How Does Internal Communication Technology Affect Internal Information? Theory and Evidence

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March 2026

Abstract

We study how internal communication technology influences firms' internal information production. Developing a model with a headquarters manager and multiple divisional managers, we formalize two competing economic forces—information access and free riding—that shape the headquarters manager's information precision. When more divisions become connected, divisional managers gain access to information produced by others, which is also transmitted to headquarters. However, this improved access reduces divisional managers' incentives to acquire information, as they can rely on others' contributions. The net effect on the headquarters manager's information precision is theoretically ambiguous, potentially generating a non-monotonic relation. Empirically, we proxy for internal communication connectivity using the share of firm sites with intranet and measure internal information precision using management forecast accuracy. We document an inverted U-shaped relation and provide evidence for both economic forces. Our findings highlight the trade-offs organizations face as internal communication technologies expand.

Keywords: organizational communication, communication technology, internal information environment

JEL Classification: D80, D83, L20, M15, M21, M41

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1 Introduction

Internal communication technologies have fundamentally reshaped how organizations produce and share information. These technologies facilitate information flows in two important ways: they enable divisional managers (DMs) to share information with each other across geographic and functional boundaries, and they improve communication between DMs and headquarters (HQ) managers. Horizontal information sharing among DMs allows them to learn from each other's local knowledge, potentially improving decision-making at the divisional level. At the same time, by pooling information across divisions and transmitting it to HQ, internal communication technologies can improve the precision of HQ managers' information and enhance forecast accuracy (e.g., McKinsey, 2020; Gallemore and Labro, 2015; Roychowdhury et al., 2019; Ferracuti and Stubben, 2019). For instance, in corporations operating across geographically dispersed markets, internal communication technologies allow DMs to share local conditions, such as market trends, sales figures, and operational challenges, both with one another and with HQ.

Despite the prevalence and importance of internal communication technologies such as intranets, how these technologies shape the trade-offs organizations face in internal information production remains under-explored. In particular, when more divisions become connected through such technologies—what we refer to as internal communication connectivity (ICC)—DMs' incentives to acquire information may change (Fischer et al., 2020; Fischer and Stocken, 2010). Whether a greater number of connected divisions ultimately improves HQ managers' information is therefore unclear. We investigate this question both theoretically and empirically.

To better understand how ICC influences HQ managers' information precision, we develop a model that endogenizes DMs' information acquisition decisions. Our theoretical framework highlights two competing economic forces through which ICC shapes the HQ manager's information precision: *information access* and *free riding*. Information access refers to DMs' access to information produced by other divisions, and this information is also transmitted to the HQ manager. Free riding, on the other hand, captures DMs' incentives to reduce their information acquisition efforts, as they can rely more on the information produced by others as ICC expands. Collectively, these two competing economic forces generate an ambiguous theoretical prediction regarding the relation

between ICC and the HQ manager's information precision.

Our model (detailed in Section 2) features a single HQ manager and multiple DMs. Each DM makes a decision for their respective division, and the optimal decision depends on an aggregate state and division-specific information. The aggregate state is a common component in the information structure across divisions. By exerting costly effort, DMs acquire a signal that is informative about both the aggregate state and their division-specific component. This information helps DMs make better decisions for their own divisions and is also transmitted to the HQ manager. For example, DMs may acquire information about new regulations or demand trends that affect multiple divisions (aggregate information), while the effects of these factors may vary across divisions due to local conditions such as regional customer preferences or competitor behavior (division-specific information) (Stein, 2002; Robinson and Stocken, 2013; Chen et al., 2018; Berger et al., 2025).

We assume that some divisions have access to an internal communication technology that enables their respective DMs to share their information perfectly with other DMs that also have access to the technology, as well as with the HQ manager. We refer to these as *connected* divisions. Because connected DMs can rely on information shared by others, they may substitute the information shared by other DMs for their own costly information acquisition. The remaining divisions are *isolated*. Their DMs cannot share information with other DMs and can communicate with the HQ manager only with greater noise compared to connected DMs. To keep our model tractable, we assume that DMs care only about decision quality within their own divisions; consequently, they do not internalize the benefit of their information acquisition efforts for the other divisions. This friction is especially relevant for large organizations with many divisions operating in various geographic areas and industries (e.g., Collis and Montgomery, 1997; Collis and Rukstad, 2008).

We study how the HQ manager's information precision changes with ICC. When only a few divisions are connected, DMs have strong incentives to acquire information because little information is shared. In this case, the HQ manager's information precision increases as more divisions become connected and share their information with the HQ manager with greater precision. However, as more divisions become connected and information sharing intensifies, connected DMs increasingly rely on information generated by others. Anticipating this outcome, each connected DM has a

stronger incentive to free ride on others' information rather than exert costly effort to acquire information independently. Consequently, as more divisions become connected, each connected DM has progressively weaker incentives to acquire information. This decline in effort can be substantial since DMs do not internalize the benefit of their effort for other divisions. As a result, further increases in ICC may reduce the HQ manager's information precision. Overall, information access and free-riding jointly produce an ambiguous relation (i.e., increasing, decreasing, or non-monotone) between ICC and the HQ manager's information precision.

We further show that free-riding incentives are more pronounced when optimal actions across divisions are more strongly correlated, i.e., when division-specific information is less important for decision-making. In this case, improvements in ICC are more likely to reduce the HQ manager's information precision.

We also show that our results are robust to centralized decision-making with misaligned preferences between the HQ manager and DMs, where the HQ manager makes all divisional decisions. In this setting, we allow for agency frictions by letting the HQ manager place less weight on division-specific information than DMs do. This preference misalignment weakens DMs' incentives to acquire information, as their information has less influence on the decision in their respective division. We also find that centralized decision-making intensifies free-riding incentives, as all DMs can rely on the HQ manager's superior information set. Our main insights regarding the non-monotonic relation between ICC and the HQ manager's information precision extend to this setting.

Our model shows that overall information production can be maximized at an interior level of ICC, raising the question of why an HQ manager might expand connectivity beyond this point. We show that doing so benefits DMs: when a DM's own acquisition cost is high, the DM can rely on information produced by others instead. Under decentralized decision-making, full adoption of internal communication technology is always optimal, as increased connectivity improves the efficiency of information production across divisions. In practice, however, firms may not achieve full adoption due to implementation costs, differences in technical capabilities across divisions, or regional differences in technology infrastructure.

The model formalizes a trade-off between information access and free-riding and guides our

cross-sectional tests by identifying conditions under which each effect is likely to be stronger. We proxy for internal communication technology using firms' use of intranet, which determines the level of ICC. A firm's intranet allows employees to store and share proprietary data securely within the firm's network, facilitating intra-firm communication and information sharing. Following Bloom et al. (2014), we measure firms' use of intranet using the Harte Hanks Ci Technology database (CiDB), which contains information on hardware, software, and personnel at the site level.[1] We construct a measure of intra-firm intranet connectivity, *Intranet*, by calculating the proportion of divisions within a firm-year that use the intranet technology, weighted by the number of employees at each division, following Bloom et al. (2014). We use management forecast accuracy as our main empirical proxy for the HQ manager's information precision. This proxy is based on the idea that more precise internal information enables the HQ manager to make more accurate forecasts, a measure widely used in prior literature on corporate internal information (e.g., Feng et al., 2009; Gallemore and Labro, 2015; Ittner and Michels, 2017; Chen et al., 2018).

We first graphically examine the shape of the relation between *Intranet* and management forecast accuracy. The figure shows an inverted U-shape relation, characterized by an initial increase followed by a subsequent decrease. We then conduct regression analyses that include the second-order polynomial of *Intranet*.[2] The coefficient on the linear term *Intranet* is positive, while the coefficient on the quadratic term $Intranet^2$ is negative, producing an inverted U-shaped relation. Interpreted through our model, this pattern suggests that the information access effect dominates at low levels of connectivity while the free-riding effect dominates at high levels. Without a formal theory, this non-monotonic pattern would be difficult to interpret (e.g., Fang et al., 2017; Kim et al., 2021). Our model provides a framework that identifies these two competing forces and clarifies the conditions under which each dominates.

We next provide evidence of the two endogenously generated economic forces that contribute to non-monotonicity: information access and free riding. Regarding the information access channel, the theory predicts that if the HQ manager already has precise prior information, the marginal

[1] Throughout the paper, we use the terms "site" and "division" interchangeably.

[2] In Online Appendix Table OA1, we include only the linear term *Intranet* and show that its coefficient is not significant.

contribution of the intranet to her information set is smaller, leading to a weaker relation between intranet connectivity and internal information precision. We use the average distance between divisional sites and the HQ to proxy for the HQ manager's ex ante informedness. When the HQ office is located closer to divisional sites, the HQ manager may already have precise information or can easily gather information on her own, reducing the incremental contribution of intranet connectivity to the HQ manager's information precision (e.g., Ayers et al., 2011; Kedia and Rajgopal, 2011; Duchin and Sosyura, 2013; Bernstein et al., 2016; deHaan et al., 2023). We find that the inverted U-shaped relation between intranet connectivity and management forecast accuracy is present when the HQ manager's ex ante informedness is lower, but largely absent when she is already well informed, consistent with theory.[3]

As for the free riding channel, the theory predicts that when the division-specific information is less important for connected divisions, DMs' free riding incentives are stronger. To empirically test this prediction, we construct a measure of similarity among connected divisions based on whether they operate in the same four-digit SIC industry. When connected divisions operate in similar industries, division-specific information is less important. Consistent with this prediction, we find that the inverted U-shaped relation is more pronounced when similarity among connected divisions is high, but attenuated when similarity is low.

While all of our tests are guided by formal theory and we provide empirical evidence to substantiate the economic forces in our model, confounding factors could arise from endogeneity of intranet adoption or potential measurement issues with our forecasting-accuracy proxy. We address each concern in turn. First, we address potential endogeneity of intranet adoption through multiple approaches. To mitigate omitted variable bias, we control for organizational complexity, including the number of sites, number of segments, earnings volatility, stock volatility, and 10K-based complexity and uncertainty measures, as well as their squared terms. These controls account for the possibility that more complex firms may adopt more intranet technology and also have less accurate forecasts for reasons unrelated to DMs' free-riding. We also exploit within-firm variation through first differencing to absorb time-invariant firm characteristics. Across these tests, we continue to

[3]In Online Appendix Table OA8, we use CEO tenure as an additional measure of HQ managers' ex ante informedness and find similar results.

find patterns consistent with the inverted U-shaped relation.

We further conduct a Bartik (shift-share) instrument analysis that constructs predicted intranet connectivity for each firm based on adoption trends in the firm's industries or counties, weighted by the firm's predetermined exposure to those industries or counties (e.g., Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022; Breuer, 2022). Because these broad trends are unlikely to be driven by any individual firm's characteristics, this approach helps alleviate endogeneity concerns related to intranet adoption, and the results remain consistent with our main findings.

To more directly address endogeneity, we exploit staggered state-level telecommunications deregulation as an alternative source of quasi-exogenous variation in intranet adoption. Deregulation reduced the cost of intranet implementation, generating plausibly exogenous increases in ICC. Using a stacked difference-in-differences design, we find that deregulation-induced increases in intranet connectivity improve forecast accuracy among low-connectivity firms but reduce accuracy among high-connectivity firms, directly mirroring the inverted U-shaped relation.

Second, we address concerns about the construct validity of our forecasting-accuracy proxy. Management forecasts may reflect strategic disclosure incentives, such as biasing forecasts to meet or beat analyst expectations (e.g., Richardson et al., 2004; Matsumoto, 2002; Rogers and Stocken, 2005). Controlling for expectations management and earnings management leaves our results unchanged. In addition, we obtain similar inferences using management forecast specificity as an alternative proxy for the HQ's information precision (Chen et al., 2018). This measure captures the precision of the forecast format (e.g., point estimate vs. range) rather than accuracy relative to realized earnings, making it less susceptible to strategic disclosure concerns.

This paper makes several contributions. First, our theory sheds light on economic forces affecting information production and sharing within multi-divisional organizations. Prior studies mainly focus on (1) internal agency frictions,[4] organizational structure (e.g., centralization vs. decentralization),[5] and information aggregation (e.g., Morgan and Stocken, 2008); and (2) commu-

[4]See Harris and Raviv (1996); Aghion and Tirole (1997); Bernardo et al. (2001, 2009); Dessein (2002); Ozbas (2005); Acemoglu et al. (2007); Baldenius et al. (2014).

[5]See Melumad and Reichelstein (1987); Melumad et al. (1995); Stein (2002); Harris and Raviv (2005); Alonso et al. (2008); Rantakari (2008); Canales and Nanda (2012); Alonso et al. (2015), and Mookherjee (2006) for a review.

nication frictions, such as geographical, language, and technological barriers.[6] Our study extends this framework by highlighting an important yet under-explored dimension. Specifically, we show that while technologies such as intranets reduce communication frictions, they also give rise to new economic trade-offs involving information access and free riding. By focusing on these forces, we shed light on issues particularly significant for multi-divisional firms.

Second, we contribute to the literature on free riding in collective information acquisition, which has been studied in contexts such as jury voting (Mukhopadhaya, 2003) and corporate boards (Harris and Raviv, 2008). More broadly, the free-riding problem we study relates to classic issues in team production (Holmstrom, 1982) and has also been examined in lobbying contexts (Friedman and Heinle, 2016, 2020). Our theory differs from this literature in two ways. One, our model considers a more complex structure of decisions, leading to richer empirical predictions. Instead of focusing on a single collective decision, we study multiple decisions that require different sets of information, involving both common and idiosyncratic components. This aspect is particularly relevant for large organizations and is key to understanding the internal informational implications for multi-divisional firms. Two, unlike some models of free riding in teams (e.g., Mukhopadhaya, 2003; Harris and Raviv, 2008), our model does not predict an interior optimal level of ICC under decentralized decision-making. Instead, it demonstrates that connecting more divisions always improves decision-making efficiency, even when the overall impact on internal information production is ambiguous. This result arises because connected DMs can leverage others' information when their own information acquisition costs are high, thereby reducing wasteful duplication of effort. We formally test our theory with real-world data, providing empirical validation for these predictions.

Third, we contribute to the empirical literature on the effects of communication technologies (e.g., Bloom et al., 2014; Fort, 2017; Akcigit and Ates, 2021). While this literature has highlighted the importance of communication technologies for productivity and organizational outcomes, their impact on information production within organizations remains relatively under-explored. One might expect that internal communication technologies would improve internal information. Instead, we document a non-monotonic relation, consistent with our theory. As such, we offer a nuanced

[6]See Aoki (1986); Bolton and Dewatripont (1994); Garicano (2000); Vayanos (2003); Cremer et al. (2007).

understanding of how ICC shapes organizations' internal information and highlight the trade-offs at different levels of ICC.

Finally, we contribute to the stream of research examining drivers and consequences of corporate internal information quality (e.g., Bernardo et al., 2004; Rajan and Saouma, 2006; Gallemore and Labro, 2015; Shroff, 2017; Samuels, 2021; Christensen et al., 2024). We study two competing economic forces—information access and free riding—arising from firms' use of internal communication technologies to facilitate information sharing among DMs and between DMs and the HQ manager. Understanding internal information quality is crucial, as it also influences communication with external parties (e.g., Hemmer and Labro, 2008; Chen et al., 2018) as well as internal controls (e.g., Feng et al., 2009; Hope et al., 2022; Berger et al., 2025).

2 A Model of Internal Information Production

2.1 Setup

There are three periods, $t = 0$, 0.5, and 1. A firm is run by an HQ manager (female) and has $N > 1$ divisions, indexed by $i = 1, \ldots, N$. Each division is managed by a divisional manager (male), whom we refer to as the "DM." We denote the manager of division i as DM_i. Each DM makes a decision for their respective division at $t = 0.5$, denoted as $a_i \in \mathbb{R}$. The payoff associated with the decision depends on an aggregate state, denoted by y, and a division-specific component, denoted by Δ_i. The aggregate state y is normally distributed with mean zero and variance σ_y^2. The division-specific state Δ_i $(i = 1, \ldots, N)$ is normally distributed with a zero mean and a variance of σ_Δ^2. Δ_i's are distributed independently from each other and from the aggregate state y.

Decisions $a_1, \ldots, a_N$ can be interpreted broadly. For example, they could represent the scale of output or service in each division. In this example, y captures the common factors that impact the demand or production costs across all divisions, while Δ_i captures idiosyncratic differences across the divisions. For instance, in industries such as pharmaceuticals, fashion, and technology startups, divisions are exposed to substantial uncertainty in demand and costs at both the aggregate and local levels, whereas in utilities or household goods manufacturing, demand and cost conditions tend to be more stable across divisions.

DMs may obtain relevant information for their decision by exerting costly effort and/or by communicating with other DMs who have acquired information. Our primary goal is to examine the interaction between these two sources of information and its implications for the overall production of internal information. To isolate the role of information sharing among DMs from that of control allocation, we assume that the decision for each division is made by its corresponding DM in our baseline model. This modeling choice is consistent with the purpose of internal communication technology, which is to improve DMs' access to information within the organization and thereby enhance their decision-making.

Equation 1 specifies DMs' preferences:

$$U_{DM_i} = -(a_i - y - \Delta_i)^2 - c_i I_i. \tag{1}$$

We see that DM_i has unimodal preferences over action a_i, maximized at $y + \Delta_i$. Furthermore, DMs are concerned only about the decision in their division. Therefore, we abstract from potential efficiency externalities across divisions, both negative (e.g., due to peer competition motives) and positive (e.g., when compensation is partly tied to overall firm performance).

At $t = 0$, each DM can research and perfectly learn his optimal action ($s_i = y + \Delta_i$) at a random cost $c_i \in [\underline{c}, \bar{c}]$, where $\bar{c} > \sigma_\Delta^2$.[7] For instance, the information acquisition cost may capture the time and effort required to collect and analyze data, or operational workload that increases the opportunity cost. $I_i \in \{0, 1\}$ indicates whether DM_i acquires information ($I_i = 1$) or not ($I_i = 0$). The values y and $\{\Delta_i\}_{i=1}^N$ are realized at $t = 1$, at which point payoffs are determined.

The information acquisition cost c_i is i.i.d. across DMs, with a continuous CDF $G(\cdot)$. We assume that c_i is privately observed by DM_i, as reports on information gathering effort could be difficult to verify. We also assume that DMs' information acquisition decision is not contractible, in line with prior theoretical models of information production in organizations (e.g., Aghion and Tirole (1997); Stein (2002)).

An internal communication technology is available to N_C DMs, whom we refer to as "*con-*

[7] This assumption ensures that DMs do not always find it optimal to acquire information.

nected" DMs. Connected DMs can frictionlessly communicate any signal they acquire with each other, including those who do not acquire information. They communicate truthfully because, according to Equation 1, they are not concerned with decision-making in other divisions. This communication technology can be broadly interpreted as a system that lowers the cost of accessing information available in other divisions. We treat the set of connected DMs as exogenous in order to focus on how information production is affected by the level of internal communication connectivity (ICC). In practice, divisions may have different levels of access to this technology due to factors outside the model, such as implementation costs, differences in technical capabilities, or organizational resistance to change.

The remaining $N_I = N - N_C$ DMs are "*isolated*." Isolated DMs neither receive information from nor send information to other DMs. We assume that connected DMs can perfectly share their information with the HQ manager, while isolated DMs communicate with the HQ manager subject to noise: if DM_j is isolated and learns $s_j = y + \Delta_j$, the HQ manager receives $\tilde{s}_j = s_j + \nu_j$, where $\nu_j \sim \mathcal{N}(0, \sigma_\nu^2)$ and is independent of all other random variables. When $\sigma_\nu^2 \to \infty$, isolated DMs cannot communicate with the HQ manager; when $\sigma_\nu^2 \to 0$, they communicate as effectively as connected DMs.

Additionally, the HQ manager observes a noisy signal $y_0 = y + \varepsilon$ at $t = 0$, where $\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ and is independent of other random variables. She perfectly shares the signal with all divisions.[8] Figure 1 illustrates the communication structure: connected DMs share information perfectly with each other and with the HQ manager, while isolated DMs communicate with the HQ manager subject to noise.[9] Figure 2 provides the timeline of the model.

The HQ manager plays a passive role in decision-making in the baseline model, as our primary objective is to analyze how ICC impacts her information set, which we examine empirically using a proxy based on management forecast accuracy. In Section 2.4, we extend the analysis to centralized decision-making, where the HQ manager makes decisions based on her information set,

[8] We introduce y_0 to generate testable predictions about how the precision of the HQ manager's private information affects her information set.

[9] For simplicity, we abstract from exogenous information sources the HQ manager might have about Δ_i and assume that she does not channel information from connected to isolated DMs (though results are similar if she does so with noise). Our results do not depend on the timing of information sharing.

with preferences that are potentially misaligned with those of DMs, and show that our main insights are robust.

2.2 Solution

We first analyze DMs' posterior beliefs and optimal actions (Section 2.2.1), then their information acquisition decisions (Section 2.2.2), and finally the relation between the HQ manager's information and N_C (Section 2.3).

2.2.1 DMs' information and internal decisions

DMs can learn the optimal action in their division at a cost. Due to the quadratic preferences in Equation 1, DM_i's optimal action is $a_i^* = y + \Delta_i$. If DM_i acquires information, he learns $y + \Delta_i$ exactly. If he does not, he sets a_i^* equal to his expectation of $y + \Delta_i$. Since signals obtained by other DMs or the HQ manager are not informative about Δ_i, the optimal action is:

$$a_i^* = \begin{cases} y + \Delta_i & \text{Info acquired,} \\ \mathbb{E}^i[y] & \text{Info not acquired,} \end{cases} \tag{2}$$

where $\mathbb{E}^i[y]$ represents DM_i's expected value of y given available information. For isolated DMs who do not acquire information, the only available information is the signal shared by the HQ manager (y_0). Connected DMs receive additional information about y from the other connected DMs that acquired information. If the first k DMs are connected and acquire information, then

$$\mathbb{E}^i[y \mid I_i = 0] = \begin{cases} \mathbb{E}[y|y_0] & \text{Division } i \text{ is isolated,} \\ \mathbb{E}[y|y_0, s_1, s_2, \ldots, s_k] & \text{Division } i \text{ is connected, } k \text{ connected DMs acquire information.} \end{cases} \tag{3}$$

The posterior variance for DMs who do not acquire information is:[10]

$$\mathrm{Var}^i(y \mid I_i = 0) = \begin{cases} \hat{\sigma}_0^2 & \text{Division } i \text{ is isolated,} \\ \hat{\sigma}_k^2 & \text{Division } i \text{ is connected, } k \text{ connected DMs acquire information,} \end{cases} \tag{4}$$

where

$$\hat{\sigma}_x^2 := \frac{1}{x\sigma_\Delta^{-2} + \sigma_y^{-2} + \sigma_\varepsilon^{-2}}. \tag{5}$$

Here x denotes the number of signals about y that a DM receives from other DMs. For isolated DMs, $x = 0$; for connected DMs, $x = k$ when k other connected DMs acquire information. As more connected DMs acquire information, the beliefs of connected DMs who do not acquire information become more precise, since they perfectly share information among themselves. However, information acquisition is an endogenous decision in our model, implying that they do not necessarily obtain more information if more DMs become connected.

The precision of the HQ manager's beliefs about y is also endogenous and depends on the number of connected and isolated DMs that acquire information. If k connected DMs and k' isolated DMs acquire information and share it with the HQ manager, then the posterior variance of the HQ manager's beliefs about y is:

$$\mathrm{Var}^{HQ}(y) = \frac{1}{k\sigma_\Delta^{-2} + k'(\sigma_\Delta^2 + \sigma_\nu^2)^{-1} + \sigma_y^{-2} + \sigma_\varepsilon^{-2}}. \tag{6}$$

Both k and k' are random, as they depend on the realization of information acquisition costs. In Section 2.3, we investigate how the expected variance, i.e., $\mathbb{E}[\mathrm{Var}^{HQ}(y) \mid N_C]$, changes with N_C, the number of connected divisions. We use $\mathbb{E}[\mathrm{Var}^{HQ}(y) \mid N_C]$ as our measure of the HQ manager's uncertainty in our baseline analysis,[11] and discuss alternative measures in Online Appendix OA1.

2.2.2 Information acquisition by divisional managers

Lemma 1 presents the expected gain from information acquisition for DMs.

[10] All derivations and proofs are provided in Appendix A.

[11] A similar measure of uncertainty is also used by Fischer and Stocken (2010).

Lemma 1. *Define*

$$\pi_x := \hat{\sigma}_x^2 + \sigma_\Delta^2, \tag{7}$$

where $\hat{\sigma}_x^2$ is defined in Equation 5.

a) *If DM_i is isolated, then his net gain from information acquisition is $\pi_0 - c_i$.*

b) *If DM_i is connected and other than DM_i, k_{-i} connected DMs ($0 \leq k_{-i} \leq N_C - 1$) acquire information, then the expected net gain from acquiring information is $\pi_{k_{-i}} - c_i$.*

In Equation 7, π_x represents the expected gain from information acquisition when x other DMs share their signals. For isolated DMs, $x = 0$; for connected DMs, $x = k_{-i}$. The gain arises from two sources: incomplete information about y (first term) and no information about Δ_i (second term). By acquiring information, DM_i eliminates these errors at cost c_i.

Lemma 1 implies that isolated DMs should acquire information if and only if their information acquisition cost is less than π_0. Therefore, their information acquisition decision does not depend on the decisions of other DMs. For connected DMs, the expected gain decreases with k_{-i}, the number of other connected DMs that acquire information. However, k_{-i} is a random variable from their perspective as DMs decide simultaneously and do not know the information acquisition costs of the other DMs. Therefore, they compare their information acquisition cost against their expected value of $\pi_{k_{-i}}$, which depends on some endogenous distribution for k_{-i}. In Proposition 1, we use these observations to characterize DMs' decision to acquire information. The characterization pins down the distribution of k_{-i}.

Proposition 1.

a) *An isolated DM acquires information if and only if*

$$c_i \leq \pi_0 = \hat{\sigma}_0^2 + \sigma_\Delta^2. \tag{8}$$

b) *No connected DM acquires information if $\pi_0 < \underline{c}$, and all connected DMs acquire information if $\pi_{N_C-1} = \hat{\sigma}_{N_C-1}^2 + \sigma_\Delta^2 \geq \bar{c}$. If neither of these conditions holds, then in the unique equilibrium that is symmetric across connected DMs, each DM acquires information if and only if $c_i \leq c^*(N_C)$,*

where $c^*(N_C) \in (\underline{c}, \pi_0)$ *is the unique solution to*

$$\sum_{k=1}^{N_C} \binom{N_C - 1}{k-1} G(c^*)^{k-1}(1 - G(c^*))^{N_C - k}(\pi_{k-1} - c^*) = 0. \tag{9}$$

Part (a) of Proposition 1 implies a constant probability of information acquisition for isolated DMs: $p_I := G(\pi_0)$.

Part (b) characterizes the equilibrium cutoff for connected DMs. When few DMs are connected, the expected gain from information acquisition exceeds $\bar{c}$, so all acquire information. When many DMs are connected, each anticipates more information from others and acquires information only when their cost is sufficiently low. Corollary 1 uses this result to examine how the probability of information acquisition by connected DMs, denoted by $p_C(N_C) := G(c^*(N_C))$, varies with N_C.

Corollary 1. *Suppose* $\bar{N}_C$ *is the largest* N_C *such that* $\pi_{N_C - 1} \geq \bar{c}$. *Then, for* $N_C \leq \bar{N}_C$, *all connected DMs acquire information with probability one, i.e.,* $p_C(N_C) = 1$. *For* $N_C > \bar{N}_C$, $p_C(N_C)$ *decreases in* N_C.

Corollary 1 states that $p_C(N_C)$ decreases with N_C when $N_C > \bar{N}_C$, as illustrated in Figure 3. This formalizes the "*free-riding effect*": as more DMs become connected, each expects others to contribute to the shared information pool, reducing their own incentive to acquire information.

Note that the HQ manager's information set is a collection of her signal and the signals obtained from DMs. As more DMs become connected, the communication technology improves the quality of bottom-up communication from DMs to the HQ manager, given a fixed level of information acquisition by DMs. We refer to this as the "*information access effect.*" However, due to the "*free-riding effect*" described earlier, expanding ICC may not necessarily make the HQ manager more informed. In particular, the HQ manager becomes more informed as ICC expands only if the effect of improved communication by newly connected divisions (information access effect) exceeds the effect of reduced effort by both newly and already connected divisions (free-riding effect). Therefore, the relation between the HQ manager's information precision and N_C could be increasing, decreasing, or non-monotonic, as illustrated in Figure 4.

2.3 Internal Communication Connectivity (ICC) and the HQ Manager's Information

In this section, we analyze how the HQ manager's information precision varies with the number of connected DMs (N_C), which captures the degree of ICC. Corollary 1 implies that if $\bar{N}_C > 1$, then for small values of N_C (i.e., $N_C \leq \bar{N}_C$), the HQ manager becomes more informed as more divisions are connected, reflected as a lower value of $\mathbb{E}[\mathrm{Var}^{HQ}(y) \mid N_C]$. To explain why $\mathbb{E}[\mathrm{Var}^{HQ}(y) \mid N_C]$ may increase for larger values of N_C, we analyze the free-riding incentives of connected DMs in more detail.

By taking expectations in Equation 6 and applying a first-order approximation, we obtain that $\mathbb{E}[\mathrm{Var}^{HQ}(y) \mid N_C]$ is related to the probabilities of information acquisition by connected and isolated DMs, $p_C(N_C)$ and p_I, as follows:

$$\begin{aligned}
\mathbb{E}[\mathrm{Var}^{HQ}(y) \mid N_C] &= \mathbb{E}[\frac{1}{k\sigma_\Delta^{-2} + k'(\sigma_\Delta^2 + \sigma_\nu^2)^{-1} + \sigma_y^{-2} + \sigma_\varepsilon^{-2}} \mid N_C] \\
&\simeq \frac{1}{\sigma_y^{-2} + \sigma_\varepsilon^{-2}} - \frac{1}{(\sigma_y^{-2} + \sigma_\varepsilon^{-2})^2}\{\sigma_\Delta^{-2}\mathbb{E}[k \mid N_C] + (\sigma_\Delta^2 + \sigma_\nu^2)^{-1}\mathbb{E}[k' \mid N_C]\} \qquad (10) \\
&= \frac{1}{\sigma_y^{-2} + \sigma_\varepsilon^{-2}} - \frac{1}{(\sigma_y^{-2} + \sigma_\varepsilon^{-2})^2}\{\sigma_\Delta^{-2} N_C p_C(N_C) + (\sigma_\Delta^2 + \sigma_\nu^2)^{-1} N_I p_I\}.
\end{aligned}$$

When a new division becomes connected (i.e., N_C increases to $N_C + 1$ and N_I decreases to $N_I - 1$), the change in $\mathbb{E}[\mathrm{Var}^{HQ}(y) \mid N_C]$, to a first-order approximation, when scaled by constant $M := (\sigma_y^{-2} + \sigma_\varepsilon^{-2})^2 \sigma_\Delta^2$, is

$$\begin{aligned}
& M\left\{\mathbb{E}[\mathrm{Var}^{HQ}(y) \mid N_C + 1] - \mathbb{E}[\mathrm{Var}^{HQ}(y) \mid N_C]\right\} \\
\simeq & \Big[N_C p_C(N_C) + \frac{\sigma_\Delta^2}{\sigma_\Delta^2 + \sigma_\nu^2} N_I p_I\Big] - \Big[(N_C + 1)p_C(N_C + 1) + \frac{\sigma_\Delta^2}{\sigma_\Delta^2 + \sigma_\nu^2}(N_I - 1)p_I\Big] \qquad (11) \\
= & \underbrace{-\frac{\sigma_\nu^2}{\sigma_\Delta^2 + \sigma_\nu^2} p_I}_{\substack{\text{Information access} \\ \text{(newly connected DM)}}} + \underbrace{p_I - p_C(N_C + 1)}_{\substack{\text{Free-riding} \\ \text{(newly connected DM)}}} + \underbrace{N_C\big(p_C(N_C) - p_C(N_C + 1)\big)}_{\substack{\text{Free-riding} \\ \text{(existing connected DMs)}}}.
\end{aligned}$$

Equation 11 illustrates how the HQ manager's uncertainty changes when a new DM becomes connected. The first term captures the information access effect: when a DM becomes connected, the

HQ manager receives the DM's information without the noise (σ_ν^2) that would have been present had the DM remained isolated. This term equals $-\frac{\sigma_\nu^2}{\sigma_\Delta^2+\sigma_\nu^2}p_I$, which is negative (reducing uncertainty) and independent of N_C because it depends only on isolated DMs' behavior. The second term captures free-riding by the newly connected DM: $p_I - p_C(N_C+1)$. This term is positive when $N_C \geq \bar{N}_C$ (increasing uncertainty) and grows with N_C as free-riding intensifies (Corollary 1), reflecting that the newly connected DM acquires information less frequently than when isolated. The third term captures intensified free-riding by existing connected DMs, which is non-negative (Corollary 1).

The second term can dominate the first term when the reduction in information acquisition due to free riding by the newly connected DM outweighs the benefit from eliminating noise in the received signal. That is, when $p_C(N_C+1)$ is much smaller than p_I. This occurs when N_C is large (more opportunities to free-ride) and σ_Δ^2 is small (division-specific information matters less, reducing incentives to acquire information).[12] In particular, as N_C grows large, free-riding incentives strengthen unambiguously: each connected DM faces an ever-larger pool of peers to free-ride on, so the marginal return to their own acquisition effort becomes small. Therefore, the overall effect on the HQ manager's uncertainty can become positive for large N_C, generating the upward-sloping portion of the relation illustrated in Figure 4.

Taken together, these forces can generate a positive (Figure 4a), U-shaped (Figure 4b), or negative (Figure 4c) relationship between $\mathbb{E}[\text{Var}^{HQ}(y) \mid N_C]$ and N_C. The free-riding effect of expanding ICC is stronger when σ_Δ^2 is small, i.e., when division-specific uncertainty is low. In this case, the expected gain from information acquisition is lower (Lemma 1), making the free-riding problem more pronounced. Intuitively, when optimal actions are more correlated across divisions, each connected DM has weaker incentives to acquire information, reducing overall internal information production. We test this prediction empirically in a subsequent section.

2.4 Centralized Decision-Making and Misaligned Preferences

In our baseline model, decision-making is decentralized to isolate the role of information sharing from control allocation. Here, we examine whether our main insights extend to centralized decision-making with potentially misaligned preferences.

[12] Our results in Online Appendix OA2 imply that $p_C(N_C)$ converges to $G(\max\{\sigma_\Delta^2 - \underline{c}, 0\})$ as N_C grows large. When $\sigma_\Delta^2 < \underline{c}$, this limit is zero, so free-riding becomes severe for large values of N_C.

Specifically, we assume that the HQ manager makes decisions for all divisions; that is, she chooses $a_1, \ldots, a_N$ based on her private information (y_0) and the reports made by DMs about their signals. The HQ manager may place less weight on the division-specific component (represented by $\beta \in [0, 1]$) than DMs do. The case $\beta < 1$ captures settings where the HQ manager places greater emphasis on firm-wide considerations relative to division-specific factors. For simplicity, we assume that β is the same across all divisions.

$$U_{HQ} = \frac{1}{N} \sum_{i=1}^{N} \{ -(a_i - y - \beta\Delta_i)^2 - c_i I_i \}. \tag{12}$$

Preference misalignment may lead DMs to disclose information strategically. Following prior studies (Dye, 1985; Farrell, 1985; Jung and Kwon, 1988), we assume that DMs may withhold information but report truthfully when they do disclose. For instance, HQ managers may require DMs to provide detailed documentation and supporting evidence, which increases the cost of manipulation.

When $\beta = 1$, DMs have no incentive to withhold information. Lemma 2 shows that this extends to all $\beta \in [0, 1]$: DMs always find it optimal to share their information with the HQ manager.

Lemma 2. *For any value of $\beta \in [0, 1]$, all DMs share their information with the HQ manager whenever they acquire information.*

The intuition is that by sharing information about $y + \Delta_i$, a DM brings the HQ manager's decision closer to the DM's preferred action. Since the HQ manager's optimal action for division i depends on both y and Δ_i, she places positive weight on DM_i's signal when setting a_i. As a result, DMs always benefit from sharing, despite disagreement about the relative importance of y and Δ_i.[13]

We now examine how information acquisition incentives change with N_C. Lemma 3 provides

[13]In our specification (Equation 12), there is no fixed bias between the optimal actions of DMs and the HQ manager, unlike in some models of strategic communication (Crawford and Sobel, 1982; Harris and Raviv, 2008). With fixed bias, DMs may withhold information with positive probability, which has offsetting effects on information acquisition: its effect on incentives is both negative (since DMs may waste information acquisition effort by later withholding) and positive (since DMs anticipate less information from others). However, the possibility of ex-post withholding does not eliminate the ex-ante incentive to free-ride on other DMs' information production.

the expected gain under centralized decision-making.

Lemma 3. *Define*

$$\hat{\sigma}^2_{x,x'} = \frac{1}{x\sigma_\Delta^{-2} + x'(\sigma_\Delta^2 + \sigma_\nu^2)^{-1} + \sigma_y^{-2} + \sigma_\varepsilon^{-2}}. \tag{13}$$

a) *If j is an isolated division, and k connected DMs and k'_{-j} other isolated DMs acquire information, the expected net gain from information acquisition under centralized decision-making is $\pi^I_{k,k'_{-j}} - c_j$, where*

$$\pi^I_{k,k'_{-j}} = \hat{\sigma}^2_{k,k'_{-j}} + \sigma_\Delta^2 - \frac{(1-\beta)^2\sigma_\Delta^4 + (\sigma_\Delta^2 + \hat{\sigma}^2_{k,k'_{-j}})\sigma_\nu^2}{\hat{\sigma}^2_{k,k'_{-j}} + \sigma_\Delta^2 + \sigma_\nu^2}. \tag{14}$$

b) *Suppose i is a connected division, and k_{-i} other connected DMs and k' isolated DMs acquire information. Then, the expected net gain from information acquisition by DM_i is $\pi^C_{k_{-i},k'} - c_i$, where*

$$\pi^C_{k_{-i},k'} = \hat{\sigma}^2_{k_{-i},k'} + \sigma_\Delta^2 - \frac{(1-\beta)^2\sigma_\Delta^4}{\hat{\sigma}^2_{k_{-i},k'} + \sigma_\Delta^2}. \tag{15}$$

By comparing these results with Lemma 1, we find that given the information acquisition behavior of other DMs, each DM has weaker incentives to acquire information under centralized decision-making.[14] This is because of two additional forces that intensify the free-riding problem:

First, the HQ manager deviates from DMs' optimal actions, lowering the gain from information acquisition. The gain increases with β, which captures the degree of alignment between the optimal actions for DMs and the HQ manager.

Second, the HQ manager is better informed than any individual DM, as she aggregates information from both connected and isolated DMs. Connected DMs, for instance, cannot access information produced by isolated DMs, but the HQ manager can. This asymmetry means that under centralized decision-making, all DMs can rely on the HQ manager's superior information set, reducing their incentives to acquire information and exacerbating free-riding incentives relative to the decentralized baseline. This result is consistent with earlier studies showing that when principals (the HQ manager in our model) retain control, agents (DMs) have weaker incentives

[14] To compare with the expected net gain under decentralized decision-making, consider the case in which $\beta = 1$ and $k' = 0$ for connected DMs and $k = k'_{-j} = 0$ for isolated DMs.

to acquire information, especially when principals are more informed (Aghion and Tirole, 1997), because agents capture fewer benefits from and have less influence over the resulting actions.[15]

Lemma 3 further implies that when some divisions become connected, thereby improving the quality of their bottom-up communication (i.e., from DMs to the HQ manager), the net effect on the HQ manager's information set is ambiguous. On the one hand, newly connected DMs have stronger incentives to acquire information because lower communication noise makes their signals more influential in the HQ manager's decision. On the other hand, existing connected DMs and isolated DMs may reduce their acquisition efforts. As the HQ manager receives more information from newly connected divisions, each DM's marginal contribution to the HQ manager's information set diminishes, lowering the gain from acquiring information.

As such, it is unclear if the HQ manager becomes more informed by expanding the communication technology to more divisions. Figure 5 illustrates how the interaction between the positive and negative forces can generate a non-monotonic pattern in $\mathbb{E}[\text{Var}^{HQ}(y) \mid N_C]$ as a function of N_C under centralized decision-making.

2.5 The Optimal Level of Internal Communication Connectivity (ICC)

Our model generates an ambiguous relation between the number of connected divisions (N_C) and internal information production, suggesting that, under certain conditions, there exists an optimal interior point for maximizing overall information production. This raises the question of why the HQ manager would allow N_C to exceed this informationally optimal level. Proposition 2 demonstrates that HQ managers may do so to reduce DMs' costs of information acquisition.

Proposition 2. *Suppose the decision-making is decentralized. For any $\beta \in [0, 1]$, the expected payoff of the HQ manager is increasing in N_C.*

To see the intuition, consider the baseline setup with decentralized decision-making and $\beta = 1$ (full alignment). In this case, the HQ manager's expected payoff is the average of the expected payoff of all DMs (Equation 12).

[15] Additionally, isolated DMs face a lower communication quality with the HQ manager than connected DMs. Consequently, the HQ manager learns less from isolated DMs and places a smaller weight on their information, further reducing their gain from acquiring information. When the noise in communication, σ_ν^2, is sufficiently large, isolated DMs never find it beneficial to produce information.

If division i is isolated, DM_i acquires information only if $c_i \leq \pi_0$ (Proposition 1) and then chooses the optimal action, resulting in a payoff of $-c_i$. Conversely, if $c_i > \pi_0$, DM_i chooses $a_i^* = \mathbb{E}[y|y_0]$, according to Equations 2 and 3, resulting in an expected payoff of $-\pi_0$. Therefore, the expected payoff of an isolated division is $\mathcal{U}^I = -\mathbb{E}[\min\{c_i, \pi_0\}]$.

If division i is connected, DM_i acquires information when $c_i \leq c^*(N_C)$ (Proposition 1). With a logic similar to the previous case, the expected payoff of a connected DM is $\mathcal{U}^C(N_C) = -\mathbb{E}[\min\{c_i, c^*(N_C)\}]$.

Since $c^*(N_C) \leq \pi_0$, connected DMs have a weakly higher expected payoff than isolated DMs. Intuitively, connected DMs can rely on the information shared by other connected DMs when their own acquisition costs are high, a benefit unavailable to isolated DMs. Moreover, connected DMs benefit from increasing N_C: as more DMs become connected, the expanded pool of shared information can substitute for costly individual information acquisition. As such, full adoption is optimal for all DMs and, therefore, for the HQ manager.

Proposition 2 formalizes this result for any $\beta \in [0, 1]$, including cases with misaligned preferences ($\beta < 1$). The intuition is that from the HQ manager's perspective, isolated DMs acquire too much information, not only because they lack access to the information available to connected DMs, but also because they overweight the importance of their division-specific component. To mitigate this overproduction of information, the HQ manager prefers to connect as many divisions as possible. By similar logic, information production by connected DMs also becomes more efficient.

An important implication is that a non-monotonic relation between ICC and information production should not be interpreted as evidence of overinvestment in internal communication technology. Firms have rational reasons to adopt high levels of ICC even if information production declines. Expanding connectivity improves decision-making efficiency by allowing DMs to rely on others' information when their own acquisition costs are high. Online Appendix Table OA9 documents a positive association between growth in return on net operating assets (RNOA) and ICC, consistent with these efficiency gains (Fairfield et al., 2003).[16]

[16] Under centralized decision-making, it may be optimal to adopt an interior level of ICC. Because the HQ manager's payoff depends directly on information quality, she may prefer a level of connectivity closer to the level that maximizes internal information production.

In practice, firms may not achieve full adoption for many reasons, including implementation costs, differences in technical capabilities across divisions, organizational resistance to change, industry-specific technology standards, and regional differences in technology infrastructure.[17] These factors generate the cross-sectional variation in ICC that we exploit in our empirical analysis.

The Online Appendix provides additional theoretical results. In Section OA1, we show that the results would be qualitatively similar under alternative measures of the HQ manager's uncertainty. Section OA2 shows that due to the free-riding effect, overall information production by connected DMs does not scale with with N_C when optimal decisions are highly correlated across divisions, suggesting that the free-riding problem can be more severe in very large organizations.

3 Data, Sample Selection, and Key Variables

Data on firms' use of intranets come from the Harte-Hanks Ci Technology database (CiDB), which provides yearly site-level data on information and communications technology (ICT). Harte-Hanks collects detailed information on hardware and software (e.g., computers, IT budget and staff, servers, and computing capacity) installed in millions of establishments worldwide. Harte-Hanks sells their data to large ICT firms such as IBM, Cisco, and Dell.[18] Harte-Hanks re-collects data annually and performs extensive quality checks to ensure accuracy. Due to broad coverage and high quality, academics have widely used these data to measure firms' software or hardware technology adoption.[19] We use data from 2001 (the first year with available intranet-related data) through 2015 (after which the survey format changed significantly).

The intranet does not allow access to anyone outside its private network and creates a platform where employees can securely store and share proprietary data. Therefore, the use of the intranet facilitates intra-firm communication and information sharing (e.g., Bloom et al., 2014). Appendix C illustrates the differences among the intranet, extranet, and internet. Following Bloom et al. (2014),

[17] Table 6 exploits county- and industry-level variation in technology trends as a source of quasi-exogenous variation in ICC, while Online Appendix Section OA3 exploits variation in implementation costs driven by state-level telecommunications deregulation.

[18] The name of the data provider for CiDB changed from Harte-Hanks to Aberdeen, and then to Spiceworks Ziff Davis (SWZD) because Aberdeen was divested from Harte-Hanks in 2015 and acquired by SWZD in 2020. We purchased the data from SWZD but refer to the data provider as Harte-Hanks to be consistent with the literature.

[19] See e.g., Bresnahan et al. (2002), Brynjolfsson and Hitt (2003), Beaudry et al. (2010), Forman et al. (2012), Bloom et al. (2016), Bloom et al. (2012), Bloom et al. (2014), and Charoenwong et al. (2024).

we measure *Intranet* as the proportion of divisions within a firm-year that adopt the intranet technology, weighted by the number of employees in each division, as an empirical proxy for the extent of the firm's internal communication connectivity (ICC). We determine whether a site uses the intranet based on whether it has installed the technologies used to connect different sites—namely frame relays, leased lines, a synchronous optical network (SONET), digital subscriber line (xDSL), asynchronous transfer mode (ATM) technology, and virtual private networks (VPN). While Bloom et al. (2014) focus on leased lines and frame relay connections, our intranet measure additionally includes successor WAN technologies that serve the same internal communication function and become prevalent in the later years of our sample period.

We use additional CiDB variables as controls, including firms' use of the internet, PCs, enterprise resource planning (ERP), and CAD/CAM, as well as employee and site counts. We aggregate the site-level CiDB data to the firm level because our dependent variable of interest is measured at the firm level. The CiDB provides a unique headquarters identifier for each site, which allows us to link sites to their parent firms. We then match firms to Compustat using company names and headquarters locations. The data provider confirms that the database primarily covers owned-and-operated locations and excludes franchise sites, mitigating concerns about franchise misclassification.

We use management forecast accuracy to proxy for the HQ manager's information precision (or quality) (e.g., Feng et al., 2009; Chen et al., 2018; Gallemore and Labro, 2015; Armstrong et al., 2014; Boone and White, 2015). We measure forecast accuracy as -1 times the forecast error, where forecast error is the absolute difference between the management EPS forecast and the actual realized EPS, scaled by the EPS forecast. Following prior literature on management forecasts (e.g., Guay et al., 2016; Noh et al., 2019; Samuels, 2021), we consider all EPS forecasts of different horizons, including point estimates, range estimates, and qualitative estimates. As a robustness check, we use forecast specificity as an alternative measure of information precision, defined as an ordinal variable equal to 4 for point forecasts, 3 for interval forecasts, 2 for open-ended forecasts, and 1 for qualitative forecasts.

Prior literature shows that forecasts issued close to earnings announcements are more sus-

ceptible to expectations management and less informative about fundamentals (e.g., Hutton et al., 2012), whereas earlier forecasts are less affected by these forces (e.g., Soffer et al., 2000; Richardson et al., 2004; Burgstahler and Eames, 2006). Accordingly, we focus on the first forecast issued for each fiscal period, defined as the first forecast released between the current fiscal-year earnings announcement (inclusive) and the subsequent fiscal-year earnings announcement (exclusive). To further address concerns about strategic disclosure incentives, we exclude forecasts issued after fiscal year-end but before the earnings announcement. These forecasts are commonly referred to as pre-announcements and account for less than 1% of first forecasts. Using forecast accuracy requires limiting the sample to firms that provide management forecasts (i.e., guiders).

To construct our main sample, we merge the CiDB data with the intersection of Compustat and CRSP. The CiDB also provides data on employees, revenues, number of sites, and industry classification, among other information. We further merge it with management and analyst forecast data obtained from I/B/E/S, litigation data from Stanford Securities Class Action Clearinghouse, and insider trading and institutional ownership data obtained from Thomson Reuters. We drop firms that have fewer than two divisional sites because free-riding incentives arise when there is more than one divisional site. Moreover, we exclude firms whose headquarters are at a zero distance from all sites, because these cases likely indicate that the divisional sites are also the headquarters offices. Firms in the utility and financial industries are also removed as they are highly regulated.

Our main sample, which requires the availability of management forecast accuracy data, is comprised of 6,593 public firm-year observations for 976 unique public firms (i.e., guiders) during the sample period from 2001 to 2015. Table 1 presents descriptive statistics for the key variables used in our empirical tests. The average value of *Intranet* is 0.51 with a standard deviation of 0.31, indicating reasonable variation in *Intranet* across firms. Our sample firms have, on average, 8,110 employees and 57 sites, suggesting that these public firms are relatively large in size.

4 Main Results

4.1 Theoretical Construct and Connection to Empirical Measures

In the empirical section, we use the fraction of connected divisions as our main construct of interest. Using a fraction rather than the number of connected divisions helps address concerns

that firm size may drive the results, as firm size is likely correlated with the number of connected divisions. Following Bloom et al. (2014), we weight by the number of employees at each division, as larger divisions likely provide more information about the aggregate state. For tractability, our theoretical model abstracts from this heterogeneity, though the key insights remain unaffected.

Moreover, given the inherent challenge of accurately measuring the HQ manager's information precision, we use management forecast accuracy as our main empirical proxy. This proxy has been widely adopted in previous literature on corporate internal information (e.g., Feng et al., 2009; Gallemore and Labro, 2015; Ittner and Michels, 2017; Chen et al., 2018). It is grounded in the notion that more precise information available to HQ managers leads to greater accuracy in their earnings forecasting. For example, Ittner and Michels (2017) demonstrate a positive correlation between a firm's internal information environment and the accuracy of the manager's earnings forecasts, using detailed survey data and publicly disclosed management earnings forecasts. As a robustness check, we use forecast specificity as an alternative proxy in the Online Appendix.

4.2 Association between Intranet and Internal Information Precision

We begin by graphically presenting the shape of the relation between expansions in internal communication technology that determine ICC, measured by firms' intranet connectivity, and internal information precision, proxied by firms' management forecast accuracy. Following Barber and Odean (2000), Ellison and Ellison (2011), Kim et al. (2021), and Samuels et al. (2021), we sort firms into quintiles based on *Intranet* and plot average values of management forecast accuracy for each quintile in Figure 6.[20] We find that management forecast accuracy first increases as the quintiles of *Intranet* increase and subsequently declines, thereby showing an inverted U-shape. This figure demonstrates the relation between our key variables in the data and visualizes the nature of our findings well.

We then conduct regression analyses to examine the association between intranet connectivity and management forecast accuracy. We estimate the following regression, including both linear and

[20]We use management forecast accuracy de-meaned by industry-year and sort *Intranet* within an industry-year to remove the effects of correlated variables when plotting relations between Y and X (Breuer and deHaan, 2024). Additionally, while using decile-based bins yields a qualitatively similar non-monotonic pattern, we present quintile-based figures for descriptive clarity and consistency with the prior literature.

second-order polynomial terms of $Intranet$:

$$\begin{aligned} Management\ Forecast\ Accuracy_{i,t+1} =& \beta_1 Intranet_{i,t} + \beta_2 Intranet_{i,t}^2 + \theta Controls_{i,t} \\ &+ \Sigma \beta_{j,t} Industry \times Year_{j,t} + \epsilon_{i,t}, \end{aligned} \tag{16}$$

where $Intranet_{i,t}$ and $Management\ Forecast\ Accuracy_{i,t+1}$ are our measures of intra-firm intranet connectivity and internal information precision, respectively, defined in Section 3 and Appendix B. We measure $Intranet_{i,t}$ as of the last calendar year ending before fiscal year t, because the CiDB provides data on firms' use of the intranet by calendar year. The measurement window for our dependent variable comes after that for the intranet.

$Controls_{i,t}$ is a vector of control variables measured for each firm i's fiscal year t, and include characteristics that could be associated with firms' forecasting accuracy (e.g., Richardson et al., 2004; Rogers and Stocken, 2005; Chen et al., 2018). These control variables include ROA, BTM, $ln(MVE)$, $R\&D$, $Loss\ Indicator$, $ln(1+analysts\ following)$, $ln(1+days\ until\ forecasts)$, $Earnings\ Volatility$, $ln(business\ segments)$, $ln(geographical\ segments)$, $Related$, $Institutional\ ownership$, $Litigation\ Indicator$, $Distress\ Indicator$, $Insider\ Trading$, and HHI. We also include $Internet$, $Number\ of\ PCs\ per\ employee$, ERP, and CAD/CAM to control for firms' other technologies, and $ln(employees)$, $ln(1+revenues)$, and $ln(sites)$ to account for firms' size and complexity. We use industry $\times$ year fixed effects to account for time-varying industry characteristics. Following Kim et al. (2021) and Samuels et al. (2021), we do not include firm fixed effects because non-linearity is better captured in the large cross-section of firms and can hardly be captured in limited within-firm variation (e.g., Armstrong et al., 2022). We address within-firm variation through first-differencing as a robustness check in Section 4.4.1.

If the shape of the relation between intranet connectivity and internal information precision is non-monotone, we expect both β_1 (i.e., the coefficient on $Intranet$) and β_2 (i.e., the coefficient on $Intranet^2$) in Equation 16 to be statistically significant. Table 2 reports a positive and significant coefficient on $Intranet$ and a negative and significant coefficient on $Intranet^2$, consistent with Figure 6

and indicative of a non-monotonic relation between *Intranet* and *Management Forecast Accuracy*.[21] The implied turning point, $-\beta_1/(2\beta_2)$, is 0.53, with a 95% confidence interval of [0.38, 0.69]. This interval lies well within the empirical distribution of *Intranet* (p25 = 0.25, median = 0.53, p75 = 0.80), indicating that the relationship reverses within the support of the data and that the downward-sloping region is economically relevant. In Online Appendix Table OA1, we show that a linear specification yields an insignificant coefficient on *Intranet*, providing further support for a non-monotonic relation.

Together, these findings are consistent with countervailing effects of "information access" and "free riding," which our theory predicts can generate an inverted U-shaped relation between ICC and internal information precision. In the next subsection, we present cross-sectional tests that provide evidence for both forces.

4.3 Evidence of the Economic Forces

4.3.1 Information access channel

To corroborate the information access channel, we explore how the relation between intranet connectivity (our proxy for ICC) and management forecast accuracy varies with the HQ manager's ex ante informedness about the firm. When the HQ manager is already well informed about divisions, the marginal contribution of the intranet to the HQ manager's information set is smaller. Put differently, when the HQ manager's private information is highly precise (low σ_ε^2), the relation between intranet connectivity and the precision of the HQ manager's information should be weak. Figure 7 Panel (a) illustrates this point visually using the fraction of connected divisions (similar to our empirical proxy *Intranet*) as a measure of ICC.

We empirically measure the precision of the HQ manager's prior knowledge (i.e., the inverse of σ_ϵ^2 in our model) using the average distance between the HQ office and the divisional offices. The distance measure rests on the assumption that closer proximity allows HQ managers to be better informed about firm operations even in the absence of internal communication technology.

[21] As an alternative test for non-monotonicity, we apply the test statistics of Hall and Heckman (2000) and Ellison and Ellison (2011), which formally test whether the relation between two variables is monotonic versus exhibits a turning point. Untabulated results confirm a non-monotonic association between *Management Forecast Accuracy* and *Intranet*, with p-values of <0.01 and <0.05, respectively. Following Ellison and Ellison (2011) (Sections III A and B), we obtained critical values using 1,000 bootstrap repetitions. Additional simulations validated the parameter values and test size, indicating rejection rates below 5% for monotonic data.

This may reflect greater exposure to similar local conditions or more frequent direct, in-person interactions (e.g., Coval and Moskowitz, 2001; Kang and Kim, 2008; Ayers et al., 2011; Duchin and Sosyura, 2013; Chen et al., 2018). Geographic proximity also increases overlap in legal, cultural, and time-zone environments, further enhancing HQ managers' information absent ICC. Consequently, the marginal effect of ICC on HQ managers' information set is likely smaller when divisions are geographically closer to headquarters.

To examine the role of HQ managers' prior information, we estimate the main regression Equation 16 separately for firms with HQ-to-divisional office distances below and above the median. In these tests, our sample size decreases because we use lagged distance and because splitting the sample into two groups increases the number of singletons within fixed-effect groups, which are dropped from the estimation.

Table 3 presents the results. Comparing Columns (2) and (4), we find a positive and statistically significant coefficient on $Intranet$ and a negative and statistically significant coefficient on $Intranet^2$ only for the subsample above the median of the distance between the headquarters and divisional offices. In contrast, neither coefficient is statistically significant for the subsample below the median. The p-values for differences across subsamples are <0.1 and <0.05 for coefficients on $Intranet$ and $Intranet^2$, respectively. Additionally, Columns (1)-(2) suggest that the relation between $Intranet$ and management forecast accuracy is not statistically different from flat. These results are consistent with our theoretical cross-sectional predictions in Figure 7 Panel (a).[22]

A potential concern is that distance reflects organizational frictions associated with geographic dispersion rather than HQ managers' ex ante informedness. We address this concern in the Online Appendix in two ways. First, we limit the sample to firms with geographically close divisions (firms with over 90% of divisions in the same time zone, within 500 miles, or in the same Census region). Within each of these restricted groups, the inverted U-shaped relation persists only for firms with above-median distance (Table OA7). Second, using CEO tenure (i.e., the number of years in the CEO position) as a non-geographic proxy for HQ managers' informedness, we find an inverted U-

[22]To assess sensitivity to the median split, we conduct untabulated analyses using terciles of distance and find similar results: the top tercile exhibits a significant concave relation, while the bottom tercile shows a flat relation.

shaped relation only for firms with below-median CEO tenure (Table OA8). These results suggest that our findings reflect differences in HQ managers' ex ante informedness rather than institutional factors correlated with distance.

Altogether, we find that the inverted U-shape relation between intranet connectivity and internal information precision is concentrated (muted) in firms where the information access force is pronounced (weakened). Our results are consistent with the information access channel being one force driving the non-monotonic relation.

4.3.2 Free riding channel

A key insight generated by our model is that DMs have incentives to free-ride on the other DMs' information production, and this motive becomes stronger with the number of connected divisions (N_C). This free-riding incentive arises because connected DMs share information about the aggregate state (y) with each other. When more connected DMs acquire information, the posterior beliefs of all connected DMs about y become more precise (Equation 5), reducing the marginal benefit of any individual DM's information acquisition (Lemma 1). As a result, each connected DM is less likely to exert effort to acquire information as N_C increases (Corollary 1).

The strength of this free-riding channel depends on the degree of similarity across divisions, which is captured by the inverse of σ^2_Δ in our model. When σ^2_Δ is small, divisions are quite similar, and optimal actions depend primarily on the common aggregate state y rather than division-specific factors. In this case, connected DMs can rely on the information about y shared by other connected DMs, reducing their own incentives to incur costs to acquire information. As a result, the free-riding motive is stronger when divisions are more similar. On the other hand, when σ^2_Δ is large and divisions are less similar, division-specific information becomes more important for each division's decision, and each DM has stronger incentives to acquire information regardless of what other DMs do. Therefore, the free-riding channel is weaker when σ^2_Δ is greater. Figure 7 Panel (b) presents this prediction in a simulation using the fraction of connected divisions, which is analogous to our empirical proxy *Intranet*. We see that when σ^2_Δ is large, the free-riding force is sufficiently weak that the relation between the HQ manager's information precision and N_C becomes monotone.

To empirically substantiate the free-riding channel, we examine whether the inverted U-

shaped relation between intranet and management forecast accuracy is more pronounced among firms with greater similarity across intranet-connected sites. We measure similarity based on whether a firm's intranet sites operate in the same four-digit SIC industry, under the assumption that sites in the same industry share common characteristics and information (e.g., Duchin and Sosyura, 2013). Specifically, we construct *Site Similarity* as the sum of squared shares of each four-digit SIC across the firm's sites with an intranet.[23] This measure, analogous to the Herfindahl-Hirschman Index (HHI), is higher if a firm's intranet-connected sites are more concentrated within the same industry. We then estimate Equation 16 separately for firms below and above the median of *Site Similarity* measured for the prior year. Our sample size decreases because we use lagged *Site Similarity* and because the number of singletons within each of the two groups increases.

Table 4 shows the results for this cross-sectional test. Firms below the median of *Site Similarity* do not exhibit an inverted U-shape between intranet and management forecast accuracy in Column (2); they demonstrate a positive linear slope in Column (1), consistent with the high σ^2_Δ group in Figure 7 Panel (b), where divisions are less similar and the free-riding motive is weaker. In contrast, firms above the median of *Site Similarity* show an inverted U-shape in Column (4). Comparing Columns (2) and (4), the coefficients on $Intranet$ and $Intranet^2$ differ significantly, with p-values <0.05 and <0.01, respectively.[24] Our finding that the inverted U-shaped pattern is more pronounced among firms with greater divisional similarity is consistent with the model's prediction that free riding is stronger when decisions are highly correlated across different divisions.

4.4 Endogeneity Discussions and Additional Robustness Tests

4.4.1 Addressing endogeneity concerns

Our empirical tests are grounded in formal theory but may be subject to endogeneity concerns.[25] This section describes the steps taken to mitigate these concerns. We first note two observations that provide initial reassurance, then discuss robustness tests addressing potential

[23] For example, if a firm has two sites with an intranet operating in an industry and three sites with an intranet operating in another industry, then this firm's *Site Similarity* is $(2/5)^2 + (3/5)^2 = 0.52$.

[24] As an alternative to the median split, we use terciles of site similarity in untabulated analyses and find similar patterns. The top tercile exhibits a significant concave relation, whereas the bottom tercile shows a linear relation. We also find similar results using alternative similarity measures, including indicators for whether intranet-connected divisions are located in the same county or state, and a maximal similarity ratio defined as the largest share of same-industry intranet-connected divisions within a firm-year.

[25] As Armstrong et al. (2022) discusses, "Theory is what allows researchers to separate spurious inferences—i.e., those based on random correlations with no particular meaning—from causal inferences" (p. 3).

omitted variables, and finally present alternative identification strategies, including Bartik instruments, telecommunications deregulation, and first-differencing.

Before discussing specific robustness tests, we note two observations that help address omitted variable concerns. First, the coefficients on $Intranet$ and $Intranet^2$ are stable when moving from the specification without controls to that with controls in Table 2 (Columns (1) and (2)), while the adjusted R^2 nearly doubles. We further find in untabulated analysis that the within-fixed-effect-group adjusted R^2 increases roughly sixfold when we add control variables. These results suggest that omitted variable bias is less of a concern (Altonji et al., 2005; Oster, 2019).[26] Second, beyond documenting an inverted U-shaped relation, our cross-sectional tests align with the two economic forces in our model: information access and free riding. We show that the inverted U-shape is concentrated among firms with high site similarity and absent among firms where headquarters managers are ex ante more informed. Thus, alternative explanations would need to account not only for the inverted U-shaped relation but also for these cross-sectional patterns predicted by the model. This approach is akin to "identification by functional form" (e.g., Lewbel, 2019; Samuels et al., 2021)

We next address omitted variable concerns that firms with greater intranet connectivity may also be more complex or face greater uncertainty, which could independently affect forecasting accuracy. We address this concern in three ways. First, we control for several proxies for organizational structure in all of our regressions, including the number of sites, the number of segments, and earnings volatility. Second, our cross-sectional test of the free-riding channel in Table 4 helps mitigate concerns over complexity: if organizational complexity were driving results, we would expect a more pronounced negative slope when divisional similarity is low, as dissimilar divisions are more likely to reflect greater complexity. Instead, we find the opposite pattern. Third, to account for potential nonlinearities, we include quadratic terms for all control variables, including those capturing complexity and uncertainty, in Table 5 Panel A, Column (1), and additionally control for the fitted value of $Intranet$ and its squared term in Column (2). Our results remain robust.

[26] Applying the coefficient stability test of Oster (2019), we obtain $\delta_{\text{Oster}} = 1.9$ for *Intranet* and $\delta_{\text{Oster}} = 1.4$ for $Intranet^2$, both exceeding the conventional threshold of one and suggesting that unobserved factors would need to be roughly 1.4–1.9 times as strong as the included controls to overturn the diminishing-returns pattern.

To further address this concern, we control for additional measures: (i) the ratio of Loughran –McDonald complexity words in the firm's 10-K (*LM complexity*); (ii) the SEC Analytics Suite complexity bag-of-words ratio in the 10-K (*10K complexity*); (iii) the standard deviation of daily returns over the fiscal year (*Stock volatility*); and (iv) the ratio of Loughran–McDonald uncertainty words in the 10-K (*LM uncertainty*). Data availability for these variables reduces the sample to 4,569 observations. The results in Panel B of Table 5 show that including these measures, the fitted value of *Intranet*, and their squared terms do not materially affect our main findings.[27]

Finally, we employ several identification strategies to more directly address endogeneity. We use Bartik (shift-share) instruments (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022; Breuer, 2022). The idea is to predict a firm's intranet adoption using broad geographic or industry trends, weighted by the firm's predetermined exposure to those trends. Specifically, we construct:

$$Intranet_{IV\,i,t} = \sum_{j} Share_{i,j,t-1} \times Intranet_{j,t} \tag{17}$$

where $Share_{i,j,t-1}$ is firm i's share of sites in county or 4-digit SIC industry j at $t-1$, and $Intranet_{j,t}$ is the adoption rate in county or 4-digit SIC industry j at time t (excluding firm i). The instrument multiplies each county's or industry's adoption rate by the firm's predetermined exposure to that county or industry, then sums across counties or industries. Because broad adoption trends are unlikely driven by any single firm's characteristics, this instrument provides plausibly exogenous variation.

Using $Intranet_{IV}$ and $Intranet^2_{IV}$ as our instruments for $Intranet$ and $Intranet^2$, respectively, we estimate the two-stage least squares (2SLS) regression of Equation 16. The second-stage coefficients on $\widehat{Intranet}$ and $\widehat{Intranet}^2$ (the fitted values from the first stage) are reported in Table 6.[28] Column (1) uses county-based instruments and column (2) uses industry-based instruments. The coefficient on $\widehat{Intranet}$ is significantly positive, while the coefficient on $\widehat{Intranet}^2$ is significantly

[27]The fitted value of *Intranet* used in Table 5, Panel A, Column (2) is estimated from Table OA2, Panel A, Column (4). The fitted value used in Table 5, Panel B is derived from Table OA2, Panel A, Column (8).

[28]We do not report R-squared as it is difficult to interpret in 2SLS (Wooldridge, 2009). Additionally, untabulated tests find that both the conditional F-statistics and the Stock-wright S-statistics exceed 10 (Sanderson and Windmeijer, 2016; Stock and Wright, 2000). As a falsification test, we find no inverse U-shape among firms with limited first-stage effects, that is, those with below-median correlations between the Bartik instruments and intranet adoption (e.g., Angrist et al. (2010)), providing support for the exclusion restriction.

negative in both columns, consistent with our main findings.[29]

While Bartik instruments mitigate firm-level endogeneity, they do not rule out all confounds and we cannot directly test the exclusion restriction. We therefore provide two additional identification strategies in the Online Appendix. First, we exploit staggered state-level telecommunications deregulation as a quasi-exogenous shock to intranet adoption (Section OA3 and Table OA3). Deregulation reduced costs and regulatory barriers to intranet implementation, providing plausibly exogenous variation. Using a stacked difference-in-differences design, we find that deregulation-induced increases in intranet connectivity improve forecasting accuracy for firms with low pre-deregulation connectivity but reduce accuracy for firms with high intranet levels, consistent with an inverse U-shaped relation. Effects emerge only after deregulation, with no evidence of pre-trends.

Second, we use a first-differencing specification to address bias from time-invariant firm characteristics (Table OA4). Focusing on within-firm changes, we similarly find that increases in intranet connectivity improve forecasting accuracy when intranet connectivity is low, reduce accuracy when it is high, and have little effect at intermediate levels. This confirms the inverted U-shape using only within-firm variation.[30]

4.4.2 Additional Robustness Tests

This subsection presents sensitivity checks showing robustness to strategic disclosure incentives, different time periods, an alternative measure of internal information precision, and sample composition.

Our main specifications control for factors related to forecast timeliness and expectations management, including *ln(1+days until forecasts)*, *Litigation Indicator*, *Distress Indicator*, *Insider*

[29]The coefficients on $Intranet^2$ (OLS estimate) and $\widehat{Intranet^2}$ (IV estimate) need not coincide because OLS estimates the average treatment effect (ATE), whereas IV identifies the local average treatment effect (LATE) for compliers, that is, firms that adopt intranet in response to industry or geographic trends. In untabulated analysis, we find that complier firms (those with above-median correlations between the Bartik instruments and their intranet adoption) have higher *Site Similarity*. This high similarity amplifies free-riding forces and helps explain the larger IV coefficient (Angrist and Pischke, 2008; Becker, 2016; Card, 1999). We acknowledge that the discrepancy between the coefficients may also reflect endogeneity in OLS, which we further address in Table 7 and the Online Appendix.

[30]Adding firm fixed effects requires substantial within-firm variation in *Intranet*, which is limited in our setting: firm fixed effects absorb over 30% of the within-group standard deviation of *Intranet*, and the median firm has only 5 annual observations, with over 30% having 3 or fewer and over 25% having 2 or fewer observations. We use first-differencing because it directly captures within-firm changes but is less sensitive to the limited panel length (Armstrong et al., 2022; Breuer and deHaan, 2024).

Trading, and *HHI* (e.g., Richardson et al., 2004; Burgstahler and Eames, 2006; Rogers and Stocken, 2005). To further address concerns that managers' expectations management or earnings management influences our dependent variable *Management Forecast Accuracy*, we add two controls: *Earnings Surprise* and *Discretionary Accruals* (e.g., Kasznik, 1999; Matsumoto, 2002; Cotter et al., 2006). These additional controls are omitted from our main analysis due to their impact on sample size. Table 7 Column (1) shows results with these additional controls, and Column (2) further includes quadratic terms for all controls. In both columns, we continue to observe a positive and significant coefficient on *Intranet* and a negative and significant coefficient on $Intranet^2$.

Our findings are also robust across different time periods. Online Appendix Table OA5 shows consistent findings when restricting the sample to earlier years (2001-2006, 2001-2009, 2001-2012, and 2001-2015), with the 2001-2006 subsample closely corresponding to the sample period of 2000–2006 in Bloom et al. (2014). These robustness checks help alleviate concerns that our results are driven by later technological developments.

We also examine forecast specificity as an alternative proxy for the HQ manager's information precision. The intuition is that more precise information enables managers to issue more specific (less coarse) forecasts (Baginski et al., 1993; Chen et al., 2018). Figure OA1 and Table OA6 show similar patterns when using this measure. Because forecast specificity does not rely on analysts' consensus, this measure mitigates concerns about managerial meet-or-beat incentives.

Finally, untabulated analyses show robust findings when excluding retail trade (SIC 5200–5999) and hotel (SIC 7000–7011) industries, which together account for nearly 10% of the sample. These industries have particularly high franchise prevalence, so this restriction alleviates concerns that our results are driven by the rare but potential inclusion of franchise locations as firm-owned sites.[31]

5 Conclusion

We theoretically and empirically investigate how expansions in internal communication technology affect information production within organizations. In our theoretical model, we endogenize information acquisition in a setting with a headquarters manager and multiple divisional managers,

[31] We conduct extensive manual verification of a large subsample and identify very few cases (less than 0.7%) as potential franchise observations, all of which are borderline and conservatively classified.

where some divisions are connected through internal communication technology that facilitates information sharing. We formalize two economic forces: information access and free riding. Theoretically and empirically, we find that these two forces jointly determine a non-monotonic relation between internal communication connectivity and internal information precision. Our findings contribute to the growing literature on factors that shape firms' internal information production.

We substantiate the two economic forces predicted by our theory—information access and free riding—through cross-sectional tests using measures of HQ managers' ex ante informedness and similarity across sites. We address potential endogeneity concerns through multiple approaches, including Bartik instruments, telecommunications deregulation, and first-differencing, and demonstrate robustness across a wide range of controls, specifications, and time periods. While other factors may influence our results, the collective evidence consistently points to information access and free riding as important drivers of the patterns we document.

Our findings have broader implications beyond intranet technology. Although intranets have become prevalent, innovations and new technologies, such as advances in AI-driven tools, will continue to facilitate communication and information sharing within organizations. Our paper provides an important insight that more advanced internal communication technologies may not necessarily improve the internal information environment. To the extent that such technologies improve executives' access to organizational knowledge, the trade-offs we identify are likely to remain relevant. Our study provides insights for researchers and practitioners navigating these evolving technologies.

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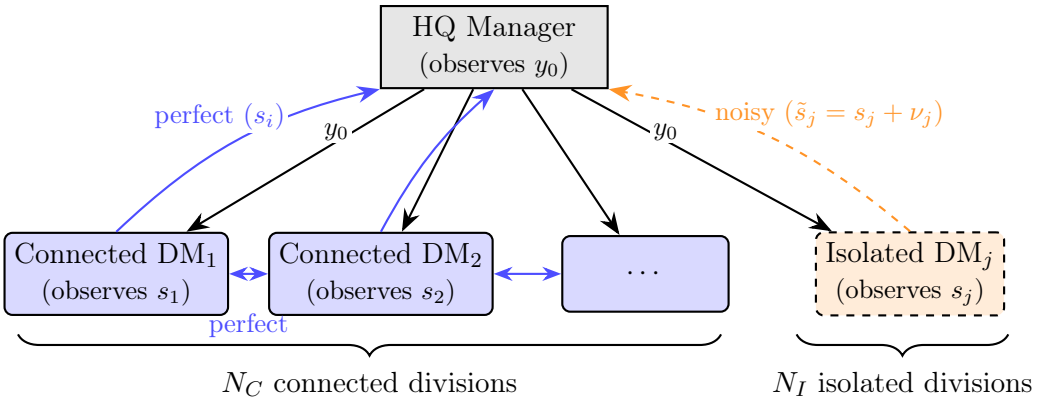
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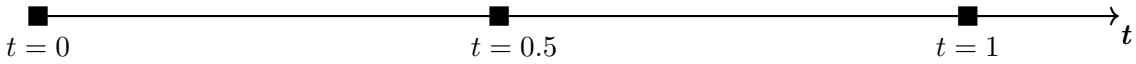
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Legend:

- Perfect communication
- Noisy communication
- Bilateral information sharing

Figure 1: Communication structure in the model. The HQ manager shares her signal y_0 with all divisions (top-down communication). Connected DMs share information perfectly with each other and with the HQ manager. Isolated DMs communicate with the HQ manager subject to noise σ_ν^2. When $\sigma_\nu^2 \to 0$, isolated DMs communicate as effectively as connected DMs; when $\sigma_\nu^2 \to \infty$, isolated DMs cannot communicate with the HQ manager.



- The HQ manager observes and shares $y_0 = y + \varepsilon$ with all DMs.
- DMs privately observe their information acquisition cost.
- DMs decide whether to acquire information.

- DMs that acquire information observe their signals and share them following the communication structure described above.
- DM_i sets a_i, $i = 1, \ldots, N$.

- y and Δ_i's realize.
- Payoffs realize.

Figure 2: Timeline of the model

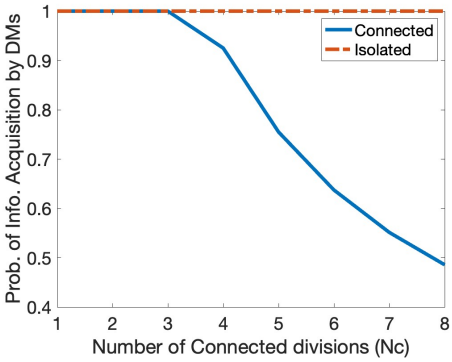


Figure 3: The figure shows the relation between the number of connected DMs and the probability of information acquisition by connected and isolated DMs. We use the following parameter values to create the figure: $\sigma_y^2 = 18, \sigma_\varepsilon^2 = 18, \sigma_\Delta^2 = 8, \sigma_\nu^2 = 15, \bar{c} = 10.25, \underline{c} = 10$, and c_i is uniformly distributed over its domain.

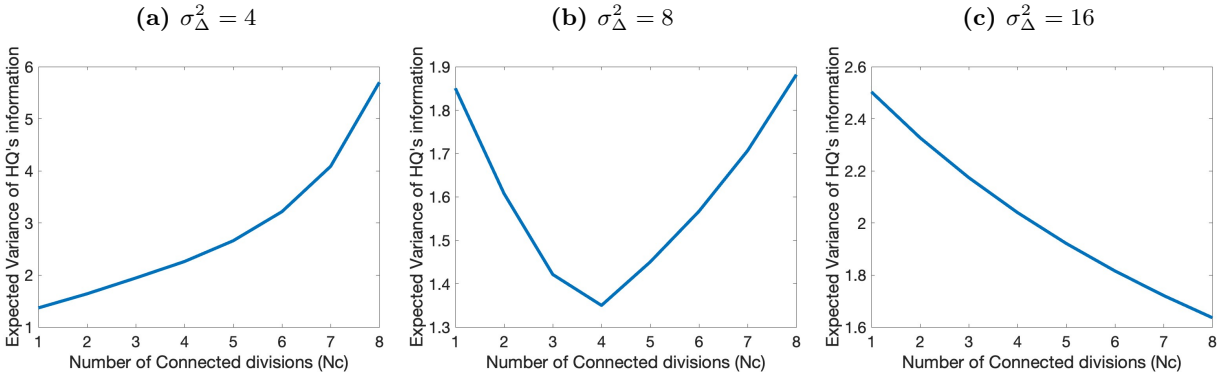


Figure 4: The figures plot $\mathbb{E}[\text{Var}^{HQ}(y) \mid N_C]$ for different levels of σ_Δ^2, capturing the magnitude of uncertainty about the division-specific component. The parameter values are the same as those used for Figure 3, unless stated otherwise.

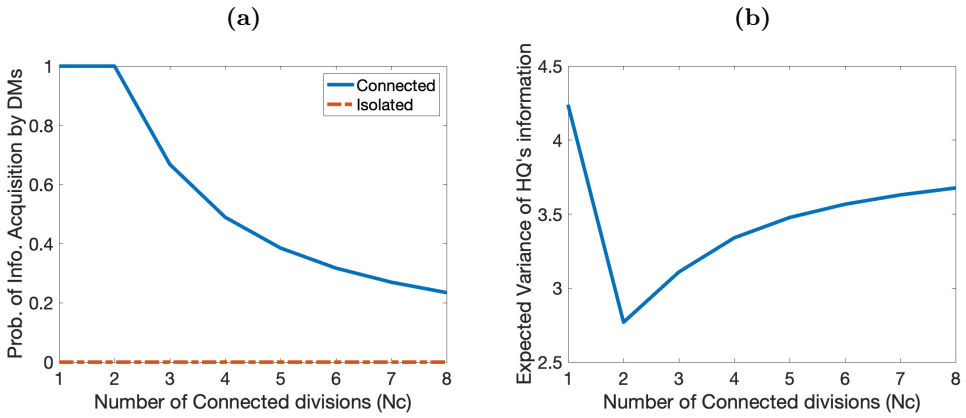


Figure 5: These figures illustrate how the number of connected DMs affects (a) DMs' information acquisition probabilities and (b) the expected variance of the HQ manager's beliefs about y under centralized decision-making. We set $\beta = 0.4$. The other parameter values are the same as those used for Figure 3.

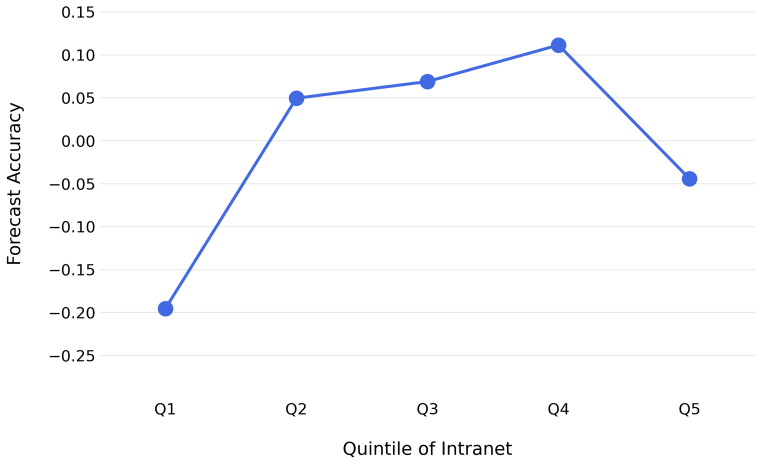


Figure 6: This figure plots the average values of *Management Forecast Accuracy* for each quintile of our sample firms' use of intranet (*Intranet*). Before taking the average by quintile, we de-mean *Management Forecast Accuracy* within each 2-digit industry-year group to partial out industry × year fixed effects. All variables are defined in Appendix B.

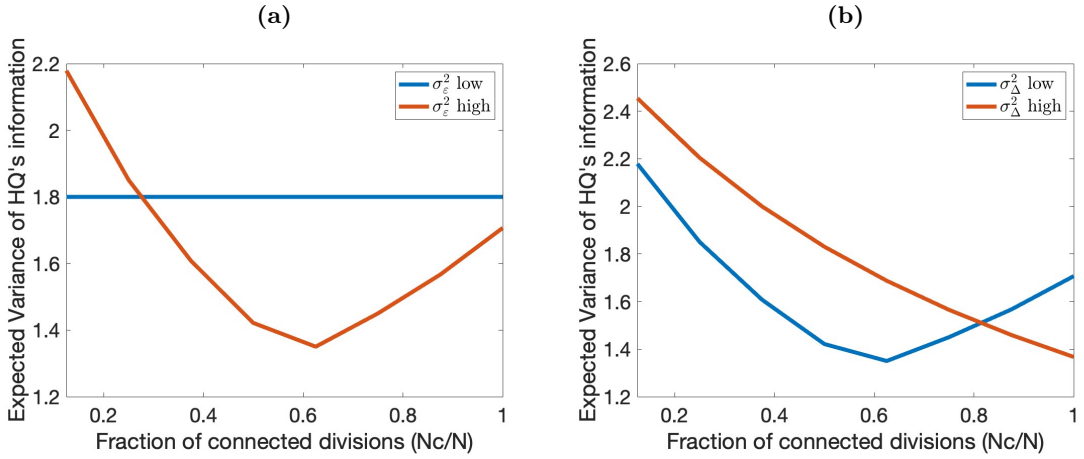


Figure 7: The relationship between the expected variance of information about y and the fraction of connected DMs. Panel (a) compares a high and a low value of σ_ε^2 ($\sigma_\varepsilon^2 = 18$ and $\sigma_\varepsilon^2 = 2$). Panel (b) compares a high and a low value of σ_Δ^2 ($\sigma_\Delta^2 = 12$ and $\sigma_\Delta^2 = 8$). All other parameter values are the same as in Figure 3.

Table 1: Summary Statistics

The table contains summary statistics of key variables used in our analyses. See Appendix B for variable definitions. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers.

Variable	**Mean**	**SD**	**p25**	**Median**	**p75**	***N***
Intranet	0.51	0.31	0.25	0.53	0.80	6,593
Management forecast accuracy	-0.64	1.29	-0.67	-0.18	-0.06	6,593
Insider Trading	-0.05	0.20	-0.01	0.00	0.00	6,593
Distress Indicator	0.07	0.26	0	0	0	6,593
HHI	0.44	0.24	0.26	0.37	0.54	6,593
ROA	0.06	0.07	0.03	0.06	0.09	6,593
BTM	0.49	0.35	0.27	0.42	0.62	6,593
MVE	9,589.9	21,801.0	803.8	2,234.2	7,109.3	6,593
R&D	0.04	0.07	0.00	0.01	0.04	6,593
Analysts following	9.52	7.40	4.00	8.00	14.00	6,593
Earnings Volatility	0.19	0.20	0.05	0.12	0.25	6,593
Employees	8,110.1	13,291.4	1,250.0	3,106.0	8,000.0	6,593
Revenues	2,260.4	4,120.1	250.0	739.0	2,161.0	6,593
Sites	56.79	106.80	7.00	19.00	51.00	6,593
Internet	0.91	0.19	0.91	1.00	1.00	6,593
ERP	0.40	0.31	0.11	0.39	0.65	6,593
CAD/CAM	0.12	0.21	0.00	0.00	0.17	6,593
Number of PCs per employee	0.60	0.35	0.38	0.56	0.77	6,593
Business segments	9.76	5.65	3.00	9.00	14.00	6,593
Geographical segments	9.22	6.73	3.00	9.00	12.00	6,593
Related	0.80	0.18	0.70	0.80	1.00	6,593
Institutional ownership	0.70	0.30	0.60	0.79	0.91	6,593
Loss indicator	0.13	0.33	0.00	0.00	0.00	6,593
Litigation indicator	0.22	0.41	0.00	0.00	0.00	6,593
Days until forecasts	102.21	35.14	84.80	97.50	119.00	6,593
Distance	703.07	480.80	391.67	617.74	914.68	6,311
Site similarity	0.43	0.38	0.00	0.33	0.81	6,222
10K complexity	0.25	0.02	0.24	0.25	0.26	4,569
Stock volatility	0.03	0.01	0.02	0.02	0.03	4,569
LM complexity	0.47	0.18	0.34	0.45	0.58	4,569
LM uncertainty	0.01	0.01	0.01	0.01	0.02	4,569
Earnings Surprise	0.001	0.003	-0.001	0.001	0.002	6,266
Discretionary Accruals	-0.04	0.13	-0.09	-0.02	0.03	6,266

Table 2: Non-linear Association between Intranet and Forecast Accuracy

This table reports estimates from the following firm-year-level regression: $Management\ Forecast\ Accuracy_{i,t+1} = \beta_1 Intranet_{i,t} + \beta_2 Intranet^2_{i,t} + \theta Controls_{i,t} + \Sigma\beta_{j,t} Industry \times Year_{j,t} + \epsilon_{i,t}$. *Management Forecast Accuracy* is -1 multiplied by the forecast error, which is the absolute difference between the management EPS forecast and the actual realized EPS, scaled by the EPS forecast. We consider the first EPS forecast corresponding to the next fiscal year that is issued after the earnings announcement for the current fiscal year and before the earnings announcement for the subsequent fiscal year. All variables are defined in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers. *t*-statistics based on standard errors clustered by firm are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

		Management Forecast Accuracy$_{t+1}$	
	Pr.	(1)	(2)
Intranet	+	1.059*	0.903*
		(1.92)	(1.92)
Intranet^2	-	-0.970**	-0.844**
		(-1.97)	(-2.05)
Insider Trading			-0.097
			(-1.26)
Distress Indicator			-0.218*
			(-1.85)
HHI			0.057
			(0.35)
ROA			0.017
			(0.03)
BTM			0.059
			(0.56)
ln(MVE)			0.116**
			(2.52)
R&D			0.376
			(0.65)
ln(1+analysts following)			-0.108*
			(-1.85)
Earnings Volatility			-0.002
			(-0.02)
ln(employees)			0.043
			(0.35)
ln(sites)			0.065
			(0.92)
Internet			0.188
			(0.67)
Number of PCs per employee			-0.065
			(-0.56)
ERP			-0.070
			(-0.62)
CAD/CAM			0.198
			(0.86)
ln(1+revenues)			-0.092
			(-1.08)
ln(business segments)			-0.061
			(-0.90)
ln(geographical segments)			0.079**
			(1.96)
Related			0.240
			(1.43)
Institutional ownership			0.229
			(1.30)
ln(1+days until forecasts)			0.048
			(1.54)
Litigation Indicator			0.062
			(0.73)
Loss Indicator			-0.107
			(-1.14)
Industry × Year FE		Yes	Yes
N		6,593	6,593
Adjusted R-squared		0.025	0.044
Clustering		Firm	

Table 3: Test on Information Access: Role of HQ's Prior Information

This table reports results from the following firm-year-level regressions estimated separately for firm-years below and above the median of *Distance*: $Management\ Forecast\ Accuracy_{i,t+1} = \beta_1 Intranet_{i,t}\ (+\beta_2 Intranet^2_{i,t}) + \theta Controls_{i,t} + \Sigma\beta_{j,t} Industry \times Year_{j,t} + \epsilon_{i,t}$. *Distance* is the average distance between the HQ office and the divisional offices measured for each firm. Control variables are the same as those used in Table 2. All variables are defined in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers. *t*-statistics based on standard errors clustered by firm are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Management Forecast Accuracy$_{t+1}$					
	Below Median Distance			Above Median Distance		
	Pr.	(1)	(2)	Pr.	(3)	(4)
Intranet	0,0	0.136	0.476	0,+	0.025	1.196*
		(0.68)	(0.95)		(0.13)	(1.77)
Intranet^2	0		-0.364	-		-1.235**
			(-0.76)			(-2.18)
$p-$value for difference between Col (2) and (4):						
Intranet			0.063*			
Intranet^2			0.024**			
Controls		Yes	Yes		Yes	Yes
Industry × Year FE		Yes	Yes		Yes	Yes
N		3,156	3,156		3,155	3,155
Adjusted R-squared		0.038	0.038		0.032	0.037
Clustering			Firm			

Table 4: Test on Free Riding: Role of Divisional Similarity

This table reports results from the following firm-year-level regressions estimated separately for firm-years below and above the median of *Site Similarity*: $Management\ Forecast\ Accuracy_{i,t+1} = \beta_1 Intranet_{i,t}\ (+\beta_2 Intranet^2_{i,t}) + \theta Controls_{i,t} + \Sigma\beta_{j,t} Industry \times Year_{j,t} + \epsilon_{i,t}$. *Site Similarity* captures the extent of similarity across a firm's divisional sites with an intranet, calculated by the sum of the square of the share of each four-digit SIC industry that the firm's sites with an intranet operate in. Control variables are the same as those used in Table 2. All variables are defined in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers. *t*-statistics based on standard errors clustered by firm are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Management Forecast Accuracy$_{t+1}$					
	Below Median Site Similarity			Above Median Site Similarity		
	Pr.	(1)	(2)	Pr.	(3)	(4)
Intranet	+,0	0.268**	0.545	0,+	-0.006	1.519*
		(2.03)	(1.15)		(-0.02)	(1.84)
Intranet^2	0		-0.299	-		-1.581**
			(-0.66)			(-2.16)
$p-$value for difference between Col (2) and (4):						
Intranet			0.036**			
Intranet^2			0.002***			
Controls		Yes	Yes		Yes	Yes
Industry × Year FE		Yes	Yes		Yes	Yes
N		3,049	3,049		3,173	3,173
Adjusted R-squared		0.025	0.025		0.071	0.077
Clustering			Firm			

Table 5: Robustness Test: Controlling for Arbitrary Non-Linearities

Columns (1) in both panels report results from the following firm-year-level regression: $Management\ Forecast\ Accuracy_{i,t+1} = \beta_1 Intranet_{i,t} + \beta_2 Intranet^2_{i,t} + \theta Controls_{i,t} + \gamma Controls^2_{i,t} + \Sigma\beta_{j,t} Industry \times Year_{j,t} + \epsilon_{i,t}$. In panel A, $Controls_{i,t}$ include: $Insider\ Trading$, $Distress\ Indicator$, HHI, ROA, BTM, $ln(MVE)$, $R\&D$, $ln(1 + analysts\ following)$, $Earnings\ Volatility$, $ln(employees)$, $ln(1+revenues)$, $ln(sites)$, $Internet$, $Number\ of\ PCs\ per\ employee$, ERP, CAD/CAM, $ln(business\ segments)$, $ln(geographical\ segments)$, $Related$, $Institutional\ ownership$, $ln(1 + days\ until\ forecasts)$, $Litigation\ Indicator$, and $Loss\ Indicator$. In Panel B, $Controls_{i,t}$ additionally include $10K\ complexity$, $LM\ complexity$, $LM\ uncertainty$, and $Stock\ Volatiltiy$ (same as those used in Table 2). Columns (2) in both panels report results that additionally control for the fitted value of $Intranet_{i,t}$ and its squared term explained by $Controls_{i,t}$. Specifically, the fitted value of $Intranet_{i,t}$ is estimated from $Intranet_{i,t} = \theta Controls_{i,t} + \Sigma\beta_{j,t} Industry \times Year_{j,t} + \epsilon_{i,t}$., whose regression results are reported in Online Appendix Table OA2. Panel A column (2) below uses the fitted value estimated from Panel A column (4) of Table OA2, while Panel B column (2) below uses the fitted value estimated from Panel A column (8) of Table OA2. All variables are defined in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers. t-statistics based on standard errors clustered by firm are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Controlling for Squared Controls and Fitted Values

		Management Forecast Accuracy$_{t+1}$	
	Pr.	(1)	(2)
Intranet	+	0.849*	0.846*
		(1.90)	(1.90)
Intranet^2	-	-0.772**	-0.764**
		(-1.98)	(-1.97)
Controls		Yes	Yes
Controls^2		Yes	Yes
Controlling for fitted value of $Intranet$			Yes
Controlling for fitted value of $Intranet^2$			Yes
Industry × Year FE		Yes	Yes
N		6,593	6,593
Adjusted R-squared		0.056	0.056
Clustering		Firm	

Panel B. Additional Controls: Uncertainty, Complexity, Squared Terms, and Fitted Values

		Management Forecast Accuracy$_{t+1}$	
	Pr.	(1)	(2)
Intranet	+	1.132**	1.138**
		(2.02)	(2.02)
Intranet^2	-	-0.972**	-0.967**
		(-2.06)	(-2.05)
Controls		Yes	Yes
Controls^2		Yes	Yes
10K complexity, LM complexity, LM uncertainty, Stock volatility		Yes	Yes
10K complexity^2, LM complexity^2, LM uncertainty^2, Stock volatility^2		Yes	Yes
Controlling for fitted value of $Intranet$			Yes
Controlling for fitted value of $Intranet^2$			Yes
Industry × Year FE		Yes	Yes
N		4,569	4,569
Adjusted R-squared		0.054	0.054
Clustering		Firm	

Table 6: Bartik Instrument Analysis: Intranet and Forecast Accuracy

This table reports second-stage estimates from the following two-stage least squares regression: $Management\ Forecast\ Accuracy_{i,t+1} = \beta_1 \widehat{Intranet}_{i,t} + \beta_2 \widehat{Intranet}^2_{i,t} + \theta Controls_{i,t} + \Sigma\beta_{j,t} Industry \times Year_{j,t} + \epsilon_{i,t}$. $\widehat{Intranet}_{i,t}$ and $\widehat{Intranet}^2_{i,t}$ are fitted values obtained from the first stage using $Intranet_{IV\,i,t}$ and $Intranet_{IV\,i,t}^2$ as instruments, respectively. In Column (1), $Intranet_{IV\,i,t}$ is the intranet adoption rate for each county, weighted by the firm's county shares based on the locations of their divisions. In Column (2), $Intranet_{IV\,i,t}$ is the nationwide intranet adoption rate for each 4-digit SIC code, weighted by the firm's division shares across industries. Control variables are the same as those used in Table 2. All variables are defined in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers. *t*-statistics based on standard errors clustered by firm are in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

		Management Forecast Accuracy$_{t+1}$	
		County-based Bartik instrument	Industry-based Bartik instrument
	Pr.	(1)	(2)
$\widehat{Intranet}$	+	7.555**	6.324*
		(1.99)	(1.72)
$\widehat{Intranet}^2$	-	-7.912**	-7.810**
		(-1.98)	(-2.18)
Controls		Yes	Yes
Industry × Year FE		Yes	Yes
N		6,593	6,593
Clustering		Firm	

Table 7: Accounting for Managers' Strategic Disclosure

This table reports estimates from the following firm-year-level regression using a subset of our sample with non-missing data for strategic disclosure proxies included as additional control variables: $Management\ Forecast\ Accuracy_{i,t+1} = \beta_1 Intranet_{i,t} + \beta_2 Intranet^2_{i,t} + \beta_3 EarningsSurprise_{i,t} + \beta_4 DiscretionaryAccruals_{i,t} + \theta Controls_{i,t} (+\theta Controls^2_{i,t} + \beta_5 EarningsSurprise^2_{i,t} + \beta_6 DiscretionaryAccruals^2_{i,t}) + \Sigma\beta_{j,t} Industry \times Year_{j,t} + \epsilon_{i,t}$. $EarningsSurprise$ is the difference between the actual EPS and analysts' consensus scaled by fiscal year-end asset per share. $DiscretionaryAccruals$ is residuals from the regression of total accruals on lagged, current, and future cash flows, following Dechow and Dichev (2002). Other controls are the same as those used in Table 2. All variables are defined in Appendix B. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers. *t*-statistics based on standard errors clustered by firm are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

		Management Forecast Accuracy$_{t+1}$	
	Pr.	(1)	(2)
Intranet	+	0.933*	0.890*
		(1.92)	(1.92)
Intranet^2	-	-0.880**	-0.821**
		(-2.03)	(-1.99)
Earnings Surprise		-0.683	-0.445
		(-0.62)	(-0.33)
Discretionary Accruals		0.620**	0.446*
		(2.23)	(1.72)
Controls		Yes	Yes
Controls^2		No	Yes
Industry × Year FE		Yes	Yes
N		6,266	6,266
Adjusted R-squared		0.047	0.060
Clustering		Firm	

Appendix A. Proofs

A.1 Derivation of Equations 5 and 6 (Variance of DMs' and the HQ manager's posterior beliefs)

The HQ manager observes the signals $y_0 = y + \varepsilon$, where $\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2)$; $s_i = y + \Delta_i$ for k connected DMs; and $\tilde{s}_j = y + \Delta_j + \nu_j$ for k' isolated DMs, where $\Delta_i, \Delta_j \sim \mathcal{N}(0, \sigma_\Delta^2)$ and $\nu_j \sim \mathcal{N}(0, \sigma_\nu^2)$. Let S_C and S_I denote the sets of signals received from connected and isolated DMs, respectively.

Note that the noise terms are Gaussian, mutually independent, and independent of y. Therefore, the posterior distribution is also Gaussian:

$$y \mid y_0, S_C, S_I \sim \mathcal{N}(\hat{\mu}_{k,k'}, \hat{\sigma}^2_{k,k'}), \tag{A.1}$$

with posterior precision (inverse variance)

$$\hat{\sigma}^{-2}_{k,k'} = \sigma_y^{-2} + \sigma_\varepsilon^{-2} + k\sigma_\Delta^{-2} + k'(\sigma_\Delta^2 + \sigma_\nu^2)^{-1}, \tag{A.2}$$

and posterior mean

$$\hat{\mu}_{k,k'} = \hat{\sigma}^2_{k,k'} \left(y_0 \sigma_\varepsilon^{-2} + \sum_{s_i \in S_C} s_i \sigma_\Delta^{-2} + \sum_{s_j \in S_I} s_j (\sigma_\Delta^2 + \sigma_\nu^2)^{-1} \right). \tag{A.3}$$

The derivation for connected and isolated DMs is analogous (see Equation 5), obtained by excluding signals in S_I for connected DMs and excluding signals in both S_C and S_I for isolated DMs.

A.2 Proof of Lemma 1 (Expected gain from information acquisition)

π_k is the expected gain from information acquisition for a connected DM when k other connected DMs acquire information. Without loss, assume that $DM_1, \ldots, DM_k$ acquire information and $i > k$. Note that DM_i's optimal decision is implemented if he acquires information (i.e., $a_i = y + \Delta_i$), which yields a utility of $-c_i$. However, if DM_i does not acquire information, he chooses $a_i = \mathbb{E}[y + \Delta_i | y_0, y + \Delta_1, \ldots, y + \Delta_k] = \hat{y}_k$. Therefore, DM_i's expected utility from not acquiring information is:

$$-\pi_k = \mathbb{E}[-(\hat{y}_k - y - \Delta_i)^2 | y_0, s_1, \ldots, s_k] = -(\hat{\sigma}_k^2 + \sigma_\Delta^2). \tag{A.4}$$

In other words, π_k can be interpreted as the expected utility loss from not acquiring information. As a result, the expected net gain from information acquisition is $\pi_k - c_i$ if exactly k other connected DMs acquire information.

A.3 Proof of Proposition 1 (Characterization of DMs' information acquisition decision)

Part (a) directly follows from Lemma 1, noting that the expected net gain from information acquisition for isolated DMs is $\pi_0 - c_i$.

For connected DMs, as discussed in Part (b), it is a Nash equilibrium that all connected DMs always acquire information if $\pi_{N_C - 1} \geq \bar{c}$, as the expected net gain of information acquisition exceeds zero with probability one. Conversely, if $\pi_0 \leq \underline{c}$, no connected DM acquires information. When neither of these conditions holds, only connected DMs with a sufficiently low c_i produce information in a symmetric equilibrium. The threshold level $c^*(N_C)$ should be set in a way that

makes DMs indifferent between acquiring and not acquiring information when $c_i = c^*(N_C)$, as ensured by Equation 9.

To establish the existence and uniqueness of $c^*(N_C)$, consider the left-hand side of Equation 9 as a function of c^*. One can show that this function is strictly decreasing in c^*. Moreover, when $c^* = \underline{c}$, the left-hand side equals $\pi_0 - \underline{c} > 0$, while when $c^* = \bar{c}$, it equals $\pi_{N_C-1} - \bar{c} < 0$. Therefore, by continuity, there exists a $c^*(N_C) \in (\underline{c}, \bar{c})$ such that Equation 9 holds. Since the function is strictly decreasing, this solution is unique.

A.4 Proof of Corollary 1 (Relation between p_N and N)

Lemma 1 states that π_k is decreasing in k. An implication of this finding is that for any $N_C \leq \bar{N}_C$, $\pi_{N_C-1} \geq \bar{c}$. From Proposition 1(b), it directly implies that $p_C(N_C) = 1$ for $N_C \leq \bar{N}_C$.

When $N_C > \bar{N}_C$, Equation 9 implies that:

$$H(p_C(N_C); N_C) = 0, \tag{A.5}$$

where

$$H(p; N_C) = \sum_{k=0}^{N_C-1} \binom{N_C - 1}{k} p^k (1-p)^{N_C-k-1} \pi_k - G^{-1}(p). \tag{A.6}$$

Since π_k is decreasing in k, one can show that $H(p; N_C) > H(p; N_C + 1)$ for all values of $p \in (0, 1)$; that is, the expected net gain from information acquisition decrease as a new DM becomes connected, and all connected DMs continue to acquire information with probability p.[32] Therefore:

$$H(p_C(N_C); N_C + 1) < H(p_C(N_C); N_C) = 0. \tag{A.7}$$

Similarly, one can show that $H(p, N_C)$ is decreasing in p, reflecting the fact that a larger p lowers the expected gain from information acquisition for each connected DM. Since $H(p_C(N_C + 1), N_C + 1) = 0 > H(p_C(N_C); N_C + 1)$, we should have $p_C(N_C + 1) < p_C(N_C)$ for $N_C \geq \bar{N}_C$.

A.5 Proof of Lemma 2 (Sharing information is always optimal)

We prove the lemma for connected DMs; the proof for isolated DMs is similar. In particular, we show that if DM_i is connected and observes $s_i = y + \Delta_i$, he is better off sharing this signal; that is, if a_i^+ and a_i^- represent the HQ manager's decisions with and without DM_i's signal, then, for any realization of s_i, we have:

$$\mathbb{E}[(a_i^- - s_i)^2 | \mathcal{F}_i, s_i] > \mathbb{E}[(a_i^+ - s_i)^2 | \mathcal{F}_i, s_i], \tag{A.8}$$

where $\mathcal{F}_i$ represents any information DM_i receives before sharing his signal. Note that DM_i does not know the HQ manager's beliefs about y in the absence of the signal. However, he knows that the HQ manager assigns a normal distribution to y, conditional on the set of signals she observes. We show that for any possible conditional distribution that the HQ manager assigns, such as $y \sim \mathcal{N}(\hat{y}_-, \sigma_-^2)$, DM_i benefits from sharing his signal. In other words, if we show that for any $\hat{y}_-$ and σ_-^2, we have

$$\mathbb{E}[(a_i^- - s_i)^2 | \mathcal{F}_i, s_i, \hat{y}_-, \sigma_-^2] > \mathbb{E}[(a_i^+ - s_i)^2 | \mathcal{F}_i, s_i, \hat{y}_-, \sigma_-^2], \tag{A.9}$$

[32] Specifically, note that $\mathcal{B}(p, N_C + 1)$ (i.e., the binomial distribution corresponding to $N_C + 1$ observations and probability p) has first-order stochastic dominance over $\mathcal{B}(p, N_C)$. Thus, $\mathbb{E}_{k \sim \mathcal{B}(p, N_C+1)}[\pi_k] < \mathbb{E}_{k \sim \mathcal{B}(p, N_C)}[\pi_k]$ since π_k is a decreasing function of k.

then the inequality in (A.8) follows from the one in (A.9) by the law of iterated expectations. Suppose $\mathcal{N}(\hat{y}_+, \hat{\sigma}_+^2)$ is the HQ manager's posterior distribution of y after observing $s_i = y + \Delta_i$. It it straightforward to show that

$$\hat{y}_+ = \frac{\sigma_-^{-2}}{\sigma_-^{-2} + \sigma_\Delta^{-2}} \hat{y}_- + \frac{\sigma_\Delta^{-2}}{\sigma_-^{-2} + \sigma_\Delta^{-2}} s_i, \qquad \hat{\sigma}_+^2 = \frac{1}{\sigma_-^{-2} + \sigma_\Delta^{-2}}. \tag{A.10}$$

Therefore,

$$\begin{aligned} a_i^- &= \mathbb{E}[y + \beta\Delta_i | \hat{y}_-, \sigma_-^2] = \hat{y}_- \\ a_i^+ = \mathbb{E}[y + \beta\Delta_i | \hat{y}_-, \sigma_-^2, s_i] &= \hat{y}_+ + \beta(s_i - \hat{y}_+) = \frac{(1-\beta)\sigma_-^2}{\sigma_-^{-2} + \sigma_\Delta^{-2}} \hat{y}_- + (\beta + \frac{(1-\beta)\sigma_\Delta^{-2}}{\sigma_-^{-2} + \sigma_\Delta^{-2}}) s_i \\ \Rightarrow a_i^+ - s_i &= \frac{(1-\beta)\sigma_-^2}{\sigma_-^{-2} + \sigma_\Delta^{-2}} (a_i^- - s_i). \end{aligned} \tag{A.11}$$

From the last equation, it is clear that the inequality in (A.9) holds for any s_i and $\hat{\sigma}_-^2$, by noting that $\frac{(1-\beta)\sigma_-^2}{\sigma_-^{-2} + \sigma_\Delta^{-2}} < 1$. This proves the inequality in (A.8), completing the proof.

A.6 Proof of Lemma 3 (Expected gain from information acquisition under centralized decision-making)

Suppose without DM_j's signal s_j, the HQ manager assigns probability distribution $y \sim \mathcal{N}(\hat{y}_-, \sigma_-^2)$ for y, where $\sigma_-^2 := \hat{\sigma}_{k,k'_{-j}}^2$ defined in Equation 13. Let the HQ manager's posterior probabilities for y and Δ_j after observing $\tilde{s}_j = y + \Delta_j + \nu_j$ be $y \sim \mathcal{N}(\hat{y}_+, \sigma_+^2)$ and $\Delta_j \sim \mathcal{N}(\hat{\Delta}_{j,+}, \sigma_{\Delta,+}^2)$, respectively. From standard results about the updating of normal distributions, we have:

$$\begin{aligned} \hat{y}_+ &= \frac{\sigma_\Delta^2 + \sigma_\nu^2}{\sigma_-^2 + \sigma_\Delta^2 + \sigma_\nu^2} \hat{y}_- + \frac{\sigma_-^2}{\sigma_-^2 + \sigma_\Delta^2 + \sigma_\nu^2} \tilde{s}_j, \\ \hat{\sigma}_+^2 &= \sigma_-^2 - \frac{\sigma_-^4}{\sigma_-^2 + \sigma_\Delta^2 + \sigma_\nu^2} \\ \hat{\Delta}_{j,+} &= \frac{\alpha(\sigma_\Delta^2 + \sigma_\nu^2)}{\sigma_-^2 + \sigma_\Delta^2 + \sigma_\nu^2} (s_j - \hat{y}_-) \\ \sigma_{\Delta,+}^2 &= \sigma_\Delta^2 - \frac{\sigma_\Delta^4}{\sigma_-^2 + \sigma_\Delta^2 + \sigma_\nu^2}, \end{aligned} \tag{A.12}$$

where $\alpha := \frac{\sigma_\Delta^2}{\sigma_\Delta^2 + \sigma_\nu^2}$ Let a_- and a_+ be the HQ manager's action for division j with and without $\tilde{s}_j$, respectively. Furthermore, denote the set of signals the HQ manager receives from other sources by $\mathcal{F}_-$. Note that

$$a_- = \mathbb{E}[y + \beta\Delta_j | \mathcal{F}_-] = \hat{y}_-, \qquad a_+ = \mathbb{E}[y + \beta\Delta_j | \mathcal{F}_-, \tilde{s}_j] = \hat{y}_+ + \beta\hat{\Delta}_{j,+}. \tag{A.13}$$

The expected gain from information acquisition given $\mathcal{F}_-$ is

$$\pi^I = \mathbb{E}[(y + \Delta_j - a_-)^2 | \mathcal{F}_-] - \mathbb{E}[(y + \Delta_j - a_+)^2 | \mathcal{F}_-]. \tag{A.14}$$

After some simplifications, one can show that

$$\pi^I = \sigma_-^2 + \sigma_\Delta^2 - \frac{(1-\beta)^2\sigma_\Delta^4 + (\sigma_\Delta^2 + \sigma_-^2)\sigma_\nu^2}{\sigma_-^2 + \sigma_\Delta^2 + \sigma_\nu^2}. \tag{A.15}$$

This proves the statement in Part a. The statement for Part b follows from the equation above by setting $\sigma_\nu^2 = 0$.

A.7 Proof of Proposition 2 (Optimality of full adoption)

Suppose the first N_C DMs are connected, and the rest are isolated. Note that the HQ manager's expected utility is

$$\begin{aligned}\mathbb{E}[U_{HQ}] &= \frac{1}{N}\sum_{i=1}^{N}\mathbb{E}[-(a_i - y - \beta\Delta_i)^2 - c_i I_i] \\ &= \frac{1}{N}\underbrace{\sum_{i=1}^{N_C}\mathbb{E}[-(a_i - y - \beta\Delta_i)^2 - c_i I_i]}_{\text{Utility from Connected Divisions}} + \frac{1}{N}\underbrace{\sum_{i=N_C+1}^{N}\mathbb{E}[-(a_i - y - \beta\Delta_i)^2 - c_i I_i]}_{\text{Utility from Isolated Divisions}}.\end{aligned} \tag{A.16}$$

The HQ manager's utility from decisions made in isolated divisions is:

$$\begin{aligned}\mathcal{U}_{HQ}^I &= \mathbb{E}[-(a_i - y - \beta\Delta_i)^2 - c_i\mathbb{I}_{\{c_i \le \pi_0\}}] \\ &= (-\hat{\sigma}_0^2 - \beta^2\sigma_\Delta^2)(1 - G(\pi_0)) + (-(1-\beta)^2\sigma_\Delta^2 - \mathbb{E}[c_i | c_i \le \pi_0])G(\pi_0) \\ &= \mathbb{E}[-\min\{c_i, \pi_0\}] + \Big[(1-\beta^2) - 2(1-\beta)p_I\Big]\sigma_\Delta^2.\end{aligned} \tag{A.17}$$

Similarly, the HQ manager's expected utility from decisions made in each connected DM is

$$\mathcal{U}_{HQ}^C(N_C) = \mathbb{E}[-\min\{c_i, c^*(N_C)\}] + \Big[(1-\beta^2) - 2(1-\beta)p_C(N_C)\Big]\sigma_\Delta^2. \tag{A.18}$$

Since $\pi_0 \ge c^*(N_C)$, which implies that $p_I \ge p_C(N_C)$, we have $U_{HQ}^C \ge U_{HQ}^I$. Likewise, it is straightforward to show that $\mathcal{U}_{HQ}^C(N_C)$ is weakly increasing in N_C. Combining these observations, we infer that the HQ manager's expected utility is also weakly increasing in N_C, implying the optimality of $N = N_C$.

Appendix B. Variable Definitions

Variable	Definition
Management Forecast Accuracy	-1 multiplied by the forecast error, which is the absolute difference of the management EPS forecast and the actual realized EPS, scaled by the EPS forecast, based on I/B/E/S. We use the first management EPS forecast provided between the earnings announcement for the current fiscal year (inclusive) and the earnings announcement for the subsequent fiscal year (exclusive).
Intranet	the firm's use of intranets which serves as a proxy for the extent of internal communication following Bloom et al. (2014). It is calculated as the average site-level intranet in a year weighted by employees at each site. Each site is assigned one if it has installed the intranet, and zero otherwise, based on the Harte-Hanks Ci Technology database (CiDB). We infer the installment of intranets based on the presence of technologies used to connect offices or product sites, including frame relays, leased lines, a synchronous optical network (SONET), digital subscriber line (xDSL), asynchronous transfer mode (ATM) technology, and virtual private networks (VPN).
Internet	the firm's use of the internet calculated as the average site-level internet in a year weighted by employees at each site. Each site is assigned 1 if it has installed the internet, and 0 otherwise, based on the Harte-Hanks Ci Technology database (CiDB).
Number of PCs per employee	the number of PCs over the number of employees within the firm in a year, based on the Harte-Hanks Ci Technology database (CiDB).
ERP	the firm's use of enterprise resource planning (ERP) calculated as the average site-level ERP in a year weighted by employees at each site. Each site is assigned 1 if it has ERP systems, and 0 otherwise, based on the Harte-Hanks Ci Technology database (CiDB).
CAD/CAM	the firm's use of computer-assisted design/computer-assisted manufacturing (CAD/-CAM) technologies calculated as the average site-level ERP in a year weighted by employees at each site. Each site is assigned 1 if it has CAD/CAM technologies, and 0 otherwise, based on the Harte-Hanks Ci Technology database (CiDB).
Insider Trading	the number of shares acquired minus the number of shares disposed of by the CEO, CFO, and President during the one-year period prior to the earnings announcement date, scaled by shares outstanding at the end of the fiscal year, following Rogers and Stocken (2005) and Brochet (2010). The insider trades data is obtained from Thomson Reuters.
Distress Indicator	1 if the firm is in the most distressed decile, following Rogers and Stocken (2005), within a SIC code $\times$ year. Financial distress is measured using the SA index (Hadlock and Pierce, 2010), defined as $-0.0737 \cdot size + 0.043 \cdot size^2 - 0.04 \cdot age$, where *size* is the log of total assets scaled to 2004 dollars, and *age* is the number of years the firm has been listed in Compustat.
HHI	the sum of the squares of firms' market shares within a 4-digit SIC code
ROA	return on assets measured as net income over average total assets between the last and current fiscal years.
BTM	book value of equity scaled by the market value of equity at the end of the fiscal year.
ln(MVE)	natural log of price per share $\times$ number of shares outstanding at the end of the fiscal year. MVE is measured in millions of USD.
Litigation Indicator	1 if the firm has previously had securities class action lawsuits based on the Stanford Securities Class Action Clearinghouse.
ln(1+ days until forecasts)	natural log of 1 plus the number of days between the earnings announcement date for the last fiscal quarter and the management forecast date.
R&D	research and development expenditures divided by revenues during the fiscal year.
Loss Indicator	1 if the firm reports losses for the fiscal year.
ln(1+analysts following)	natural log of 1 plus the number of analysts following the firm during the fiscal year, obtained from I/B/E/S.
Earnings Volatility	standard deviation of quarterly earnings over the last 12 quarters, divided by the average quarterly asset value of these quarters.
ln(employees)	natural log of the firm's total employees in a year based on the Harte-Hanks Ci Technology database (CiDB).

Appendix B (cont'd). Variable Definitions

Variable	Definitions
ln(1+revenues)	natural log of 1 plus the firm's revenues in a year based on the Harte-Hanks Ci Technology database (CiDB). Revenues are measured in millions of USD.
ln(sites)	natural log of the total number of sites operated by the firm in a year based on the Harte-Hanks Ci Technology database (CiDB).
ln(business segments)	natural log of 1 plus the number of business segments as of the fiscal year-end, measured using Compustat Segments.
ln(geographical segments)	natural log of 1 plus the number of geographical segments as of the fiscal year-end, measured using Compustat Segments.
Related	the number of related business segments divided by the total number of business segments as of the fiscal year-end. The number of related segments is the difference between the total number of segments reported for the firm and the number of segments with different two-digit SIC codes. We assign Related =1 if all of the firm's business segments have the same two-digit SIC code.
Institutional ownership	percent of institutional investors at the fiscal year-end, obtained from Thomson Reuters.
Distance	average distance (measured in miles) between the firm's HQ office and divisional offices, based on the Harte-Hanks Ci Technology database (CiDB). The distance is based on the zipcode of each office and the latitude/longitude coordinate if the zipcode is missing. It is used to partition the sample in Table 3 and is included in logged form when included as a regressor in Table OA2.
Site Similarity	sum of squared shares of four-digit SIC industries in which the firm's sites with an intranet operate. If a firm has two sites with an intranet operating in an industry and three sites with an intranet operating in another industry, this firm's *Site Similarity* is $(2/5)^2 + (3/5)^2 = 0.52$. It is used to partition the sample in Table 4.
10K complexity	ratio of complex words to total words in the firm's 10-K filing for the most recent fiscal year. A word is classified as complex if it contains three or more syllables and appears in a sentence with at least five words. Data are from WRDS SEC Analytic Suite.
Stock volatility	standard deviation of daily stock returns over the fiscal year, based on CRSP.
LM complexity	complexity measure from Loughran and McDonald (2024), defined as the ratio of complexity words to total words in the firm's 10-K filing for the most recent fiscal year. Obtained from the Notre Dame Software Repository for Accounting and Finance (SRAF): `https://sraf.nd.edu/`.
LM uncertainty	uncertainty measure from Loughran and McDonald (2024), defined as the ratio of uncertainty words to total words in the firm's 10-K filing for the most recent fiscal year.Obtained from the Notre Dame Software Repository for Accounting and Finance (SRAF): `https://sraf.nd.edu/`
Earnings Surprise	the difference between the actual EPS and analysts' consensus scaled by fiscal year-end asset per share, based on I/B/E/S.
Discretionary Accruals	residuals from the regression of total accruals on lagged, current, and future cash flows, following Dechow and Dichev (2002).

Appendix C. The Intranet

The figure illustrates the differences between the internet, extranet, and intranet. Source: https://jesseokeya.medium.com/building-blocks-of-the-internet-3dc6c39fbd75.

