Shared information and the limits of firm performance

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Abstract

This paper develops a microfounded model in which integrating decisions through a shared signal improves local inference but weakens the diversification of decision errors inside the firm. Shared information lowers posterior variance at the decision level while raising the covariance of errors across decisions, generating conditional and potentially non-monotonic effects on aggregate firm performance. Digital integration provides the motivating application, but the mechanism is more general: changing the informational structure of the firm changes the extent to which errors diversify across choices. The model delivers an interior optimum and a structural interpretation for heterogeneous productivity effects and persistent partial adoption.

Keywords: Shared information, firm performance, information integration, productivity, common errors, D83; D81; D21.

1. Introduction

When does better information stop improving performance? Digital technologies have transformed how firms process and share information, yet the productivity effects of this transformation remain highly uneven. While some firms experience substantial gains, others exhibit weak, delayed or incomplete effects despite adopting similar technologies (Brynjolfsson and Hitt, 2000, 2003; Andrews et al., 2016; Brynjolfsson et al., 2021). At the same time, digital transformation is often partial, with firms operating under hybrid arrangements that combine digital and legacy processes (Calvino and Criscuolo, 2019; Blichfeldt and Faullant, 2021). Recent evidence from Industry 4.0 likewise points to productivity effects that depend on organizational conditions and integration depth rather than on adoption alone (Bettiol et al., 2024).

The usual interpretation emphasizes complementarities with organizational capital and intangible assets (Milgrom and Roberts, 1990; Brynjolfsson et al., 2002; Bresnahan and Trajtenberg, 1995). That perspective captures an important part of the problem, but it usually treats coordination as an external complement or an implementation residual. It therefore leaves open a more fundamental question: can integrating information itself generate the frictions that limit its own returns? This omission is increasingly problematic in

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environments where production, monitoring, logistics and managerial routines are connected through shared digital infrastructures (Shapiro and Varian, 1999; Brynjolfsson et al., 2017).

This paper identifies a different mechanism. I model digital integration as a change in the firm's signal structure. Each decision initially relies on decentralized local information. Integration supplements that local information with a shared system-wide signal. This improves local inference, but it also makes distinct decisions depend on the same informational pipeline. As a consequence, decision errors become positively correlated. The relevant trade-off is therefore not between information and adjustment costs, but between lower posterior variance and higher cross-decision error covariance.

The contribution is to show that this mechanism alone is sufficient to generate conditional returns to digital integration. At low levels of integration, the dominant effect is the reduction in local prediction error. At higher levels, the dominant effect becomes the increase in common informational exposure across decisions. The model therefore delivers an interior level of integration and a structural interpretation for two recurrent empirical facts: heterogeneous productivity effects and persistent partial adoption. Unlike approaches that treat coordination as an external complement, the present framework shows that integrating information changes the joint distribution of decision errors and, through that channel, the extent to which errors diversify inside the firm.

2. Model

Consider a firm composed of $n \geq 2$ decisions indexed by $i = 1, \ldots, n$. Each decision requires choosing an action $a_i \in \mathbb{R}$ to match an underlying state s_i. The firm's performance depends not only on the accuracy of individual decisions, but also on whether their errors diversify or instead accumulate because they are driven by the same informational source.

2.1. States and signals

Let the state relevant for decision i be

$$s_i = \theta + \eta_i, \tag{1}$$

where $\theta \sim \mathcal{N}(0, \tau^2)$ is a common component and $\eta_i \sim \mathcal{N}(0, \omega^2)$ is an idiosyncratic component. The variables θ and $\{\eta_i\}_{i=1}^n$ are mutually independent.

Each decision always observes a decentralized local signal

$$x_i = s_i + \varepsilon_i, \tag{2}$$

where $\varepsilon_i \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ is independent across i and independent of all states.

Digital integration is indexed by $D \in [0, 1]$. A decision is connected to the shared system with probability D, independently across decisions. When connected, decision i also observes a common system-wide signal

$$y = \theta + \nu, \tag{3}$$

where $\nu \sim \mathcal{N}(0, \sigma_\nu^2)$ is independent of θ, $\{\eta_i\}$ and $\{\varepsilon_i\}$. The signal y is the same for all connected decisions. It improves inference about the common component θ, but it also creates a common source of informational error.

Let $m_i \in \{0, 1\}$ indicate whether decision i is connected. Then

$$\mathbb{P}(m_i = 1) = D. \tag{4}$$

For any pair (i, j),

$$w_{ij} \equiv m_i m_j \qquad \Rightarrow \qquad \mathbb{E}[w_{ij}] = D^2. \tag{5}$$

Hence joint reliance on the shared system is endogenous to the extent of digital integration.

2.2. Optimal actions

Under quadratic loss, optimal actions are posterior means. If decision i is not connected, it chooses

$$a_i^L = \mathbb{E}[s_i \mid x_i] = \alpha x_i, \qquad \alpha = \frac{\tau^2 + \omega^2}{\tau^2 + \omega^2 + \sigma_\varepsilon^2}. \tag{6}$$

The associated posterior variance is

$$V_L \equiv \mathrm{Var}(s_i \mid x_i) = \frac{(\tau^2 + \omega^2)\sigma_\varepsilon^2}{\tau^2 + \omega^2 + \sigma_\varepsilon^2}. \tag{7}$$

If decision i is connected, it chooses

$$a_i^I = \mathbb{E}[s_i \mid x_i, y] = b_x x_i + b_y y, \tag{8}$$

with coefficients

$$b_x = \frac{\tau^2\omega^2 + (\tau^2 + \omega^2)\sigma_\nu^2}{\Delta}, \qquad b_y = \frac{\tau^2\sigma_\varepsilon^2}{\Delta}, \tag{9}$$

where

$$\Delta \equiv \sigma_\varepsilon^2\sigma_\nu^2 + \tau^2\sigma_\varepsilon^2 + \tau^2\sigma_\nu^2 + \omega^2\sigma_\nu^2 + \tau^2\omega^2. \tag{10}$$

The posterior variance under integration is

$$V_I \equiv \mathrm{Var}(s_i \mid x_i, y) = \frac{\sigma_\varepsilon^2\left(\tau^2\sigma_\nu^2 + \omega^2\sigma_\nu^2 + \tau^2\omega^2\right)}{\Delta}. \tag{11}$$

Because the shared signal adds information about the common component, $V_I < V_L$.

The key difference, however, is that two integrated decisions share the same signal y. Their posterior errors are therefore positively correlated. For $i \neq j$,

$$C_I \equiv \mathrm{Cov}(s_i - \mathbb{E}[s_i \mid x_i, y],\ s_j - \mathbb{E}[s_j \mid x_j, y]) = \frac{\sigma_\varepsilon^4\sigma_\nu^2\tau^2(\sigma_\nu^2 + \tau^2)}{\Delta^2} > 0. \tag{12}$$

This cross term arises mechanically from shared conditioning on the common signal. It vanishes without the shared system.

2.3. Firm objective

The firm chooses actions to minimize expected aggregate execution error:

$$\mathcal{L} = \mathbb{E}\left[\left(\sum_{i=1}^{n}(a_i - s_i)\right)^2\right]. \tag{13}$$

This objective is natural when overall firm performance depends on the cumulative alignment of many interdependent tasks. Expanding (13) gives

$$\mathcal{L} = \sum_{i=1}^{n}\mathbb{E}[(a_i - s_i)^2] + \sum_{i \neq j}\mathbb{E}[(a_i - s_i)(a_j - s_j)]. \tag{14}$$

The first term captures local execution error. The second term captures the extent to which errors diversify inside the firm. When decisions rely on independent information, these cross terms vanish. When they rely on the same shared signal, they become positive.

Using (5), expected loss can be written as

$$\Phi(D) = n\big[(1 - D)V_L + DV_I\big] + n(n-1)D^2C_I. \tag{15}$$

Equation (15) isolates the mechanism. Integration lowers the posterior variance of each connected decision by replacing V_L with V_I, but it simultaneously raises the covariance of errors across decisions because more pairs rely on the same signal. The relevant trade-off is therefore between lower local uncertainty and weaker diversification of decision errors.

3. Results and implications

Differentiating (15) with respect to D yields

$$\frac{d\Phi}{dD} = n(V_I - V_L) + 2n(n-1)D\,C_I. \tag{16}$$

Since $V_I - V_L < 0$ and $C_I > 0$, the sign of the marginal effect is ambiguous.

Proposition 1. *If*

$$D^* = \frac{V_L - V_I}{2(n-1)C_I} \in (0, 1), \tag{17}$$

then information integration admits an interior optimum. The equilibrium level of integration is determined by the point at which the marginal reduction in posterior variance is exactly offset by the marginal increase in cross-decision error covariance.

The intuition is immediate. When D is low, few decisions are connected, so the dominant effect of integration is the reduction in posterior variance from V_L to V_I. In that region, more integration lowers expected loss. As D rises, however, an increasing number of decisions rely on the same signal y. Their errors cease to diversify, and aggregate performance becomes more sensitive to system-wide informational mistakes. Beyond a threshold, better local inference no longer compensates for the rise in common informational exposure.

The model yields three implications. First, information integration need not generate monotonic productivity gains. Weak or delayed effects may arise even when adoption is fully rational, because the firm internalizes the fragility created by common informational dependence. Second, the optimal level of integration is lower in more complex firms, since the number of potentially correlated decision pairs grows with $n(n-1)$. Third, integration is most productive when the shared signal is sufficiently precise, that is, when σ_ν^2 is low enough to limit C_I.

Relative to the existing literature, the mechanism isolated here is distinct. Acemoglu and Restrepo (2019, 2020) study how technology reshapes task content and labor demand, while Brynjolfsson and coauthors emphasize complementarities, intangible assets and implementation lags (Brynjolfsson and Hitt, 2000, 2003; Brynjolfsson et al., 2002, 2017, 2021). By contrast, the present paper shows that integrating information can itself generate an internal fragility by making decision errors less diversifiable inside the firm. The relevant object is not digital adoption per se, but the covariance structure induced by shared informational conditioning.

The framework also yields a direct empirical implication. The marginal productivity effect of digital integration should be weaker in firms with greater organizational complexity and stronger where shared systems are more reliable. Measures based only on software, ICT or automation investment are therefore incomplete. What matters is the interaction between digital intensity, organizational scale and the quality of the shared informational system.

4. Conclusion

This paper develops a model in which integrating decisions through a shared signal affects firm performance through two opposing channels. It improves local prediction by supplementing decentralized information, but it also raises the covariance of decision errors because more choices depend on the same informational pipeline. Once this mechanism is made explicit, shared information no longer operates as a pure performance enhancer. It changes the extent to which decision errors diversify inside the firm.

The main implication is that heterogeneous productivity effects and persistent partial adoption can arise even in a fully rational environment, without appealing to ad hoc adjustment costs or externally imposed coordination penalties. More broadly, the analysis suggests that the economic effects of digital integration depend not only on how much information firms process, but also on how much common informational exposure that processing creates.

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