>
</tr>
<tr>
<td>St.dev. of mgmt. forecast error</td>
<td>71</td>
<td>.19</td>
<td>.21</td>
<td>.05</td>
<td>.12</td>
<td>.28</td>
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<tr>
<td>Reject zero mgmt. forecast error</td>
<td>71</td>
<td>.32</td>
<td>.47</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Pre-forecast analyst consensus</td>
<td>71</td>
<td>.52</td>
<td>.28</td>
<td>.33</td>
<td>.49</td>
<td>.66</td>
</tr>
</tbody>
</table>

Panel B: Industry Level

<table>
<thead>
<tr>
<th>GICS2</th>
<th>N</th>
<th>Avg.earnings</th>
<th>SD.earnings</th>
<th>Avg.forecasts</th>
<th>SD.forecasts</th>
<th>Consensus</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy</td>
<td>2</td>
<td>0.36</td>
<td>0.32</td>
<td>0.23</td>
<td>0.19</td>
<td>0.22</td>
</tr>
<tr>
<td>Materials</td>
<td>6</td>
<td>0.52</td>
<td>0.29</td>
<td>0.66</td>
<td>0.27</td>
<td>0.48</td>
</tr>
<tr>
<td>Industrials</td>
<td>18</td>
<td>0.53</td>
<td>0.22</td>
<td>0.62</td>
<td>0.31</td>
<td>0.52</td>
</tr>
<tr>
<td>Consumer Discretionary</td>
<td>11</td>
<td>0.42</td>
<td>0.31</td>
<td>0.47</td>
<td>0.28</td>
<td>0.50</td>
</tr>
<tr>
<td>Consumer Staples</td>
<td>9</td>
<td>0.48</td>
<td>0.17</td>
<td>0.50</td>
<td>0.17</td>
<td>0.44</td>
</tr>
<tr>
<td>Health Care</td>
<td>7</td>
<td>0.52</td>
<td>0.24</td>
<td>0.60</td>
<td>0.22</td>
<td>0.57</td>
</tr>
<tr>
<td>Financials</td>
<td>4</td>
<td>0.77</td>
<td>0.64</td>
<td>0.80</td>
<td>0.45</td>
<td>0.78</td>
</tr>
<tr>
<td>Information Technology</td>
<td>10</td>
<td>0.51</td>
<td>0.46</td>
<td>0.53</td>
<td>0.40</td>
<td>0.54</td>
</tr>
<tr>
<td>Telecommunication Services</td>
<td>1</td>
<td>0.23</td>
<td>0.23</td>
<td>0.35</td>
<td>0.06</td>
<td>0.34</td>
</tr>
<tr>
<td>Utilities</td>
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<td>0.25</td>
<td>0.79</td>
<td>0.39</td>
<td>0.70</td>
</tr>
<tr>
<td>Total</td>
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<td>0.51</td>
<td>0.30</td>
<td>0.57</td>
<td>0.29</td>
<td>0.52</td>
</tr>
</tbody>
</table>
Table 3. Summary Statistics of Model Estimates – Firm Level

Panel A summarizes the key estimates of our three models (in superscripts, null, model “a” non-strategic, and model “b” naive-investors). $k_1$ ($k_2$) is the probability of the manager not bound by the disclosure friction conditional on being not bound (bound) in the previous period. $\sigma$ is the standard deviation from the true (un-truncated) distribution of management forecasts. $v_\infty$ is the steady-state probability that the manager is withholding news and $p_\infty$ is the steady-state probability that the manager is bound by the disclosure friction. Panel B groups firms according to their historical 1998 two-digit Global Industry Classification Scheme (GICS) and reports the average of the key model estimates by these groupings (note that these are not model re-estimates at the industry level).

### Panel A: Model Estimates – Firm Level

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>P25</th>
<th>P50</th>
<th>P75</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_{null}^1$</td>
<td>71</td>
<td>.7</td>
<td>.24</td>
<td>.59</td>
<td>.73</td>
<td>.91</td>
</tr>
<tr>
<td>$k_{null}^2$</td>
<td>71</td>
<td>.34</td>
<td>.31</td>
<td>.08</td>
<td>.24</td>
<td>.53</td>
</tr>
<tr>
<td>$\sigma_{null}$</td>
<td>71</td>
<td>.36</td>
<td>.35</td>
<td>.12</td>
<td>.26</td>
<td>.43</td>
</tr>
<tr>
<td>$k_a^1$</td>
<td>71</td>
<td>.85</td>
<td>.11</td>
<td>.8</td>
<td>.89</td>
<td>.93</td>
</tr>
<tr>
<td>$k_a^2$</td>
<td>71</td>
<td>.48</td>
<td>.32</td>
<td>.19</td>
<td>.45</td>
<td>.76</td>
</tr>
<tr>
<td>$\sigma_a$</td>
<td>71</td>
<td>.29</td>
<td>.26</td>
<td>.13</td>
<td>.25</td>
<td>.34</td>
</tr>
<tr>
<td>$k_b^1$</td>
<td>71</td>
<td>.81</td>
<td>.11</td>
<td>.74</td>
<td>.81</td>
<td>.91</td>
</tr>
<tr>
<td>$k_b^2$</td>
<td>71</td>
<td>.55</td>
<td>.24</td>
<td>.37</td>
<td>.57</td>
<td>.68</td>
</tr>
<tr>
<td>$\sigma_b$</td>
<td>71</td>
<td>.49</td>
<td>.54</td>
<td>.17</td>
<td>.3</td>
<td>.53</td>
</tr>
<tr>
<td>$v_\infty$</td>
<td>71</td>
<td>.13</td>
<td>.06</td>
<td>.09</td>
<td>.13</td>
<td>.19</td>
</tr>
<tr>
<td>$p_\infty$</td>
<td>71</td>
<td>.49</td>
<td>.25</td>
<td>.3</td>
<td>.5</td>
<td>.68</td>
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</table>

### Panel B: Model Estimates – Industry Level

<table>
<thead>
<tr>
<th>GICS2</th>
<th>N</th>
<th>$k_1$</th>
<th>$k_2$</th>
<th>$\sigma$</th>
<th>$k_1^a$</th>
<th>$k_2^a$</th>
<th>$\sigma^a$</th>
<th>$k_1^b$</th>
<th>$k_2^b$</th>
<th>$\sigma^b$</th>
<th>$v_\infty$</th>
<th>$p_\infty$</th>
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</thead>
<tbody>
<tr>
<td>Energy</td>
<td>2</td>
<td>0.85</td>
<td>0.52</td>
<td>0.12</td>
<td>0.93</td>
<td>0.59</td>
<td>0.19</td>
<td>0.88</td>
<td>0.60</td>
<td>0.11</td>
<td>0.09</td>
<td>0.79</td>
</tr>
<tr>
<td>Materials</td>
<td>6</td>
<td>0.63</td>
<td>0.55</td>
<td>0.50</td>
<td>0.86</td>
<td>0.69</td>
<td>0.27</td>
<td>0.75</td>
<td>0.59</td>
<td>0.47</td>
<td>0.15</td>
<td>0.57</td>
</tr>
<tr>
<td>Industrials</td>
<td>18</td>
<td>0.72</td>
<td>0.31</td>
<td>0.39</td>
<td>0.85</td>
<td>0.42</td>
<td>0.31</td>
<td>0.80</td>
<td>0.52</td>
<td>0.41</td>
<td>0.13</td>
<td>0.49</td>
</tr>
<tr>
<td>Consumer Discretionary</td>
<td>11</td>
<td>0.75</td>
<td>0.39</td>
<td>0.26</td>
<td>0.84</td>
<td>0.50</td>
<td>0.28</td>
<td>0.80</td>
<td>0.62</td>
<td>0.67</td>
<td>0.12</td>
<td>0.52</td>
</tr>
<tr>
<td>Consumer Staples</td>
<td>9</td>
<td>0.72</td>
<td>0.27</td>
<td>0.24</td>
<td>0.87</td>
<td>0.49</td>
<td>0.17</td>
<td>0.83</td>
<td>0.51</td>
<td>0.25</td>
<td>0.15</td>
<td>0.55</td>
</tr>
<tr>
<td>Health Care</td>
<td>7</td>
<td>0.82</td>
<td>0.35</td>
<td>0.22</td>
<td>0.86</td>
<td>0.45</td>
<td>0.22</td>
<td>0.87</td>
<td>0.51</td>
<td>0.52</td>
<td>0.11</td>
<td>0.54</td>
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<tr>
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<td>0.45</td>
<td>0.54</td>
<td>0.52</td>
<td>0.92</td>
<td>0.94</td>
<td>0.45</td>
<td>0.79</td>
<td>0.83</td>
<td>1.08</td>
<td>0.13</td>
<td>0.57</td>
</tr>
<tr>
<td>Information Technology</td>
<td>10</td>
<td>0.70</td>
<td>0.16</td>
<td>0.46</td>
<td>0.78</td>
<td>0.30</td>
<td>0.40</td>
<td>0.80</td>
<td>0.49</td>
<td>0.47</td>
<td>0.11</td>
<td>0.27</td>
</tr>
<tr>
<td>Telecommunication Services</td>
<td>1</td>
<td>0.22</td>
<td>0.67</td>
<td>0.06</td>
<td>0.92</td>
<td>0.67</td>
<td>0.06</td>
<td>0.81</td>
<td>0.57</td>
<td>0.13</td>
<td>0.18</td>
<td>0.50</td>
</tr>
<tr>
<td>Utilities</td>
<td>3</td>
<td>0.66</td>
<td>0.17</td>
<td>0.59</td>
<td>0.84</td>
<td>0.25</td>
<td>0.39</td>
<td>0.81</td>
<td>0.38</td>
<td>0.70</td>
<td>0.19</td>
<td>0.39</td>
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<tr>
<td>Total</td>
<td>71</td>
<td>0.70</td>
<td>0.34</td>
<td>0.36</td>
<td>0.85</td>
<td>0.48</td>
<td>0.29</td>
<td>0.81</td>
<td>0.55</td>
<td>0.49</td>
<td>0.13</td>
<td>0.49</td>
</tr>
</tbody>
</table>
Table 4. Summary of Specification Tests

Panel A tests for what fraction of the firms in our sample we are able to reject the null of managers’ probability of having a fraction being iid at various significance levels. Panel B describes summary statistics of the three different model’s log likelihoods. Panels C and D use the LRT to test for whether we can reject the DJK null versus the non-strategic or naive-investors models as described in the text respectively. Panel E is a test of whether DJK jointly applies to all firms. Panel F is a test for whether managers are overconfident in their forecasts with respect a Bayesian forecaster.

### Panel A: Test of iid assumption in DJK

<table>
<thead>
<tr>
<th>Significance</th>
<th>Percent of Firms Rejected</th>
</tr>
</thead>
<tbody>
<tr>
<td>1%</td>
<td>23%</td>
</tr>
<tr>
<td>5%</td>
<td>42%</td>
</tr>
<tr>
<td>10%</td>
<td>48%</td>
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</table>

### Panel B: Log-likelihoods of three models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>P25</th>
<th>P50</th>
<th>P75</th>
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</thead>
<tbody>
<tr>
<td>Log Likelihood: DJK</td>
<td>71</td>
<td>-11.57</td>
<td>25.47</td>
<td>-26.91</td>
<td>-13.52</td>
<td>-1.69</td>
</tr>
<tr>
<td>Log Likelihood: model non-strategic</td>
<td>71</td>
<td>-15.77</td>
<td>18.48</td>
<td>-24.01</td>
<td>-16.23</td>
<td>-6.8</td>
</tr>
<tr>
<td>Log Likelihood: model naive investor</td>
<td>71</td>
<td>-14.74</td>
<td>19.14</td>
<td>-23.84</td>
<td>-16.02</td>
<td>-10.47</td>
</tr>
</tbody>
</table>

### Panel C: Likelihood Ratio Test: $H_0$ vs. non-strategic model

<table>
<thead>
<tr>
<th>Reject $H_0$</th>
<th>Freq.</th>
<th>Percent</th>
<th>Cum.</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>39</td>
<td>54.93</td>
<td>54.93</td>
</tr>
<tr>
<td>Yes</td>
<td>32</td>
<td>45.07</td>
<td>100</td>
</tr>
<tr>
<td>Total</td>
<td>71</td>
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<td></td>
</tr>
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</table>

### Panel D: Likelihood Ratio Test: $H_0$ vs. naive-investors model

<table>
<thead>
<tr>
<th>Reject $H_0$</th>
<th>Freq.</th>
<th>Percent</th>
<th>Cum.</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>33</td>
<td>46.48</td>
<td>46.48</td>
</tr>
<tr>
<td>Yes</td>
<td>38</td>
<td>53.52</td>
<td>100</td>
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<tr>
<td>Total</td>
<td>71</td>
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<td></td>
</tr>
</tbody>
</table>

### Panel E: Global Test: Critical values of mean $LogLik_{H_0} − LogLik_{H_a}$

<table>
<thead>
<tr>
<th>Significance</th>
<th>vs. non-strategic model</th>
<th>vs. naive-investors model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1%</td>
<td>5.962</td>
<td>6.933</td>
</tr>
<tr>
<td>5%</td>
<td>6.190</td>
<td>7.700</td>
</tr>
<tr>
<td>10%</td>
<td>6.322</td>
<td>8.223</td>
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</table>

### Panel F: Variance Test of Overconfidence

<table>
<thead>
<tr>
<th>Reject $H_0$</th>
<th>Freq.</th>
<th>Percent</th>
<th>Cum.</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
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<td>35.21</td>
<td>35.21</td>
</tr>
<tr>
<td>Yes</td>
<td>46</td>
<td>64.79</td>
<td>100</td>
</tr>
<tr>
<td>Total</td>
<td>71</td>
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<td></td>
</tr>
</tbody>
</table>
Table 5. Cross-Correlation of Estimated Parameters

This table reports the correlation across parameters estimates from Panel A of Table 3.  
$k_1$ ($k_2$) is the probability of the manager not bound by the disclosure friction conditional on being not bound (bound) in the previous period.  $\sigma$ is the standard deviation from the true (un-truncated) distribution of management forecasts.  $v_\infty$ is the steady-state probability that the manager is withholding news and $p_\infty$ is the steady-state probability that the manager is bound by the friction.  P-values are reported in parentheses below each correlation.

<table>
<thead>
<tr>
<th>Variables</th>
<th>$k_1$</th>
<th>$k_2$</th>
<th>$\sigma$</th>
<th>$p_\infty$</th>
<th>$v_\infty$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_1$</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$k_2$</td>
<td>-0.1032</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.3916)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma$</td>
<td>-0.0599</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.6199)</td>
<td>(0.0175)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_\infty$</td>
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<td>0.7859</td>
<td>0.1711</td>
<td>1.0000</td>
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<tr>
<td></td>
<td>(0.0195)</td>
<td>(0.0000)</td>
<td>(0.1536)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$v_\infty$</td>
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<td>-0.1197</td>
<td>-0.0248</td>
<td>-0.1972</td>
<td>1.0000</td>
</tr>
<tr>
<td></td>
<td>(0.0000)</td>
<td>(0.3201)</td>
<td>(0.8372)</td>
<td>(0.0992)</td>
<td></td>
</tr>
</tbody>
</table>
Figure 1. Distribution of Estimated Parameters Under DJK. These figures plot the distribution of firm level estimates for $\hat{z}$, the disclosure threshold, $\hat{p}_i,\infty$, the steady-state probability that the manager is bound by the disclosure friction, $v_i,\infty$, the steady-state probability the manager is strategically withholding, and $\hat{\sigma}^2$, the estimated precision of the manager’s information.
Figure 2. Evolution of Market Beliefs of The Probability of the Manager Being Subject to Friction. This figure plots the average probability of the market’s belief that the manager is subject to the friction averaged across two sets of firm in our sample where the partition is determined by whether the firm is above or below the median Q (frequency of voluntary forecasts) in our sample. The gray regions represent the 95% confidence intervals.