AI's Use of Knowledge in Society

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September 2025

Prepared for NBER Volume on the Economics of Transformative AI.

Abstract

Hayek's famous insight was that central planning – even if economically efficient – is not feasible because the necessary knowledge is inherently dispersed throughout the economy. The advent of transformative AI demands a reappraisal of Hayek's "knowledge problem" and its implications for how decision rights are allocated within firms and society. We develop a property rights framework in which powerful AI shifts the optimal locus of control through two channels: (i) by codifying local knowledge that was previously tacit and inalienable, and (ii) by expanding the information processing capacity of agents to aggregate, interpret, and act on data. These forces erode the informational advantage of maintaining on-the-spot decision-makers, making centralized coordination and control more feasible and more efficient—especially where complementarities across assets are important. The framework yields several predictions: larger average firm size, greater industry concentration, and reduced local managerial autonomy. We review early evidence and find that it is largely consistent with these patterns. We also discuss conditions that can still favor decentralization. The implications of our analysis extend beyond economic considerations: centralization of economic power can lead to centralization of political power and dampen incentives to invest in human capital.

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Acknowledgements: We are grateful to Seth Benzell, Avi Goldfarb, Ben Golub, Andreas Haupt and Andrew Ng for valuable conversations and comments on this topic and the Stanford Digital Economy Lab for funding. Any errors remain our own.

The 'data' from which the economic calculus starts are never for the whole society 'given' to a single mind... and can never be so given.

— F. A. Hayek, 1945

We (the whole industry, not just OpenAI) are building a brain for the world.

— Sam Altman, 2025

1 Introduction

Hayek's 1945 essay "The Use of Knowledge in Society" opens by criticizing a plan for constructing a "rational economic order" from the top down (Hayek, 1945). He was responding primarily to Oskar Lange and Abba Lerner, whose writings of the 1930s and early 1940s argued that a central planner armed with enough information could efficiently direct an entire economic system (Lange, 1936; Lerner, 1938). That is, economic decision-making could be highly centralized: a planning board would set prices and production targets, guiding what producers make and, through those prices, what consumers choose to buy. Lange and Lerner, in turn, were responding to Ludwig von Mises's earlier critiques of socialism (von Mises, 1920, 1935), which argued that, without private ownership of the means of production, no genuine market prices for capital goods can form, making efficient allocation by a central planner impossible. Together, these exchanges formed what became known as the Socialist Calculation Debate.

Hayek's contribution to the debate was epistemic: it is impossible, he argued, to make all the knowledge required for efficient allocations known to a central entity. As he put it, "The 'data'... are never for the whole society 'given' to a single mind... and can never be so given." There are physical limits on which forms of information can travel, and how, and how quickly. Much of what people know – all that is relevant to choosing the best economic outcomes – is local or specialized knowledge, tailored to the instant, or otherwise tacit and difficult to articulate. It is impossible, he argued, to gather, codify and transfer that "knowledge of the particular circumstances of time and place" in real-time. Any analysis that imagines otherwise, Hayek warned, simply "assumes the problem away." Recognizing that local knowledge was ubiquitous and indispensable led Hayek to conclude that efficient choices must be decentralized.

But the rise of powerful machine learning systems – the kind of transformative AI that is the subject of this volume – demands a reappraisal of Hayek's assumptions and thus their implications for organizational design at the scale of firms, sectors, and indeed entire economies. By "transformative AI" we mean systems whose aggregate capability and speed would approximate, in Dario Amodei's phrase, "a country of geniuses in a datacenter," i.e., AI that can perform all cognitive work that humans can perform and thereby reconfigure possibilities for production and coordination (Amodei, 2024). The case for taking this possibility seriously is bolstered by regularities in scaling and in inputs: empirically, model performance obeys power-law scaling with increases in data, compute and the number of parameters (Kaplan et al., 2020; Hestness et al., 2017), with revised "compute-optimal" training rules further improving efficiency (Hoffmann et al., 2022). In parallel, training compute at the frontier has grown on the order of 4–5× per year since 2010, reflecting sustained increases in spending and infrastructure (Sevilla and Roldán, 2024); industry tracking likewise documents rapid capability gains across benchmarks (Stanford HAI, 2025; Maslej et al., 2025). Taken together, these trends suggest continued movement toward significantly more powerful AI systems.

In this chapter, we investigate the implications of the rise of AI for the organization of economic production, starting from the observation that many claims about the inherently dispersed nature of knowledge are now in question. We offer a simple conceptual framework to understand the potential of transformative AI to centralize decision-making, and early evidence of the causes and consequences of this centralization.

Our analysis is based on a straightforward application of the property rights theory of the firm (Grossman and Hart, 1986; Hart and Moore, 1990), which we outline in section 2. In section 3, we show the attraction of centralized planning: it can take into account the myriad interdependencies that inevitably exist among local decisions. However, the knowledge needed to address these interdependencies is dispersed, a fact which we introduce into our analysis in section 4. This analysis mirrors Hayek's argument that it is infeasible to centralize this knowledge because most of it is inalienable, and so decentralization is necessary. In section 5 we capture another argument for decentralized decision-making noted by (Simon, 1955): human information processing capacity is bounded. Even if the entirety of the relevant information in a medium-sized business, let alone an industry or whole economy, could be transmitted to a central decision-maker, no human brain has the capacity to consider and analyze it all. We model the rise of AI as affecting the allocation of decision rights through these two channels: (i) changes in the alienability of information and (ii) increases in information processing capacity. We discuss several countervailing forces that could instead push toward decentralization, even in a world with transformative AI in section 6.

We are not the first to point out AI's potential for greater centralization of decision-making. As we discuss in more detail in section 7, there is a growing empirical literature documenting increasing concentration across industries (Autor et al., 2020; De Loecker et al., 2020) and some research linking this phenomenon to the rise of information technologies (Brynjolfsson et al., 2008; Bessen, 2020; Brynjolfsson et al., 2023). However, these analyses have not yet incorporated the change that could result from transformative AI. Other writers have framed the observation that machine learning may centralize economic power in political rather than strictly economic terms, and we too discuss the political implications of centralization in section 8.[1] A few have offered more casual and speculative explorations of how AI enables centralization (Bastani, 2019; Drago and Laine, 2025) or offered policy-relevant analyses that share the spirit of this chapter (Brynjolfsson and Ng, 2021; Agrawal et al., 2022; Acemoglu, 2023).

2 Framework

We use a three-party incomplete contracts framework (Grossman and Hart, 1986; Hart and Moore, 1990) to analyze the economic efficiency of regimes in which decision-making is centralized and decentralized.

The parties $N = \{M_1, M_2, H\}$ include two local "managers," M_1 and M_2, and a central "headquarters," H. There is a set of assets $a \in A$. For example, H could be the central

[1] Some have argued – noting the ironies – that the very corporations held up as symbols of modern capitalism also reveal new infrastructural possibilities for socialism in the 21st century (Jameson, 2016; Phillips and Rozworski, 2019; Morozov, 2019).

office of a cafe franchise and M_1 and M_2 could be local managers of cafes, or H could be a dispatcher and M_1 and M_2 could be field service technicians.

An ownership regime $\rho\colon N \to 2^A$ is a map assigning to each party the subset of assets it owns. Assets are excludable,[2] and for a coalition $S \subseteq N, \rho(S) = \cup_{k\in S}\rho(k)$. Throughout our analyses, we will consider two ownership regimes: a "centralized" regime in which the HQ owns as many assets as is technologically feasible, and a "decentralized" regime in which the local managers own as many assets as is technologically feasible.

Contracts are incomplete. That is, there are at least some contingencies that the parties cannot foresee and as a result, investments are non-contractible. At stage 0, the parties (cooperatively) choose an ownership regime. At stage 1, the parties make non-contractible relationship-specific investments x_k and incur convex costs $c_k(x_k)$, for $k = 1, 2, H$. These investments could represent mastering a popular neighborhood cuisine and supply network in the case of the local cafe, or building a reputation for expertise and reliability in the case of the field service operation. At stage 2, output V is realized and the parties divide the surplus via the Shapley value, where each hypothetical "coalition" can deploy the assets controlled by its members.

More specifically, the output or production surplus of a coalition $S \subseteq N$ is given by $V(S, \rho(S), x)$ where $x = (x_1, x_2, x_H)$ is the investments made by the members of the coalition S and $\rho(S)$ is the set of assets owned by the members of the coalition. Throughout, we make the following assumptions on V: (i) it is strictly increasing in each party's investment, (ii) it exhibits diminishing returns to each party's investment, and (iii) it exhibits weak complementarities in the parties' investments. Often we will suppress the dependence of V on the investment decisions. Furthermore, we assume that manager-manager coalitions cannot form: the only coalitions that can form are singleton coalitions, coalitions with one manager and headquarters, and the grand coalition (with the two managers and headquarters).[3]

In the following sections we will make specific assumptions on the technological environment. In particular, we make assumptions about the nature of the assets in A, which will constrain both how they are deployed in production and the ownership regimes. As in the usual incomplete contracts logic, the ownership regime determines residual rights of control, affecting the value of different coalitions and therefore the parties' incentives to invest ex-ante. Throughout, the same first-order conditions for managers M_i $i = 1, 2$ and headquarters H define incentives. We wrote them below, denoting V_k to be the marginal value of k's investment for the coalition[4].

General Investment Incentives for M_i and H

$$\tfrac{1}{3}V_i(N, A) + \tfrac{1}{6}V_i(M_i, H, \rho(M_i, H)) + \tfrac{1}{2}V_i(i, \rho(i)) = c_i'(x_i) \tag{1}$$

$$\tfrac{1}{3}V_H(N, A) + \tfrac{1}{6}\sum_{i=1,2} V_H(M_i, H, \rho(M_i, H)) + \tfrac{1}{3}V_H(H, \rho(H)) = c_H'(x_H). \tag{2}$$

The different technological assumptions that we explore will often eliminate several terms in (1)-(2) and determine the relative magnitudes of others.

[2] For all distinct parties $k \neq j$, $\rho(k) \cap \rho(j) = \varnothing$ and $\cup_{k\in N}\rho(k) = A$.

[3] This restriction on coalitions follows the star communication network restriction studied in Myerson (1977).

[4] That is, the marginal product of x_i given coalition S and investment profile x is

$$V_i(S, \rho(s)) \equiv \frac{\partial V}{\partial x_i}(S, \rho(S), x).$$

3 The Need for Coordination Favors Centralization

In many production settings, distinct local assets generate value only when their use is coordinated. When decisions are technologically interdependent, a central hub can translate those interdependencies into higher surplus by choosing compatible actions and enforcing them.

The communication architecture also matters: a hub-and-spoke (HQ with each manager) replaces the $n(n-1)$ lateral links of full decentralization with only n links to the center, making it cheaper to aggregate information and propagate consistent plans (Malone and Smith, 1988). This helps not only communication, but also incentives and enforcement. Instead of n contracts with the hub, they might they require $n(n-1)$ pairwise contracts. [5] Furthermore, in a hub-and-spoke system, the hub has stronger leverage for enforcing contracts than any individual manager. As the nexus of contracts, it has a variety of other incentive tools, including withholding access to the whole network, while in pairwise contact, individual managers can only withhold their own assets. (Jensen and Meckling, 1992)

As a result, local units may not internalize system-wide complementarities absent central ownership and authority. We capture these interdependencies with two reduced-form primitives: a coordination multiplier $\lambda \geq 1$ that scales the marginal product of a manager's investment when assets are jointly directed by HQ, and a local autonomy parameter $\alpha \in [0, 1]$ that measures how much of that marginal product the manager can realize alone.

Assumption 1 (Interdependence of assets)**.** *For each manager $i = 1, 2$, there is a coordination multiplier $\lambda \geq 1$ such that for any coalition S with $k \in S$, $k = 1, 2, H$, and for any asset $a_j \in A$,*

$$V_k(S, a_1, a_2) = \lambda V_k(S, a_j),$$

and a local autonomy multiplier $\alpha \in [0, 1]$

$$\alpha \equiv \frac{V_i(M_i, a_i)}{V_i(M_i, H, a_i)},$$

with all derivatives evaluated at the relevant equilibrium investment level.

We now consider the investment decisions in the two regimes. In the centralized ownership regime,[6] investment decisions are determined by (3) and (4).

Centralized Ownership

$$\tfrac{1}{3}V_i(N) + \tfrac{1}{6}\underbrace{V_i(M_i, H, a_1, a_2)}_{=\lambda V_i(M_i, H, a_i)} = c_i'(x_i) \tag{3}$$

$$\tfrac{1}{3}V_H(N) + \tfrac{1}{6}\sum_{i=1,2} V_H(M_i, H, a_1, a_2) + \tfrac{1}{3}V_H(H, a_1, a_2) = c_H'(x_H). \tag{4}$$

In the decentralized ownership regime,[7] investment decisions are determined by (5) and (6).

Decentralized Ownership

[5] The number of contracts is far larger if contracts between every coalition are considered, approximatly 2^{2n-1} for large n

[6] In the centralized regime, $\rho^{\text{cen}}(H) = \{a_1, a_2\}$ and for $i = 1, 2$, $\rho^{\text{cen}}(M_i) = \varnothing$.

[7] In the decentralized regime, $\rho^{\text{dec}}(H) = \varnothing$ and for $i = 1, 2$, $\rho^{\text{dec}}(M_i) = a_i$.

$$\tfrac{1}{3}V_i(N) + \tfrac{1}{6}V_i(M_i, H, a_i) + \tfrac{1}{2}\underbrace{V_i(M_i, a_i)}_{=\alpha V_i(M_i,H,a_i)} = c_i'(x_i) \tag{5}$$

$$\tfrac{1}{3}V_H(N) + \tfrac{1}{6}\sum_{i=1,2} V_H(M_i, H, a_i) = c_H'(x_H). \tag{6}$$

We can understand the efficiency of each ownership arrangement by comparing the first-order conditions. For headquarters, comparing (4) and (6) shows that incentives are unambiguously stronger under centralization: HQ enjoys the extra singleton term and, by Assumption 1, the pair terms are weakly larger (strictly if $\lambda > 1$). For managers, centralization strengthens the pair term by a factor λ whereas decentralization adds a singleton fallback term weighted by $\frac{1}{2}\alpha$. Thus these investment incentives readily give the following sufficient condition for centralization to be more efficient than decentralization.

Proposition 1. *If $\lambda > 1 + 3\alpha$,[8] then centralized ownership yields strictly higher surplus than decentralized ownership.*

Note that in the case of zero local autonomy, $\alpha = 0$, any positive coordination gain ($\lambda > 1$) will make centralization more efficient. More generally, the more interdependencies matter (α low, λ high) the more attractive centralization becomes. Because this is a sufficient (not necessary) condition, centralization can still dominate even when $\lambda \leq 1 + 3\alpha$, for example if the marginal value of headquarters' investment is particularly large relative to that of the managers.

4 Local Knowledge and the Alienability of Information Assets

The previous section showed that the need for coordination leads to more centralized decision-making and asset ownership. However, Hayek argued that local knowledge makes such centralization infeasible, and so decisions should still be made by the person on the spot who holds the knowledge and information most relevant to the decision. In this section we formalize Hayek's epistemic argument by introducing the concept of "local knowledge" into the framework outlined in section 2.

For each local manager i there are two assets: an information asset ("local knowledge") $a_{I(i)}$ initially possessed by the corresponding manager, and a tangible asset a_i. We assume that each information asset is strictly complementary with its corresponding tangible asset—that is, in order for a_i to be valuable in a coalition, $a_{I(i)}$ must also be controlled by the coalition.[9]

4.1 The Need for Local Knowledge Favors Decentralization

We assume first, to capture Hayek's argument, that the information assets are *inalienable*, i.e. the only party that can own information asset $a_{I(i)}$ is the local manager M_i. This assumption determines the possible centralized and decentralized ownership regimes. Recall, we take the "centralized" regime to be where headquarters owns as many assets as is technologically feasible, so here,

$$\rho^{\text{cen}}(H) = \{a_1, a_2\} \quad \text{and} \quad \rho^{\text{cen}}(M_i) = \{a_{I(i)}\} \text{ for } i = 1, 2,$$

[8] Note, α in this condition is evaluated at the decentralized equilibrium investment level.

[9] Formally, for $i = 1, 2$, if $a_{I(i)} \notin \rho(S)$ but $a_i \in \rho(S)$, then $V(S, \rho(S)) = V(S, \rho(S) \setminus a_i)$. This set up mirrors (Bryjolfsson, 1994).

and the decentralized regime is one in which the local managers own their assets, so here,

$$\rho^{\text{dec}}(H) = \varnothing \quad \text{and} \quad \rho^{\text{dec}}(M_i) = \{a_i, a_{I(i)}\} \text{ for } i = 1, 2.$$

The investment incentives in the centralized regime are given by (7) and (8).

Centralized Ownership Under Inalienable Information Assets

$$\tfrac{1}{3}V_i(N, A) + \tfrac{1}{6}\underbrace{V_i(M_i, H, a_1, a_2, a_{I(i)})}_{=V_i(M_i, H, a_i, a_{I(i)})} = c_i'(x_i) \tag{7}$$

$$\tfrac{1}{3}V_H(N, A) + \tfrac{1}{6}\sum_{i=1,2}\underbrace{V_H(M_i, H, a_1, a_2, a_{I(i)})}_{=V_H(M_i, H, a_i, a_{I(i)})} = c_H'(x_H). \tag{8}$$

Meanwhile, under the decentralized ownership regime, investment incentives are given by (9) and (10).

Decentralized Ownership Under Inalienable Information Assets

$$\tfrac{1}{3}V_i(N, A) + \tfrac{1}{6}V_i(M_i, H, a_i, a_{I(i)}) + \tfrac{1}{2}V_i(M_i, a_i, a_{I(i)}) = c_i'(x_i) \tag{9}$$

$$\tfrac{1}{3}V_H(N, A) + \tfrac{1}{6}\sum_{i=1,2} V_H(M_i, H, a_i, a_{I(i)}) = c_H'(x_H). \tag{10}$$

These two sets of first-order conditions show that giving ownership of the tangible asset to the managers increases the incentives of the managers while leaving the headquarters' incentives unchanged.

To see this, first note that in the terms involving a coalition of headquarters and just one manager i, there are three assets present: the manager i's information asset $a_{I(i)}$ (controlled by i) and the two tangible assets a_1, a_2 controlled by H. However, the presence of a_j does not affect production without its complement $a_{I(j)}$, so the second term in (8) is in fact the same as the second term in (10), and thus headquarters' incentives are exactly the same in the two regimes.

Meanwhile, comparing (7) to (9), we see that managers' incentives are strictly stronger given the extra third term that appears in (9) but not (7), which represents what the manager can obtain in a coalition on their own with control of the tangible asset that complements their information. This comparison of incentives is unambiguous and directly translates to an increase in surplus under the decentralized regime.

Proposition 2. *If the information assets $a_{I(i)}$ are inalienable, then joint surplus is higher when the managers own the complementary tangible assets a_i than it is when the headquarters owns the assets.*

This result formalizes Hayek's intuition that effective control should rest with the agent who possesses non-transferable, decision-relevant knowledge. Without this knowledge, the interdependencies that pushed toward centralization in section 3 cannot be realized. When $a_{I(i)}$ cannot be transferred, as Hayek posits is the case for local knowledge, giving the local party (M_i) decision rights over the complementary physical asset maximizes investment incentives.

In the cafe example, if the local manager owns the store and ovens, any extra effort she puts into learning neighborhood tastes raises not only joint revenue but also her fallback income should negotiations with the franchiser fail. When the ex-post division of surplus takes into account this possibility via the singleton coalition in the Shapley Value, the manager's ex-ante incentives for investment, and thus total surplus, are greater. Under franchiser ownership, that fallback is zero, so the manager has diminished incentives to invest in the local adaptations that could drive profits.

4.2 AI Increases Codifiability of Knowledge

Transformative AI sharply expands what counts as codifiable – and therefore transferrable – "local knowledge," in three main ways. First, it makes *explicit knowledge* more accessible to decision-makers: for example, OCR and related pipelines have digitized vast archives and operational records (LeCun et al., 1998; Firmani et al., 2018; Lubna et al., 2021; Hsu et al., 2022), while frontier models internalize broad factual and scientific content (Hendrycks et al., 2021; Kwiatkowski et al., 2019; Joshi et al., 2017; Jin et al., 2019). Second, AI increasingly extracts *tacit know-how* once embedded in human perception and practice: systems match or exceed human baselines in language and vision (OpenAI, 2024; Peters, 2024; Schroff et al., 2015); they learn from telemetry and transcripts at industrial scale (e.g., autonomous fleets) (Shepardson, 2025); and they distill workplace heuristics from expert traces (eye-tracking, transcripts), overcoming Polanyi's paradox (Brynjolfsson et al., 2025; Autor, 2014). Third, AI generates *machine-native knowledge*—patterns no human could feasibly enumerate—spanning protein structure prediction, fraud and anomaly detection, and microsecond market microstructure (Jumper et al., 2021; Evans et al., 2022; Dal Pozzolo et al., 2018; Jain et al., 2020). Collectively, these advances shift a growing share of economically relevant facts, heuristics, and predictive signals into databases, embeddings, and model weights that can be centrally stored, copied, and recombined at negligible marginal cost—much of the information that once required being "on the spot" can now travel more or less costlessly. For instance, as Hayek posited, a local shopkeeper might once have had better knowledge of "otherwise empty or half-filled journeys" of a semi-truck, "surplus stock which can be drawn upon during an interruption of supplies," or a customer's loyalty to peppermint ice cream than a distant business executive. But today, sophisticated machine learning systems, drawing on detailed point-of-sale data at Walmart's Data Café in Bentonville can reverse these advantages.

We offer more detail about these developments in the Appendix.

4.3 AI Tips the Scales Toward Centralization

When transformative AI makes the local information asset codifiable and transferable, we can treat it as alienable. Using strict complementarity, we can bundle the information and tangible assets so that the coordination logic from section 3 applies verbatim.

For each manager i, the information asset $a_{I(i)}$ and the tangible asset a_i are strict complements in the sense that a coalition's marginal product in x_i is zero unless *both* a_i and $a_{I(i)}$ are available to that coalition. If $a_{I(i)}$ is codifiable and transferable, we can bundle

$$\tilde{a}_i \equiv \{ a_i, a_{I(i)} \}$$

and restrict attention to ownership regimes that keep complements together.

We consider the same two regimes as before, now phrased in terms of the bundled assets $\tilde{A} = \{\tilde{a}_1, \tilde{a}_2\}$: the centralized regime[10] and the decentralized regime.[11]

[10] In which $\rho^{\text{cen}}(H) = \tilde{A}$ and $\rho^{\text{cen}}(M_i) = \varnothing$ for $i = 1, 2$.

[11] In which $\rho^{\text{dec}}(M_i) = \{\tilde{a}_i\}$ for $i = 1, 2$ and $\rho^{\text{dec}}(H) = \varnothing$.

Because each $\tilde{a}_i$ moves as a unit, the coalition values with bundles are the same functions as in section 3, and the relevant first-order conditions revert exactly to (3)–(4) under centralization and (5)–(6) under decentralization (with a_i understood to denote $\tilde{a}_i$). Therefore, the same sufficient condition from Proposition 1 applies here.

Intuitively, once information can move, *co-locating* decisions with information can be achieved by transferring the information to H together with its physical complement, restoring the coordination gains characterized in section 3. This aligns with insights in Jensen and Meckling (1992) and Brynjolfsson and Mendelson (1993), and challenges Hayek's intuition when he wrote, for example, "Practically every individual has some advantage over all others because he possesses unique information of which beneficial use might be made, but of which use can be made only if the decisions depending on it are left to him."

If some of HQ's own information assets also become codifiable and transferable to the periphery, the logic can run the other way: bundling those with local physical assets can make decentralization feasible where it previously was not. Nonetheless, when interdependencies are significant (α low and λ high), the coordination advantages in section 3 will still make centralization more attractive.

5 Information Processing Capacity

Hayek's side of the socialist calculation debate pointed not just to the difficulty of codifying knowledge, but also to the finite processing power of any single decision-making entity. "The problem," he wrote, is "how to extend the span of our utilization of resources beyond the span of the control of any one mind" (Hayek, 1945). This challenge, rooted in the inherent limits of human cognition, finds a more formal expression in Herbert Simon's concept of "bounded rationality" (Simon, 1955). Because attention is scarce, modern organizational economics treats decision-making as necessarily distributed across agents, teams and hierarchies rather than vested in a single planner (Arrow, 1974; Radner, 1993; Radner and Van Zandt, 1992; Bolton and Dewatripont, 1994; Garicano, 2000). Here we first discuss how bounded information processing has historically hampered the value of centralized control in production, and then present evidence that AI is rapidly expanding the amount of information that can be processed by a single entity.

5.1 Limits on Information Processing Push Toward Decentralization

A single mind, or collection of minds in a firm, can only process so much information. While the brain's unconscious processing capacity is vast, estimates for conscious, deliberate reasoning are as low as 60 bits per second (Csikszentmihalyi, 1990). This biological bottleneck is more or less fixed. While estimates vary, some place the computational power of the human brain around 10^15 FLOP/s, a threshold that modern supercomputers can now surpass (Carlsmith, 2020). And moreover, not all the information contained in the minds of the people who make up a firm can be deployed all at once. There is friction – information held by different people cannot be instantaneously accessed, introducing delays and misunderstandings, imprecision due to incentive misalignment, and other communication challenges. As a result, organizations pay processing costs each time knowledge crosses a human boundary – this puts an overall limit on the amount of information any collection of human minds can effectively process.

These bounds mean that even if centralized control may be more efficient and information is alienable, there may be other bottlenecks to centralization because of the sheer amount of information that needs to be processed to realize the valuable interdependencies.

To formalize how bounds on information processing limit the returns to centralized ownership, we extend the GHM environment to N local managers and a central headquarters on a star communication network as in (Myerson, 1977). Let the parties be

$$N = \{M_1, \dots, M_N, H\}, \qquad A = \{a_1, \dots, a_N\},$$

where a_i is manager i's local asset bundle. As before, for a coalition $S \subseteq N$, the assets available to S under ρ are $\rho(S) := \{a \in A : \rho^{-1}(a) \in S\}$, and its surplus is $V(S, \rho(S), x)$ with $x = (x_{M_1}, \dots, x_{M_N}, x_H)$.

As before, we compare two regimes. The *centralization* regime ρ^{cen} with $\rho^{\text{cen}}(H) = A$ and *decentralization* ρ^{dec} with $\rho^{\text{dec}}(M_i) = a_i$ for all i.

Assumption 2 (Limited information processing)**.** *Headquarters can* process *at most* $\bar{K} \in \{0, 1, \dots, N\}$ *assets at stage 2. Let* $s_i \in \{0, 1\}$ *indicate whether asset* i *is processed, with* $\sum_{i=1}^{N} s_i \leq \bar{K}$*. Interdependence gains are summarized by* $\lambda \geq 1$ *and realized only for processed assets under centralization.*

It is useful to introduce notation for the marginal value of each manager's investment in a bilateral coalition with HQ when only one asset $a_i = \rho(M_i)$ is present: $\tilde{V}_i = V_i(M_i, H, \rho(M_i))$ for all $i = 1, \dots, N$. Similarly, we define the marginal value of H's investment in a bilateral coalition with M_i when only asset i is present by $\tilde{V}_H(i) = V_H(M_i, H, a_i)$. With this notation, we can extend the interdependence assumption (Assumption 1) to the N manager case.

Assumption 3 (Interdependence of assets; N managers)**.** *Assume that for any bilateral coalition between a manager* M_i *and headquarters* H*, with assets* $\rho(M_i), \rho(H)$*,*

$$V_i(M_i, H, \rho(M_i), \rho(H)) = \lambda \tilde{V}_i \qquad V_H(M_i, H, \rho(M_i), \rho(H)) = \lambda \tilde{V}_H(i).$$

Note that the symmetry imposed by this assumption is quite strong—anytime an asset a_i is coordinated with any additional assets, the marginal value of investment is multiplied by the same factor λ, regardless of *which* other assets are present or *how many* there are.[12]

Under centralization with capacity $\bar{K}$, incentives are determined by the following first order conditions. Note that the conditions from section 2 must be adapted to account for N players using the Shapley Value on a star coordination network; for ease of exposition we write the coefficient on pairwise coalitions as $\Phi(N) \equiv \frac{N-1}{2(N+1)}$.

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$$\tfrac{1}{N+1} V_i(N, A) + \Phi(N) s_i \lambda \tilde{V}_i = c_i'(x_i) \tag{11}$$

$$\tfrac{1}{N+1} V_H(N, A) + \Phi(N) \sum_{i=1}^{N} s_i \lambda \tilde{V}_H(i) + \tfrac{1}{N+1} V_H(H, A) = c_H'(x_H) \tag{12}$$

Under decentralization with capacity $\bar{K}$, incentives are determined by

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[12] In other words, the coordination multiplier is uniform across all pairwise matchings (a_i, a_j) and also across all larger combinations (a_i with any subset of the remaining assets). This simplifies the exposition, and can be read conservatively by treating λ as a lower bound on coordination gains across configurations. A richer version could let the multiplier depend on the number or identity of complements.

$$\tfrac{1}{N+1}V_i(N,A) + \Phi(N)\tilde{V}_i + \tfrac{1}{2}\alpha_i\tilde{V}_i = c_i'(x_i). \tag{13}$$

$$\tfrac{1}{N+1}V_H(N,A) + \Phi(N)\sum_{i=1}^{N}\tilde{V}_H(i) = c_H'(x_H) \tag{14}$$

The grand-coalition terms (the first terms on the LHS of (11)–(14)) are identical across regimes because the grand coalition controls all assets and includes H either way so they are irrelevant to regime comparisons. By Shapley weighting on the star, the "pair-with-H" terms receive weight $\Phi(N)$, while the manager's singleton fallback has coefficient $1/2$. Under centralization, only the $\bar{K}$ assets that headquarters actually processes ($s_i = 1$) realize the coordination gain $\lambda\tilde{V}_i$ while under decentralization, each manager gets the unscaled pair term $\tilde{V}_i$ plus a singleton fallback contribution $\frac{1}{2}\alpha_i\tilde{V}_i$.[13] By a similar logic to that of section 3, with an additional symmetry condition, these comparisons readily give a simple sufficient condition for the efficiency of centralized control.[14]

Proposition 3. *Assume symmetry across managers, i.e. for all $i \neq j, \tilde{V}_i = \tilde{V}_j$. If*

$$\lambda \;>\; \frac{N}{\bar{K}}\Big(1 + \frac{N+1}{N-1}\,\alpha\Big),$$

then centralized ownership yields higher surplus than decentralization.

Intuitively, the right-hand side of the sufficient condition rises with N and with local autonomy α (which strengthens decentralized fallbacks) and falls with processing capacity $\bar{K}$. When $\bar{K} = N$ the condition simplifies to $\lambda > 1 + \frac{N+1}{N-1}\alpha$ (recovering $\lambda > 1 + 3\alpha$ when $N = 2$). As $\bar{K}$ increases—for example via AI-enabled processing—the sufficient condition for centralization becomes easier to satisfy.

5.2 AI Eases Limits on Information Processing Capacity

In the past, the headquarters' effective processing capacity $\bar{K}$ was limited because coordinating interdependent local assets means taking in, storing, and reasoning over large, fast-changing information within each decision cycle. Recent AI advances relax this bottleneck in four main ways.

First, models can now consider inputs ("context") on the order of hundreds to a couple thousand pages at once (roughly 200K–1M tokens), which lets a single decision process see more of the firm's state in one pass (Anthropic, 2024; Pichai and Hassabis, 2024; OpenAI, 2025). Second, software techniques speed up inference—faster attention implementations alongside techniques like "speculative decoding" reduce the time and cost per output (Dao et al., 2022; Kwon et al., 2023; Leviathan et al., 2023). Third, information processing capacity also scales via external memory: retrieval methods let models look up only the relevant facts from very large data sets (e.g., RETRO with document retrieval; FAISS for

[13] Note that the coefficient on the managers' standalone value is $\frac{1}{2}$ regardless of the size of N. To see why, recall the random-order view of the Shapley value in which we average each player's marginal contribution over all arrival sequences. For a manager M_i on a star, any sequence where the hub H arrives after M_i yields a standalone marginal $\tilde{V}_i$, and this event has probability $\frac{1}{2}$ independent of N.

[14] Note that here we cannot compare the incentive conditions manager-by-manager comparisons, instead we must sum across the managers. Because payoffs use Shapley weights, each manager's first order condition is linear in marginal contributions, and with separable convex costs the sum of these first-order conditions equals the derivative of a common potential (expected surplus). Summing therefore provides a valid aggregate incentive comparison.

efficient similarity search) and call tools like search and coding when needed (Borgeaud et al., 2022; Johnson et al., 2017; Schick et al., 2023; Yao et al., 2023). Finally, new architectures are under development that route compute to what matters most—activating only a few expert modules or using long-document readers that avoid inspecting every word—so larger coordination problems fit into the same time and compute budget (Fedus et al., 2021; Beltagy et al., 2020; Choromanski et al., 2021; Gu and Dao, 2023; Munkhdalai et al., 2024). Together these developments raise the information processing capacity $\bar{K}$, allowing a central decision-maker to process more of the firm's state each cycle and making the coordination gains that favor centralization available more often. We discuss these advances in more detail in **??**.

5.3 AI Tips the Scales Toward Centralization

Returning to the key condition in Fact 3, we see that as $\bar{K}$ increases, the sufficient condition for the domination of centralization becomes easier to satisfy. This is because headquarters can realize the coordination synergies across a larger and larger fraction of the firm's assets. While decentralized ownership still provides stronger individual investment incentives for managers, the value created by this effect becomes increasingly outweighed by the surplus generated through firm-wide coordination.

6 Countervailing Forces

While we've laid out some reasons that powerful AI systems strengthen the economic efficiency of centralized decision-making, there are three counterarguments to consider.

First, AI may simply not be capable of making all types of economic decisions or processing all economically relevant information. Humans could retain an advantage in some categories and this may, in turn, necessitate decentralization for those types of decisions. Second, even if we assume that AI is capable of all decisions and there are no reasons that humans need to be involved in decision-making, there may still be a decentralization of decision-making among different AI entities. Third, even if AI is capable of making economic decisions as well as humans, we may still decide that we want humans to make certain decisions. This may be expressed through preferences or legislation that prevents centralization. We consider each of these cases in turn.

6.1 Limits to codifiability or machine information processing

As Hayek emphasized, not all information is readily codifiable. Humans still hold advantages in embodied and affective skills, e.g. perception, dexterity, and social sensing. Competent people can still fold laundry, button a shirt, or throw a curve ball more reliably than machines, and they often better read micro-expressions and vocal cues. When decisions hinge on such locally perceived signals, delegating to the human on the spot will continue to dominate centralized control.

A second limit to the codifiability of knowledge comes from the "long tail." Many domains exhibit long-tailed distributions: a mass of common patterns but also a vast set of rare situations with little or no data. ML systems trained on historical data handle the frequently observed mass but can fail in the tail. For example, large language models struggle to learn long-tail knowledge (Kandpal et al., 2023), and humans retain a comparative advantage on rare diagnostic cases (Agarwal et al., 2025). Moreover, people often generalize better than machines from few examples—classic one-shot learning (Fei-Fei et al., 2006; Lake et al., 2015). A toddler may recognize elephants after a couple of pictures; current systems typically need many. In medicine, radiologists "know the long tail" (Langlotz, 2019), which is precisely where safety-critical errors matter most. Furthermore, human preferences themselves are a form of knowledge that machines may always struggle to learn perfectly. While many digital platforms run on predictive models of consumer preferences,[15] these predictive models work less well when preferences are highly idiosyncratic.

That said, these claims push against the premise of this Conference Volume. They assume enduring human superiority on some capabilities. Over time, AI systems may accumulate data deeper into the tail and, more importantly, improve few-shot generalization, shrinking human advantages. If so, the frontier of uniquely human value will recede—remaining real, but increasingly concentrated in rarer, more idiosyncratic cases.

6.2 When would a fully AI-powered economy be decentralized?

Even in a world where all decisions are made by AI, there may be reasons to decentralize decision-making because communication is neither instantaneous nor perfectly reliable. First, propagation is bounded (roughly at the speed of light) and links can degrade; as a result, a local decision-maker can sometimes react faster and more dependably than a distant controller when milliseconds matter. This shows up at multiple scales: at the hardware level, signal delay across a chip—on the order of picoseconds per inch—can bind at high clock speeds (Ott, 2009); in markets, algorithmic trading benefits from colocated autonomy (Steiner, 2010); and in combat, drone operations may require millisecond responses, making local autonomy tactically valuable. Second, when the distance between nodes in a communication network is especially large, decentralization may be indispensable: communications between Earth and Mars impose round-trip lags of about 4.3–21 minutes, so landers and rovers must act autonomously (NASA Jet Propulsion Laboratory, 2023). Taken together, finite latency and the realities of physics imply that even in an all-AI world, distributing decision rights toward the edge can yield operational and tactical advantages whenever required reaction times approach—or fall below—end-to-end communication delays.

Furthermore, even among machines, contracts remain incomplete: the world's contingencies cannot be fully specified ex-ante, and the combinatorics of real tasks outpace any fixed model, especially when the machines themselves multiply the number of contingencies that need to be considered, creating a "red queen" scenario. As in human organizations, non-contractible investments still matter, so distributed AI agents may need residual rights of control to act when unforeseen states arise.

That said, the direction of travel could still favor centralization if communication frictions keep falling and frontier models keep scaling. In many workloads, a single strong agent with rich tool use can outperform multi-agent schemes: recent studies find multi-agent LLM systems frequently fail to beat robust single-agent baselines and can even degrade accuracy (Cemri et al., 2025); likewise, a single search agent has outperformed multi-agent search variants (Nguyen et al., 2025).

6.3 Legislative requirements for decentralization

While the focus of this article has been on the economic efficiency of alternative arrangements for ownership and control, the "ownership regimes" of organizations at all scales—from small

[15] Consider, for example Amazon's anticipatory shipping (Spiegel et al., n.d.; Opam, n.d.), and the not un-common refrain in popular media that digital platforms and their algorithms "know you better than you know yourself" (Carmichael, 2014; Harari, 2017; Thompson, n.d.).

businesses to entire economies—are, of course, not made on the basis of economics alone. Law, policy, and social norms set the feasible—and legitimate—set of arrangements.

Competition rules (merger control, structural separation) can limit centralization even when scale economies favor it. Data governance—privacy, localization, purpose limits—can block large, centralized data pools, while interoperability and data-portability mandates can open paths for decentralized entrants. Sectoral laws in finance, health, transport, and criminal justice may continue to require human oversight, contestability, and auditability; that often anchors decisions where traceability is strongest, not where coordination is cheapest. Liability and insurance rules for AIs are also yet to be written. Professional licensing (e.g. for pilots, physicians, engineers) impose human-in-the-loop obligations that could, if upheld, continue to distribute decision rights.

Even without mandates, people may continue to want humans in control of consequential or meaning-laden decisions: a judge for sentencing, a pilot during critical phases, players on the field, or a human coach, poet, or therapist. These preferences create *de facto* limits on full centralization and sustain local agency where legitimacy, dignity, or narrative matter.

6.4 Summary

To be sure, there are some important counterarguments to the idea that even AI that surpasses human cognition would lead to centralization. Some types of information might defy codification, and some types of information processing might be better done locally. Thus, not every decision would be centralized. But if transmission and processing speeds for machine-readable information are orders of magnitude larger than today, and the capabilities of AI grow commensurately, then we might reasonably expect that these cases account for a smaller and smaller share of the economy. Thus transformative AI implies significantly more centralization of decision-making.

That's not to say that centralization will necessarily increase monotonically during the transition period, or that the transition period will be short. In particular, local decision-making may be advantageous during periods of turbulence, innovation or uncertainty, when rapid reactions to local information can be especially valuable. [16]

7 Early Empirical Evidence of Centralization

There is already clear evidence that economic decision-making is shifting toward the center in much of the economy. Specific case studies and broader trends in market concentration both point in this direction, and many of these shifts have been explicitly linked to the growing use of information technology (IT)—transformative AI would supercharge these trends.

Some of the earliest and most striking demonstrations come from retailing. Mrs. Fields Cookies, for example, developed a headquarters-controlled expert system to prescribe store-level actions in real time in the 1980s. As company co-founder Debbi Fields put it, "We have removed the decision-making process from the store level. The manager's responsibility is to execute the plan – not to plan" (Richman, 1987). The system dictated when to mix dough, when to bake, which varieties to emphasize, whether to call in extra labor, and even when to hand out free samples, all based on live traffic forecasts (Harvard Business School, 1990).

[16] For instance, there is some evidence that smaller companies have performed better after recessions (Morgan Stanley Research, 2023), and that they were especially resilient during the COVID-19 Pandemic (Wood, 2023).

In short, "*the system not only tells her what's happening, it tells the stores what to do about it*" (Richman, 1987). By removing local discretion, Mrs. Fields used IT to optimize quality, labor and customer experience across all outlets.

Large multi-product retailers soon adopted similar playbooks – none more aggressively than Walmart, as mentioned in section 1. Beginning in 1987, Walmart linked every store to Bentonville via what was then the nation's largest private satellite network, giving headquarters real-time visibility into SKU-level sales. By 1991 it had launched Retail Link, an extranet that auto-generated store-specific replenishment orders and shared live data with suppliers. Central category managers – not local store managers – decided exactly which items each outlet would stock, in what quantities, while negotiating directly with manufacturers. The result was a coast-to-coast network that behaved like one centrally optimized warehouse (Lee, 2006; Fishman, 2006).

As digital technologies have advanced, centralized business models—franchising, corporate chains, and, more recently, private-equity-backed roll-ups—have increasingly reshaped U.S. retailing. Private-equity "add-on" deals, the hallmark of roll-up strategies, made up 43 percent of all buyouts in 2002 but almost 72 percent by 2020, and they now span countless services from optometrists to car-washes (*Serial Acquisitions and Industry Roll-ups: Background Note*, 2023). At the same time, private equity's share of all U.S. corporate equity grew from about 4 percent in 2000 to nearly 20 percent in 2021 (Institute for Local Self-Reliance, 2019).

Academic evidence points to parallel changes in market structure. Decker et al. (2020) note – drawing on prior Census studies – that in retail trade the share of sales and employment accounted for by single-unit ("mom-and-pop") establishments fell from roughly one-half to one-third between 1977 and 2007, as national big-box chains spread. Smith and Ocampo (2025) find that the geographic expansion of multi-market retailers accounts for most of the post-1990 rise in national retail concentration. These structural shifts have come at the expense of smaller firms. The Institute for Local Self-Reliance (2019) reports that retailers with fewer than 100 employees captured more than half of U.S. retail spending in 1982 but only about one-quarter by 2017. The sector's four-firm concentration ratio (C4) has risen from less than 15% in the 1970s to over 40% today (Figure 1).

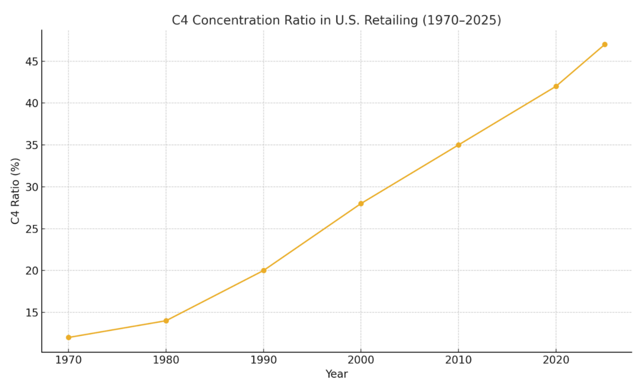

Figure 1: Growth of the U.S. retail C4 concentration ratio.

Increased concentration is not confined to retail. Across the U.S. private sector, the C4 index has risen 5–8 percentage points since the late 1990s, with particularly significant increases in manufacturing, banking, telecommunications and airlines, sparking what has been called the ”rise of superstar firms” (Autor et al., 2020). Stock-market data tell a similar story: the ten largest U.S. firms now account for roughly 38% of total market capitalization – double their share in 2010 (Capitalist, 2025).

Recent literature links these patterns to IT intensity. Brynjolfsson et al. (2023) show that firms making heavier IT investments grow larger and more concentrated, primarily reflecting increases in sales not headcount consistent with earlier evidence in Brynjolfsson et al. (2008). Industry-level studies likewise find that rising concentration coincides with higher R&D and IT spending (Kwon et al., 2022), and that large software investments predict subsequent increases in market share (Bessen, 2019).

Looking ahead, AI may amplify these forces. Sam Altman predicts the emergence of "one-person, billion-dollar" companies (Altman, 2025), and Anthropic's *Project Vend* has already let an LLM make every key decision for a small online shop—albeit with mixed results (Anthropic, 2025). While the project failed to make a profit, making some comically bad choices along the way, one can imagine a future version doing much better.

The trends to date are not necessarily predictive of what we can expect as AI becomes more powerful. However, the evidence of increasing concentration is consistent with the idea that increased codifiabilty and digitization of data, combined with increased computer processing power, makes it possible to centralize more decisions.

8 Economic Centralization and Political Power

AI can make larger, more centralized organizations economically attractive by easing information bottlenecks and enabling tighter coordination. Whether this is politically problematic will depend less on centralization itself than on how power is made accountable.

Two channels link economic centralization to the concentration of political power. First, economic concentration can increase agenda-setting and lobbying capacity, a classic prediction of political-economy models in which organized interests leverage concentrated rents (Grossman and Helpman, 1994). Empirically, U.S. policy responsiveness appears more closely aligned with economic elites and organized interests than with average citizens, consistent with concerns about unequal influence (Gilens and Page, 2014). Second, when firms that concentrate economic power also serve as information intermediaries, there are new avenues for political power. As large AI systems shape search, summarization, and content curation, they become gatekeepers of public discourse. Prior work on social media's role in misinformation and opinion formation documents the scale and stakes of such gatekeeping (Allcott and Gentzkow, 2017); adjacent scholarship highlights how data-extraction business models can amplify those dynamics (Zuboff, 2019) and how automated moderation infrastructures embed political choices (Gorwa et al., 2020). Recent analyses of generative AI underscore parallel risks for democratic representation, accountability, and trust if synthetically generated content floods civic channels (Allen and Weyl, 2024; Jain et al., 2025).

A third, longer-run channel operates through human capital and civic capacity. Education and civic skills are robustly associated with democratic stability and participation (Glaeser et al., 2007). Technological change can complement or substitute for skills in ways that alter incentives to invest in education (Acemoglu and Autor, 2011; Goldin and Katz, 2008). If AI shifts the perceived returns to certain cognitive investments, the downstream effects on civic engagement—and thus on democratic resilience—are an open and important empirical question.

Because the political consequences turn on governance, not technology alone, it is useful to note (without endorsing) strands of institutional design discussed in the literature. Work on deliberative institutions studies mechanisms for structured public input to high-stakes decisions (e.g., citizens' assemblies) (OECD, 2020; Collective Intelligence Project, 2023), and related experiments in blockchain communities include decentralized autonomous organizations (DAOs) (Hassan and De Filippi, 2021) and new forms of decentralized finance (Buterin et al., 2019). Work on data governance explores rights to access, portability, and control (GDPR, 2016; Act, 2023), collective vehicles such as data trusts (Delacroix and Lawrence, 2019; Hardjono and Pentland, 2019), and proposals to treat contributions of data as compensable "labor" (Arrieta-Ibarra et al., 2018; Posner and Weyl, 2018). Distributional proposals—including social wealth funds, or universal dividends—have also been analyzed as ways to broaden claims on AI-concentrated rents (O'Keefe et al., 2020; Huang and Manning, 2025).

9 Conclusion

This paper has examined the implications of transformative AI for the organization of economic decision-making, revisiting Hayek's epistemic critique of central planning in light of recent technological advances. We develop a simple framework in which knowledge codification and information-processing capacity are key determinants of the optimal allocation of decision rights and ownership. Our analysis highlights two central channels through which AI influences economic organization: first, by expanding the set of knowledge that is codifiable and transferable, AI and related technologies relax the constraints that once favored local autonomy; second, by dramatically increasing information-processing capacity, AI enables greater integration and coordination of decisions across larger scales. Together, these channels diminish the informational advantages previously held by distributed human agents, thus making centralized control more feasible and, in some contexts, more efficient.

These theoretical results are consistent with emerging empirical evidence on increasing concentration in U.S. industries, rising firm size and market share among IT-intensive firms, and the documented use of AI and IT to remove discretion from local managers in retail and other industries. This suggests that centralization is likely to intensify as AI capabilities advance.

We also note that the centralizing tendencies of AI extend beyond efficiency considerations—to potentially reshaping the distribution of economic rents and political power. As decision-making authority and residual control rights become more concentrated, human agents may see diminished bargaining power and weaker incentives to invest in human capital. At a societal level, reduced education and participation risk undermining civic engagement and democratic resilience, while concentrated economic resources and control over information flows may amplify the influence of elites over policy and public discourse.

The framework and findings we present point to several directions for further research. One avenue is to test whether AI adoption within firms predicts shifts in centralization of decision-making authority. Another is to examine whether industries with higher AI intensity exhibit greater concentration of market power or declines in local autonomy. Further work could also investigate how AI-mediated control over information flows shapes political outcomes and public attitudes.

More broadly, our analysis suggests that the radically centralizing potential of AI may demand equally radical new ideas about how to preserve human agency and build new foundations for democracy. Understanding and addressing these questions may become one of the central economic and political issues of the coming years.

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