The Dynamics of Concealment

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Abstract

Firm managers likely have more information than outsiders. If managers strategically conceal information, market uncertainty will increase. We develop a dynamic corporate disclosure model, estimating the model using the management earnings forecasts of US public companies. The model, based on the buildup of reputations by managers over time, matches key facts about forecast dynamics. We find that 80% of firms strategically manage information, that managers have superior information around half of the time, and that firms conceal information about 40% of the time. Concealment increases market uncertainty by just under 8%, a sizable information loss.

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

1. Introduction

Where does news about future firm performance come from? In the US, public firms regularly release financial statements, but earnings are largely anticipated by investors (Ball and Brown, 1968). We investigate a voluntary channel used by corporations to transmit forward-looking information. Firms sometimes supplement financial statements with disclosure of earnings forecasts. Empirically, these forecasts contain most of the price-relevant news in financial statements (Beyer et al., 2010).

But voluntary manager forecasts also come with strategic incentives to withhold information. Evaluating the process through which information is received and selected for public disclosure is the main theme of this paper. We ask several quantitative questions. How much more information do managers possess than investors, and what portion is concealed? To what extent does strategic withholding cause deviations between market prices and fundamentals, and what increases in price efficiency could we expect if strategic withholding were eliminated?

We do not directly observe management's information; instead, we observe the output of a disclosure process that presumably selects which information is publicly reported. Therefore, we rely on an estimated, quantitative structural model linking observed disclosures to assumptions about strategic management behavior and the evolution of market expectations. Extending static theories of disclosure in Dye (1985) and Jung and Kwon (1988) to a dynamic case, we model management disclosure as a process depending both upon the past and forward-looking strategic considerations.

We lay out three motivating facts. We exploit a data set combining public earnings forecasts by US listed firm executives with analyst consensus forecasts and realized earnings. Our data include thousands of firms and tens of thousands of firm-fiscal years spanning 2004-2016. Fact 1 reveals that disclosure is far from random. Managers tend to release earnings forecasts in good years with higher average realized profits. This fact is inconsistent with

unravelling theories in which all firms continually make forecasts (Grossman and Hart, 1980; Milgrom, 1981). Therefore, we employ a model with strategic concealment by managers during bad times. Fact 2 reveals that changes in disclosure are also far from random. Managers tend to begin to release forecasts in years with unusually high realized earnings growth and tend to stop disclosing in years with unusually low earnings growth. This fact is consistent with the idea that markets react both to a firm's current disclosure decisions as well as to its past behavior (Kothari et al., 2009), a feature we build into our dynamic model in which a firm's reputation depends upon its past behavior. Fact 3 reveals that disclosure varies more with realized earnings, and is more likely, for firms that have disclosed forecasts recently. Motivated by this fact, we build a model in which management information is persistent over time and in which forward-looking strategic considerations link such persistence with sensitivity to earnings news.

Our dynamic model includes three main ingredients: (a) forward-looking managers who consider the effect of disclosure on future prices (Beyer and Dye, 2012; Guttman et al., 2014; Marinovic et al., 2018), (b) serially correlated arrival of private information for managers only in some periods, information arrival about which markets update their beliefs (Einhorn and Ziv, 2008), and (c) a public news process, analyst consensus forecasts, which affect firm disclosure (Acharya et al., 2011).

The model implies a threshold level of private earnings news below which informed managers conceal information. The threshold is time-varying and depends on the market's current assessment of the likelihood that the manager has private information, which in turn depends upon the past history of outcomes. Forward-looking managers benefit from maintaining reputations that they are uninformed because markets draw less negative conclusions from non-disclosure in that case. Disclosing a forecast reveals that a manager currently has private information, increasing investors' beliefs that the manager will be informed in future. This logic generates an endogenous cost of disclosure, especially after long periods without a forecast. Rationalizing the evidence from Graham et al. (2005), firms in this position disclose

less often and only with highly favorable news.

Our theory also has a dynamic channel through which mandatory disclosure of realized earnings affects voluntary disclosure. In a static model, public signals like realized earnings do not affect disclosure (Acharya et al., 2011). In our model, realizations do help discipline managers. If realized earnings are poor, investors infer that a manager is more likely to have concealed private information, hindering the buildup of misleading reputations.

We solve our analytically challenging model numerically. We structurally estimate its parameters in a simulated method of moments (SMM) procedure targeting moments from our main data set. We estimate parameters of the firm earnings process and the process governing the arrival of manager private information. We also estimate information precision for managers and analysts. We find high persistence of private information for managers, who are better informed than markets about half of the time and tend to possess more precise information than analysts. We also estimate a highly persistent but volatile earnings process.

In the cross section of our data, not all firms change their disclosure behavior. Some firms always make forecasts, while others never disclose. Allowing for the possibility that not all firms are strategic, we enrich our theory by assuming that some fraction of firms always disclose any available information, that a different fraction of firms never disclose, and that the remaining firms follow the strategic concealment model discussed above. The extensive margin fractions, which we also estimate in our SMM procedure by targeting cross-sectional patterns, reveal that around 80% of firms are strategic information managers. The remaining firms are about evenly split between always, or never, disclosing information.

Overall, our estimated model fits the targeted moments well. Our model also qualitatively reproduces Facts 1-3, which are untargeted in our estimation. By contrast, a model without strategic concealment does not match any of Facts 1-3. However, we do highlight some discrepancies between the model and the data in our discussion, as motivation for future work.

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We simulate firms and compute market uncertainty about earnings as the root mean squared error (RMSE) of market expectations. Comparing our benchmark model to one with no concealment, we find that strategic withholding increases market uncertainty by about 8%, a sizable loss of accuracy implying investor earnings guesses which are typically off by about $60 million more for an average firm in our sample. This information loss, which directly translates to market valuation uncertainty, arises because informed managers conceal private information about 40% of the time. These sizable magnitudes validate the attention traditionally paid to firm disclosure by US policymakers. We also compute the contribution of analyst forecasts, finding that analysts reduce investor uncertainty substantially. Finally, a static version of our model with myopic managers displays less concealment, underscoring the importance of our model's dynamic forces.

Our quantitative findings are robust to reasonable alternative parameterizations of our model. We also explore heterogeneity by re-estimating our model in subsamples of firms chosen to likely be subject to different information environments, revealing that strategic concealment appears most impactful for firms with less volatile and more persistent earnings.

We build on a substantial body of disclosure theory. Our dynamic model is a part of what Milgrom (1981) defines as persuasion theory, namely, a class of sender–receiver problems in which the sender's preference depends only on the receiver's posterior belief. The early disclosure literature is mostly static (Jovanovic 1982; Verrecchia 1983; Dye 1985; Shin 1994; Shavell 1994; Ben-Porath, Dekel, and Lipman 2018). Persuasion theory has only been recently extended to a dynamic context. Three recent examples of two-period disclosure models are illustrative. Acharya et al. (2011) develop a model in which managers delay disclosure after the release of public news. Beyer and Dye (2012) consider a model in which some managers may be forthcoming and disclose all of their information. Guttman et al. (2014) examine a model in which more information may be received at some later date. The traditional methods of persuasion theory fail to apply or, at least, are significantly changed for repeated versions of these models. One approach preserves the basic structure of

persuasion theory with dynamics. Einhorn and Ziv (2008) and Marinovic (2013) are models in which markets update dynamically to new information, but myopic managers maximize only current short-term stock prices. The stock price is the sole channel through which future periods affect current actions. We add reputational dynamics to this structure.

Our model shares its focus with a recent literature applying structural models to analyze strategic financial communication. Bertomeu et al. (2020) is the paper closest to ours and estimates the Dye (1985) model under the assumption that the manager, when informed, statically maximizes current stock prices. Several studies estimate strategic withholding with disclosure costs rather than uncertainty about information (Bertomeu et al., 2016; Zhou, 2020; Cheynel and Liu-Watts, 2020). Their research questions are quite different than ours, focusing on the estimation of disclosure costs themselves.

Several studies focus on incentives to manipulate the earnings process rather than selectively withhold forecasts. Beyer et al. (2019) structurally estimate a dynamic model of costly earnings misreporting (Fischer and Verrecchia 2000; Frankel and Kartik 2019). Zakolyukina (2018) examines a model in which managers trade off higher stock prices versus a greater probability of prosecution when misreporting. Terry (2016) and Terry et al. (2018) study models in which manager earnings misreporting interacts with real manipulation of long-term investments.

Section 2 describes our data and three motivating facts. Section 3 presents our model. Section 4 describes our model estimation. Section 5 examines the model's ability to match our motivating facts. Section 6 reports the quantitative consequences of strategic concealment. Section 7 explores parameter robustness checks and subsample heterogeneity. Section 8 concludes. Appendix A includes proofs. Appendix B has details on the data. Appendix C lays out the numerical solution algorithm. Appendix D present econometric derivations used in the model estimation.

2. Manager forecasts in the data

We present three motivating facts about managers' earnings forecasts. Our data combine information from three sources on US public firms: 1) the I/B/E/S management earnings forecast database, 2) the I/B/E/S analyst forecast database, and 3) Compustat. I/B/E/S manager earnings forecast data include voluntary forecasts made by executives about their own firm's profits in a given fiscal year. Typically, these forecasts are bundled with the previous year's financial statements. I/B/E/S analyst forecast data include projections made by equity analysts for the same firm's profits. We compute consensus forecasts as the median across analysts. I/B/E/S also reports pro-forma realized earnings. Finally, Compustat contains standard firm financials. Throughout the paper, we normalize firm earnings, analyst forecasts, and manager forecasts by firm assets.

Our analysis spans 2004-2016, a period of time with consistent regulation of firm disclosure following the Regulation Fair Disclosure and Sarbanes-Oxley Act shifts in regulation in 2000-2002. We match I/B/E/S data to Compustat. Our sample includes around 5,000 firms and about 30,000 firm-fiscal years. Data Appendix B and Table 9 in that appendix present details of our sample selection and variable construction. Table 1 in this section reports descriptive statistics. Managers disclose earnings forecasts in about 24% of years. Forecast errors in our sample are small, with an average bias of 0.3% of assets. Most firms in our sample are medium- or large-sized, with median assets of $1.4 billion and median market valuations of $1 billion.

Table 1. Descriptive Statistics

	Mean	Std. Dev.	Min.	5%	25%	50%	75%	95%	Max.
Forecast characteristics									
Forecast frequency	23.49%	36.02%	0%	0%	0%	0%	39.23%	92.31%	100%
Management forecast	6.87%	4.39%	-10.68%	1.10%	3.80%	6.21%	9.23%	15.10%	23.81%
Forecast surprise	0.000	0.015	-0.158	-0.014	-0.003	-0.001	0.001	0.008	0.523
Forecast error	0.003	0.031	-0.256	-0.023	-0.006	0.001	0.005	0.038	0.690
Realized I/B/E/S earnings	3.12%	9.92%	-71.6%	-12.07%	0.91%	3.90%	7.67%	14.83%	25%
Firm characteristics									
Number of years	9.30	3.30	1	5	6	10	13	13	13
Total assets (bil.)	19.98	130.34	0.003	0.064	0.374	1.381	5.222	50.096	3,065.553
Market capitalization (bil.)	7.782	26.038	0.001	0.051	0.285	1.036	3.957	34,813	638,976
Book to market	0.630	2.333	-337	0.098	0.300	0.510	0.809	1.626	31.73

Note: This table reports descriptive statistics. Forecast frequency is computed as the average of the frequency of management forecasts by firm. Management forecast (MF) is the management forecast scaled by assets where, in the case of a range forecast, we select the mid-point between each bound of the range. Realized I/B/E/S earnings are the pro-forma earnings reported by I/B/E/S. Forecast surprise is the difference between the MF and the market expectation from I/B/E/S. Forecast error is the difference between MF and the realized I/B/E/S earnings. Firm characteristics are obtained from Compustat. Market capitalization is obtained from CRSP and measured as the closing price multiplied by the fully diluted number of shares. Book-to-market is the ratio of the firm's equity to its market capitalization.

Fact 1: Manager earnings forecasts tend to be disclosed during good times.

Few firms disclose forecasts in all years. 90% of firms don't issue forecasts at least once, and the average frequency of disclosure for firms having done so at least once is only 59%. So we ask whether periods in which firms disclose are different. The answer is yes: firms disclose more often in periods when earnings are high. We estimate a regression of the form

$$\text{Earnings}_{jt} = f_j + g_t + \beta \, \text{Disclosure}_{jt} + \varepsilon_{jt}, \tag{1}$$

linking realized earnings for firm j in year t to an indicator of forecast disclosure, controlling for firm and time effects. Panel A in Table 2 reports our estimates of Eq. (1). On average, earnings are 1.8% higher in disclosure years, a large shift compared to mean earnings at 3% of assets.
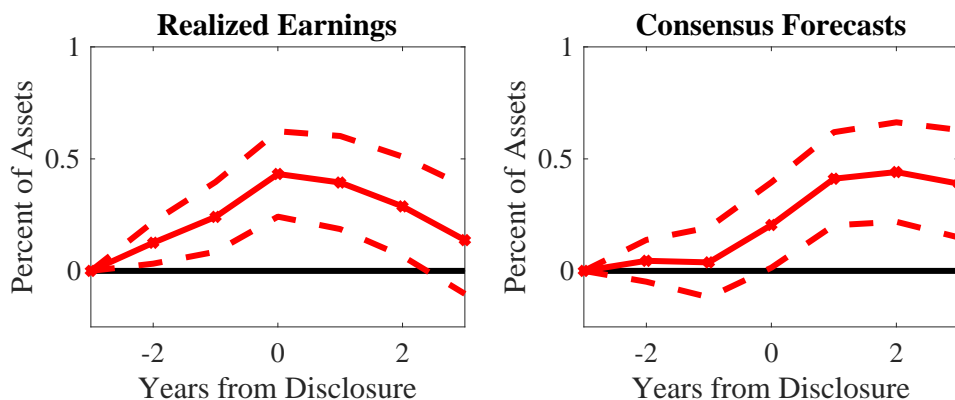

Figure 1. Earnings and Consensus Forecasts around Disclosure
Note: This plot reports the average change in realized earnings (left panel, solid line) and realized consensus forecasts (right panel, solid line) in the empirical data in the three years before and after disclosure of manager forecasts at year 0. Each panel also includes pointwise 90% confidence intervals, computed using a firm-level block bootstrap with 500 repetitions.

Disclosure occurs during persistently good times. The left panel of Fig. 1 plots the average realized path of earnings before and after a disclosure event, with a steady increase before disclosure and then gradual decline afterwards. The right panel plots the average path of consensus analyst forecasts, showing a rise concentrated after disclosure.

Table 2. Three Empirical Facts on Disclosure

Panel A: Earnings and Disclosure	
	Earnings$_t$
Disclose$_t$	0.018***
	(0.003)
Fixed Effects	Year, Firm
Years	2004-2016
Firms	5,023
Firm-Fiscal Yr. Obs.	31,246

Panel B: Earnings and Disclosure Breaks	
	Earnings Growth$_t$
Start Disclosing$_t$	0.004*
	(0.002)
End Disclosing$_t$	-0.006**
	(0.003)
Disclose$_t$	0.002***
	(0.001)
Fixed Effects	Year, Firm
Years	2004-2016
Firms	4,990
Firm-Fiscal Yr. Obs.	30,906

Panel C: Disclosure Dynamics	
	Disclose$_t$
Earnings$_t$	0.082***
	(0.017)
Disclose$_{t-1}$	0.267***
	(0.014)
Earnings$_t$ × Disclose$_{t-1}$	0.639***
	(0.110)
Fixed Effects	Year, Firm
Years	2004-2016
Firms	5,023
Firm-Fiscal Yr. Obs.	31,246

Note: The table reports estimates from our sample of realized earnings and manager forecasts from the I/B/E/S guidance database. Starting in Panel A, Earnings$_t$ is realized profits in year t, scaled by a firm's assets. Disclosure$_t$ is an indicator for whether the firm releases manager profit forecasts in year t. Starting in Panel B, Earnings Growth$_t$ is the change in Earnings$_t$ from $t-1$ to t. Start Disclosing$_t$ is an indicator activated if the firm releases manager guidance in year t but did not in $t-1$. End Disclosing$_t$ is an indicator activated if the firm does not release manager guidance in year t but did in $t-1$. In Panel C, we estimate a regression involving lags of some of these variables. The standard errors, in parentheses, are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

We conclude that manager forecast disclosure is not random. Earnings are persistently higher around disclosure periods. Theories in which manager forecasts represent cheap talk or costly signaling do not make predictions about whether managers are more likely to disclose forecasts during good versus bad times. We therefore later build a model that relies upon strategic earnings disclosure of only favorable news.

Fact 2: Managers change their disclosure behavior more often during years with large earnings shifts.

Changes in manager disclosure tend to occur in years with large changes in profits. We measure the endpoints or breaks of disclosure spells, years in which firms start or stop forecasting. We estimate a regression of the form

$$\text{Earnings Growth}_{jt} = f_j + g_t + \beta \, \text{Start Disclosing}_{jt} + \gamma \, \text{End Disclosing}_{jt} + \delta \, \text{Disclose}_{jt} + \varepsilon_{jt} \quad (2)$$

linking earnings growth for firm j in year t to indicators for the start of a disclosure spell, the end of a disclosure spell, and current disclosure while controlling for firm and time effects. Panel B of Table 2 reports our estimates of Eq. (2). We find around 0.004+0.002=0.6% higher earnings growth when firms start forecasting and about 0.6% lower earnings growth when firms stop, substantial shifts relative to average profits at about 3% of assets.

Fact 2 is consistent with dynamics in manager disclosure, i.e., with the idea that managers must face large shifts in news to break with past practice. The dynamic model we build below endogenizes such hesitance to switch from past disclosure behavior.

Fact 3: Manager disclosure varies more with earnings, and is more likely, if recent disclosure has occurred.

Disclosure is persistent, with around an 80% chance that firms disclosing last year will do so this year. The model we build generates disclosure persistence with a reputational mechanism. Investors, normally suspicious of the lack of a profit forecast which tends to predict bad times, are less suspicious if a firm has established a persistent reputation for non-disclosure. Naturally, firms that have not disclosed recently place value on maintaining their reputation and are less likely to disclose even fairly good news. Motivated by this logic, we estimate the following regression

$$\text{Disclosure}_{jt} = f_j + g_t + \beta\,\text{Earnings}_{jt} + \gamma\,\text{Disclosure}_{jt-1} + \delta\,\text{Earnings}_{jt} \times \text{Disclosure}_{jt-1} + \varepsilon_{jt} \quad (3)$$

linking an indicator for disclosure at firm j in year t to their current earnings, an indicator for their lagged disclosure, and the interaction of the two, controlling for firm and time effects. Panel C in Table 2 reports our estimates of Eq. (3). Consistent with the logic above, we see that firms are more likely to disclose if they have done so in the past ($\hat{\gamma} > 0$), and we also see that current disclosure varies more with earnings for firms who have disclosed recently ($\hat{\delta} > 0$). The magnitudes are large. A previously non-disclosing firm with earnings that are one standard deviation higher discloses with only 9.92 * 0.082 ≈ 0.8% higher probability. By contrast, for a previously disclosing firm, the same one standard deviation increase in earnings predicts a much larger 9.92*(0.082+0.639) ≈ 7% increase in the likelihood of disclosure.

## 3.   A model of disclosure dynamics

We extend the model in Dye (1985) and Jung and Kwon (1988) to a dynamic setting with forward-looking motives and public information flows. Each firm is traded by a large number of risk-neutral investors, "the market." Time t is discrete. Following Benmelech et al. (2010) and Beyer and Dye (2012), managers maximize the discounted value of a firm's stock price

with expected utility in period t

$$\mathcal{U}_t = \mathbb{E}_t\left(\sum_{k=t}^{\infty}\beta^{k-t}P_k\right). \tag{4}$$

Here, $\beta \in (0,1)$ is a subjective discount factor interpretable as the rate at which managers sell shares or are exposed to share prices via compensation vesting schedules (Edmans et al., 2013; Marinovic and Varas, 2019), P_k is the firm's market price, and $\mathbb{E}_t(.)$ is the expectation at the beginning of period t.

Figure 2. Timeline
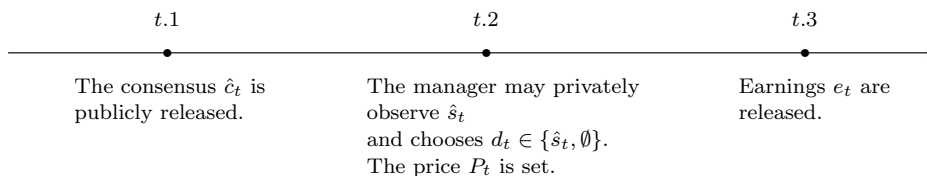
Each period t has three event dates or subperiods indicated by $t.1$, $t.2$ and $t.3$ in Fig. 2. At the start of the period $t.1$, the market observes an early public signal $\hat{c}_t$ about end-of-period earnings e_t. Empirically, we will match $\hat{c}_t$ to consensus analyst forecasts but we can think of $\hat{c}_t$ more generally as a sufficient statistic capturing all new signals available to investors prior to a firm's disclosure.

At date $t.2$, the manager may receive additional information in the form of a private signal $\hat{s}_t$, a signal observed if the indicator variable $\theta_t = 1$. Conversely, if $\theta_t = 0$, the manager does not receive additional material information. The market does not know the realization of θ_t but forms expectations about manager informedness given by a probability $p_t = 1 - \mathbb{E}_t(\theta_t)$. If information is received, the manager may decide to voluntarily disclose $\hat{s}_t$, i.e., issue a forecast $d_t = \hat{s}_t$ about end-of-period earnings e_t. By convention, $d_t = \emptyset$ indicates that no forecast is made. Then, the price P_t forms, reflecting the value of future earnings discounted at an objective market rate of return r and conditional on all public information $\mathcal{H}_{t-1}$ up to

the end of period $t - 1$ as well as any new information $\{\hat{c}_t, d_t\}$,

$$P_t = \mathbb{E}\left(\sum_{k=t}^{\infty} \frac{e_k}{(1+r)^{k-t}} | \mathcal{H}_{t-1}, \hat{c}_t, d_t\right). \tag{5}$$

At date $t.3$, the reporting period ends and the firm releases its earnings e_t. These earnings are publicly observed and the public information set is updated to $\mathcal{H}_t = \{\mathcal{H}_{t-1}, \hat{c}_t, d_t, e_t\}$.

Following Dye (1985), the manager's information endowment $\theta_t \in \{0, 1\}$ is exogenous. We use earnings forecasts in our empirical analysis given that Dye emphasizes such forecasts as a primary motivation for the model, e.g., "it is commonly believed that managers possess information about the firms they run, such as annual earnings forecasts, whose release would affect the prices of their firms" (p.124). Over a horizon of up to a year, managers may be informed, or may not know more than the market (Chen et al., 2006), but whether they have received information is not known to outsiders.

We observe that earnings realizations exhibit a significant amount of serial correlation empirically and assume that information endowments are also autocorrelated as in Einhorn and Ziv (2007). In formal terms, the manager's information endowment θ_t is a hidden Markov chain with a transition matrix

$$\Pi = \begin{pmatrix} 1 - \lambda_1 & \lambda_1 \\ \lambda_0 & 1 - \lambda_0 \end{pmatrix}, \tag{6}$$

where $\lambda_0 \equiv \mathbb{P}(\theta_{t+1} = 0 | \theta_t = 1) \in (0, 1)$ denotes the probability of moving from the informed to the uninformed state, and $\lambda_1 \equiv \mathbb{P}(\theta_{t+1} = 1 | \theta_t = 0) \in (0, 1)$ denotes the probability of moving from the uninformed to the informed state. The information endowment is persistent when becoming uninformed is less likely than remaining uninformed, or $\lambda_0 < 1 - \lambda_1$. We will sometimes describe the process θ_t by using the long-run probability of being uninformed $\bar{p}$

as well as the persistence of information endowments $\overline{m}$:

$$\overline{p} = \frac{\lambda_0}{\lambda_0 + \lambda_1}, \qquad \overline{m} = 1 - \frac{1}{2}(\lambda_0 + \lambda_1). \tag{7}$$

The process of earnings, the consensus analyst signal, and the manager's signal jointly satisfy (i) $e_t = \rho e_{t-1} + u_t$, (ii) $\hat{c}_t = e_t + v_t$ and (iii) $\hat{s}_t = e_t + w_t$, where $\varepsilon_t = (u_t, v_t, w_t)'$ is an iid normal vector with variance-covariance matrix $diag(\tau_u, \tau_v, \tau_w)^{-1}$. Earnings e_t follow an AR(1) process, and information observed by investors and managers $\hat{c}_t$ and $\hat{s}_t$ are noisy orthogonal signals.[1] The model's predictions turn out to be invariant to means, so without loss of generality we normalize all processes and signals to mean zero.

While we can state the model in terms of a vector of signals $(\hat{c}_t, \hat{s}_t)$, we observe empirically that analysts and managers communicate in terms of their expectation about future earnings. In the model, we therefore renormalize our variables to posterior expectations: $c_t = \mathbb{E}(e_t | \hat{c}_t, \mathcal{H}_{t-1})$ for the analyst consensus forecast and $s_t = \mathbb{E}(e_t | \hat{s}_t, \hat{c}_t, \mathcal{H}_{t-1})$ for the manager's forecast. From an informational perspective, there exists a one-to-one mapping between signals and posteriors, so this transformation has no consequence on equilibrium payoffs or disclosure choices. When restating the model in terms of posterior expectations, the joint stochastic process of earnings and expectations becomes

$$\begin{pmatrix} e_t \\ c_t \\ s_t \end{pmatrix} = \rho \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} e_{t-1} + \begin{pmatrix} 1 \\ \frac{\tau_v}{\tau_u + \tau_v} \\ \frac{\tau_v + \tau_w}{\tau_u + \tau_v + \tau_w} \end{pmatrix} u_t + \begin{pmatrix} 0 \\ \frac{\tau_v}{\tau_u + \tau_v} \\ \frac{\tau_v}{\tau_u + \tau_v + \tau_w} \end{pmatrix} v_t + \begin{pmatrix} 0 \\ 0 \\ \frac{\tau_w}{\tau_u + \tau_v + \tau_w} \end{pmatrix} w_t. \tag{8}$$

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[1]We assume that errors are uncorrelated. Under sequential normal updating, correlation between errors is not separately identified from the noise in the signals. To see this, suppose the consensus forecast is $c = e + \varepsilon_c$ and the manager's forecast is $s = \mathbb{E}(e|c, x)$, where the manager's private signal is $x = e + \varepsilon_m$. Suppose that all random variables are Gaussian and that the errors, ε_c and ε_m, are correlated. Then, by the Projection Theorem, we know that earnings can be represented as $e = s + \omega$ where ω is white noise. Hence, a model where the manager observes both the consensus signal and their own signal is informationally equivalent to a model where the manager observes the consensus signal and a conditionally uncorrelated signal.

In a Markov Perfect Equilibrium (MPE), the payoff relevant public information is given by $z_t = (e_{t-1}, c_t)$ and p_t, and the information of the manager is (z_t, θ_t, s_t). From this point onwards, unless needed for clarity, we omit the time subscripts and refer to unrealized end-of-period variables using the $'$ notation.

For any public state (p, z), let $D(p, z) \equiv \{s \in \mathbb{R} | d(p, z, s) = 1\}$ be the manager's disclosure set when the manager disclosure strategy is an indicator variable $d(p, z, s)$. Let $P^D(z, s)$ and $P^{ND}(p, z)$ be the market prices conditional upon disclosure and non-disclosure, respectively. We require prices to be consistent with Bayes' Rule and the manager's disclosure strategy:

$$P^D(z, s) = \frac{1 + r}{1 + r - \rho} \mathbb{E}(e' | z, s), \tag{9}$$

$$P^{ND}(p, z) = \frac{1 + r}{1 + r - \rho} \frac{p\mathbb{E}(e' | z) + (1 - p)\mathbb{E}(e' \mathbf{1}_{D^c(p,z)} | z)}{p + (1 - p)\mathbb{E}(\mathbf{1}_{D^c(p,z)} | z)}. \tag{10}$$

In Eq. (10), as in Jung and Kwon (1988), $P^{ND}(p, z)$ is a weighted average between the payoff if the manager is uninformed $\mathbb{E}(e' | z)$ and if the manager is informed but strategically withholding $\mathbb{E}(e' \mathbf{1}_{D^c(p,z)} | z)$. Prices are given by the expected present value of the firm's economic earnings, depending upon the AR(1) persistence parameter ρ and the market interest rate r. The market reassesses the probability that the manager was informed in the current period on the basis of earnings realization e'. Conditional on non-disclosure and earnings realization e', the updated probability that the manager will be uninformed in the next period is given by

$$p' = \varphi(p, z, e') \equiv \frac{p(1 - \lambda_1) + (1 - p)\lambda_0 \mathbb{E}(\mathbf{1}_{D^c(p,z)} | e')}{p + (1 - p)\mathbb{E}(\mathbf{1}_{D^c(p,z)} | e')}. \tag{11}$$

When the manager withholds their signal, they retain an informational advantage about the firm's fundamentals and their expected information endowment. Specifically, investors do not know whether the manager strategically withheld unfavorable information or was uninformed. By contrast, if the manager discloses their signal, the market learns that the manager was informed and updates the probability that the manager will be uninformed in

future to the probability λ_0.

We can now define the manager's optimization problem, when informed, as

$$V_1^D(p, z, s) = P^D(s, z) + \beta \mathbb{E}\left[(1 - \lambda_0)V_1(\lambda_0, z', s') + \lambda_0 V_0(\lambda_0, z')\Big| z, s\right] \tag{12}$$

$$V_1^{ND}(p, z, s) = P^{ND}(p, z) + \beta \mathbb{E}\left[(1 - \lambda_0)V_1(p', z', s') + \lambda_0 V_0(p', z')\Big| z, s\right] \tag{13}$$

$$V_1(p, z, s) = \max_{d \in \{0,1\}} \left[dV_1^D(p, z, s) + (1 - d)V_1^{ND}(p, z, s)\right] \tag{14}$$

$$V_0(p, z) = P^{ND}(p, z) + \beta \mathbb{E}\left[\lambda_1 V_1(p', z', s') + (1 - \lambda_1)V_0(p', z')\Big| z\right], \tag{15}$$

where $V_1^{ND}(p, z, s)$ (resp.,$V_1^D(p, z, s)$) is the value function for an informed manager conditional on withholding (resp., disclosing), $V_1(p, z, s)$ is the informed manager's value function prior to making a disclosure choice, and $V_0(p, z)$ is the value function of an uninformed manager.

The market posterior expectation evaluated at alternative information sets is given by

$$e'|z \sim \mathcal{N}\left(c, \frac{1}{\tau_u + \tau_v}\right), \quad e'|z, s \sim \mathcal{N}\left(s, \frac{1}{\tau_u + \tau_v + \tau_w}\right), \tag{16}$$

$$s|z \sim \mathcal{N}\left(c, \frac{1}{\tau_u + \tau_v}\right), \quad s|c, e' \sim \mathcal{N}\left(e', \frac{\tau_w}{(\tau_u + \tau_v + \tau_w)^2},\right). \tag{17}$$

We can now formally define the equilibrium concept.

Definition 1. *An MPE is a tuple $\langle P^D, P^{ND}, d, \varphi, V_0, V_1, V_1^D, V_1^{ND}\rangle$, such that*

1. *The market price is*

$$P = \begin{cases} P^{ND}(p, z) & \text{if } d(p, z, s) = 0 \\ P^D(z, s) & \text{if } d(p, z, s) = 1, \end{cases} \tag{18}$$

where P^D and P^{ND} are given by (9) and (10).

2. *The disclosure strategy $d(p, z, s) \in \{0, 1\}$ is*

$$d(p, z, s) \in \arg \max_{d \in \{0,1\}} \left[dV_1^D(p, z, s) + (1 - d)V_1^{ND}(p, z, s) \right], \tag{19}$$

   if the manager is informed and is $d(p, z, s) = 0$ if the manager is uninformed.

3. *The evolution of market beliefs is*

$$p' = \begin{cases} \varphi(p, z, e') & \text{if } d(p, z, s) = 0 \\ \lambda_0 & \text{if } d(p, z, s) = 1, \end{cases} \tag{20}$$

   where $\varphi(p, z, e')$ is given by (11).

4. *The value function of the informed manager solves*

$$V_1(p, z, s) = \max \left\{ V_1^D(z, s), V_1^{ND}(p, z, s) \right\}, \tag{21}$$

   where

$$V_1^D(z, s) = P^D(s, z) + \beta \mathbb{E} \left[(1 - \lambda_0)V_1(\lambda_0, z', s') + \lambda_0 V_0(\lambda_0, z') | z, s \right] \tag{22}$$

$$V_1^{ND}(p, z, s) = P^{ND}(p, z) + \beta \mathbb{E} \left[(1 - \lambda_0)V_1(p', z', s') + \lambda_0 V_0(p', z') | z, s \right]. \tag{23}$$

5. *The value function of the uninformed manager solves*

$$V_0(p, z) = P^{ND}(p, z) + \beta \mathbb{E} \left[\lambda_1 V_1(p', z', s') + (1 - \lambda_1)V_0(p', z') | z \right]. \tag{24}$$

Below we develop intuition for the model's economic tradeoffs. Consider the manager's disclosure and withholding incentives. Withholding information carries two benefits for the manager. First, by hiding bad news, the manager delays a stock price decline because the market is uncertain about the true cause of a non-disclosure. The manager benefits from

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higher short-term stock prices, so delays are attractive. Second, the manager influences the market's perception about their future information endowment. By pretending to be uninformed, the manager increases the perceived probability that they will be uninformed in future. This, in turn, mitigates the price penalty triggered by non-disclosure and increases the option value from continuing to withholding information. Withholding information thus entails a reputational benefit.

Naturally, when the information endowment is iid, namely, $\lambda_0 = 1 - \lambda_1$, the reputation benefit of withholding is absent. In this case, market beliefs are constant and independent of the manager's disclosure choices. For this reason, the manager's disclosure strategy collapses to that of a static model. We provide this observation as a benchmark.

Proposition 2. *When the information endowment is iid, i.e., $\lambda_0 = 1 - \lambda_1$, there is a unique equilibrium where in each period the manager uses a threshold τ, defined by*

$$f(\tau; \frac{\lambda_0}{\lambda_1}) = \int_{-\infty}^{\tau} \Phi(x)dx + \frac{\lambda_0}{\lambda_1}\tau = 0. \tag{25}$$

In each period, the manager discloses when observing $\frac{s_t - E[s_t|z_t]}{\sqrt{Var(s_t|z_t)}} \geq \tau$.

The optimal disclosure strategy in the static model is a threshold $\tau < 0$ such that the manager discloses any standardized signal above the threshold. Notice that the threshold depends only on the information endowment process. In the static case, the frequency of disclosure is independent of most firm characteristics, including the variance of the manager's signal $\sigma_w^2 = 1/\tau_w$, the variance of the analyst consensus signal $\sigma_v^2 = 1/\tau_v$, or the variance of firm fundamental shocks $\sigma_u^2 = 1/\tau_u$. Hence, these characteristics of the information environment can only affect disclosure behavior via dynamic channels.

To gain intuition for the effect of a manager's information endowment on disclosure in the static model, let $\ell = \lambda_0/\lambda_1$. The Implicit Function Theorem and (25) imply

$$\frac{\partial \tau}{\partial \ell} = -\frac{f_\tau}{f_\ell} = -\frac{\tau}{\Phi(\tau) + \ell} > 0.$$

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So strategic withholding becomes more likely when the probability that the manager is uninformed increases (Dye, 1985; Jung and Kwon, 1988). We next consider the structure of the manager's payoffs after a disclosure in the full dynamic model, obtaining a simple formula linking manager value in the case of disclosure to the corresponding market price.

Proposition 3. *In any equilibrium, $V_1^D(p,z,s) = \frac{P^D(z,s)}{1-\rho\beta}$.*

A manager's payoff conditional on disclosure is linear in both public information z and the manager's private information s. On the surface, this result seems to ignore the option value of withholding information in future periods: the disclosing manager's payoff is the same as if the manager had committed to full disclosure forever. However, upon disclosure, the manager's and market's information sets coincide, disallowing any further manipulation of market prices by managers on average.

The manager's payoff given non-disclosure also increases in the value of their information s because a higher value of s has a positive expected reputation effect. Since higher values of s are correlated with higher realizations of earnings e, the market is more likely to believe the manager was uninformed conditional on non-disclosure. However, the payoff given non-disclosure is non-linear in s. The existence of a threshold equilibrium is therefore not guaranteed. Indeed, when the information endowment is persistent and the manager's signal is very precise, there is no threshold equilibrium in our game. We show this result in a special case of the model with no public information c and iid earnings e.

Proposition 4. *Assume (i) the information endowment is persistent with $\lambda_0 < 1 - \lambda_1$, (ii) there is no public information c ($Var(v_t) \to \infty$), (iii) the manager is almost perfectly informed ($Var(w_t) \to 0$), and (iv) the earnings process e_t is iid with $\rho = 0$. Then there is no equilibrium such that for any current market belief p the manager adopts a threshold equilibrium defined as disclosing if $s \geq k_p$ and withholding if $s < k_p$ for some value k_p.*

The intuition behind Proposition 4 follows Grubb (2011), which shows that equilibrium disclosure strategies are mixed in a dynamic model with reputations. We can understand

this property by assuming that the firm does use a threshold equilibrium and considering two informed managers, A and B, whose signals lie slightly below and slightly above a conjectured threshold, respectively. Manager A must prefer to withhold; hence, the net effect of withholding on the current price and on the reputation is non-negative. Now, suppose that manager B deviates to withhold information, as well. This will cause almost the same current price effect; however, the reputational effect is different. After earnings are revealed, the market will attribute the above-threshold earnings to an uninformed manager with probability one because this is the updated belief on the equilibrium path. Hence, manager B benefits more from withholding more than manager A does, a contradiction.

Endogenous reputations which depend on market expectations are key to this argument, so to preserve generality in our model with reputations we employ a numerical solution algorithm which does not rely on the assumption of threshold equilibria. Appendix C provides more information on the solution algorithm. Fortunately, some amount of noise in realized earnings can preserve threshold equilibria. In particular, for our empirically estimated levels of noise in earnings, the optimal policy is still in fact a threshold equilibrium.

Some simple comparative statics reveal the impact of dynamic factors for strategic withholding. We numerically trace out strategic disclosure behavior as a function of the market's perceived probability p that a manager is uninformed, the key endogenous state variable in our model. We do this exercise for various illustrative parameterizations in Fig. 3 and Fig. 4. Note that in all cases we explore, the probability that an informed manager strategically withholds their forecast is increasing in p. Intuitively if markets are more certain that a manager is uninformed, then disclosing information today is more costly because the manager loses more reputational value.

In Fig. 3 we vary the information switching probabilities λ_0 and λ_1 to values that imply different levels of information persistence $\bar{m}$.[2] In the case of iid information with $\lambda_0 = 1 - \lambda_1$ and low persistence (green line with diamonds), managers withhold information less often

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[2]We remind the reader that above we defined the convenient measure $\bar{m}$ of information persistence $\bar{m} = 1 - \frac{1}{2}(\lambda_0 + \lambda_1)$.
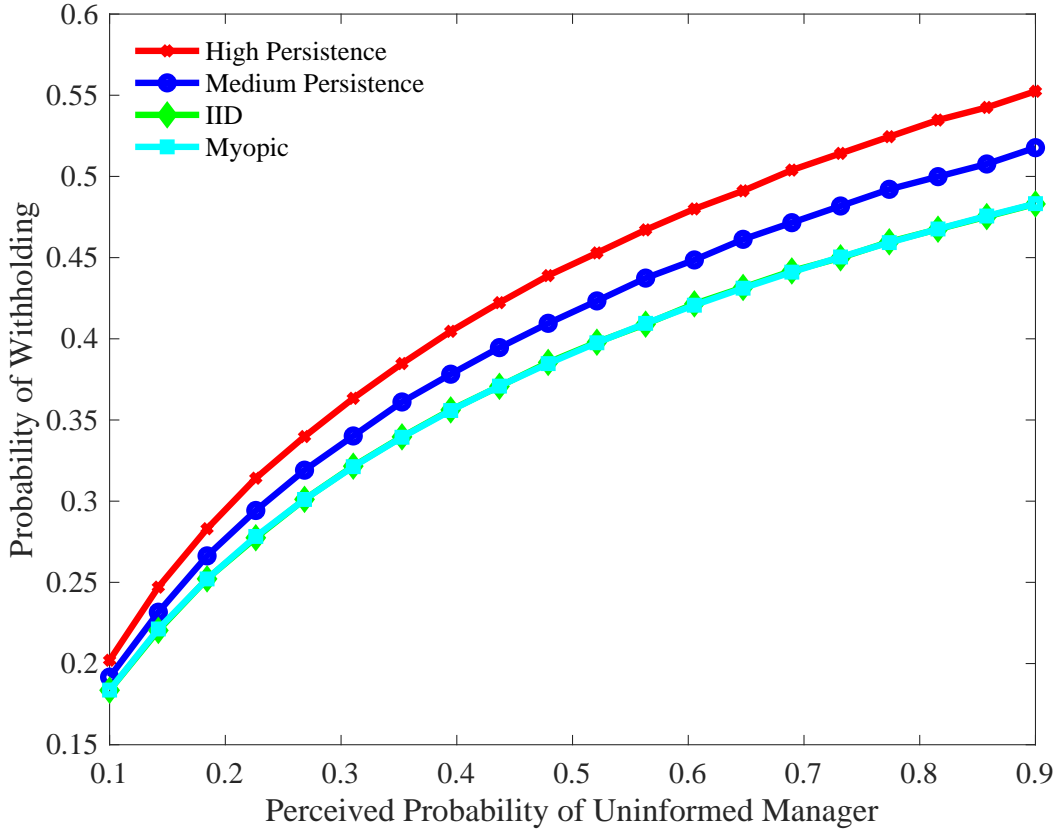
Figure 3. Effect of manager information persistence on disclosure choices

Note: The figure reports the likelihood of strategic withholding, i.e., the probability of non-disclosure $d = 0$ for an informed manager with $\theta = 1$, as a function of the market's perception p that the manager is uninformed. The results were computed numerically from the stationary distribution of the model. Each of the first three lines reflects an illustrative parameterization with information switching probabilities λ_0 and λ_1 chosen to involve high persistence, medium persistence, or low persistence (in the iid case). The final line plots manager withholding likelihoods under myopia with $\beta = 0$.

than in cases with $\lambda_0 < 1 - \lambda_1$ and medium levels of persistence (blue line with circles) or high levels of persistence (red line with $\times$ markers). Intuitively, with more persistent information, disclosure is more costly because a manager's reputation for being uninformed is stickier and therefore more valuable. Because the case of a myopic or statically optimizing manager is the traditional one analyzed in Dye (1985) and Jung and Kwon (1988), we also add a line for myopic managers with $\beta = 0$ to the figure (light blue line with squares). The myopic case coincides with the iid information withholding curve and involves lower withholding than other cases in the model, which assume $\beta > 0$, because managers don't internalize any future reputational gains from concealing information. To summarize, more persistent

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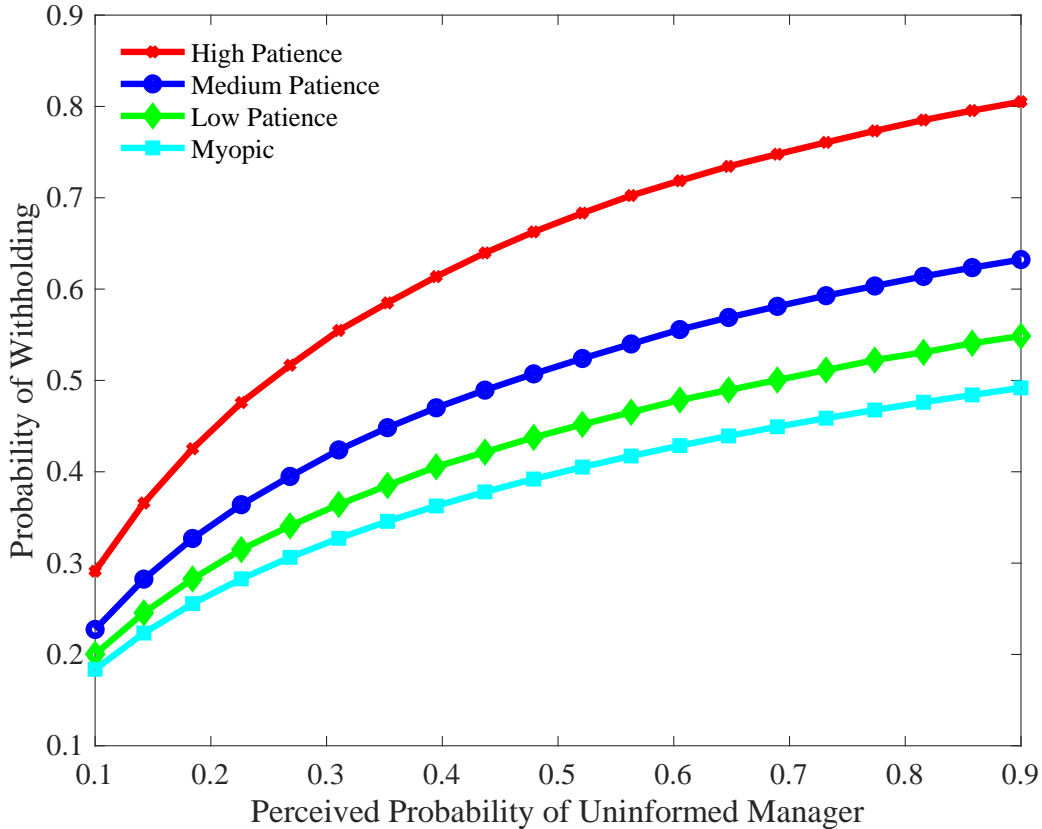dynamics in manager information imply more strategic withholding by managers.

Figure 4. Effect of manager patience on disclosure choices

Note: The figure reports the likelihood of strategic withholding, i.e., the probability of non-disclosure $d = 0$ for an informed manager with $\theta = 1$, as a function of the market's perception p that the manager is uninformed. The results were computed numerically from the stationary distribution of the model. Each of the first three lines reflects an illustrative parameterization with the manager's patience β set to high, medium, or low values, all of which are positive. The final line plots manager withholding likelihoods under myopia with $\beta = 0$.

In Fig. 4 we vary the patience of managers β to a high level (red line with $\times$ markers), a medium level (blue line with circles), a low level (green line with diamonds), and finally even lower to the myopic case with $\beta = 0$ (light blue line with squares) that, as we noted above, corresponds to a traditional static disclosure model. Because more patient managers with higher values of β care more about the future reputational benefits of withholding information, such managers choose to conceal information more often, with each of the curves in Fig. 4 shifted to reflect this force.

4. Estimation of the model

We choose our model's parameters over multiple steps. We start by fixing a few parameters, relating to time preferences and discounting, based on external information or common choices from related papers. Then, we estimate the remaining parameters with a two-step simulated method of moments (SMM) structural estimation exercise (Bazdresch et al., 2018). In Step 1, we estimate parameters in the model's exogenous block relating to earnings and analyst consensus forecasts. In Step 2, conditional upon Step 1's estimates, we estimate parameters in the model's endogenous block governing the evolution and precision of manager information among others directly linking to firm disclosure. We provide further econometric details in the estimation Appendix D.

We first discuss our choice of the time discounting parameters. Our model period is one year, matching our I/B/E/S data, so we set the value of the real interest rate to $r = 4\%$ following standard practice (Cooper and Ejarque, 2003; Hennessy and Whited, 2005, 2007). We set the manager's subjective discount factor to $\beta = 1 - (1/3.29)$ based on the median vesting duration in Gopalan et al. (2014). This choice is consistent with horizons induced by vesting practices in Edmans et al. (2013). In robustness checks, we also later change impatience to values spanning the typical CEO tenure in Taylor (2010) of 6 years.

The model's exogenous block involves two earnings parameters (the autocorrelation ρ and the standard deviation σ_u of the AR(1) process) and one consensus analyst forecast parameter (the standard deviation of the analyst signal σ_v). In Step 1 of our SMM procedure, we estimate these three parameters to match three data moments within a model simulation of a panel of firms. The bottom three rows of Table 3 present the data values (middle column) and simulated model values (right column) for each of our three targeted moments: the autocorrelation and standard deviation of earnings, and the variance of consensus forecast errors. These three chosen moments map quite naturally to, and are the rough empirical analogues of, our three parameters. Step 1 of our SMM procedure is exactly identified, and

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Table 3. Targeted Moments for the SMM Estimation

Moment	Data	Model
$\mathbb{P}(d_t = 1\mid \text{Change})$	0.4262 (0.0108)	0.5643 (0.0048)
$\mathbb{P}(d_t = 1 \mid d_{t-1} = 1, \text{Change})$	0.7959 (0.0072)	0.6948 (0.0080)
$\mathbb{P}(d_t = 1 \mid d_{t-2} = 1, \text{Change})$	0.7037 (0.0097)	0.6220 (0.0074)
$\mathbb{P}(d_t = 1 \mid d_{t-3} = 1, \text{Change})$	0.6348 (0.0113)	0.5872 (0.0058)
St Dev$(s_t - e_t \mid d_t = 1, \text{Change})$	0.0158 (0.0005)	0.0152 (0.0058)
$\mathbb{E}(e_t\mid d_t = 1, \text{Change}) - \mathbb{E}(e_t\mid \text{Change})$	0.0217 (0.0017)	0.0191 (0.0186)
$\mathbb{P}(d_t = 1 \text{ Never})$	0.5211 (0.0085)	0.5389 (0.0164)
$\mathbb{P}(d_t = 1 \text{ Always})$	0.1042 (0.0054)	0.1539 (0.0189)
Corr(e_t, e_{t-1})	0.1557 (0.0186)	0.1557 (0.0186)
Std (e_t)	0.0572 (0.0013)	0.0572 (0.0013)
Std $(c_t - e_t)$	0.0481 (0.0009)	0.0481 (0.0009)
Number of firms	5,056	
Number of observations	31,883	

Note: The table reports the empirical (middle column) and model (right column) values of the targeted moments for Steps 1 and 2 of our SMM estimation. Each value includes standard errors in parentheses. d_t is an indicator for firm disclosure, e_t refers to firm earnings, and c_t is a consensus analyst forecast. The empirical data set is from I/B/E/S and Compustat, spanning the years 2004-16 with sample details in Appendix B. The model data come from a simulation of 30,000 firms. In both the model and the data, moments conditioned upon "Change" are from the subsample of firms who change their disclosure behavior, while "Never" and "Always" reflect firms that never disclose or always disclose forecasts, respectively. The model standard errors come from a parametric bootstrap, and the empirical standard errors are clustered at the firm level.

we perfectly match each moment with our model. Note that we treat the model data and empirical data comparably throughout our procedure. For example, the data set has about 5,000 firms with an average of five fiscal years for each. Matching the time structure of this panel, we simulate 20,000 firms for five years each in our model after discarding an initial burn-in period for each firm.[3] The bottom three rows of Table 4 report our Step 1 point estimates and standard errors. Earnings are quite persistent, with an autocorrelation $\hat{\rho}$ of about 0.7. Shocks to earnings are volatile with a standard deviation $\hat{\sigma}_u$ just under 7%. And analyst signals contain about as much noise as the earnings process itself, with a standard deviation $\hat{\sigma}_v$ around 7%.

In Step 2, we estimate a total of five parameters in the model's endogenous disclosure block. Three of these parameters relate to the manager's information: the probability of switching between informed and uninformed states λ_0 and λ_1 as well as the standard deviation of the manager's signal σ_w. We also add two parameters to the model in Section 3, to capture the fact that in the cross section of firms in our data, many never disclose while many disclose every year. We assume that a fraction ξ of firms are non-strategic, always disclosing when informed, and that a fraction ζ of firms never disclose. We assume that the remaining fraction of firms $1 - \xi - \zeta$ in our data are strategic withholders, as in Section 3's model.

To estimate these five parameters in Step 2, we target a total of eight moments laid out in the top eight rows of Table 3. The standard deviation of manager forecast errors helps identify the standard deviation of the manager signal σ_w. The unconditional probability of disclosure, as well as the persistence of disclosure over one, two, and three periods help identify the information switching probabilities λ_0 and λ_1. Because the persistence and precision of information — linked to each of λ_0, λ_1, and σ_w — determine the extent to which market inference reacts to disclosure, and because this market reaction determines the endogenous selection into disclosure by managers, we also target the difference between the

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[3]Our estimation requires attention to this sort of detail. To account for permanent firm heterogeneity unrelated to earnings innovations, we target the autocorrelation and standard deviation of earnings after removing firm fixed effects. So we must match the empirical implications of removing fixed effects in short samples within our simulated data to ensure appropriate inference about the earnings process.

Table 4. SMM Parameter Estimates

Parameter, Role	Estimate
λ_0, $\mathbb{P}$(Switch to Uninformed)	0.0551 (0.0039)
λ_1, $\mathbb{P}$(Switch to Informed)	0.0474 (0.0044)
σ_w, Manager Signal Std. Dev.	0.0125 (0.0003)
ξ, $\mathbb{P}$ (Never Disclose)	0.0817 (0.0357)
ζ, $\mathbb{P}$ (Always Disclose)	0.1179 (0.0411)
ρ, Earnings e_t Autocorr.	0.7070 (0.0428)
σ_u, Earnings Shock Std. Dev.	0.0661 (0.0017)
σ_v, Analyst Signal Std. Dev.	0.0700 (0.0023)

Note: The table reports point estimates and standard errors (in parentheses) for each of the parameters estimated via SMM. The bottom three parameters are estimated in Step 1, while the top five parameters are estimated in Step 2. The standard errors reflect covariance matrices clustered at the firm level as well as asymptotically efficient weighting of moments in the overidentified Step 2.

average level of earnings when disclosing versus unconditionally. Since the three information parameters relate to strategic disclosure, we compute all of the moments discussed above only among firms in our data that change their disclosure behavior at least once. By contrast, to help piece apart the fraction of firms in the cross section of our model that always disclose (ξ) or never disclose (ζ), we also target as moments the fractions of firms in our data that always disclose and never disclose.

When implementing Step 2, note that we compute subsamples in our simulated data, and the associated moments, in exactly the same manner in the model simulation as in the data. Also, since Step 2's estimation is overidentified, we choose our parameter estimates to minimize the difference between model and data moments while weighting moments in an asymptotically efficient manner using the inverse of the estimated moment covariance matrix from our data. Appendix D includes information on our calculation of this moment covariance matrix, on our approach to computing the parameter estimates, and on the asymptotic formulas we use to compute standard errors.

Table 4 reports Step 2 parameter estimates and standard errors in the first five rows. Manager information is quite persistent, with only about a $\hat{\lambda}_0 \approx \hat{\lambda}_1 \approx 5\%$ probability of switching from informed to uninformed, or vice-versa, in each year. We reject the hypothesis

of static information endowments $\lambda_0 = 1 - \lambda_1$ at the 1% significance level, with a point estimate of persistence of $\overline{m} = 1 - \frac{1}{2}(\lambda_0 + \lambda_1) = .95$. The estimated probability of being uninformed, conditional on being a strategic firm, is $\overline{p} = \lambda_0/(\lambda_1 + \lambda_0) = 46\%$, implying that managers are about equally likely to possess private information as to be uninformed. Managers possess more precise information than outside analysts, with the standard deviation of their signal $\hat{\sigma}_w$ at just over 1% of assets and more than five times smaller than the analysts' signal volatility $\hat{\sigma}_v$. We estimate that around $1 - \hat{\xi} - \hat{\zeta} \approx 80\%$ of firms strategically manage information, with about $\hat{\xi} \approx 10\%$ of firms choosing to never disclose and about $\hat{\zeta} \approx 10\%$ of firms always disclosing. Note that we can reject the hypothesis that all firms are non-strategic, i.e., that $1 = \xi + \zeta$, at any conventional level of significance.

The estimated model's fit to the data is reported in the top eight rows of Table 3. We cannot expect an exact match between data and model moments given our nonlinear model and overidentified Step 2 estimation. However, the model reasonably reproduces the key economic features of the data, including the magnitude of manager forecast errors at around 1.5%, the high persistence of disclosure with around a 70% probability of continued disclosure after one year, and the magnitude of the average difference in earnings when disclosing versus unconditionally at about 2%. This final moment, reflecting higher disclosure propensity in periods with favorable news, is a moment that can only be endogenously matched by a model such as ours with strategic disclosure.

However, there are interesting discrepancies between model and data that highlight new forces worth future exploration. The model overstates the probability of disclosure, at about 55% versus around 40% in the data. The model also overpredicts the fraction of firms always disclosing at about 15% versus around 10% in the data. We note that our structure omits various adverse consequences that might arise from disclosure in practice, such as the revelation of proprietary information (Verrecchia, 1983) or potential exposure from future lawsuits (Francis et al., 1994). We speculate that a model with these additional frictions might match the slightly lower disclosure rates we see in the data. The model also implies a

slower decline in the likelihood of disclosure as a function of time since past disclosure, with probabilities declining by about 10% over two years versus around 20% in the data. We note that our model assumes perfect inference by the market from a firm's disclosure behavior, but there is some empirical evidence that investors imperfectly update their information in response to firm disclosure (Zhou and Zhou, 2020; Kartik et al., 2007). We speculate that a richer investor updating process might allow for different declines in disclosure propensities over time.

5.   Manager disclosure in the data and the model

We revisit our empirical Facts 1-3 within the estimated model. These facts are untargeted in our structural estimation of the model. Our model's overall qualitative match to these untargeted outcomes, discussed below, serves to provide confidence that the assumptions of the model capture key economic mechanisms. But in our discussion we also use these facts to point out aspects of the data that are not well captured in the model.
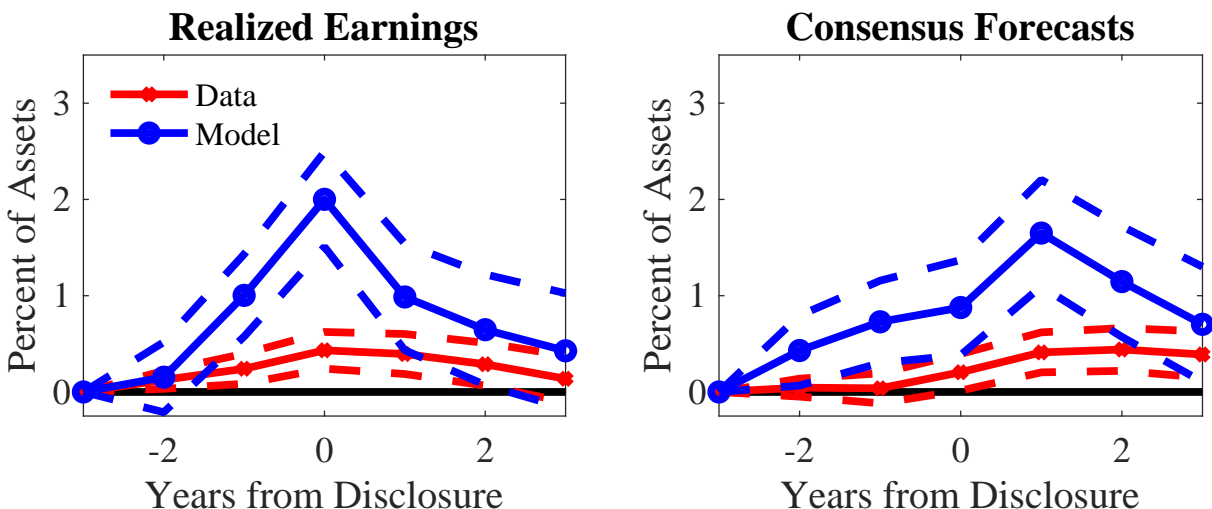
Figure 5. Earnings and Consensus Forecasts in the Model
Note: This plot reports the average change in realized earnings (left panel, solid lines) and realized consensus forecasts (right panel, solid lines) in the empirical data (red) and simulated benchmark estimated model data (blue) in the three years before and after disclosure of manager forecasts at year 0. Pointwise 90% confidence intervals, computed using a firm-level block bootstrap with 500 repetitions, accompany each line in dashes.

Table 5 reproduces empirical Facts 1-3 in the left column. The middle column reports comparable estimates from simulated data in the benchmark estimated model. We also consider a counterfactual case with no strategic disclosure and $\xi + \zeta = 1$. The no-withholding model estimates are reported in the right column.

Empirical Fact 1 highlighted that earnings were persistently higher around disclosure. In Panel A of Table 5 we see that the baseline model also generates higher earnings around disclosure due to strategic withholding of bad news. By contrast, the no withholding model, in which disclosure is uncorrelated with news, generates no such selection.

Fig. 5 studies dynamics, comparing the path of realized earnings (left panel) and consensus forecasts (right panel) around disclosure in the empirical data (red lines) and simulated data from the baseline estimated model (blue lines). Realistically, the model generates the persistent increase in earnings before disclosure, followed by gradual subsequent decline. Since forecasts are disclosed strategically during good times, and since earnings are persistent in the model, this pattern is natural. The model also reproduces the increase in consensus forecasts that builds up primarily after disclosure. This pattern arises because disclosure is more likely when managers' signals, and hence earnings on average, are high relative to the analysts' consensus beliefs. Note that the no withholding model, omitted from the figure, does not produce any selection whatsoever in earnings nor in consensus forecasts around disclosure.

Empirical Fact 2 revealed that breaks in disclosure were more likely in periods with large earnings shifts. Panel B of Table 5 shows that the baseline model reproduces this result, with particularly higher earnings growth when firms start disclosing and particularly lower earnings growth when firms stop disclosing. Intuitively, since firms previously engaging in strategic withholding give up a reputation for non-disclosure if they start disclosing, a manager must receive a higher signal to be tempted to disclose a forecast. The reverse is true for firms that have been disclosing. With no current reputation for non-disclosure, such firms benefit less from withholding and must receive more extreme news to be induced to

Table 5. Disclosure in the Model and the Data

Panel A: Earnings and Disclosure			
Dependent var. Earnings$_t$	Data	Model Benchmark	Model No Withholding
Disclose$_t$	0.018***	0.057***	-0.002
	(0.003)	(0.002)	(0.002)
Fixed Effects	Year, Firm	Year, Firm	Year, Firm
Years	2004-2016	-	-
Firms	5,023	5,000	5,000
Firm-Fiscal Yr. Obs.	31,246	33,715	33,715
Panel B: Earnings and Disclosure Breaks			
Dependent var. Earnings Growth$_t$	Data	Model Benchmark	Model No Withholding
Start Disclosing$_t$	0.004*	0.053***	-0.004
	(0.002)	(0.002)	(0.002)
End Disclosing$_t$	-0.006**	-0.056***	0.002
	(0.003)	(0.001)	(0.003)
Disclose$_t$	0.002***	0.004***	0.000
	(0.001)	(0.001)	(0.001)
Fixed Effects	Year, Firm	Year, Firm	Year, Firm
Years	2004-2016	-	-
Firms	4,990	4,996	4,996
Firm-Fiscal Yr. Obs.	30,906	32,847	32,847
Panel C: Disclosure Dynamics			
Dependent var. Disclose$_t$	Data	Model Benchmark	Model No Withholding
Earnings$_t$	0.082***	0.766***	-0.031
	(0.017)	(0.033)	(0.025)
Disclose$_{t-1}$	0.267***	0.279***	0.561***
	(0.014)	(0.001)	(0.008)
Earnings$_t$ × Disclose$_{t-1}$	0.639***	0.836***	0.018
	(0.110)	(0.075)	(0.039)
Fixed Effects	Year, Firm	Year, Firm	Year, Firm
Years	2004-2016	-	-
Firms	5,023	5,000	5,000
Firm-Fiscal Yr. Obs.	31,246	33,715	33,715

Note: The table reports estimates from our empirical sample of realized earnings and manager forecasts from the I/B/E/S guidance data set (left column), from a simulated sample in the benchmark estimated model (middle column), and from a simulated sample in a counterfactual model with no withholding (right column). Starting in Panel A, Earnings$_t$ is realized profits in year t, scaled by a firm's assets. Disclose$_t$ is an indicator for whether the firm releases manager profit forecasts in year t. Starting in Panel B, Earnings Growth$_t$ is the change in Earnings$_t$ from $t-1$ to t. Start Disclosing$_t$ is an indicator activated if the firm releases manager guidance in year t but did not in $t-1$. End Disclosing$_t$ is an indicator activated if the firm does not release manager guidance in year t but did in $t-1$. In Panel C, we estimate a regression involving lags of some of these variables. The standard errors, in parentheses, are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

cease disclosure. The no withholding model, featuring none of these concerns, fails to capture the empirical link between earnings growth and disclosure breaks.

Empirical Fact 3 revealed that disclosure varies more with earnings in the data, and is more likely, for firms that have recently disclosed. Panel C of Table 5 shows that the baseline model reproduces this fact, with more sensitivity of observed disclosure to earnings for firms having disclosed in the last period. Intuitively, previously non-disclosing firms are more likely to be strategically withholding. Such firms conceal even some moderately good news, resulting in lower sensitivity of their disclosure to earnings. In the no withholding model, persistence in information endowments generates disclosure persistence but fails to generate the heterogeneous responsiveness of disclosure to earnings seen in the data.

We conclude that the benchmark estimated model with strategic disclosure qualitatively matches all of the untargeted empirical Facts 1-3, while a model with no strategic withholding fails to match them. This analysis helps to validate the underlying strategic disclosure mechanism in the model. However, we also note that the baseline model overpredicts the quantitative magnitude of selection into disclosure in each case. We speculate that an extended model including the factors discussed in the previous section, such as proprietary or legal costs of disclosure, might be at work in the data, reducing disclosure in some periods and dampening the sharp selection we see in the model.

6. Consequences of manager withholding

We explore three quantitative questions. First, we ask to what extent concealment of information by managers increases market uncertainty. US policymakers have, through the enactment of safe harbor provisions in the Private Securities Litigation Reform Act of 1995 and additional rules in Regulation Fair Disclosure in 2000, explicitly encouraged public disclosure of information by firms. So understanding the impact of withholding on market information can directly inform debates on disclosure regulation. Second, we ask how much

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distinct sources of information, e.g., managers versus analysts, contribute to the accuracy of market beliefs. Disentangling the contributions of each source is difficult without a structural model such as ours that includes a public signal. Third, we investigate whether dynamic considerations matter for the impact of concealment. Modeling these dynamic considerations is a novel contribution of our theory.

Table 6. Consequences of Withholding

	Market RMSE (% of Assets)	$\mathbb{P}$(Withhold)
No Information	6.61%	-
Benchmark (a)	4.52%	0.40
No Withholding (b)	4.20%	0.00
No Analyst Forecasts	5.73%	0.36
Myopic Manager	4.45%	0.34
Δ RMSE (a)-(b)	0.32%	
Std. error	(0.02%)	

Note: The middle column reports the root mean squared error (RMSE) of market posterior beliefs in simulated data from the model. Market beliefs are formed for earnings relative to firm assets, so these figures are in percent of firm assets. The right column, where relevant, reports the probability of withholding, i.e., the probability with which an informed manager conceals information. Each row reports a different case or counterfactual in the model. The bottom panel reports the difference in the RMSE of the Benchmark and No Withholding cases, together with the standard error of this difference computed by sampling repeatedly from the approximating distribution of our estimated parameters in Table 4.

To answer each question, we use simulated model data drawn from our benchmark estimated model and various counterfactuals. In the simulations, we compute investors' beliefs or best forecasts of earnings after observing all available information. We then measure accuracy by computing the RMSE, i.e., the magnitude of the market's forecast error reported in the middle column of Table 6. Given the AR(1) fundamentals process, firm value is a multiple of current expected earnings in the model, so we emphasize that imprecise beliefs about earnings directly map to proportional imprecisions in market valuations. Each row reports a different case of our model or counterfactual. In the first row, as a point of comparison, we note that with no information whatsoever, shutting down analyst forecasts and manager disclosure completely, the RMSE or level of market uncertainty is equal to the

standard deviation of the earnings shock σ_u at just below 7% of assets. The right column reports, where relevant, the probability that an informed firm withholds information from the market.

To answer our first question, we examine the benchmark estimated model marked (a) in Table 6. Market uncertainty is around 4.5% of assets, an improvement of around a third relative to the no information case, but informed managers do withhold their forecasts 40% of the time. By contrast, in the no withholding counterfactual marked (b), in which all informed managers disclose, market uncertainty drops to 4.2% of assets. Strategic concealment by managers therefore results in a sizable increase of uncertainty by around 4.52/4.2-1 $\approx$ 8%, the figure cited in our abstract. To provide more context, note that the firms in our sample have mean assets of about $20 billion, so the increase in uncertainty from the no withholding to benchmark case of 0.32% of assets translates into around $64 million on average. We view this meaningful information loss from concealment as validating the traditional attention paid to firm disclosure by policymakers.

To answer our second question, on the relative importance of information sources, we consider a no analyst forecasts counterfactual. Compared to our benchmark model, with market uncertainty around 4.5% of firm assets, uncertainty increases substantially to 5.73% of assets. This increase closes more than half of the gap between the benchmark and no information cases, implying that analysts provide a bit more than half of the information available to markets. Analyst forecasts contribute substantial information to markets.

To answer our third question, on the importance of dynamic considerations, we consider a myopic manager counterfactual with $\beta = 0$. This counterfactual yields the traditional static disclosure model without reputational benefits of withholding. Managers withhold less at around 34% of the time when informed than the benchmark's 40%, and market uncertainty declines to 4.45% of assets from the benchmark's 4.52%. While typically managerial myopia is found to distort decisions (Edmans et al., 2017; Terry et al., 2018), our result points to a separate communication channel where a more patient manager may strategically release

less information.

We close with a word of caution. Our market uncertainty calculations do not measure welfare. In fact, investors in our model trade the firm at its expected price conditional on all public information, implying few costs if investors are either risk-neutral or well diversified. Explicit policy statements in this context would require a richer investor structure featuring risk aversion (Manela 2014; Kadan and Manela 2018). Our model also omits channels through which information withholding could have direct real effects on outcomes such as firm investment, channels that might prove meaningful in practice for quantifying the overall impact of disclosure. Although we focus our quantification on the targeted information loss channel, we hope to spur further research in each of these other promising directions.

7. Robustness and subsample analysis

Table 7 reports various parameter robustness checks. Starting at our benchmark point estimates from Table 4, we vary our parameters up and down to round values while keeping other parameters fixed.[4] For each row, corresponding to a different robustness check, we recompute the RMSE of market beliefs in simulated data with strategic withholding, the RMSE in a corresponding counterfactual with no withholding, and the underlying probability of withholding for informed firms. The consequences of withholding vary only moderately across alternative parameterizations. In each case, strategic withholding leads to market uncertainty higher than in a no withholding environment, with RMSEs increasing by between 6.7% and 8.8% for all checks compared to a $4.52/4.20\text{-}1 \approx 7.6$ % benchmark increase. The probability of withholding also varies fairly little from its 40% benchmark value in most cases, although less patient managers do choose to conceal less.

In Table 8 we re-estimate the model via our two-step SMM procedure for various subsamples sorted by observables. For each column or subsample, Table 8 reports SMM parameter

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[4]We do not perform a similar check for the standard deviation of the analyst signal, since Table 6 already varies this parameter to extreme values.

Table 7. Robustness to Alternative Parameters

		Market RMSE (% of Assets)	Market RMSE (No Withholding)	$\mathbb{P}$(Withhold)
Benchmark		4.52	4.20	0.40
High Autocorrelation	$\rho = 0.75$	4.55	4.21	0.39
Low Autocorrelation	$\rho = 0.65$	4.50	4.19	0.38
High Volatility	$\sigma_u = 0.075$	4.92	4.55	0.41
Low Volatility	$\sigma_u = 0.05$	3.73	3.49	0.39
High $\mathbb{P}$(Switch to Uninformed)	$\lambda_0 = 0.065$	4.58	4.28	0.40
Low $\mathbb{P}$(Switch to Uninformed)	$\lambda_0 = 0.045$	4.44	4.10	0.39
High $\mathbb{P}$(Switch to Informed)	$\lambda_1 = 0.055$	4.45	4.09	0.40
Low $\mathbb{P}$(Switch to Informed)	$\lambda_1 = 0.045$	4.60	4.31	0.40
Imprecise Manager Signal	$\sigma_w = 0.015$	4.55	4.25	0.40
Precise Manager Signal	$\sigma_w = 0.010$	4.50	4.15	0.40
High Patience	$\beta = 0.87$	4.55	4.20	0.44
Low Patience	$\beta = 0.55$	4.49	4.20	0.34

Note: The left column reports the root mean squared error (RMSE) of market posterior beliefs in simulated data from a model with strategic withholding. Market beliefs are formed for earnings relative to firm assets, so these figures are in percent of firm assets. The middle column reports the RMSE of market posterior beliefs in a counterfactual for a comparable model with no strategic withholding by managers. The right column reports the probability of withholding, i.e., the probability that an informed manager conceals their forecast. Different rows report these values for robustness checks varying the value of the indicated parameter, holding all other parameters fixed at their benchmark values from Table 4.

estimates in the top panel, the model's fit to targeted moments in the middle panel, and the consequences of withholding in the bottom panel. We sort firms by the average number of analysts forecasting their earnings, by their average total asset value, and by the standard deviation of analyst consensus forecast errors. We split firms at the median into high and low bins for each characteristic, resulting in a total of six subsamples (three characteristics × two high vs low bins). We emphasize that our chosen characteristics do not result in "exogenously" sorted subsamples. We intentionally choose characteristics to investigate heterogeneity in firm information or disclosure environments (Beyer et al., 2010).

Our estimates in the top panel of Table 8 imply that firms with less analyst coverage face more volatile and less persistent earnings, less persistent manager information, and less precise information for managers and analysts than firms with many analysts. Firms with few analysts are also less likely to be strategic disclosers. In the middle panel, we see that the model fits acceptably in both subsamples. Since managers with few analysts have less precise and less persistent information on which to build reputations, the bottom panel reveals less strategic withholding at around 17% of informed periods compared to 31% for firms with many analysts. The increase in market uncertainty with strategic withholding versus no withholding is smaller for firms with fewer analysts, at around $7.72/7.58 \approx 2\%$ versus more than 6% for firms with many analysts. Strategic disclosure is more important for firms with more information, and more stable information, available to manipulate. Comparing small versus large firms, Table 8 reveals similar patterns. Smaller firms face more volatile and less persistent earnings, less persistent information, and less precise information for managers and analysts. Small firms are also less likely to be strategically disclosers than large firms.

We estimate in the top panel of Table 8 that in firms with imprecise analyst forecasts, managers retain quite accurate information with a signal standard deviation of $\hat{\sigma}_w \approx 2\%$ of assets versus $\hat{\sigma}_v \approx 17\%$ for analysts. These estimates are driven directly by the empirical standard deviations of manager versus analyst forecast errors in the middle panel. Given their more precise information, managers are hesitant to disclose even moderately negative

Table 8. Subsample Analysis

Subsample Estimates	Many analysts	Few analysts	High size	Low size	High analyst errors	Low analyst errors
$\lambda_0, \mathbb{P}(\theta_t = 0 \mid \theta_{t-1} = 1)$	.05 (.00)	.20 (.01)	.03 (.00)	.18 (.01)	.05 (.01)	.05 (.01)
$\lambda_1, \mathbb{P}(\theta_t = 1 \mid \theta_{t-1} = 0)$	.06 (.02)	.06 (.00)	.04 (.00)	.08 (.00)	.03 (.00)	.05 (.00)
σ_w, Std Manager Signal	.01 (.00)	.02 (.00)	.01 (.00)	.02 (.00)	.02 (.00)	.02 (.00)
$\xi, \mathbb{P}$ (Never d_t)	.11 (.08)	.22 (.03)	.03 (.02)	.06 (.02)	.05 (.06)	.12 (.04)
$\zeta, \mathbb{P}$ (Always d_t)	.31 (.08)	.47 (.04)	.19 (.05)	.40 (.04)	.12 (.06)	.24 (.11)
ρ, Earnings e_t Autocorr.	.84 (.05)	.48 (.06)	.80 (.02)	.90 (.08)	.44 (.06)	.94 (.04)
σ_u, Std Earnings Shock	.04 (.05)	.09 (.01)	.02 (.00)	.13 (.00)	.14 (.00)	.02 (.00)
σ_v, Std Analyst Signal	.04 (.00)	.12 (.01)	.02 (.00)	.13 (.01)	.17 (.01)	.02 (.00)
Number firms	2,507	2,549	2,230	2,826	2,626	2,432
Number obs.	17,396	14,487	17,178	14,705	15,574	16,309

Subsample Moments: Data (Standard Error) Model

	Many analysts	Few analysts	High size	Low size	High analyst errors	Low analyst errors
$\mathbb{P}(d_t = 1 \mid \text{Ch.})$	.47 (.01) .54	.35 (.02) .43	.45 (.01) .58	.40 (.01) .46	.48 (.02) .55	.48 (.02) .55
$\mathbb{P}(d_t = 1 \mid d_{t-1} = 1, \text{Ch.})$	.82 (.01) .74	.75 (.02) .65	.81 (.01) .77	.77 (.01) .60	.82 (.01) .68	.83 (.01) .70
$\mathbb{P}(d_t = 1 \mid d_{t-2} = 1, \text{Ch.})$	.73 (.01) .65	.63 (.02) .50	.73 (.01) .70	.67 (.02) .46	.75 (.01) .61	.76 (.01) .61
$\mathbb{P}(d_t = 1 \mid d_{t-3} = 1, \text{Ch.})$	.67 (.01) .59	.54 (.02) .42	.67 (.01) .66	.59 (.02) .40	.68 (.02) .58	.70 (.02) .57
Std $(s_t - e_t \mid d_t = 1, \text{Ch.})$	.01 (.00) .01	.02 (.00) .02	.01 (.00) .01	.02 (.02) .02	.02 (.00) .02	.01 (.00) .01
$\mathbb{E}(e_t \mid d_t = 1, \text{Ch.}) - \mathbb{E}(e_t \mid \text{Ch.})$	.02 (.00) .01	.03 (.00) .02	.01 (.01) .01	.03 (.00) .03	.03 (.00) .05	.01 (.01) .00
$\mathbb{P}(d_t = 1 \text{ Never})$	.40 (.01) .47	.67 (.01) .70	.49 (.01) .50	.56 (.01) .64	.50 (.01) .62	.53 (.01) .58
$\mathbb{P}(d_t = 1 \text{ Always})$	.15 (.01) .19	.04 (.00) .05	.15 (.01) .16	.05 (.00) .09	.10 (.01) .11	.13 (.01) .16
Corr(e_t, e_{t-1})	.34 (.02) .34	.04 (.03) .04	.40 (.01) .40	.04 (.03) .04	.02 (.03) .02	.39 (.02) .39
Std (e_t)	.04 (.00) .04	.08 (.00) .08	.02 (.00) .02	.10 (.00) .10	12 (.00) .12	.02 (.00) .02
Std $(c_t - e_t)$	.03 (.00) .03	.08 (.00) .08	.02 (.00) .02	.09 (.00) .09	.11 (.00) .11	.01 (.00) .01

Subsample Withholding Magnitudes

	Many analysts	Few analysts	High size	Low size	High analyst errors	Low analyst errors
RMSE (% of Assets)	2.89	7.72	1.58	9.51	9.84	1.59
RMSE (No Withholding)	2.72	7.58	1.49	8.93	9.27	1.57
$\mathbb{P}(\text{Withhold})$	0.31	0.17	0.34	0.24	0.64	0.33

Note: The top panel reports SMM parameter estimates and standard errors. The middle panel reports targeted moments in the data, with their standard errors, together with simulated moments from the estimated model. The SMM estimation process follows the two-step procedure outlined in the main text. All standard errors are clustered by firm. The bottom panel reports the root mean squared error (RMSE) of market posterior beliefs in simulated model data with strategic withholding, the RMSE in a model counterfactual with no withholding, and the probability of withholding by informed managers. The RMSE figures are for earnings relative to firm assets, so they are interpretable as percent of firm assets.

news, resulting in more strategic withholding — in around 64% of informed years — in the bottom panel. By contrast, firms with more precise analysts are less likely strategically manage their disclosure. We conclude that policy interventions to increase disclosure could

be most impactful for firms with less informed analysts.

8.   Conclusion

A comprehensive data set of earnings forecasts by managers of US public firms reveals patterns consistent with the idea that firms selectively conceal bad information from investors. We extend traditional static models of disclosure to incorporate fully dynamic, forward-looking strategic withholding of information by managers. The model, in which managers are concerned about the precedent set by or reputational effects of disclosing information, can qualitatively match a rich set of facts in our data related to the persistence of disclosure and its comovement with realized earnings. In a quantitative, structurally estimated version of our model, strategic concealment of information by managers results in a sizable loss of information for investors, increasing the uncertainty of firm market valuations. These results validate the traditional attention paid to firm disclosure regulation by US policymakers.

Overall, our estimates suggest that voluntary channels filter out a meaningful portion of manager information, in contrast to the predictions of unravelling theory (Grossman, 1981; Milgrom, 1981). Yet, having focused on an environment where information endowments are exogenous (Dye, 1985; Jung and Kwon, 1988), we know little of the potential mechanisms affecting disclosure frictions or whether corporate choices ranging from investment to capital structure could interact with the voluntary disclosure process. Building strategic models of the interaction between factors affecting the production of information and its dissemination is likely a rich avenue for future research.

Appendix

A.   Proofs

In this Appendix we provide the proofs of theoretical results provided in the main text.

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Proof. [Proof of Proposition 2] This result comes from noting that when $\lambda_0 = 1 - \lambda_1$, we get

$$V^D(p, z, s) - V^{ND}(z, s) = P^D(p, z, s) - P^{ND}(p, z), \tag{A.1}$$

which means that the manager maximizes their myopic price gain when choosing whether or not to disclose. $\square$

Proof. [Proof of Proposition 3] The result follows directly from iterated expectations. The expected payoff given disclosure at time t is

$$V^D(p_t, z_t, s_t) = P^D(z, s) + \mathbb{E}\left(\sum_{k=1}^{\infty} \beta^k P_{t+k} | p_t, z_t, s_t\right), \tag{A.2}$$

where

$$P_{t+k} = \mathbb{E}\left(\sum_{j=0}^{\infty} \frac{e_{t+k+j}}{(1+r)^j} | \mathcal{H}_{t+k-1}, \hat{c}_{t+k}, d_{t+k}\right). \tag{A.3}$$

In the event of disclosure at time t, the manager and market information set coincide, so by iterated expectations

$$\mathbb{E}\left(P_{t+k} | p_t, z_t, s_t\right) = \sum_{j=0}^{\infty} \frac{\mathbb{E}\left(e_{t+k+j} | z_t, s_t\right)}{(1+r)^j} = \frac{1+r}{1+r-\rho} \mathbb{E}(e_{t+k} | z_t, s_t). \tag{A.4}$$

Substituting in the value function, we get

$$\begin{aligned}
V^D(p_t, z_t, s_t) &= \frac{1+r}{1+r-\rho} \mathbb{E}(e_t | z_t, s_t) + \frac{1+r}{1+r-\rho} \sum_{k=1}^{\infty} (\rho\beta)^k \mathbb{E}(e_t | z_t, s_t) \\
&= \frac{1+r}{1+r-\rho} \frac{1}{1-\rho\beta} \mathbb{E}(e_t | z_t, s_t) \\
&= \frac{P^D(z_t, s_t)}{1-\rho\beta}.
\end{aligned}$$

$\square$

Proof. [Proof of Proposition 4] For expositional purposes, we normalize the unconditional mean of e to zero because it plays no role in the proof, and we drop the dependence on z.

(1) Suppose that there is an equilibrium, such that information is withheld (case a) or disclosed (case b) for all s conditional on some belief $p \in (0,1)$,

$$
\begin{aligned}
V_1^{ND}(p,s) &= P^{ND}(p) + \beta \mathbb{E}[\lambda_0 V_0(p') + (1-\lambda_0)V_1(p',s')|s] \\
&= \beta \mathbb{E}[\lambda_0 V_0(p') + (1-\lambda_0)V_1(p',s')], \quad (\text{A.5})
\end{aligned}
$$

where $p' = p(1-\lambda_1) + (1-p)\lambda_0$ (case a) or $p' = 1 - \lambda_1$ (case b) so that $V_1^{ND}(p,s)$ does not depend on s. On the other hand, from proposition 3, $V_1^D(p,s)$ is unbounded in s, implying that the manager would prefer to disclose for s large enough (case a) or withhold for s small enough (case b), a contradiction.

(2) Suppose that there is an equilibrium, such that the manager adopts a threshold strategy k_p for any p, i.e., discloses if $s > k_p$ and withholds if $s < k_p$. We know from (1) that k_p is finite. Then,

$$
V_1^{ND}(p,s) = P^{ND}(p) + \beta \mathbb{E}[\lambda_0 V_0(p') + (1-\lambda_0)V_1(p',s')|s], \quad (\text{A.6})
$$

where $p' = p(1-\lambda_1) + (1-p)\lambda_0$ if $s < k_p$ and $p' = 1 - \lambda_1$ if $s > k_p$.

(2.a) Suppose that

$$
\mathbb{E}(\lambda_0 V_0(p(1-\lambda_1) + (1-p)\lambda_0) + (1-\lambda_0)V_1(p(1-\lambda_1) + (1-p)\lambda_0, s')) \quad (\text{A.7})
$$

$$
= \mathbb{E}(\lambda_0 V_0(1-\lambda_1) + (1-\lambda_0)V_1(1-\lambda_1, s')) = 0, \quad (\text{A.8})
$$

where the last equality follows from proposition 2. It follows that $\mathbb{E}(\lambda_0 V_0(p') + (1-\lambda_0)V_1(p') = 0$ for any belief p' that may occur on the equilibrium path, and k_p must be the static threshold

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in proposition 2. Then, $V_0(p') = P^{ND}(p')$, which is increasing in p', and $V_1(p', s)$ is not a function of p' from proposition 3, a contradiction to (A.8).

(2.b) Suppose that

$$\mathbb{E}(\lambda_0 V_0(p(1 - \lambda_1) + (1 - p)\lambda_0) + (1 - \lambda_0)V_1(p(1 - \lambda_1) + (1 - p)\lambda_0, s')) \qquad \text{(A.9)}$$

$$< \mathbb{E}(\lambda_0 V_0(1 - \lambda_1) + (1 - \lambda_0)V_1(1 - \lambda_1, s')) = 0, \qquad \text{(A.10)}$$

so that $\mathbb{E}(\lambda_0 V_0(p') + (1 - \lambda_0)V_1(p', s')) < 0$ for any p' on the equilibrium path. Because $\mathbb{E}(V_1(p', s')) \geq V_0(p')$ for any p', it must hold that

$$\mathbb{E}(p'V_0(p') + (1 - p')V_1(p', s')) \leq \mathbb{E}(\lambda_0 V_0(p') + (1 - \lambda_0)V_1(p', s')) < 0, \qquad \text{(A.11)}$$

for any p' on the equilibrium path. The left-hand side of this inequality is equal to the unconditional mean of e from iterated expectations, a contradiction.

(2.c) Suppose that

$$\mathbb{E}(\lambda_0 V_0(p(1 - \lambda_1) + (1 - p)\lambda_0) + (1 - \lambda_0)V_1(p(1 - \lambda_1) + (1 - p)\lambda_0, s')) \qquad \text{(A.12)}$$

$$> \mathbb{E}(\lambda_0 V_0(1 - \lambda_1) + (1 - \lambda_0)V_1(1 - \lambda_1, s')) = 0. \qquad \text{(A.13)}$$

Note that $V_1^D(s)$ is increasing and continuous in s from proposition 3 so that we must have $V_1^{ND}(p, k_p - a) \leq V_1^D(k_p) \leq V_1^{ND}(p, k_p + a)$ for any $a > 0$, where Eq. (A.13) implies that at least one inequality is strict. Assume that $V_1^{ND}(p, k_p - a) < V_1^D(k_p)$. Then, there exists $\epsilon > 0$ sufficiently small, such that $V_1^{ND}(p, k_p - a) < V_1^D(k_p - \epsilon)$, which contradicts that k_p is the disclosure threshold. The case of $V_1^{ND}(p, k_p - a) > V_1^D(k_p)$ follows from a symmetric argument. $\qquad \square$

B.   Data

In this Appendix we provide more detail on our empirical data and sample construction. Our sample is from the I/B/E/S earnings announcement database for fiscal years ending between January 1, 2004 and December 31, 2016 and firms traded on a major US exchange. The details of the sample selection are reported in Table 9. We start the sample in 2004 because of significant changes in US regulation in 2000 and 2002 that have altered both the incentives to disclose information and the collection of forecasts. Since August 2000, Regulation Fair Disclosure (Reg FD) prohibits most private communications between managers and market analysts. By shutting down this communication channel, Reg FD appears to have increased the frequency of public managerial forecasts. Also, since July 2002, the Sarbanes-Oxley Act (SOX) dramatically increased internal controls and management responsibilities. From a data-collection perspective, SOX also required conference calls to be in transcript form, allowing for convenient identification of manager forecast disclosure.

Table 9. Sample Selection

	Nb. of EA	Unique firms	Nb. of MF
I/B/E/S EA sample 2004-2016	83,935	10,542	
Matched to Compustat and CRSP	67,145	9,665	
I/B/E/S CIG sample 2004-2016			
Matched to I/B/E/S EA	67,145	9,665	66,602
After prior EA date but prior period end	67,145	9,665	59,285
Minimum 6 month before period end	67,145	9,665	29,671
Retain only earliest MF	67,145	9,665	13,513
Must have market expectation	53,167	8,109	13,309
Full sample	**53,167**	**8,109**	**13,309**

Note: This table summarizes the sample selection criteria. Annual earnings announcements (EA) and management forecasts (MF) are obtained from I/B/E/S. Firms in our sample must be present in the CRSP and Compustat database using the I/B/E/S ticker, gvkey and permno matching tables from Wharton Research Data Services. Market expectation is calculated from the I/B/E/S analyst forecast file based on the median of the last five unique analyst forecasts.

We construct a sample of raw earnings per share (EPS). Earnings in I/B/E/S are reported as pro-forma earnings calculated under the same accounting principles as analysts' and management forecasts. The initial sample includes $83,935$ firm-years from $10,542$ unique firms. We match to Compustat and CRSP, non-missing and non-negative equity, and require non-missing announcement and lagged announcement dates to create a window for management forecasts.

We obtain management forecasts from the I/B/E/S management forecast guidance (CIG) database. Managers can make forecasts on a variety of items (earnings, revenue, gross margins, etc.) and for different time horizons, in press releases or conference calls. The most common forecasts are one-quarter earnings forecasts; however, these tend to occur at a point where most of the uncertainty has already realized and are typically on a schedule. Hence, we focus on one-year ahead earnings forecast, which are the next most common type of forecast. The majority of forecasts are made bundled with the prior earnings announcement, that is, are made in a single press release including both current earnings and the forecast for next-year earnings. In our final sample, such bundled forecasts form 90.2% of the forecasts, which implies a fairly consistent forecasting horizon of between 10 and 11 months before a fiscal year end.

We merge them with the I/B/E/S earnings database by using I/B/E/S unique tickers and the forecast period end date, retaining only annual forecasts where the forecast period end date can be matched to the I/B/E/S earnings announcement sample. This selection yields a sample of $66,602$ forecasts. We require a forecast to be made after the prior earnings announcement date but at least six months before the period end date. We remove forecasts made after the fiscal year end because they are less likely to be consistent with a model of incomplete information endowment. For periods with multiple forecasts, we use the earliest forecast, which yields a sample of $13,513$ forecasts.

We calculate the raw forecast, as it was made, by multiplying the forecast in I/B/E/S, adjusted for the number of shares with the I/B/E/S adjustment factor. For each firm-

year with or without a forecast, we require a measure of market expectation about realized earnings. For any firm-year with a forecast, we use the I/B/E/S CIG analyst consensus; this number is provided adjusted for stock splits by I/B/E/S, and we unadjust it by multiplying by the adjustment factor. This consensus measure reflects the consensus before a management forecast is made. We calculate a consensus by using the I/B/E/S analyst file, which reports all annual forecasts made by financial analysts. The consensus is defined as the median of the last five unique analyst forecasts made prior to the forecast or, in the absence of a forecast, prior to the earnings announcement. Therefore, the consensus is always constructed from analyst forecasts made prior to the management forecast. We remove observations for which we are unable to form a market expectation and drop observations with missing assets or earnings, implying a sample of $53,167$ unique earnings announcements in $8,109$ unique firms; during this period, a total of $13,309$ management forecasts were made. Lastly, we winsorize all variables at the 1% level and scale realized earnings, forecasts and consensus by assets, in order to control for changes in the size of firms that are not within the scope of our analysis.

C. Numerical methods

In this appendix, we describe the computational strategy we use to numerically solve our model. Our approach is based on policy iteration. The steps are as follows:

1. Discretize the state space.

2. On the s-th iteration of the solution algorithm, guess a disclosure policy $d^{(s)}(p, e_{-1}, c, s)$.

   (a) Assume that market beliefs and manager actions are governed by $d^{(s)}$, and iterate forward on the system of Bellman equations above until the implied $V_1^{(s)}$, $V_0^{(s)}$ converge to some tolerance.

   (b) Compute the stationary distribution $\mu_1^{(s)}(p, e_{-1}, c, s)$ and $\mu_0^{(s)}(p, e_{-1}, c)$ of the model given $d^{(s)}$, as well as the exogenous distributions in the model. This involves re-

peatedly pushing forward weight on a histogram given the policies and exogenous transitions until the distributions stabilize to within some tolerance.

(c) Compute a *new* policy $d^{(s+1)}(p, e_{-1}, c, s)$, simply given by

$$\arg \max_d \left(d V_1^{D(s)} + (1 - d) V_1^{ND(s)} \right). \tag{C.1}$$

(d) Then, compute an error measure given by the mean absolute difference between $d^{(s+1)}$ and $d^{(s)}$, weighted by the ergodic distributions $\mu_1^{(s)}$ and $\mu_0^{(s)}$. This error is exactly equal to the probability of disclosure policy deviation given assumed market beliefs. When this error is sufficiently small, you have computed an equilibrium.

3. Once we have solved the model, we can simulate and compute moments as desired for input into the structural estimation routine.

We implement our solution algorithm in Fortran, discretizing driving exogenous processes for earnings, consensus forecasts, and manager signals using the method of Tauchen (1986). Broadly, our numerical approach to the resulting discrete-state dynamic programming problem follows the methods outlined in Judd (1998).

D. *Structural estimation of the model*

In this appendix, we lay out the details of the structural estimation of our model, which follows a simulation- and overidentification-adapted version of two-step GMM estimation. We discuss the broader framework first, and then we specialize to our estimation. In a two-step estimation such as ours, the econometrician wishes to estimate the value of a joint parameter vector

$$(\theta', \gamma')'. \tag{D.1}$$

In a first-step, an estimator $\hat{\gamma}$ for the subvector γ is computed in a manner that matches a vector m of moments, with

$$\frac{1}{N}\sum_i m(X_i, \hat{\gamma}) = 0. \tag{D.2}$$

Here, i indexes data observations X_i. Then, conditional upon these first-step estimates, the second estimation step involves computing an estimator for the remaining parameters $\hat{\theta}$ to solve

$$\min_\theta \left(\frac{1}{N}\sum_i g(X_i, \theta, \hat{\gamma})\right)' W_g \left(\frac{1}{N}\sum_i g(X_i, \theta, \hat{\gamma})\right), \tag{D.3}$$

where g reflects an additional vector of moments and W_g is a symmetric positive definite weighting matrix for these moments. Note that the first-step estimator $\hat{\gamma}$ has sampling variation depending only upon the variation in the moment vector m. In particular, assume that the target moments m follow a standard central limit theorem with

$$\sqrt{N}\left(\frac{1}{N}\sum_i m(X_i, \gamma)\right) \to_d N(0, \Omega_m), \tag{D.4}$$

where Ω_m is the asymptotic covariance matrix of m. Then the asymptotic distribution of the estimator $\hat{\gamma}$ is characterized by the standard exactly identified GMM formulas which depend upon Ω_m as well as the Jacobian $\frac{\partial m}{\partial \gamma}$ via

$$\sqrt{N}(\hat{\gamma} - \gamma) \to_d N\left[0, \left(\mathbb{E}\frac{\partial m(X_i, \gamma)}{\partial \gamma}\right)^{-1} \Omega_m \left(\mathbb{E}\frac{\partial m(X_i, \gamma)}{\partial \gamma}\right)^{-1'}\right]. \tag{D.5}$$

However, the two-step estimator $\hat{\theta}(\hat{\gamma}, ...)$ has an asymptotic distribution which depends both upon variation in the moments g as well as variation in the parameter vector $\hat{\gamma}$. In cases with exactly identified two-step structures, i.e., in contexts with identical lengths of the vectors θ and g, Newey and McFadden (1994) provides formulas for the asymptotic covariance matrix of the second-step estimator $\hat{\theta}$. Our case is similar, but the overidentified nature of the second-step estimation requires us to instead conduct asymptotics based upon the first-order conditions of the optimization problem defining $\hat{\theta}$. More precisely, note that the relevant

optimality condition defining $\hat{\theta}$, computed by differentiating the objective above, is given by

$$\left(\frac{1}{N} \sum_i \frac{\partial g(X_i, \theta, \hat{\gamma})}{\partial \theta} \right)' W_g \sqrt{N} \left(\frac{1}{N} \sum_i g(X_i, \theta, \hat{\gamma}) \right) = 0 \tag{D.6}$$

Now, note that asymptotically we have by assumption of an underlying central limit theorem for the target moments that

$$\sqrt{N} \left(\frac{1}{N} \sum_i g(X_i, \theta, \hat{\gamma}) \right) \to_d N(0, \Omega_g) \tag{D.7}$$

where Ω_g is the asymptotic covariance matrix of the second-stage moment vector g. Also, we have by a law of large numbers that

$$\left(\frac{1}{N} \sum_i \frac{\partial g(X_i, \theta, \hat{\gamma})}{\partial \theta} \right)' W_g \to \mathbb{E} \frac{\partial g(X_i, \theta, \gamma)'}{\partial \theta} W_g. \tag{D.8}$$

So then by Slutsky's Lemma we have that the optimality condition for the second-stage estimation of θ behaves asymptotically in the same manner as

$$\mathbb{E} \frac{\partial g(X_i, \theta, \gamma)'}{\partial \theta} W_g \sqrt{N} \left(\frac{1}{N} \sum_i g(X_i, \theta, \hat{\gamma}) \right) \to_d N \left[0, \mathbb{E} \frac{\partial g(X_i, \theta, \gamma)'}{\partial \theta} W_g \Omega_g W_g \mathbb{E} \frac{\partial g(X_i, \theta, \gamma)}{\partial \theta} \right]. \tag{D.9}$$

In other words, the optimality conditions for the second-stage estimator $\hat{\theta}$ behave like a carefully weighted exactly identified moment vector. At this point the two-step formulas for the exactly identified case of Newey and McFadden (1994) apply, replacing the moment condition in that chapter with the equivalent condition for the overidentified case, i.e.,

$$\frac{1}{N} \sum_i \left[\begin{array}{c} \mathbb{E} \frac{\partial g(X_i, \theta, \gamma)'}{\partial \theta} W_g g(X_i, \hat{\theta}, \hat{\gamma}) \\ m(X_i, \hat{\gamma}) \end{array} \right] = 0. \tag{D.10}$$

Application of those formulas reveals that the two-step parameter vector has an asymptotic distribution given by

$$\sqrt{N}\left(\begin{pmatrix} \hat{\theta} \\ \hat{\gamma} \end{pmatrix} - \begin{pmatrix} \theta \\ \gamma \end{pmatrix}\right) \to_d N(0, \Sigma^*). \tag{D.11}$$

We have that the joint asymptotic covariance matrix of the estimators is given by

$$\Sigma^* = G^{*-1}\Omega^* G^{*-1'}, \tag{D.12}$$

where Ω^* is the asymptotic covariance matrix of the stacked vector in Eq. (D.10) above, given by

$$\Omega^* = \begin{bmatrix} \mathbb{E}\frac{\partial g(X_i,\theta,\gamma)'}{\partial \theta}W_g & 0 \\ 0 & \mathbb{I} \end{bmatrix} \begin{bmatrix} \Omega_g & \Omega_{gm} \\ \Omega'_{gm} & \Omega_m \end{bmatrix} \begin{bmatrix} \mathbb{E}\frac{\partial g(X_i,\theta,\gamma)'}{\partial \theta}W_g & 0 \\ 0 & \mathbb{I} \end{bmatrix}'. \tag{D.13}$$

The joint Jacobian of the stacked moment vector with respect to $(\theta' \ \gamma')'$ is given by

$$G^* = \begin{bmatrix} \mathbb{E}\frac{\partial g(X_i,\theta,\gamma)'}{\partial \theta}W_g\mathbb{E}\frac{\partial g(X_i,\theta,\gamma)}{\partial \theta} & \mathbb{E}\frac{\partial g(X_i,\theta,\gamma)'}{\partial \theta}W_g\mathbb{E}\frac{\partial g(X_i,\theta,\gamma)}{\partial \gamma} \\ 0 & \mathbb{E}\frac{\partial m(X_i,\gamma)}{\partial \gamma} \end{bmatrix}. \tag{D.14}$$

Given the weighting matrix W_g, as well as the estimates $\hat{\theta}$ and $\hat{\gamma}$, all of the elements in the covariance matrix Σ^*, on which inference for θ can be based, are computable.

With this general discussion of two-step overidentified GMM in hand, we can discuss our particular application. First, note that in our case the moments are given via simulation, making this a two-step overidentified simulated method of moments (SMM) estimator. This simulation introduces uncorrelated Monte Carlo error requiring a standard adjustment. The modified asymptotic formulas we use in practice are therefore given by

$$\sqrt{N}\left(\begin{pmatrix} \hat{\theta} \\ \hat{\gamma} \end{pmatrix} - \begin{pmatrix} \theta \\ \gamma \end{pmatrix}\right) \to_d N(0, \Sigma_S^*), \tag{D.15}$$

where the adjusted covariance matrix Σ_S^* is

$$\Sigma_S^* = \left(1 + \frac{1}{S}\right) G^{*-1} \Omega^* G^{*-1'}. \tag{D.16}$$

In this context, S is the ratio of the model sample size to the empirical sample.

Second, note that we employ covariance matrix calculations allowing for firm-level clustering, so the asymptotics above are all in the number of firms N rather than the total number of observations.

Third, in our case note that the full vector of 8 parameters structurally estimated in the paper is given by

$$(\lambda_0, \lambda_1, \sigma_w, \sigma_u, \sigma_v, \rho, \xi, \zeta)'.$$

We estimate three of the parameters

$$\gamma = (\rho, \sigma_u, \sigma_v)', \tag{D.17}$$

in our first-step estimation, and we then estimate the remainder of the parameters in the vector

$$\theta = (\lambda_0, \lambda_1, \sigma_w, \xi, \zeta)' \tag{D.18}$$

in our second-step estimation.

Fourth, note that we also compute the weighting matrix W_g based on the choice which is asymptotically efficient for the second step, i.e., we set W_g equal to the inverse of an estimate of Ω_g. All moment covariance matrices are computed based on analytic formulas for estimators of the clustered asymptotic covariance matrices of appropriately chosen means, followed by application of the Delta Method.

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