Endogenous Plucking Through Networks: The Plucking Paradox*

Hanbaek Lee† Ye Sun‡

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Abstract

We study an *endogenous plucking* mechanism in a parsimonious general equilibrium model where firms choose production linkages (network intensity). In expansions, high productivity encourages denser linkages, raising efficiency and output. Yet greater connectedness amplifies adverse TFP shocks, so downturns are disproportionately severe when recessions begin from a highly connected state. The model implies *network-size* and *duration dependence* of shock propagation. Due to a pecuniary externality, the decentralized equilibrium underinvests in network intensity. We characterize an optimal fiscal policy that decentralizes the constrained efficient allocation and delivers a *Plucking Paradox*: the planner prefers higher output in normal times even though it increases exposure to rare, severe disasters.

Keywords: Endogenous plucking, production network, duration dependence, optimal fiscal policy, plucking paradox

JEL codes: E32, E62, D58, D62

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†University of Cambridge. Email: hl610@cam.ac.uk

‡University of Cambridge. Email: ys627@cam.ac.uk

1 Introduction

Business cycles are rarely symmetric fluctuations around trend. As noted by Friedman (1964), economic activity often resembles a "plucking model": recessions are abrupt, deep deviations below potential, while expansions are gradual returns toward a ceiling. Recently, Hall and Kudlyak (2022a,b) sharpen this view by documenting systematic regularities in recessions and recoveries, suggesting that the key empirical content of plucking lies in the state dependence of downturn severity rather than in symmetric movements around trend. A central implication is *state dependence* not only in levels but also in *duration*: the economy's vulnerability to large downturns appears to depend on how long it has been since the last major contraction. Why do long, tranquil expansions so often end in sharp breaks? And why do recoveries display such regular patterns across episodes? Understanding the origins of this asymmetry, duration dependence, and historical regularity is key to explaining why fragility builds during periods of prolonged stability.

We provide a parsimonious theory of *endogenous plucking* based on production networks. In our framework, firms endogenously choose a network intensity, α, which governs the strength of input linkages. While higher α boosts efficiency by expanding the use of intermediate inputs, it simultaneously makes aggregate output more sensitive to productivity shocks. Crucially, because α is a sluggish state variable—subject to convex adjustment costs and partial depreciation—the economy cannot instantaneously unwind its network exposure when productivity deteriorates. This "double-edged" nature of networks makes mature booms intrinsically more fragile than young ones.

Our key contribution is twofold. First, we demonstrate that endogenous network accumulation generates nonlinear shock propagation with two distinct forms of state dependence. We prove that the optimal network choice is procyclical: firms gradually accumulate linkages during expansions. At the same time, we show that the output response to a negative shock is strictly increasing in pre-shock network intensity. Together, these results imply: (i) *size dependence*—the impact of a negative shock scales with the network state—and (ii) *duration dependence*—recessions are deeper following longer expansions because network intensity has had more time to build up. In equilibrium, the economy "crawls" up an efficiency frontier during expansions but suffers disproportionately severe contractions when productivity turns, reproducing the plucking property endogenously. We validate this mechanism empirically, documenting that sectors with higher network intensity exhibit significantly more negative skewness in output growth.

Our second contribution characterizes the efficient allocation and uncovers a striking policy implication. We solve the constrained planner's problem to characterize an implementable fiscal policy that decentralizes the efficient allocation. The optimal tax schedule decomposes into a static term offsetting markups and a dynamic component correcting a pecuniary network externality. This yields a Plucking Paradox: the planner optimally subsidizes network formation, raising average output in normal times despite increasing the economy's exposure to severe recessions. The welfare gains from higher productivity during expansions outweigh the losses from deeper downturns, rendering the efficient economy observably "less stable" yet strictly welfare-superior.

In good times, deep input linkages are socially valuable because they improve resource allocation across intermediate varieties and reduce effective production costs. However, like physical capital, these linkages are slow to adjust: once the economy reorganizes around a complex supply chain, this structure cannot be costlessly unwound when conditions deteriorate. Optimal policy therefore accepts a tradeoff, pushing the economy toward a high-linkage steady state that is productive but more pluckable.

Related literature This paper is closely related to four strands of literature. First, we contribute to the growing literature on dynamic endogenous production networks and state-dependent macroeconomic dynamics. Acemoglu et al. (2012) establishes that the topology of input-output linkages governs whether idiosyncratic shocks dissipate or propagate into aggregate fluctuations; Carvalho et al. (2020) provide causal evidence that production networks transmit adverse shocks using the 2011 Great East Japan Earthquake. A growing body of work endogenizes network formation and studies its implications for shock propagation and amplification (Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2017; Ghassibe, 2021; Kopytov et al., 2024; Kopytov, Taschereau-Dumouchel, and Xu, 2025). Most closely related is (Kopytov, Taschereau-Dumouchel, and Xu, 2026), who study how endogenous technology adoption generates returns to scale through a supply-chain amplification channel. We share the insight that production structure choices feed back through input prices, but focus on a distinct implication: in our framework, the endogenous network state interacts with aggregate productivity shocks to produce business cycle asymmetry — the same structure that amplifies booms deepens busts, generating the plucking property and duration dependence. We differ from Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017) in that asymmetric dynamics in our model do not rely on asymmetric shocks, but instead arise endogenously from the accumulation of network participation over prolonged expansions. Ghassibe (2021) and Ghassibe and Nakov (2025) demonstrate that endogenous networks interacting with nominal rigidities generate powerful state-dependent amplification of demand shocks. Our paper complements this insight by showing that a distinct but related mechanism operates on the real side: even with flexible prices, network intensity acts as a slow-moving state variable whose accumulation during expansions generates history-dependent amplification of supply shocks. The two channels are likely to reinforce each other in richer environments combining both nominal and real frictions. Methodologically, our model is solved *globally* using the repeated transition method developed by Lee (2025) without relying on perfect foresight assumption.

Second, we connect to the plucking model of business cycles and its subsequent empirical and theoretical developments (Friedman, 1964; Kim and Nelson, 1999; De Simone and Clarke, 2007; Dupraz, Nakamura, and Steinsson, 2025). While this literature documents sharp downturns and systematic recovery dynamics, it remains largely agnostic about the underlying macroeconomic mechanisms. We propose a novel real-side mechanism in which plucking dynamics arise from endogenous production-structure accumulation: expansions gradually build network intensity (complexity), a slow-moving state that raises efficiency in good times but amplifies adverse productivity shocks, generating negative skewness and strong duration dependence. Our focus is complementary to Dupraz, Nakamura, and Steinsson (2025). Whereas they emphasize a ceiling-and-rebound mechanism and a related one-sided predictability moment (contractions forecasting recoveries more strongly than expansions forecasting contractions), we study endogenous vulnerability: boom maturity predicts downside risk through the accumulation of network intensity.

Third, our paper relates to the literature on pecuniary externalities. Individual firms' network participation decisions affect aggregate network intensity and equilibrium prices, but these effects are not internalized at the firm level. More broadly, our mechanism connects to classic financial amplification and overborrowing frameworks in which private balance-sheet or borrowing choices move prices or collateral and generate wedges between private and social allocations (Kiyotaki and Moore, 1997; Bernanke, Gertler, and Gilchrist, 1999; Mendoza, 1991, 2010; Bianchi, 2011). The key distinction is that the externality here operates through endogenous network participation and intermediate-input prices rather than leverage or collateral values. Furthermore, because network participation is a predetermined and slow-adjusting state variable, such pecuniary externalities have intertemporal consequences. We also relate to the literature on externalities in production networks. Ferrari and Pesaresi (2026) study a related productivity-resilience tradeoff in supply chains with search frictions. In their framework, equilibrium features over-specialization because firms fail to internalize how specialization, combined with search frictions, slows supplier replacement after disruptions—the planner prefers less specialization, which as a result leads to faster recovery. Our model delivers the opposite: because network intensity amplifies aggregate shocks rather than slowing idiosyncratic link replacement, the decentralized economy under-invests in networks. Therefore, the planner accepts deeper recessions as the price of higher average productivity—a Plucking Paradox rather than a resilience dividend. Capponi, Du, and Stiglitz (2024) further develop this theme by analyzing whether supply networks are efficiently resilient under perfect foresight. We build on these foundations by embedding network externalities in a stochastic dynamic environment where aggregate shocks interact with the slow-moving network state. This extension reveals that the wedge between the competitive equilibrium and the constrained efficient allocation is itself state-dependent—the inefficiency is largest precisely when the economy is most vulnerable—and provides a rationale for policy intervention that varies over the cycle.

Finally, our mechanism relates to the literature on returns to scale and intermediate goods in business cycles. Basu (1995) shows that intermediate inputs create a 'round-about' production multiplier that amplifies productivity shocks, a channel that our network multiplier endogenizes. Lashkari, Bauer, and Boussard (2024) and Argente et al. (2025) document how production structure shapes firms' returns to scale through information technology and standardization. Hyun, Kim, and Lee (2024) study business cycles with cyclical returns to scale. Related to this, our model's production returns to scale is endogenous and procyclical: as firms accumulate network intensity during booms, the economy's output elasticity with respect to TFP rises, generating time-varying amplification. The distinguishing feature of our model is that this amplification is asymmetric — it raises output in expansions but deepens contractions — producing the plucking property rather than symmetric volatility amplification.

Roadmap The remainder of the paper proceeds as follows. Section 2 introduces the model and equilibrium. Section 3 establishes the monotone buildup of network intensity in expansions and the amplification of negative shocks, delivering size and duration dependence. Section 4 quantifies the mechanism and documents the implied asymmetry in simulated data. Section 5 characterizes the constrained efficient allocation and derives the optimal fiscal policy. Section 6 discusses empirical implications and validation. Section 7 concludes.

2 Baseline model

This section introduces a parsimonious dynamic stochastic general equilibrium model with representative firms in which firms endogenously choose their production network intensity. The key state variable is the share of network participation.

Environment We describe the static component of the model that underlies the dynamic network-adjustment problem. The economy features two types of goods-producing firms: network firms (indexed by j) that use a continuum of intermediate inputs whose composition is determined endogenously, and simple firms (indexed by l) that use labor only. Both the network sector and the simple sector sell to (i) the network sector as intermediate input for network goods, and (ii) the representative retailer for producing final goods. A representative retailer aggregates network and simple goods into the final consumption good. Throughout, A denotes aggregate TFP, and w denotes the wage.

Technology Each network firm produces with one continuum of intermediate inputs. A fraction $\alpha \in [0, 1]$ of its intermediate inputs are network goods and a fraction $1-\alpha$ are simple goods. The value of α is predetermined at the beginning of the period. In the representative firm setting, all the network firms choose the same α. We distinguish between the firm's own network intensity α and the aggregate network participation α^{agg}, though they coincide in the representative firm setting. The production function of the network sector is Cobb-Douglas that combines network and simple intermediate inputs,

$$y_j^N = A \exp\left(\int_0^{\alpha} \ln x_{ij}^N \, \mathrm{d}i + \int_{\alpha}^1 \ln x_{kj}^S \, \mathrm{d}k \right), \tag{1}$$

where x_{ij}^N and x_{kj}^S are intermediate inputs of network and simple goods, respectively. Simple firms use labor only,

$$y_l^S = A\ell_l. \tag{2}$$

The aggregate TFP process A follows a two-state Markov chain with support $\{G, B\} \in \mathbb{R}_+$, such that $B < 1 < G$.

Retail aggregation A representative retailer combines varieties of network and simple goods into the final consumption good using a CES aggregator,

$$Y = \frac{1}{\zeta^{\zeta}(1-\zeta)^{1-\zeta}} \left[\left(\int_0^1 (X_j^N)^{\frac{\sigma-1}{\sigma}} \mathrm{d}j \right)^{\frac{\sigma}{\sigma-1}} \right]^{\zeta} \left[\left(\int_0^1 (X_l^S)^{\frac{\sigma-1}{\sigma}} \mathrm{d}l \right)^{\frac{\sigma}{\sigma-1}} \right]^{1-\zeta}, \tag{3}$$

where $\zeta \in (0,1)$ is the network share in final demand and $\sigma > 1$ is the elasticity of substitution across varieties within each block.

Equilibrium conditions Labor, network goods, and simple goods markets clear:

$$\begin{aligned} \int_0^1 \ell_l \, \mathrm{d}l &= L, \\ \int_0^1 x_{ji}^N \mathbf{1}\{i \text{ buys from } j\} \, \mathrm{d}i + X_j^N &= y_j^N, \quad \forall j, \\ \int_0^1 x_{li}^S \mathbf{1}\{i \text{ buys from } l\} \, \mathrm{d}i + X_l^S &= y_l^S, \quad \forall l. \end{aligned} \tag{4}$$

Network firms participate in perfect competition in the intermediate input markets, and monopolistic competition in the selling to the retailer. Simple firms operates under perfect competition in both intermediate input and final goods markets. Under perfect competition in input markets, marginal cost for network should satisfy

$$\ln \lambda^N = \alpha \ln \lambda^{N,\text{agg}} + (1-\alpha) \ln \lambda^{S,\text{agg}} - \ln A, \tag{5}$$

where λ^N is the marginal costs of the network firm controlling for its own network intensity α. $\lambda^{N,\text{agg}}$ and $\lambda^{S,\text{agg}}$ are the prices of network and simple goods, which is not controlled by the individual firm, though in the representative firm setting they coincide with the average prices of network and simple goods. Normalizing the retail price index to one, $P \equiv 1$, the wage can be expressed as a function of productivity A and network intensity α^{agg},

$$\ln w = \left(\frac{\zeta}{1-\alpha^{\text{agg}}} + 1 \right) \ln A - \zeta \ln \frac{\sigma}{\sigma - 1}, \tag{6}$$

Detailed derivations are in Appendix A.

Static national accounting Retailers spend a fraction ζ of total expenditure on network goods and $1-\zeta$ on simple goods. Operating profits from the two sectors are

$$\pi^N = \frac{\zeta}{\sigma - \zeta} wL, \qquad \pi^S = 0. \tag{7}$$

Detailed derivations are in Appendix A. Total consumption equals total revenue,

$$C = \frac{\sigma}{\sigma - \zeta} wL = wL + \pi^N, \tag{8}$$

and all markets clear. These static relationships pin down equilibrium prices, profits, and output as functions of productivity A and aggregate network intensity α^{agg}.

2.1 Recursive competitive equilibrium

We now embed the static ingredients into a dynamic setting where firms choose their network intensity α over time. Time is discrete. For the beginning of the period, firms' predetermined α from last period depreciates at rate $\delta \in (0, 1)$, so that the effective network intensity at the beginning of the period is $(1 - \delta)\alpha$. This is the same for α^{agg}.

Decentralized choice of network intensity A firm takes the aggregate network participation α^{agg}, the marginal cost of the network goods $\lambda^{N,\text{agg}}$, the marginal cost of the simple goods $\lambda^{S,\text{agg}}$ as given and chooses its own α, which then determines its own marginal cost λ^N through (5), leading to profits of the form

$$\pi^N(\alpha; X) = \frac{\zeta}{\sigma - \zeta}\left(\frac{\sigma - 1}{\sigma}\right)^{\zeta} A^{\frac{\zeta}{1-(1-\delta)\alpha^{\text{agg}}} + \frac{(1-(1-\delta)\alpha)(1-\sigma)}{1-(1-\delta)\alpha^{\text{agg}}} + \sigma} L, \tag{9}$$

Detailed derivations are in Appendix A.

The value of network firms is given by the Bellman equation

$$J(\alpha; X) = \max_{\alpha'} \quad \pi(\alpha; X) - \Phi(\alpha, \alpha') + \mathbb{E}M(X, X')J(\alpha'; X') \tag{10}$$

$$\text{s.t.} \quad 0 \leq \alpha' \leq 1 \tag{11}$$

$$\alpha^{agg'} = \Gamma_{endo}(X) \tag{12}$$

where X is the aggregate state vector, Γ_{endo} is a law of motion for the endogenous aggregate state α^{agg}.

$$X = [\alpha^{agg}, A] \tag{13}$$

and $M(X, X')$ is the stochastic discount factor between periods with states X and X'. The adjustment cost $\Phi(\alpha, \alpha')$ takes the form

$$\Phi(\alpha, \alpha') = \frac{\mu}{2}\frac{(\alpha' - (1 - \delta)\alpha)^2}{1 - (1 - \delta)\alpha}$$

where parameter $\mu > 0$ governs the speed of adjustment of network intensity, and the denominator $1 - (1 - \delta)\alpha$ captures the idea that it is more costly to adjust network intensity when the effective network intensity at the beginning of the period is higher. [1] Household with GHH utility owns all the firms

$$V(a,X) = \max_{c,n,a'} \frac{1}{1-\rho}\left(c - \eta\frac{n^{1+\frac{1}{\chi}}}{1+\frac{1}{\chi}}\right)^{1-\rho} + \beta\mathbb{E}[V(a',X')] \tag{14}$$

$$\text{s.t.} \quad c + \int M(X,X')a'(X')\mathrm{d}\Gamma_{X'} = a + w(X)n \tag{15}$$

$$\alpha^{agg'} = \Gamma_{endo}(X) \tag{16}$$

where Γ_{endo} is a law of motion for the endogenous aggregate state α^{agg}. We assume the law of motion conceived by the household is consistent with the one for firms, without separately assuming different form and requiring the consistency in the equilibrium condition.

Equilibrium conditions In equilibrium, the labor market clears such that household labor supply equals aggregate demand, $n = L$, and the representative firm's network choice is consistent with the aggregate network state, $\alpha = \alpha^{\text{agg}}$.

We formally define the Recursive Competitive Equilibrium (RCE) for this economy as follows:

Definition 1 (Recursive competitive equilibrium (RCE))**.**
Given the exogenous aggregate state transition $X' \sim \Pi(\cdot \mid X)$, a recursive competitive equilibrium consists of price functions q, household and firm policy/value functions (V, g^h) and (J, g^f), and an aggregate law of motion Γ for endogenous aggregates, such that for every admissible state:

(i) *(V, g^h) solves the household problem given (q, Π, Γ);*

(ii) *(J, g^f) solves the firm problem given (q, Π, Γ);*

(iii) *all markets clear at prices q; and*

(iv) *aggregation is consistent, i.e. the aggregates used in q and Γ coincide with those implied by individual decisions, so that the perceived law of motion equals the actual one.*

[1] We include this denominator as a regularization to prevent the overrepresentation of corner solution $\alpha = 1$. This keeps the objective well-behaved and the problem concave (e.g., under SPP, profits scale roughly as $A^{1/(1-(1-\delta)\alpha)}$). The parametric form is not essential for our results.

3 A theory of endogenous plucking

This section theoretically investigates the equilibrium properties of the network formation process and its implications for aggregate output fluctuations. The core mechanism rests on a tension between efficiency and stability: complex production networks amplify productivity during booms but create structural fragility that deepens recessions.

To derive analytical closed-form results, we restrict attention to a partial equilibrium setting where the stochastic discount factor is fixed.[2] Our goal is to formally prove that this economy exhibits *duration dependence*: the longer a boom lasts, the more severe the subsequent recession will be—the hallmark of the plucking model.

3.1 Network dynamics during booms

We begin by characterizing how the economy's network structure evolves during a period of sustained productivity growth. Because network adjustments are subject to convex costs, the optimal network intensity α is not a static choice but a state variable that accumulates over time.

Definition 2 (Equilibrium policy path)**.**
Let $f(\alpha; X)$ denote the optimal policy function solving the firm's problem. We define the iterated policy function $g^{(n)}(\alpha; G)$ as the network choice after n consecutive periods of state $A = G$, starting from state α:

$$g^{(1)}(\alpha; G) := f(\alpha; G, \alpha) \tag{17}$$

$$g^{(n)}(\alpha; G) := f(g^{(n-1)}(\alpha; G); G, g^{(n-1)}(\alpha; G)) \quad \forall n \in \{2, 3, \dots\} \tag{18}$$

This sequence characterizes the evolution of network intensity during a prolonged boom.

The following proposition establishes that network formation is self-reinforcing. A higher existing stock of network capital reduces the marginal cost of maintaining or expanding connections, creating momentum in network accumulation.

[2] Later in the quantitative analysis, we show that the general equilibrium effect through the stochastic discount factor dampens the aggregate fluctuations while the theoretical predictions stay unaffected.

Proposition 1 (Weak monotonicity in network size)**.**
The policy function $g^{(1)}(\alpha;G)$ is weakly increasing in α. That is, $\frac{\partial g^{(1)}}{\partial \alpha} \geq 0$.

Proof. In the partial-equilibrium problem, the firm chooses $\alpha' \in \mathcal{A} \subset [0,1)$ to maximize

$$F(\alpha',\alpha;G) \equiv \Pi(\alpha';G) - \phi(\alpha',\alpha),$$

where $\mathcal{A}$ does not depend on α. Assume $F(\cdot,\alpha;G)$ is strictly concave in α' so that the optimizer is unique and characterized by the first-order condition

$$F_{\alpha'}(\alpha',\alpha;G) = 0.$$

Since $\Pi(\alpha';G)$ does not depend on α, we have

$$F_{\alpha'\alpha}(\alpha',\alpha;G) = -\phi_{\alpha'\alpha}(\alpha',\alpha).$$

Using $\phi(\alpha',\alpha) = \frac{\mu}{2}\frac{(\alpha'-(1-\delta)\alpha)^2}{1-(1-\delta)\alpha}$, a direct calculation gives

$$\phi_{\alpha'\alpha}(\alpha',\alpha) = \mu(1-\delta)\frac{\alpha'-1}{\big(1-(1-\delta)\alpha\big)^2} \leq 0 \qquad \text{for all } \alpha' \in [0,1),$$

and therefore $F_{\alpha'\alpha}(\alpha',\alpha;G) \geq 0$.

Let $\alpha_2 > \alpha_1$. Consider the function $\psi(\alpha') \equiv F_{\alpha'}(\alpha',\alpha_2;G) - F_{\alpha'}(\alpha',\alpha_1;G)$. Because $F_{\alpha'\alpha} \geq 0$, we have $\psi(\alpha') \geq 0$ for all α', i.e., the marginal benefit of increasing α' is (weakly) higher when the inherited state α is larger. Since $F(\cdot,\alpha;G)$ is strictly concave, $F_{\alpha'}(\cdot,\alpha;G)$ is strictly decreasing in α'. Hence the unique zero of $F_{\alpha'}(\cdot,\alpha_2;G)$ must occur at a (weakly) higher α' than the unique zero of $F_{\alpha'}(\cdot,\alpha_1;G)$, implying $g^{(1)}(\alpha_2;G) \geq g^{(1)}(\alpha_1;G)$. ■

Corollary 1 (Iterated weak monotonicity)**.**
The n-th iterated policy $g^{(n)}(\alpha;G)$ is weakly monotone increasing in α.

Proof. This follows by induction from Proposition 1. Since $g^{(1)}$ is non-decreasing, and composition of non-decreasing functions preserves monotonicity, $g^{(n)}$ remains non-decreasing. ■

Proposition 1 implies that history matters: the network choice today depends on the network choice yesterday. The next logical step is to determine the *direction* of this accumulation during a boom. We show that if firms find it optimal to increase network intensity at the start of a boom, they will continue to do so as the boom persists.

Proposition 2 (Monotone preservation property)**.**
If the initial network adjustment is positive, i.e., $g^{(1)}(\alpha; G) \geq \alpha$*, then subsequent adjustments maintain this trajectory:* $g^{(2)}(\alpha; G) \geq g^{(1)}(\alpha; G)$*.*

Proof. This property relies on the weak monotonicity established in Proposition 1. Let $g(\alpha)$ denote the policy function $g^{(1)}(\alpha; G)$. We know from Proposition 1 that $g(\alpha)$ is non-decreasing in α. Assume the initial condition holds: $g(\alpha) \geq \alpha$. Because $g(\cdot)$ is non-decreasing, we can apply the function g to both sides of this inequality without changing the sign:

$$g(g(\alpha)) \geq g(\alpha) \tag{19}$$

By definition, $g^{(2)}(\alpha; G) \equiv g(g(\alpha))$ and $g^{(1)}(\alpha; G) \equiv g(\alpha)$. Therefore, the inequality simplifies to:

$$g^{(2)}(\alpha; G) \geq g^{(1)}(\alpha; G) \tag{20}$$

Intuitively, if the firm wants to grow the network today (investment is positive), the higher resulting network state tomorrow will motivate them to grow it even further (or at least maintain it) due to the complementarity of the network stock. ■

Corollary 2 (Iterated monotonicity preservation)**.**
If $g^{(1)}(\alpha; G) \geq \alpha$*, then* $g^{(n)}(\alpha; G) \geq g^{(n-1)}(\alpha; G)$ *for all* $n \in \{2, 3, \ldots\}$*.*

Proof. Let T be the operator such that $\alpha_{t+1} = T(\alpha_t) = g^{(1)}(\alpha_t; G)$. If $T(\alpha) \geq \alpha$, applying the monotone operator T to both sides (by Proposition 1) yields $T(T(\alpha)) \geq T(\alpha)$, which is equivalent to $g^{(2)}(\alpha; G) \geq g^{(1)}(\alpha; G)$. By induction, α_n is a non-decreasing sequence converging to the steady state associated with $A = G$. ■

Taken together, these results paint a picture of *gradual network buildup*. During a boom, firms do not immediately jump to the high-network steady state due to adjustment costs. Instead, α rises monotonically over time. Consequently, a "mature" boom (large n) is characterized by a strictly higher network intensity than a "young" boom (small n).

3.2 Endogenous fragility and plucking

Having established that network intensity accumulates during booms, we now examine how this structure performs when the economy is hit by a negative shock. We show that the network acts as a double-edged sword: the same leverage that amplifies output in good times amplifies the contraction in bad times.

Proposition 3 (Output monotonicity in network)**.**
Conditional on the bad aggregate state $A = B$, aggregate output $Y(\alpha, B)$ is strictly decreasing in α.

Proof. From the static equilibrium, output satisfies

$$Y(\alpha, A) = A^{\frac{\zeta}{1-(1-\delta)\alpha}+1} L(\alpha, A).$$

Under GHH preferences, labor supply satisfies $L(\alpha, A) = \big(w(\alpha, A)/\eta\big)^{\chi}$, and the static wage is

$$w(\alpha, A) = \Big(\frac{\sigma-1}{\sigma}\Big)^{\zeta} A^{\frac{\zeta}{1-(1-\delta)\alpha}+1}.$$

Therefore $L(\alpha, A) \propto A^{\chi\left(\frac{\zeta}{1-(1-\delta)\alpha}+1\right)}$, and hence

$$Y(\alpha, A) \propto A^{(1+\chi)\left(\frac{\zeta}{1-(1-\delta)\alpha}+1\right)}.$$

Taking logs and differentiating yields

$$\frac{\partial \ln Y}{\partial \alpha} = (1+\chi)\frac{\zeta(1-\delta)}{\big(1-(1-\delta)\alpha\big)^2} \ln A.$$

Since $(1+\chi)\frac{\zeta(1-\delta)}{(1-(1-\delta)\alpha)^2} > 0$, the sign is determined by $\ln A$. Because $B < 1$ implies $\ln B < 0$, we obtain $\partial Y(\alpha, B)/\partial \alpha < 0$. ■

This result identifies the source of *endogenous fragility*. The term $\Gamma(\alpha)$ serves as an elasticity of output with respect to TFP. A high α implies a high elasticity. When TFP is low ($A = B < 1$), a high elasticity magnifies the decline.[3]

[3] It is worth noting that the result in Proposition 3 is not an artifact of normalizing A around one. Let $\bar{A}$ denote the reference productivity level that pins the stationary allocation (e.g., the unconditional mean or the deterministic steady state), and define $\tilde{A} \equiv A/\bar{A}$. Then the comparative

Finally, we connect the network accumulation dynamics (Corollary 2) with this fragility result (Proposition 3) to formally derive the plucking property.

Corollary 3 (Size dependence)**.**
$Y(g^{(n)}(\alpha; G), B)$ weakly decreases in the initial state α.

Proof. From Corollary 1, $g^{(n)}(\alpha; G)$ increases in α. From Proposition 3, $Y(\cdot, B)$ decreases in the network argument. The composition of a decreasing function and an increasing function is decreasing. ■

Corollary 4 (Duration dependence)**.**
If the economy starts with $g^{(1)}(\alpha; G) \geq \alpha$, then $Y(g^{(n)}(\alpha; G), B)$ weakly decreases in n for all $n \in \{2, 3, \dots\}$.

Proof. By Corollary 2, the sequence of network states $\{\alpha_n\}_{n=1}^{\infty}$ generated by a sequence of positive shocks is non-decreasing in n. Let $\alpha_n = g^{(n)}(\alpha; G)$. Since $\alpha_n \geq \alpha_{n-1}$ and $\frac{\partial Y(\alpha, B)}{\partial \alpha} < 0$ (Proposition 3), it follows that:

$$Y(\alpha_n, B) \leq Y(\alpha_{n-1}, B) \tag{21}$$

This establishes the theoretical basis for endogenous plucking: the severity of the recession (output level in state B) is monotonically increasing in the duration of the preceding boom. ■

In summary, the model generates business cycle asymmetry not through asymmetric shocks, but through the *endogenous evolution of the state variable*. A long boom allows the economy to build a complex, efficient network structure. When the inevitable downturn arrives, this "over-optimized" structure becomes a liability, leading to a deeper recession than would have occurred after a short boom.

statics can be written as

$$\frac{\partial \ln Y}{\partial \alpha} = \frac{\zeta(1-\delta)}{\left(1-(1-\delta)\alpha\right)^2} \ln \tilde{A} \quad (\times \text{a positive labor term, discussed below}),$$

so networks raise output when productivity is above its reference level ($\tilde{A} > 1$) and lower output when productivity is below it ($\tilde{A} < 1$). The mechanism is therefore structural: network intensity increases the elasticity of output with respect to *TFP deviations* from normal times, which is precisely why inherited network exposure turns expansions into fragile peaks.

4 Quantitative equilibrium analysis

4.1 Disciplining the baseline model

We calibrate the baseline model to match key moments of U.S. business cycles using annual data. The exogenous TFP process follows a two-state Markov chain with "good" and "bad" levels. Transition probabilities are chosen to replicate average expansion and recession durations (four years), while the shock levels $\{G, B\}$ match the volatility and skewness of output growth in the data.

The quantitative analysis proceeds in three steps. First, given parameters, we solve for the recursive equilibrium policy functions for network intensity, prices and output. Second, we simulate long artificial histories under the calibrated Markov process to compute ergodic moments. Lastly, we compare simulated moments to their data counterparts and update parameters until they match.

Symbol	Description	Value	Reference
Steady state			
ρ	Risk aversion	1.000	log utility
β	Discount factor	0.960	annual model frequency
δ	Depreciation rate of network	0.100	annual breaking rate $= 10\%$
σ	Elasticity of substitution	6.000	markup $\approxeq 20\%$
η	Disutility of labor	1.215	labor supply $\approxeq 0.33$
χ	Frisch elasticity of labor	4.000	Ramey (2020)
ζ	Share of network goods	0.450	weighted upstreamness $\approxeq 1.78$ (Antràs et al., 2012)
μ	Adjustment cost parameter	0.003	steady state $\alpha_{ss} \approxeq 0.6$
Aggregate fluctuation			
G	TFP value of "good time"	1.002	$\text{skewness}(\Delta \log(Y)) = -0.5527, \text{std}(\text{HP}(\log(Y))) = 0.0129$
B	TFP value of "bad time"	0.999	$\text{skewness}(\Delta \log(Y)) = -0.5527, \text{std}(\text{HP}(\log(Y))) = 0.0129$

Table 1: Value of parameters and exogenous variables

Notes: Annual calibration. Preference, technology, and adjustment-cost parameters are set to standard values or targeted moments described in the text. Good/bad TFP levels (G, B) are chosen to match the volatility and skewness of output growth.

The quantitative mechanism is driven by the predetermined nature of network intensity: α_{t+1} is chosen in period t. A high choice in a good state can carry into a bad state and amplify the contraction. This intertemporal link is what generates plucking in the simulations, regardless of the size of adjustment costs.

The parameters are summarized in Table 1, and the resulting steady-state values are in Table 2.

Symbol	Description	Value
α_{ss}	Cobb-Douglas share of network inputs	0.6000
w_{ss}	Wage	0.9219
L_{ss}	Labor	0.3315
C_{ss}	Consumption	0.3304
Y_{ss}	Output	0.3304

Table 2: Steady state endogenous variables

Notes: Implied steady-state values under the baseline calibration, computed from the closed-form equilibrium conditions in Section 2.

4.2 Solution method

The key contribution of this paper lies in the analysis of state-dependent equilibrium dynamics. Local linearization techniques are not suitable for this purpose: by construction, they approximate the policy function around a single steady state and cannot capture the sign-switching behavior that is central to our mechanism—the marginal effect of network intensity on output is positive when $A > 1$ and negative when $A < 1$. Global solution methods are therefore essential.

We adopt the Repeated Transition Method (RTM) developed by Lee (2025), which globally solves the recursive competitive equilibrium without imposing perfect foresight or relying on local approximations. The core idea is to exploit the ergodicity of the equilibrium allocations: if the economy is simulated for a sufficiently long horizon under the true stochastic process, nearly all relevant combinations of endogenous states (network intensity α) and exogenous states (productivity A) will be realized along the equilibrium path.

This property enables an accurate computation of conditional expectations directly from the simulated history. To evaluate $\mathbb{E}[V(\alpha', A') \mid \alpha, A]$, we identify all periods along the simulated path where the economy visits approximately the same endogenous state α, but experiences different subsequent realizations of the exogenous shock A'. By averaging continuation values across these periods, we obtain a nonparametric estimate of the conditional expectation that respects the global structure of the value function—including the state-dependent asymmetries that are central to our results.

4.3 Benchmark results

We simulated the calibrated model for 10,000 periods using the RTM. Figure 1 summarizes the dynamics of the benchmark model. We then fit in a linear law of motion to the simulated data to showcase the non-linearity of the model. The shaded area represents the recession periods ($A = B$).

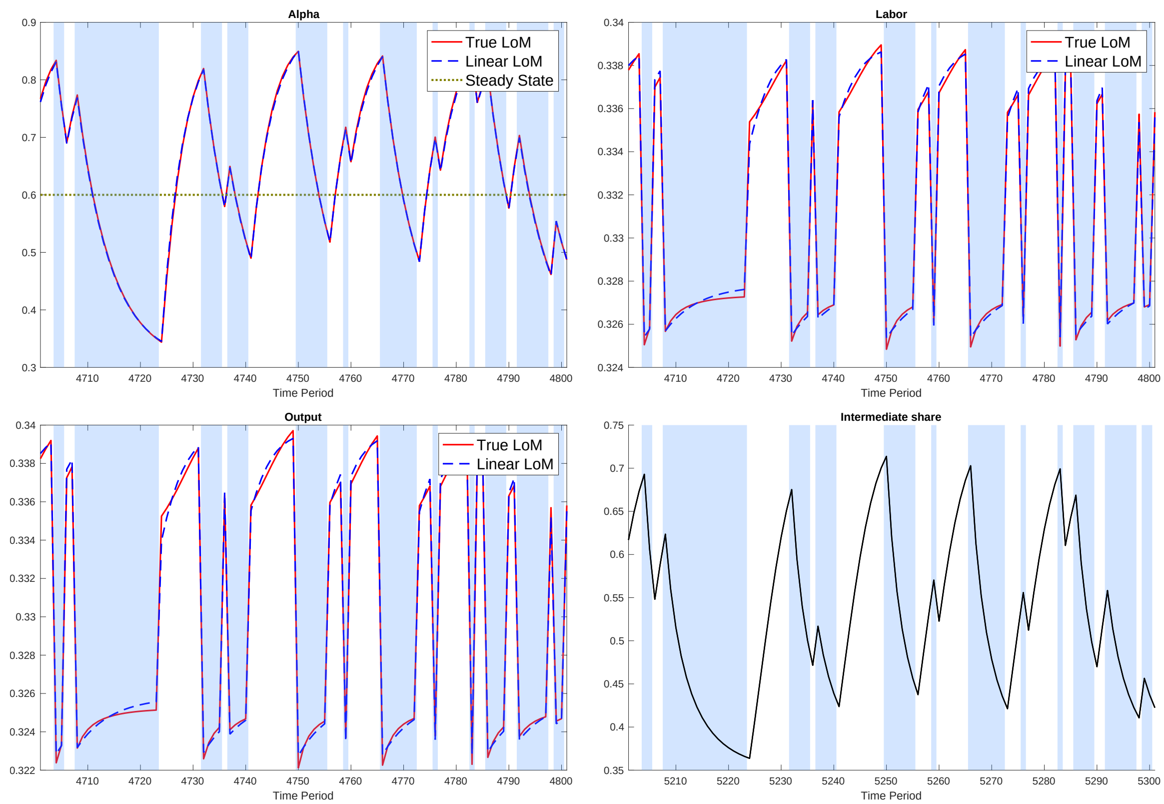


Figure 1: Simulated sequence for α_t, N_t, Y_t, and intermediate share

Notes: Simulated 10,000 periods under the baseline calibration. Panels show the joint dynamics of network intensity α_t, labor N_t, output Y_t, and the intermediate-input share. Shaded areas indicate recession regimes ($A = B$). The figure illustrates the gradual buildup of α_t in good times and the sharp contraction in Y_t and N_t when a bad TFP draw hits a high-network state.

The simulated paths display asymmetry: network intensity α builds up slowly in good times due to adjustment costs, but when a bad productivity draw arrives, the α inherited from previous good periods amplifies the drop, causing a sharp plunge in output Y, and labor N. After the initial plunge, there are three stages of slow recovery. First, during the subsequent bad periods after the initial shock, the network remains a "liability" for firms, and they optimally choose to shrink it, but due to adjustment cost this process is gradual. Second, when recession is over, and productivity recovers, the network already shrunk to a low level which limits the network amplification effect in good times, leading to a slow recovery of output. Thirdly, the gradual rebuilding of the network in high productivity times due to adjustment costs then further prolongs the recovery phase.

This contrasts with standard RBC capital: capital accumulation in booms amplifies output in good times and tends to buffer bad shocks, whereas network participation behaves like capital in booms but amplifies downturns in recessions.

Figure 2 compares the benchmark model with a partial equilibrium version where the stochastic discount factor is set to β. The comparison highlights that the SDF channel dampens fluctuations but does not overturn the plucking mechanism. In general equilibrium, the endogenous SDF partially smooths consumption and investment incentives; in partial equilibrium, fluctuations are larger. The qualitative asymmetry—sharp drops following high-network peaks—remains in both cases.

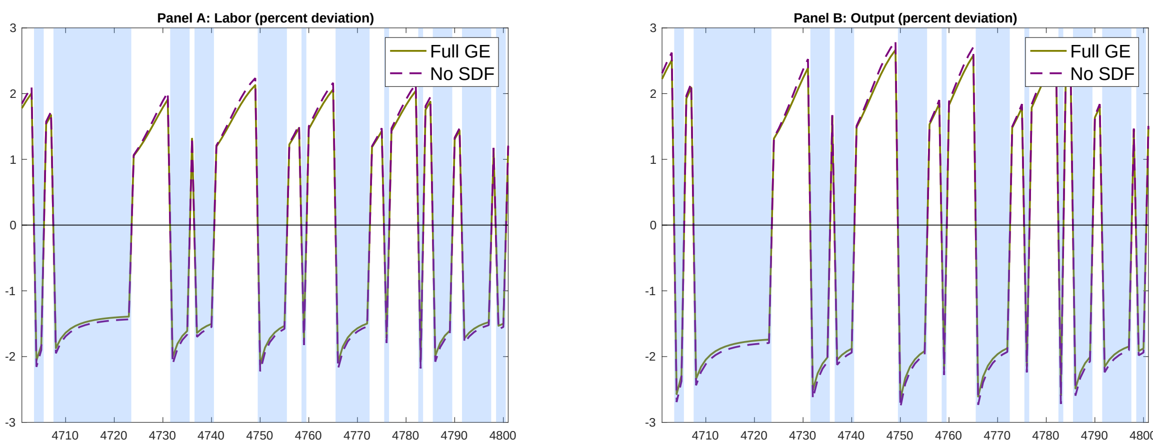


Figure 2: General equilibrium vs. partial equilibrium: SDF channel

Notes: Comparison of simulated output and labor dynamics under general equilibrium (endogenous stochastic discount factor) versus partial equilibrium (fixed $M = \beta$). The SDF channel smooths fluctuations but preserves the asymmetric response: contractions are larger when the network state is high at impact.

To further quantify the non-linearity of the model, we follow Krusell and Smith

(1998) and run the following regressions separately for the good and bad regimes:

$$
\begin{aligned}
\alpha_{t+1} &= \beta_1(A_t)\alpha_t + \beta_2(A_t) \\
\log(N_t) &= \beta_3(A_t)\alpha_t + \beta_4(A_t) \\
\log(Y_t) &= \beta_5(A_t)\alpha_t + \beta_6(A_t)
\end{aligned}
$$

This regime dependence is summarized in Table 3. Nonlinearity is observed in the slope coefficients for $\log(N_t)$ and $\log(Y_t)$, which have opposite signs in good and bad states. In contrast to Krusell and Smith (1998), where the law of motion for aggregate capital features similar coefficients across regimes, here the coefficients are not only different in magnitude but flip sign, highlighting a much stronger state dependence. This sign flip is a structural implication of the model's elasticity channel: network intensity raises the elasticity of output and wages with respect to TFP deviations, so inherited α amplifies expansions when A is above its reference level and amplifies contractions when A is below it. For $\log(N_t)$, the channel runs through wages: from Equation (6), $\partial \log w/\partial\alpha$ has the same sign as $\log A$. With GHH utility, labor supply depends on the real wage but has no wealth effect, so N_t inherits the same sign flip—higher α raises labor in good states but lowers it in bad states.

Table 3: Regime-specific Log-linear Regressions

	Regime 1 (Bad times, $A = 0.999$)			Regime 2 (Good times, $A = 1.002$)		
Variable	α_{t+1}	$\log N_t$	$\log Y_t$	α_{t+1}	$\log N_t$	$\log Y_t$
α_t	0.8533	-0.0140	-0.0175	0.7829	0.0256	0.0320
$\log A_t$	-30.5598	749.6008	753.0050	87.4842	-496.8525	-498.3741
R^2	1.0000	0.9030	0.9030	0.9995	0.9117	0.9117
Obs.	5254	5254	5254	5247	5247	5247

Notes: OLS on simulated data from the benchmark model. Regressions are run separately in bad ($A = B$) and good ($A = G$) regimes. The sign flip in the α_t coefficients for $\log N_t$ and $\log Y_t$ reflects the state-dependent amplification implied by the model.

4.4 Endogenous plucking and duration dependence

4.4.1 Simulation results for the propositions

We verify the two key Corollaries 3 and 4 using simulated paths. For each n we identify subsequences with n consecutive good states and record the output right after the first subsequent bad draw. We then plot these output against the initial network state α at the start of the good spell. The Y axis of Figure 3 plots the output level immediately after a bad shock following n consecutive good periods (i.e., $Y(g^n(\alpha, G), B)$). The X axis is the level of α at the beginning of the boom. Two patterns emerge: (i) for a fixed n, the curve is decreasing in α, confirming size dependence; (ii) as n increases, the curve shifts down, confirming duration dependence. Intuitively, longer booms allow α to drift upward, so the same bad shock induces a larger contraction. Figure 4 provides a time-domain illustration for Corollaries

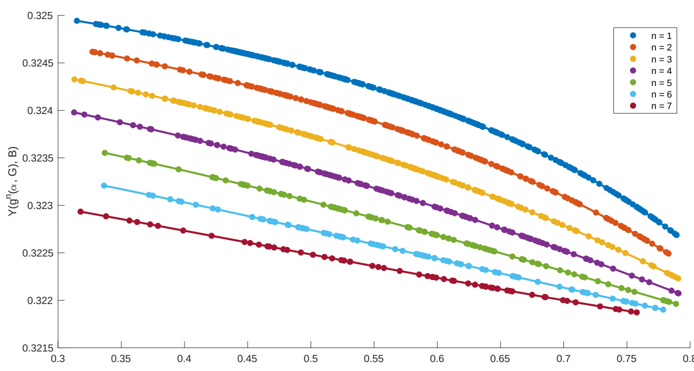


Figure 3: Corollary 3 and 4: size and duration dependence

Notes: Each curve plots the output level immediately after a bad shock following n consecutive good states, $Y(g^n(\alpha, G), B)$, against the initial network state α at the start of the good spell. Within each n, the curve slopes down (size dependence). As n rises, the curve shifts down (duration dependence), showing that longer booms generate deeper subsequent recessions.

4. We select two simulated histories that start from (almost) the same initial α but differ in the length of the preceding good spell: (i) $G \times 8$ (repeated G for 8 periods) versus (ii) $G \times 2$ (repeated G for 2 periods), and then apply the same transition to B. Plotting output deviations from steady state shows that the recession following the longer boom is visibly deeper. This isolates the duration effect: holding the initial network state essentially fixed, a longer run of good draws raises the inherited α at the onset of the bad state, leading to a larger drop. The recession drop

is larger after the longer boom (blue falls from $+2.84\%$ to -2.49%), whereas the shorter boom exhibits a smaller drop (orange falls from $+1.97\%$ to -2.00%).

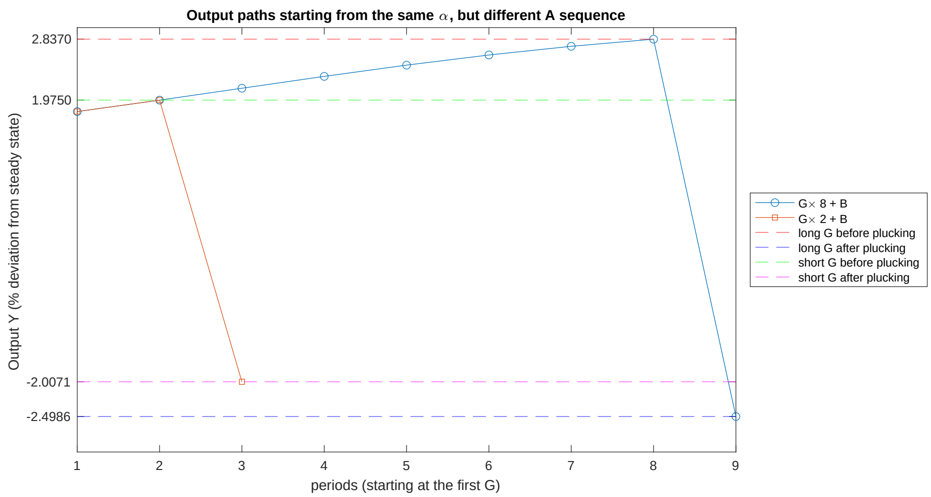


Figure 4: Corollary 4: duration dependence

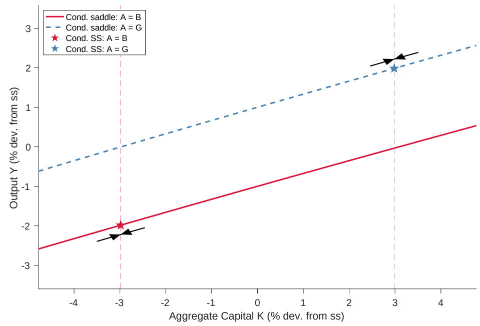
Notes: Two simulated histories start from nearly identical α but differ in boom length: $G \times 8$ versus $G \times 2$, then both switch to B. Output is plotted in deviations from steady state. The longer boom inherits a higher α and exhibits a larger drop on impact, isolating the duration channel.

4.5 Conditional saddle paths and the RBC benchmark

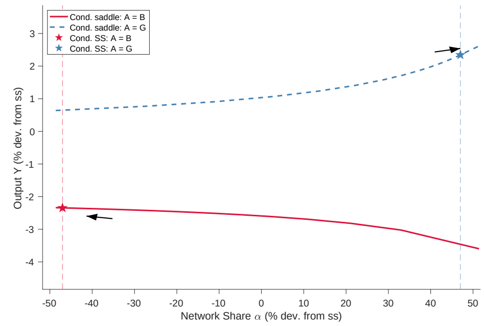
The theoretical results in Section 3 establish that network intensity builds monotonically during booms (Corollary 2) and amplifies contractions (Proposition 3). We now show that these two properties have a single geometric representation through *conditional saddle paths* (Lee, 2026).

Formally, fix $A \in \{G, B\}$ and an initial network state α_0. The *conditional saddle path* $\mathcal{M}(A; \alpha_0) := \{(\alpha_t, Y_t)\}_{t\geq 0}$ is the orbit generated by the equilibrium policy function $\alpha_{t+1} = f(\alpha_t; A)$ and the output mapping $Y_t = Y(\alpha_t, A)$ under the frozen regime A. The *conditional steady state* is its limit point $(\alpha_A^{\text{cs}}, Y_A^{\text{cs}})$. This construction recovers phase-diagram intuition familiar from deterministic models while remaining consistent with the full stochastic recursive competitive equilibrium: along any realized path, the economy moves along a conditional saddle when the regime persists and jumps across saddles when the regime switches.

Figure 5 plots conditional saddle paths for the canonical RBC and our network



(a) Canonical RBC: (K, Y)



(b) Network model: (α, Y)

Figure 5: Conditional saddle paths: RBC benchmark versus endogenous networks.

Notes: Each panel plots conditional saddle paths—the equilibrium transition loci under frozen regimes $A \in \{G, B\}$—computed from the globally solved model. Stars mark the regime-specific conditional steady states. Panel (a): canonical RBC in (K, Y) space; both loci slope upward, differing mainly by a level shift (sign-preserving state dependence). Panel (b): network economy in (α, Y) space; the G locus slopes upward while the B locus slopes downward (sign-reversing state dependence). The vertical distance between the two loci at any α equals the impact effect of a regime switch $\Delta Y(\alpha)$ defined in (22). This distance widens with α, so longer booms—which push α rightward along the G path—produce deeper contractions when the regime switches to B.

economy.[4] The comparison isolates the geometric difference between standard business cycle dynamics and endogenous plucking.

RBC benchmark: sign-preserving state dependence. Panel (a) plots the canonical RBC economy in (K, Y) space. Both conditional saddle paths slope upward: inherited capital is productive regardless of the regime, so a regime switch generates a vertical displacement without reversing the qualitative relationship between the slow-moving state and output. The two conditional saddles are approximately parallel, differing mainly in their vertical position. State dependence in the RBC model is *sign-preserving*: a bad shock reduces output by more when capital is higher, but the direction of the effect—capital supports output—is the same in both regimes.

Network economy: sign-reversing state dependence. Panel (b) plots the network economy in (α, Y) space. The geometry is fundamentally different. Under G, the conditional saddle slopes upward—higher network intensity raises output

[4]The canonical RBC model setup for Panel (a) is available in Appendix D.

during expansions. Under B, it slopes downward—inherited network intensity now amplifies contractions. This *slope reversal* means that the sign of the relationship between the inherited state and output flips across regimes: network intensity is an asset in good times but a liability in bad times.

The upward slope of the G locus is the geometric expression of the monotone network buildup established in Corollary 2: during a sustained expansion, firms gradually accumulate linkages, moving the economy rightward along the conditional saddle toward the high-α conditional steady state α_G^{cs}. The downward slope of the B locus is Proposition 3, which proved $\partial Y(\alpha, B)/\partial\alpha < 0$: conditional on bad productivity, output is strictly decreasing in inherited network exposure. The conditional saddle diagram thus provides a compact visual representation of the theoretical mechanism that Section 3 established algebraically.

Plucking as across-saddle geometry. Because α is predetermined, a regime switch from G to B at inherited state α corresponds to a *vertical jump* from the G saddle to the B saddle at the same α. The vertical distance between the two conditional saddle paths at a given α,

$$\Delta Y(\alpha) \;:=\; Y(\alpha, G) - Y(\alpha, B), \tag{22}$$

is exactly the *impact effect* of the regime switch. Because the two saddle paths diverge—one slopes up, the other down—$\Delta Y(\alpha)$ is strictly increasing in α. This is the geometric content of size dependence (Corollary 3): the impact of a negative shock scales with the pre-shock network state. Duration dependence (Corollary 4) follows immediately, since a longer boom moves α further rightward along the G saddle toward α_G^{cs}, increasing the vertical gap at the point of regime switch.

The distance between the two conditional steady states, $\alpha_G^{\text{cs}} - \alpha_B^{\text{cs}}$, measures the *range of plucking exposure*: it is the maximal rightward drift that α can undergo during a prolonged expansion before the next contraction. The wider this range, the more scope the economy has to build up fragility during long booms. In the calibrated model, this range is substantial (Figure 5, Panel (b)), consistent with the large output drops observed after extended expansions in the simulations of Section 4.4.1.

The conditional saddle diagram also provides a direct bridge to the generalized impulse response functions in Section 5: the GIRF at a given initial α is the vertical gap $\Delta Y(\alpha)$ on impact, followed by the subsequent along-the-B-saddle convergence toward $(\alpha_B^{\text{cs}}, Y_B^{\text{cs}})$. The diverging saddle paths in Panel (b) thus explain why the GIRFs fan out with the initial network state (Figure 6).

4.6 Generalized impulse response functions

We compute generalized impulse response functions (GIRFs) as follows. First, we choose a common initial state in the simulated history by selecting periods with $A = G$ and and find "low α" (e.g., the minimum of the α_t sequence), "high α" (e.g., the maximum), and "median α" within those $A = G$ periods. Second, conditional on that same initial state, we generate 5,000 stochastic TFP paths using the Markov transition matrix. Third, for each path we use the policy function backed out from the ergodic path and the simulated TFP paths to construct two trajectories that share identical future shocks: a baseline path (no intervention) and a counterfactual path that differs only by a one-time switch to $A = B$ at impact. The GIRF is the average difference between the counterfactual and baseline paths across all simulated histories. Intuitively, the GIRF isolates the causal effect of the one-time negative shock, holding fixed the initial state and the subsequent shock realizations. Figure 6 reports the response of output. The GIRFs confirm that the impact of a negative shock is larger when the economy enters the shock with a higher network state. Depending on the initial α, the same shock can imply an impact on output ranging from 3% to 6%.

5 The plucking paradox and the optimal fiscal policy

We have established that endogenous network formation generates business cycle asymmetry. A natural question follows: is this asymmetry efficient? Does the decentralized economy generate "too much" fragility?

In this section, we solve the social planner's problem. We find that because individual firms do not internalize the aggregate productivity gains from their network choices, the decentralized economy *under-invests* in networks. Consequently, the optimal policy requires subsidizing network formation, which paradoxically leads to an economy that is more volatile and prone to deeper recessions, yet yields

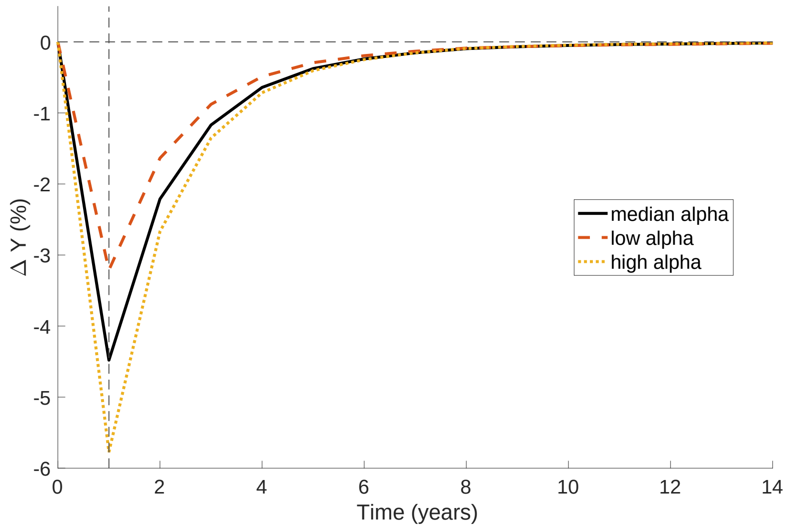


Figure 6: Generalized impulse response function (GIRF)

Notes: GIRFs are computed from 5,000 stochastic TFP paths. Initial conditions are selected from $A = G$ periods with low, median, and high α. The GIRF measures the average effect of a one-time switch to $A = B$ at impact while holding subsequent shocks fixed. Higher initial α produces a larger output decline.

higher welfare.

5.1 Planner's problem: constrained Pareto-efficiency

We consider a constrained social planner who dictates the network intensity α and labor supply n to maximize the representative household's utility. The planner is subject to the aggregate resource constraint and the economy's production technology but disregards the frictional prices arising from monopolistic competition.

The planner's recursive problem is given by:

$$V^{SP}(\alpha, A) = \max_{c,\alpha',n} \left\{ \frac{1}{1-\rho} \left(c - \eta \frac{n^{1+1/\chi}}{1+1/\chi} \right)^{1-\rho} + \beta \mathbb{E} \left[V^{SP}(\alpha', A') \mid A \right] \right\} \quad (23)$$

subject to:

$$c + \Phi(\alpha, \alpha') = Y(\alpha, A) \quad (24)$$

$$Y(\alpha, A) = \Omega \cdot A^{\Gamma(\alpha)+1} n \quad (25)$$

$$\alpha' \in [0, 1) \quad (26)$$

where $\Gamma(\alpha) \equiv \frac{\zeta}{1-(1-\delta)\alpha}$ is the aggregate network multiplier and $\Omega \equiv \frac{\sigma}{\sigma-\zeta}(\frac{\sigma}{\sigma-1})^{-\zeta}$ is a constant derived from the CES aggregation technology.

The key difference between the planner's problem and the decentralized firm's problem lies in the objective. The firm chooses α to maximize profits, treating the aggregate price index (and thus the aggregate efficiency of the network) as given. The planner, however, internalizes that a higher α reduces the cost of intermediate bundles for *all* firms, effectively acting as an aggregate productivity shifter in equation (25).

5.2 The optimal fiscal policy

We implement the efficient allocation in the decentralized economy using a state-contingent subsidy $\tau(\alpha)$ on network maintenance/creation. The following proposition characterizes the optimal wedge.

Proposition 4 (Optimal network subsidy)**.**
The Pareto-efficient allocation is decentralized by a labor tax (to correct labor supply distortions) and a network subsidy $\tau(\alpha)$ applied to the firm's adjustment costs, defined as:

$$1 + \tau(\alpha) = \underbrace{\left[\frac{\sigma - \zeta}{\sigma - 1} \left(\frac{\sigma}{\sigma - \zeta} \right)^{1+\chi} \right]}_{\textit{Static Markup Correction}} \times \underbrace{\left[\frac{1}{1 - (1-\delta)\alpha} \right]}_{\textit{Dynamic Network Externality}} \quad (27)$$

Proof. Let $\tilde{c}(X)$ denote household consumption in state X. The firm Euler in CE with a proportional tax/subsidy τ on network profits is

$$\mathbb{E}\left[\beta\frac{(\tilde{c}'(X'))^{-\rho}}{(\tilde{c}(X))^{-\rho}}\left(\pi_1(\alpha';X')(1+\tau')-\Phi_1(\alpha',\alpha'')\right)\Big|X\right]=\Phi_2(\alpha,\alpha')-\lambda_{CE}+\mu_{CE} \tag{28}$$

where

$$\pi_1(\alpha;S)=\frac{\zeta}{\sigma-\zeta}\left(\frac{\sigma-1}{\sigma}\right)^{\zeta(1+\chi)}\eta^{-\chi}A^{\left(\frac{\zeta}{1-(1-\delta)\alpha}+1\right)(1+\chi)}\log(A)\,\frac{(\sigma-1)(1-\delta)}{1-(1-\delta)\alpha}, \tag{29}$$

The social planner's euler equation is

$$\begin{aligned}\beta\mathbb{E}\Bigg[(\tilde{c}')^{-\rho}\Bigg(\left(\frac{\sigma}{\sigma-\zeta}\right)^{1+\chi}\left(\frac{\sigma-1}{\sigma}\right)^{\zeta(1+\chi)}\eta^{-\chi}(A')^{\left(\frac{\zeta}{1-(1-\delta)\alpha'}+1\right)(1+\chi)}\log(A')\,\frac{\zeta(1-\delta)}{(1-(1-\delta)\alpha')^2}\\ -\Phi_1(\alpha',\alpha'')\Bigg)\Bigg]=(\tilde{c})^{-\rho}\Phi_2(\alpha,\alpha')-\lambda_{SP}+\mu_{SP}.\end{aligned} \tag{30}$$

Equating (28) and (30) (and matching multipliers via $(\tilde{c})^{\rho}\lambda_{SP}=\lambda_{CE}$ and $(\tilde{c})^{\rho}\mu_{CE}=\mu_{SP}$) yields

$$1+\tau'=\frac{\sigma-\zeta}{\sigma-1}\left(\frac{\sigma}{\sigma-\zeta}\right)^{1+\chi}\frac{1}{1-(1-\delta)\alpha'} \tag{31}$$

The subsidy is rebated lump-sum to households, the production function remains unchanged. The tax leaves aggregate resources unchanged. ■

The markup distortion (static) The optimal policy corrects two distinct frictions. The first is the standard correction for monopolistic competition. Since firms charge a markup over marginal cost, output and input usage are inefficiently low. This term is constant and independent of the state. As $\sigma \to \infty$ (perfect competition), this term converges to 1.

The network externality (dynamic) The second term, $\frac{1}{1-(1-\delta)\alpha}$, captures the pecuniary externality unique to our model. When a firm increases its network intensity, it lowers the ideal price index of intermediate goods. This benefits other firms by lowering their marginal costs—an effect the individual firm ignores. Crucially, this term is *increasing in α*. The planner incentivizes network creation most aggressively when the network is already dense, as the marginal social value of an additional link is highest when the supply chain is complex.

5.3 The plucking paradox

The structure of the optimal subsidy yields a striking normative implication which we term the *Plucking Paradox*. Standard macro-prudential intuition suggests that policy should aim to dampen volatility and prevent deep recessions. Our model suggests the opposite. Because the planner subsidies α, the efficient economy exhibits a higher average network intensity than the decentralized economy ($\alpha^{SP} > \alpha^{DE}$).

From our theoretical results in Section 3, we know that fragility is increasing in α. Therefore, by pushing the economy toward a higher-network steady state, the planner *endogenously increases* the economy's exposure to downside risk.

Our results overturn the conventional macro-prudential wisdom that policy should always aim to dampen business cycle fluctuations. In our framework, the Pareto-efficient economy exhibits strictly deeper recessions and more negative skewness than the decentralized outcome. This is because the social planner recognizes that network fragility is the necessary price of high productivity. By aggressively subsidizing linkages, the planner pushes the economy onto a steeper efficiency frontier. While this makes the subsequent "fall" (when productivity turns) more severe, the welfare gains from the higher average level of consumption during the boom dominate the utility cost of the increased volatility. Thus, an observably "safer" economy may actually be stuck in an inefficient trap of low complexity.

5.4 Comparison of equilibria

We can interpret the hierarchy of equilibria as a progression of internalizing distortions, moving from a "safe but stagnant" economy to a "volatile but prosperous" one.

Decentralized Equilibrium (the "stunted" economy) The laissez-faire economy suffers from a double failure. First, monopolistic markups restrict the scale of production, reducing the demand for intermediate inputs. Second, and more subtly, individual firms fail to internalize the pecuniary externality: they do not see that their own network investment lowers the aggregate price index for everyone else. Consequently, firms "play it safe," maintaining low network intensities (α) that dampen both the potential highs of a boom and the potential lows of a bust. The economy is stable not because it is robust, but because it lacks the complex structure required for high efficiency.

Perfect Competition (the "partial" fix) As $\sigma \to \infty$, the static markup distortion vanishes. Firms produce more and demand more inputs, naturally driving α higher than in the monopolistic case. However, the coordination failure persists. Since perfectly competitive firms still take aggregate prices as given, they continue to ignore the dynamic benefit their network choices confer on aggregate productivity. The economy captures the static gains from trade but remains below its potential dynamic complexity.

Social Planner (the "efficiently fragile" economy) The planner actively corrects the coordination failure, using subsidies to effectively "force" the economy into a high-network state. This reveals the true trade-off: to achieve the maximum possible living standards, the economy must build a highly interconnected production structure that is inherently difficult to unwind. The planner willingly accepts the risk that a future productivity shock will wreak havoc on this complex web, because the accumulated gains from the "long boom" far exceed the costs of the eventual crash. The "safe" path of the decentralized economy is revealed to be a trap of under-development, where the fear of fragility prevents the realization of full productive potential.

6 Empirical validation

6.1 Revisiting evidence for plucking

The plucking view originates with Friedman (1964) and has been tested in a variety of time-series settings. Early empirical work uses unobserved-components models with Markov switching on U.S. macro series (Kim and Nelson, 1999). Cross-country evidence in De Simone and Clarke (2007) and Hartley (2021) suggests that plucking-style asymmetry is broadly present across countries, and particularly pronounced in advanced economies. More recent work by Dupraz, Nakamura, and Steinsson (2025) documents the plucking properties in U.S. monthly unemployment data and identifies peaks and troughs that closely align with the NBER chronology.

In this paper, we do not re-estimate the aggregate plucking property (nor target the one-sided predictability moment emphasized by Dupraz, Nakamura, and Steinsson (2025)). Instead, we use plucking-style asymmetry as motivation and turn to the model's distinctive cross-sectional implication. We focus on sectoral employment dynamics, construct a peak-to-trough "drop" measure that maps naturally to the model's state variable (network intensity), and test whether industries with higher intermediate-input intensity are more exposed to downside risk, as implied by the theory.

6.2 Evidence for plucking through the networks

This section revisits the empirical "plucking" property in the cross-industry employment dynamics of U.S. manufacturing sectors. Our goal is twofold. First, we construct a recession-severity measure at the industry level that can be directly related to our model's state variable capturing network intensity. Second, we test the central implication of the model: more network-intensive industries exhibit deeper peak-to-trough contractions.

Data We use the NBER–CES Manufacturing Industry Database, which provides annual measures of industry employment and cost components at detailed NAICS levels. The sample spans 1958–2018, with industry-year observations indexed by NAICS code and calendar year.

Identifying peaks and troughs For each industry, we extract the cyclical component of log employment using an HP filter for annual data (smoothing parameter $\lambda = 6.25$). Let $\widetilde{e}_{i,t}$ denote the HP cycle of employment for industry i in year t. We identify a local peak as a year in which the cycle satisfies $\widetilde{e}_{i,t} > \max\{\widetilde{e}_{i,t-1}, \widetilde{e}_{i,t+1}\}$, and a local trough analogously as $\widetilde{e}_{i,t} < \min\{\widetilde{e}_{i,t-1}, \widetilde{e}_{i,t+1}\}$. For each peak, we then match it to the *next* trough in the same industry to form a peak–to–trough episode.

Plucking depth Given a matched peak year $t_{i,k}^{\text{peak}}$ and subsequent trough year $t_{i,k}^{\text{trough}}$ for episode k in industry i, we define the contraction depth ("drop") as

$$\text{Drop}^{\text{emp}}{}_{i,k} \equiv \log\left(\text{emp}_{i,t_{i,k}^{\text{peak}}}\right) - \log\left(\text{emp}_{i,t_{i,k}^{\text{trough}}}\right).$$

This statistic is the industry-level counterpart of the peak-to-trough measures used in the empirical plucking literature, and it will be the main outcome variable in our network-based validation below.

We now test the central mechanism implied by the model: industries that operate with a more intermediate-input-intensive production structure are more vulnerable to downturns, exhibiting deeper peak-to-trough employment contractions. Since the NBER–CES data are not input–output matrices, we proxy network intensity using a cost-based intermediate-input measure.

Network intensity proxy: material share We construct an industry-year *material share* as

$$\text{material\_share1}_{i,t} \equiv \frac{\text{matcost}_{i,t}}{\text{vship}_{i,t}},$$

where matcost is the cost of materials and vship is the value of shipments. This proxy captures the intensity of intermediate input use in production, which is the empirical analog of the model's endogenous network/intensity state. [5]

Baseline specification We estimate the relationship between contraction depth and pre-determined network intensity using the following regression:

$$\text{Drop}^{Y}{}_{i,k} = \beta\,\text{material\_share}_{i,t_{i,k}^{\text{peak}}} + \gamma X_{i,t_{i,k}^{\text{peak}}} + \mu_i + \lambda_{t_{i,k}^{\text{peak}}} + \varepsilon_{i,k},$$

where Y is one of two outcome variables: employment (emp) or total payroll (pay). The key regressor is the material share measured at the peak year, capturing the industry's network intensity at the onset of the contraction. μ_i are industry fixed effects and $\lambda_{t^{\text{peak}}}$ are peak-year fixed effects. Standard errors are clustered at the in-

[5] We also construct an alternative measure including energy costs: $\text{material\_share2}_{i,t} \equiv \frac{\text{matcost}_{i,t}+\text{energycost}_{i,t}}{\text{vship}_{i,t}}$. Results using this alternative measure are qualitatively similar and available in the Appendix.

dustry level. The inclusion of peak-year fixed effects absorbs aggregate conditions at the onset of the contraction, so identification comes from cross-industry variation in material share within a given peak year. The control vector $X_{i,t_{i,k}^{\text{peak}}}$ includes the pre-drop industry characteristics: log capital stock or log lagged outcome, all measured at the peak year.

Results Table 4 (Panel A) reports the baseline estimates. The coefficient on material share is positive and statistically significant: industries with higher material intensity experience larger peak-to-trough employment declines. Quantitatively, the point estimate implies that an 1% increase in the material share is associated with a 0.14% deeper employment contraction during downturn episodes. This finding is consistent with the model's prediction that greater reliance on intermediate inputs—a more network-intensive production structure—amplifies the severity of recessionary adjustments. This result holds when we use total payroll as the outcome variable (columns 3–4), suggesting that the mechanism operates not only through employment adjustments but also through wage and hours changes embedded in total payroll. After including the booming duration in the regression (columns 5-6), the coefficient on material share declines and becomes less significant, suggesting that part of the effect operates through the duration channel, which is consistent with the model's mechanism (Corollary 4).

We also estimate the same set of regressions using the model generated data, as proposed in Section 2 and calibrated in Section 4. The result is displayed in Table 4 (Panel B). The coefficient on material share is positive and statistically significant, confirming that the model's mechanism generates the same cross-sectional relationship between network intensity and recession severity as observed in the data. This provides a direct validation of the model's core prediction: endogenous network formation leads to deeper contractions for more network-intensive industries during downturns.

The coefficients are also comparable in magnitude to the empirical estimates, suggesting that the model not only captures the qualitative relationship but also produces quantitatively realistic effects. This strengthens our confidence that the model's mechanism is a plausible explanation for the observed plucking-style asymmetry in sectoral employment dynamics. Similar to the empirical results where a 1% increase in material share is associated with a 0.14% deeper employment con-

Table 4: Material share and peak-to-trough drop

Drop^Y, Y=	(1) emp	(2) pay	(3) emp	(4) pay	(5) emp	(6) pay
Panel A: Data						
Material Cost Share	0.132	0.143			0.120	0.123
	(0.040)	(0.044)			(0.043)	(0.045)
Booming Duration			0.014	0.011	0.014	0.011
			(0.002)	(0.002)	(0.002)	(0.002)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Peak year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.349	0.352	0.363	0.365	0.365	0.367
N	5882	5882	5518	5518	5518	5518
Panel B: Model						
Material Cost Share	0.118	0.148			0.115	0.144
	(0.002)	(0.003)			(0.003)	(0.003)
Booming Duration			0.004	0.005	0.001	0.001
			(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.392	0.392	0.082	0.082	0.393	0.393
N	2555	2555	2554	2554	2554	2554

Notes: Dependent variable is the peak-to-trough drop in employment and payroll. Material share is measured at the peak year (pre-determined). Industry and peak-year fixed effects are included. Capital stock at the peak level is included as control; standard errors are clustered by industry. Panel A reports data estimates; Panel B reports model estimates (simulated). Standard errors in parentheses.

traction, the model estimates imply that a 1% increase in material share leads to approximately a 0.12% deeper contraction, which is remarkably close to the empirical finding.

Table 5 presents the results from the trough-level regressions. The coefficient on material share is negative and statistically significant across all specifications. This indicates that industries with higher material intensity not only experience deeper contractions but also reach lower levels of employment, total payroll at the trough. This finding further corroborates the model's mechanism: a more network-intensive production structure exacerbates the depth of downturns, lead-

Table 5: Trough level regression

$Drop^Y$, Y=	(1) emp	(2) pay	(3) emp	(4) pay	(5) emp	(6) pay
Panel A: Data						
Material Cost Share	-0.131	-0.143			-0.118	-0.122
	(0.040)	(0.044)			(0.043)	(0.046)
Booming Duration			-0.014	-0.011	-0.014	-0.011
			(0.002)	(0.002)	(0.002)	(0.002)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Peak year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.989	0.992	0.989	0.991	0.989	0.991
N	5882	5882	5518	5518	5518	5518
Panel B: Model						
Material Cost Share	-0.081	-0.101			-0.059	-0.074
	(0.003)	(0.003)			(0.003)	(0.003)
Booming Duration			-0.005	-0.006	-0.003	-0.004
			(0.000)	(0.000)	(0.000)	(0.000)
Pre-drop controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.263	0.263	0.217	0.217	0.319	0.319
N	2555	2555	2554	2554	2554	2554

Notes: Dependent variable is the log trough level in employment, payroll. Material share is measured at the peak year (pre-determined). Industry and peak-year fixed effects are included. Capital stock and outcome variable at the peak level are included as control; standard errors are clustered by industry. Panel A reports data estimates; Panel B reports model estimates (simulated). Standard errors in parentheses.

ing to more pronounced declines in key economic indicators during recessions. This is in line with the theoretical prediction in Section 3, Proposition 3.

Such a relationship is consistent with the model generated data as well, where the same regression yields a negative and significant coefficient on material share, confirming that the model's mechanism produces not only deeper contractions but also lower trough levels for more network-intensive industries. The quantitative magnitude of the coefficients in the model-generated data is also comparable to the empirical estimates, reinforcing the validity of the model in capturing the key dynamics observed in the real-world data.

7 Concluding remarks

This paper proposes a theory of endogenous plucking in which business-cycle asymmetry arises not from skewed shocks, but from the endogenous evolution of the production structure. During expansions, firms accumulate network linkages that raise productivity, yet these same linkages amplify contractions when aggregate productivity falls—generating duration dependence and negative skewness in output growth consistent with the data.

Our normative analysis uncovers a Plucking Paradox: because firms fail to internalize the dynamic network externality, the decentralized economy is, in a welfare sense, ”too safe”—featuring shallower supply chains and milder recessions, but also lower average consumption. The constrained efficient allocation entails deeper networks, higher output, and sharper downturns. Efficiency requires tolerating—and in good times, even encouraging—a particular form of structural fragility.

A natural extension is to study interactions with monetary policy. In our framework, the economy's sensitivity to shocks is not fixed but rises endogenously with the duration of an expansion as network intensity accumulates. This means the central bank faces a stabilization problem that evolves over the cycle: the same interest rate intervention has different effects depending on the inherited network state. Effective policy must therefore manage booms not only for inflation and output, but also for the evolving fragility of the production structure.

References

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2012. “The Network Origins of Aggregate Fluctuations.” *Econometrica* 80 (5):1977–2016. URL https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA9623.

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2017. “Microeconomic Origins of Macroeconomic Tail Risks.” *American Economic Re-*

view 107 (1):54–108. URL https://www.aeaweb.org/articles?id=10.1257/aer.20151086.

Antràs, Pol, Davin Chor, Thibault Fally, and Russell Hillberry. 2012. "Measuring the Upstreamness of Production and Trade Flows." *American Economic Review* 102 (3):412–16. URL https://www.aeaweb.org/articles?id=10.1257/aer.102.3.412.

Argente, David, Sara Moreira, Ezra Oberfield, and Venky Venkateswaran. 2025. "Scalable Expertise: How Standardization Drives Scale and Scope." NBER Working Papers 34160, National Bureau of Economic Research, Inc. URL https://ideas.repec.org/p/nbr/nberwo/34160.html.

Basu, Susanto. 1995. "Intermediate Goods and Business Cycles: Implications for Productivity and Welfare." *The American Economic Review* 85 (3):512–531. URL http://www.jstor.org/stable/2118185.

Bernanke, Ben S., Mark Gertler, and Simon Gilchrist. 1999. "The Financial Accelerator in a Quantitative Business Cycle Framework." In *Handbook of Macroeconomics*, vol. 1, edited by John B. Taylor and Michael Woodford. Elsevier, 1341–1393.

Bianchi, Javier. 2011. "Overborrowing and Systemic Externalities in the Business Cycle." *American Economic Review* 101 (7):3400–3426.

Capponi, Agostino, Chuan Du, and Joseph E Stiglitz. 2024. "Are Supply Networks Efficiently Resilient?" Working Paper 32221, National Bureau of Economic Research. URL http://www.nber.org/papers/w32221.

Carvalho, Vasco M, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi. 2020. "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake*." *The Quarterly Journal of Economics* 136 (2):1255–1321. URL https://doi.org/10.1093/qje/qjaa044.

De Simone, Francisco Nadal and Sean Clarke. 2007. "Asymmetry in business fluctuations: International evidence on Friedman's plucking model." *Journal of International Money and Finance* 26:64–85.

Dupraz, Stéphane, Emi Nakamura, and Jón Steinsson. 2025. "A plucking model of business cycles." *Journal of Monetary Economics* 152:103766.

Ferrari, Alessandro and Lorenzo Pesaresi. 2026. "Specialization, Complexity, and Resilience in Supply Chains." Working paper.

Friedman, Milton. 1964. "Monetary Studies of the National Bureau." In *The National Bureau Enters Its 45th Year*, 44th Annual Report. New York: National Bureau of Economic Research, 7–25.

Ghassibe, Mishel. 2021. "Endogenous Production Networks and Non-Linear Monetary Transmission." Working paper.

Ghassibe, Mishel and Anton Nakov. 2025. "Business Cycles with Pricing Cascades." Working paper.

Hall, Robert E. and Marianna Kudlyak. 2022a. "The inexorable recoveries of unemployment." *Journal of Monetary Economics* 131:15–25. URL https://www.sciencedirect.com/science/article/pii/S0304393222000939.

———. 2022b. "Why Has the US Economy Recovered So Consistently from Every Recession in the Past 70 Years?" *NBER Macroeconomics Annual* 36:1–55. URL https://doi.org/10.1086/718588.

Hartley, Jonathan S. 2021. "Friedman's plucking model: New international evidence from Maddison Project data." *Economics Letters* 199:109724.

Hyun, Jay, Ryan Kim, and Byoungchan Lee. 2024. "BUSINESS CYCLES WITH CYCLICAL RETURNS TO SCALE." *International Economic Review* 65 (1):253–282. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/iere.12656.

Kim, Chang-Jin and Charles R. Nelson. 1999. "Friedman's Plucking Model of Business Fluctuations: Tests and Estimates of Permanent and Transitory Components." *Journal of Money, Credit and Banking* 31 (3):317–334.

Kiyotaki, Nobuhiro and John Moore. 1997. "Credit Cycles." *Journal of Political Economy* 105 (2):211–248.

Kopytov, Alexandr, Bineet Mishra, Kristoffer Nimark, and Mathieu Taschereau-Dumouchel. 2024. "Endogenous Production Networks under Supply Chain Uncertainty." *Econometrica* 92 (5):1621–1659. URL https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA20629.

Kopytov, Alexandr, Mathieu Taschereau-Dumouchel, and Zebang Xu. 2025. "The Origin of Risk." Working paper.

———. 2026. "Endogenous Returns to Scale." Working paper.

Krusell, Per and Anthony A. Smith, Jr. 1998. "Income and Wealth Heterogeneity in the Macroeconomy." *Journal of Political Economy* 106 (5):867–896. URL https://www.journals.uchicago.edu/doi/10.1086/250034.

Lashkari, Danial, Arthur Bauer, and Jocelyn Boussard. 2024. "Information Technology and Returns to Scale." *American Economic Review* 114 (6):1769–1815. URL https://www.aeaweb.org/articles?id=10.1257/aer.20220522.

Lee, Hanbaek. 2025. "Global Nonlinear Solutions in Sequence Space and the Generalized Transition Function." *Working paper* .

———. 2026. "Dancing on the Saddles: A Geometric Framework for Stochastic Equilibrium Dynamics." Working paper.

Mendoza, Enrique G. 1991. "Real Business Cycles in a Small Open Economy." *American Economic Review* 81 (4):797–818.

———. 2010. "Sudden Stops, Financial Crises, and Leverage." *American Economic Review* 100 (5):1941–1966.

Ramey, Valerie A. 2020. "The Macroeconomic Consequences of Infrastructure Investment." NBER Working Paper.