Endogenous Plucking Through Networks: The Plucking Paradox*

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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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1 Introduction

Business cycles are rarely symmetric fluctuations around a 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. 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 systematic regularities across episodes (Hall and Kudlyak, 2022a,b)? 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 sensitizes aggregate output 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 first contribution demonstrates 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. Conversely, 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 is normative. 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, these linkages function as quasi-capital: once the economy reorganizes around a complex supply chain, it cannot be costlessly reversed. When productivity falls, firms desire a simpler production structure, yet adjustment frictions keep network intensity high on impact, magnifying the contraction. 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 three strands of literature. First, we contribute to the growing literature on dynamic endogenous production networks and state-dependent macroeconomic dynamics. Recent work emphasizes how endogenous network formation can generate nonlinear amplification, history dependence, and tail risks in aggregate fluctuations (Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2017; Ghassibe, 2021; Ghassibe and Nakov, 2025). 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. Moreover, unlike Ghassibe (2021); Ghassibe and Nakov (2025), which rely on nominal rigidities to generate state-dependent responses to shocks, our mechanism operates entirely on the real side with flexible prices. Network participation is a slow-moving state variable with adjustment costs, which generates history-dependent amplification even in the absence of price stickiness. 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 the plucking literature documents asymmetric recoveries and sharp downturns following prolonged expansions, it remains largely agnostic about the underlying macroeconomic mechanisms. We propose a novel real-side mechanism that generates plucking dynamics through endogenous production network formation, even in a frictionless labor market setting, contrasting with Dupraz, Nakamura, and Steinsson (2025). In our framework, expansions lead to a gradual buildup of network complexity, which increases the economy's vulnerability to negative shocks and produces endogenous plucking with strong duration dependence.

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 (e.g., (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; Capponi, Du, and Stiglitz, 2024). We propose a DSGE model that features dynamic adjustment of network structure in response to aggregate shocks, extending beyond the stationary equilibrium in Ferrari and Pesaresi (2026) and the perfect-foresight framework of Capponi, Du, and Stiglitz (2024), and highlighting the intertemporal consequences of such externalities. Our analysis highlights how internalizing this externality gives rise to a wedge between the competitive equilibrium and the constrained Pareto-efficient allocation, providing a rationale for policy intervention.

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 $B < 1 < G$.[1]

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.

[1] We assume this for the most parsimonious setup in the spirit of Krusell and Smith (1998).

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

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

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. [2] 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);*

[2]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.

- *(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.*

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.[3] 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.

[3] 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.

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.

Proposition 1 (Weak monotonicity in network size).

The policy function $g^{(1)}(\alpha; G)$ is weakly monotone increasing in α. That is, $\frac{\partial g^{(1)}}{\partial \alpha} \geq 0$.

Proof. To understand why higher current network intensity α leads to higher future investment α', consider the firm's marginal cost of investment. The firm chooses next period's network α' to equate the marginal benefit of networking to its marginal cost.

The adjustment cost function is given by:

$$\phi(\alpha', \alpha) = \frac{\mu}{2} \frac{(\alpha' - (1-\delta)\alpha)^2}{1 - (1-\delta)\alpha} \tag{19}$$

Let $I = \alpha' - (1-\delta)\alpha$ represent the net investment required to reach state α'. The marginal cost of choosing a higher α' is determined by how much "new" investment is needed.

A higher initial state α reduces the effective investment gap for any given target α', because more of the network stock is already in place. Mathematically, this lowers the marginal cost of reaching a higher target:

$$\frac{\partial^2 \phi}{\partial \alpha' \partial \alpha} < 0 \tag{20}$$

This condition implies a complementarity: having a larger existing network makes it cheaper at the margin to maintain or expand to a large network next period. Since the marginal cost of α' falls as α rises (while the marginal benefit remains unchanged), the optimal choice $g^{(1)}(\alpha; G)$ is non-decreasing in α. ■

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:

$$g(g(\alpha)) \geq g(\alpha) \tag{21}$$

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

$$g^{(2)}(\alpha; G) \geq g^{(1)}(\alpha; G) \tag{22}$$

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 monotone decreasing in α.

Proof. The output function is given by $Y(X) = A^{\frac{\zeta}{1-(1-\delta)\alpha}+1}L$. Taking the log of output:

$$\ln Y = \left(\frac{\zeta}{1-(1-\delta)\alpha} + 1\right)\ln A + \ln L \tag{23}$$

Differentiating with respect to α:

$$\frac{\partial \ln Y}{\partial \alpha} = \frac{\zeta(1-\delta)}{(1-(1-\delta)\alpha)^2}\ln A \tag{24}$$

Since $\zeta, \delta, \alpha \in (0,1)$ implies the fraction is strictly positive, the sign of the derivative depends strictly on $\ln A$. $B < 1$, which implies $\ln B < 0$. Therefore:

$$\frac{\partial Y(\alpha, B)}{\partial \alpha} < 0 \tag{25}$$

Thus, higher network intensity strictly amplifies the output loss when $A = B$. ∎

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.

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 $n \in \{2, 3, \ldots\}$.

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:

$$Y(\alpha_n, B) \leq Y(\alpha_{n-1}, B) \tag{26}$$

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.

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	Chetty et al. (2011)
ζ	Share of network goods	0.450	weighted upstreamness $\approxeq$ 1.78 (Antras 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

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

4.2 Benchmark results

We simulated the calibrated model for 10,000 periods using the repeated transition method developed by Lee (2025). 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 ($A = B$).

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.

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

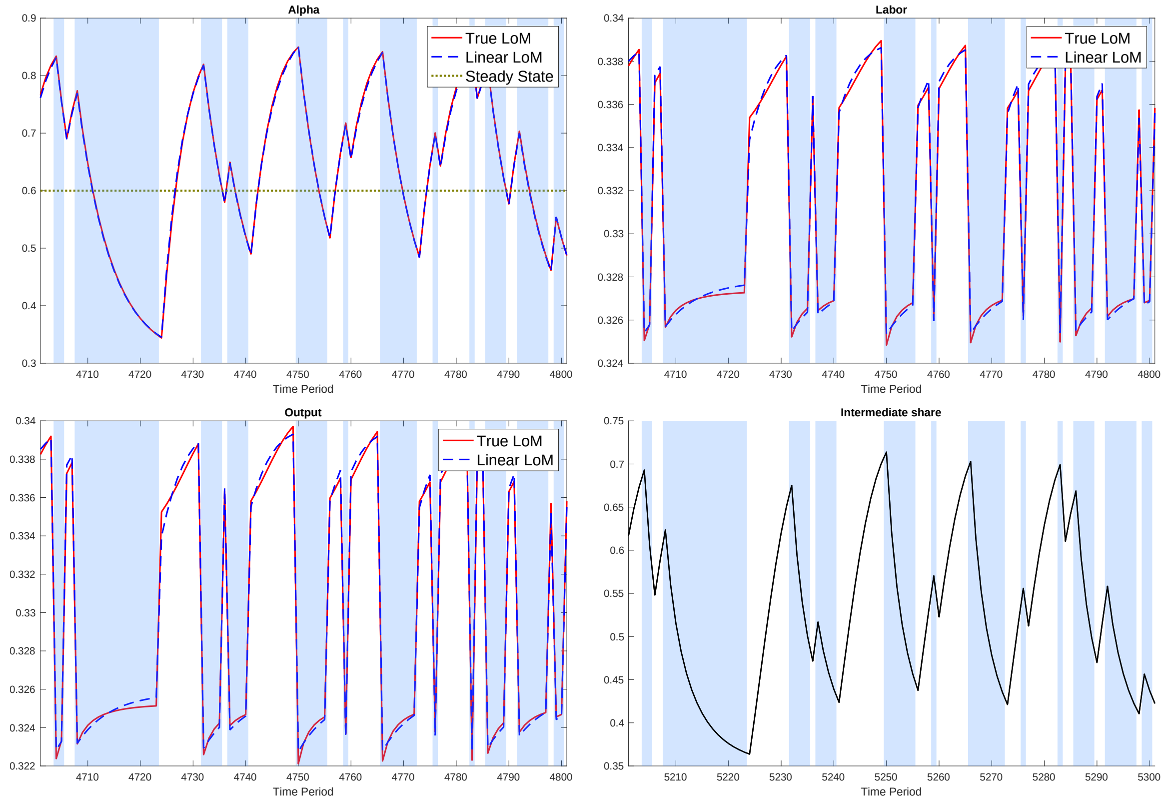

Figure 1: Simulated sequence for α_t, N_t, Y_t, and intermediate share

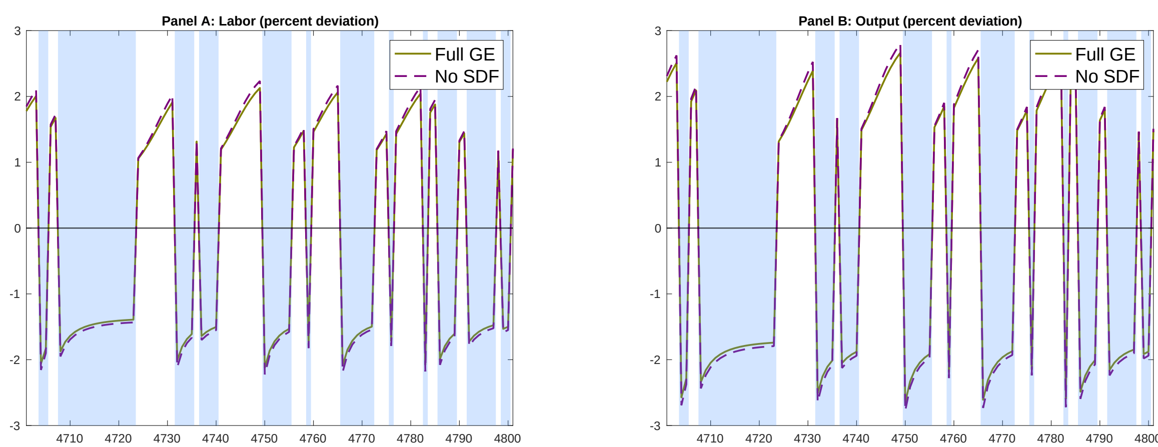

Figure 2: General equilibrium vs. partial equilibrium: SDF channel

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 mechanical in the model: $\partial \log Y/\partial\alpha$ has the same sign as $\log A$, so the marginal effect of α on output is positive when $A = G > 1$ and negative when $A = B < 1$. 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, $A = 0.9985$)			Regime 2 (Good times, $A = 1.0022$)		
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

4.3 Endogenous plucking and duration dependence

4.3.1 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.

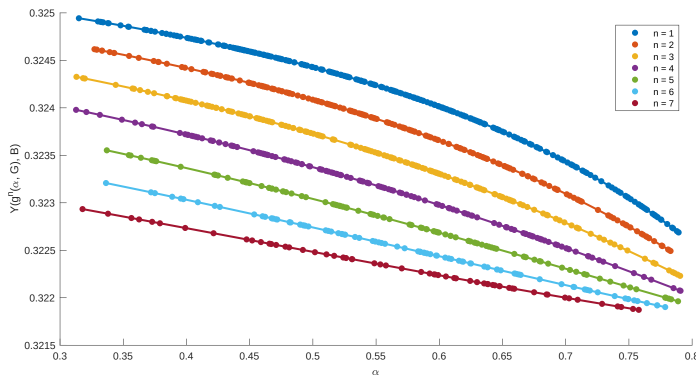

Figure 3: Corollary 3 and 4: size and duration dependence

Figure 4 provides a time-domain illustration for Corollaries 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%).

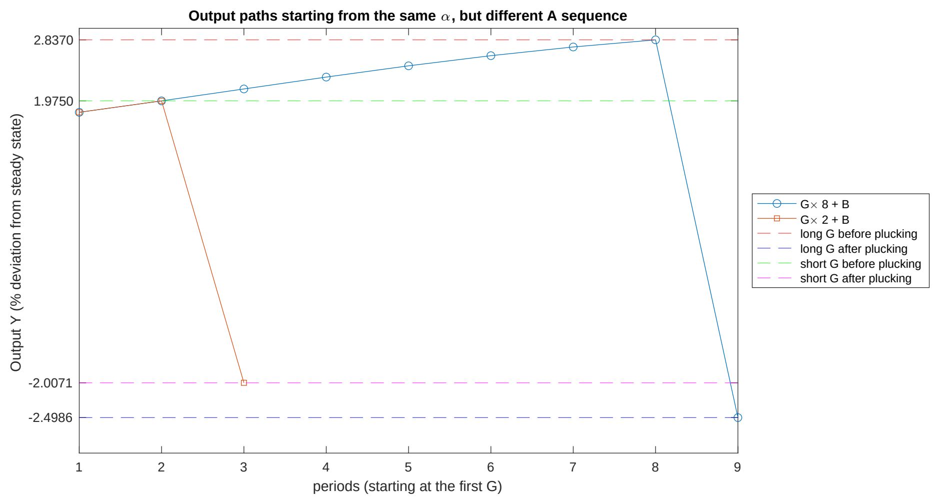

Figure 4: Corollary 4: duration dependence

4.4 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 (Lee, 2025). Intuitively, the GIRF isolates the causal effect of the one-time negative shock, holding fixed the initial state and the subsequent shock realizations. Figure 5 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 a impact on output ranging from 3% to 6%.

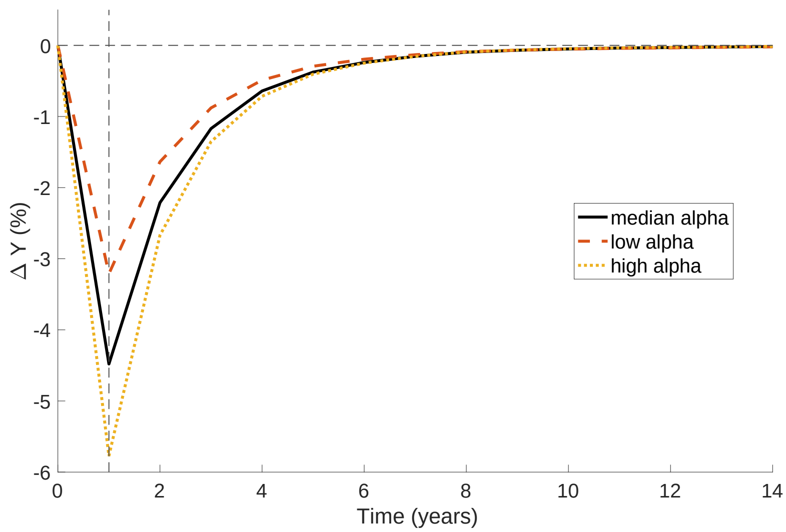

Figure 5: Generalized impulse response function (GIRF)

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 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:

$$V^{SP}(\alpha, A) = \max_{c,\alpha',n} \left\{ \frac{1}{1-\rho} \left(c - \eta \frac{n^{1+1/\chi}}{1+1/\chi} \right)^{1-\rho} + \beta \mathbb{E} \left[V^{SP}(\alpha', A') \mid A \right] \right\} \quad (27)$$

subject to:

$$c + \Phi(\alpha, \alpha') = Y(\alpha, A) \quad (28)$$

$$Y(\alpha, A) = \Omega \cdot A^{\Gamma(\alpha)+1} n \quad (29)$$

$$\alpha' \in [0, 1) \quad (30)$$

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 (29).

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:

$$1 + \tau(\alpha) = \underbrace{\left[\frac{\sigma - \zeta}{\sigma - 1}\left(\frac{\sigma}{\sigma - \zeta}\right)^{1+\chi}\right]}_{\textit{Static Markup Correction}} \times \underbrace{\left[\frac{1}{1 - (1 - \delta)\alpha}\right]}_{\textit{Dynamic Network Externality}} \tag{31}$$

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

$$\mathbb{E}\left[\beta \frac{(\tilde{c}'(X'))^{-\rho}}{(\tilde{c}(X))^{-\rho}} \left(\pi_1(\alpha'; X')(1 + \tau') - \Phi_1(\alpha', \alpha'')\right) \middle| X\right] = \Phi_2(\alpha, \alpha') - \lambda_{CE} + \mu_{CE} \tag{32}$$

where

$$\pi_1(\alpha; S) = \frac{\zeta}{\sigma - \zeta}\left(\frac{\sigma - 1}{\sigma}\right)^{\zeta(1+\chi)} \eta^{-\chi} A^{\left(\frac{\zeta}{1-(1-\delta)\alpha}+1\right)(1+\chi)} \log(A) \frac{(\sigma - 1)(1 - \delta)}{1 - (1 - \delta)\alpha}, \tag{33}$$

The social planner's euler equation is

$$\begin{aligned} &\beta\mathbb{E}\left[(\tilde{c}')^{-\rho}\left(\left(\frac{\sigma}{\sigma - \zeta}\right)^{1+\chi}\left(\frac{\sigma - 1}{\sigma}\right)^{\zeta(1+\chi)} \eta^{-\chi}(A')^{\left(\frac{\zeta}{1-(1-\delta)\alpha'}+1\right)(1+\chi)} \log(A') \frac{\zeta(1 - \delta)}{(1 - (1 - \delta)\alpha')^2}\right.\right. \\ &\left.\left. - \Phi_1(\alpha', \alpha'')\right)\right] = (\tilde{c})^{-\rho}\Phi_2(\alpha, \alpha') - \lambda_{SP} + \mu_{SP}. \end{aligned} \tag{34}$$

Equating (32) and (34) (and matching multipliers via $(\tilde{c})^{\rho}\lambda_{SP} = \lambda_{CE}$ and $(\tilde{c})^{\rho}\mu_{CE} =$

μ_{SP}) yields

$$1 + \tau' = \frac{\sigma - \zeta}{\sigma - 1} \left(\frac{\sigma}{\sigma - \zeta} \right)^{1+\chi} \frac{1}{1 - (1 - \delta)\alpha'} \tag{35}$$

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. One of the early empirical tests of the plucking model using unobserved-components with Markov-switching models on U.S. macro series (Kim and Nelson, 1999). Cross-country evidence from De Simone and Clarke (2007) and Hartley (2021) suggests that the plucking property is broadly evident across time and countries and particularly strong in advanced economies in East Asia (Japan), Europe (Western Europe) and North America (US and Canada) while to a lesser extent elsewhere in emerging economies. More recent work by Dupraz, Nakamura, and Steinsson (2025) demonstrated the plucking properties in US monthly u-rate data, and identified peaks and troughs that matches the result from National Bureau of Economic Research.

In this paper, we do not re-estimate the aggregate plucking property. Instead, we take the empirical regularity as a starting point and focus on sectoral employment dynamics to construct a peak-to-trough "drop" measure that maps directly to the model's state variable (network intensity). This allows us to 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 $t^{\text{peak}}_{i,k}$ and subsequent trough year $t^{\text{trough}}_{i,k}$ for episode k in industry i, we define the contraction depth ("drop") as

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

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. [4]

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

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

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 industry 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 $X_{i,t^{\text{peak}}_{i,k}}$ includes the pre-drop industry characteristics: log capital stock and log gross output, all measured at the peak year.

[4] 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.

We then estimate the following trough-level regression to further validate the mechanism:

$$\log(Y_{\text{trough}})_{i,k} = \beta \, \text{material\_share}_{i,t_{i,k}^{\text{peak}}} + \gamma X_{i,t_{i,k}^{\text{peak}}} + \mu_i + \lambda_{t_{i,k}^{\text{peak}}} + \varepsilon_{i,k},$$

where Y is again one of the two outcome variables: employment (emp) or total payroll (pay). This specification tests whether industries with higher material shares end up at lower levels of activity at the trough, consistent with the model's prediction that higher network intensity amplifies recession severity, which is proved in Section 3 (Corollary 3 and 4).

Results Table 4 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).

Table 5 presents the results from the trough-level regressions. The coefficient

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

	(1)	(2)	(3)	(4)	(5)	(6)
Drop^{Y}, Y=	emp	pay	emp	pay	emp	pay
matshare1	0.138***	0.148**			0.125**	0.129**
	(0.040)	(0.045)			(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
Pre-drop controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.349	0.352	0.363	0.366	0.366	0.368
N	5882	5882	5518	5518	5518	5518

Standard errors in parentheses

Pre-drop controls: log(peak_capital_stock), log(peak_vship)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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

Table 5: Trough level regression

	(7)	(8)	(9)	(10)	(11)	(12)
log(Y_trough), Y=	emp	pay	emp	pay	emp	pay
matshare1	-0.751***	-0.877***			-0.655***	-0.785***
	(0.176)	(0.136)			(0.170)	(0.134)
booming_duration			-0.010**	-0.009**	-0.010**	-0.009**
			(0.003)	(0.003)	(0.003)	(0.003)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Peak year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pre-drop controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.964	0.981	0.964	0.979	0.965	0.980
N	5882	5882	5518	5518	5518	5518

Clustered standard errors in parentheses

Pre-drop controls: log(peak_capital_stock), log(peak_vship)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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. We show that the pursuit of efficiency is the architect of its own fragility: during expansions, firms accumulate complex network linkages that raise productivity, yet become a "golden set of handcuffs" when conditions deteriorate. The resulting buildup in network intensity makes downturns disproportionately severe after long booms, generating duration dependence and negative skewness in output growth consistent with the data, and providing a microfounded explanation for why deep recessions so often follow prolonged tranquility.

Our normative analysis uncovers a *Plucking Paradox* that challenges a narrow interpretation of stabilization policy. Because firms fail to internalize the dynamic network externality, the decentralized economy chooses a path that is, in a welfare sense, "too safe": it features shallower supply chains and lower average consumption, but also milder recessions. By contrast, the constrained efficient allocation entails deeper production networks, higher average output and consumption, and, crucially, sharper downturns when negative shocks arrive. A policy agenda focused solely on minimizing volatility can therefore inadvertently lock the economy into an inefficiently low-complexity production structure. In this environment, efficiency requires tolerating—and in good times, even encouraging—a particular form of structural fragility.

More broadly, our framework reframes the resilience–efficiency trade-off as an *intertemporal* and *state-contingent* policy problem. A natural next step is to study interactions with monetary policy. If the economy's shock sensitivity rises endogenously with the duration of an expansion, then the central bank is not stabilizing around a fixed Phillips curve or a fixed transmission mechanism: its actions shape the future state by influencing the accumulation of network intensity. This suggests that the relevant stabilization problem is two-dimensional: mitigating contemporaneous downturns *and* leaning against (or deliberately accommodating) the buildup of endogenous "structural leverage" embedded in production networks. In such a world, recession severity is partly a consequence of preceding success, and effective policy must manage booms not only for inflation and output, but also for the evolving fragility of the production structure.

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