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Keywords: Innovation, Financial Market Effectiveness, Endogenous Growth, Total Factor Productivity

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Abstract

Innovativity—an economy's ability to produce the innovations that drive total factor productivity (TFP) growth—requires both ideas and the ability to process those ideas into new products and/or techniques. We model innovativity as a function of endogenous idea processing capacity subject to an exogenous idea supply constraint and derive an empirical measure of innovativity that is independent of the TFP data itself. Using exogenous shocks and theoretical restrictions, we establish that: i) innovativity predicts the evolution of average TFP growth; ii) idea processing capacity is the binding constraint on innovativity; and iii) average TFP growth declined after 1970 due to a constraints on idea processing capacity, not idea supply.

Keywords: Innovation, Financial Market Effectiveness, Endogenous Growth, Total Factor Productivity

The innovations that drive economic growth require both an inventor who creates an idea and an entrepreneur who processes that idea into a new product and/or technique (Schumpeter 1947). Yet, the extensive literature on endogenous growth theory sparked by Romer (1986, 1990), Lucas (1988), Aghion and Howitt (1992), and Jones (1995) focuses overwhelmingly upon idea supply and essentially ignores idea processing all together. The exception to this consensus is Weitzman (1998), who conjectures that "the ultimate limits to growth lie not so much in our ability to generate new ideas as in our ability to process an abundance of potentially new ideas into usable form". In this paper we advance this debate by developing a theory of *innovativity*—where by innovativity we mean an economy's ability to produce the innovations that drive TFP growth—in which both idea supply and idea processing capacity play a central role. We then use this theory to identify the binding constraint on the TFP growth process in the US over the 1899/2019 period.

We posit that: i) innovativity is equal to the minimum of exogenous idea supply and endogenous idea processing capacity; and ii) the TFP growth process is a function of innovativity. We solve for equilibrium innovativity and derive a method to identify innovtivity regimes (periods of constant innovativity) that is independent of the TFP data itself. Exploiting exogenous shocks to idea supply and idea processing capacity together with restrictions imposed by our theory, we establish that: i) innovativity predicts the evolution of average US TFP growth over the last 120 years; ii) idea processing capacity (rather than idea supply) is the binding constraint on innovativity; and iii) contrary to the highly influential Gordon (2012, 2014) hypothesis, the post-1970 decline in US TFP growth is due to constraints on idea processing capacity rather than idea supply.[1] While our analysis here is exploratory, our results suggest that Weitzman's conjecture is plausibly correct and hence that the role of idea processing in economic growth merits further investigation.[2]

In our analysis of innovativity, we treat idea supply as a simple exogenous (but possibly time-varying) constraint that is either binding or not binding. We believe that this approach captures the key operational difference between the endogenous growth theory (EGT) consensus and Weitzman (1998)

[1]See also Cowen (2011) and Bloom, Jones, Van Reenan, and Webb (2020).

[2]For example, Weitzman (1998) is not cited in either Acemoglu (2009) or Jones and Vollrath (2013), the leading graduate and undergraduate textbooks on economic growth.

in a tractable reduced form fashion.

We contribute to EGT by endogenizing idea processing capacity. We begin with the premise that the economy's idea processing capacity is determined by the strategies that profit-maximizing entrepreneurs (or firms) choose to develop their projects (Arora, Belenzon, Patacconi, and Suh 2019).

A project is a success and produces a payoff if its unobservable type is *Good* and if the firm attracts a specific investment by an outside party. The probability that a firm attracts that specific investment increases with the market's estimate of the probability that it has a *Good* project, and the accuracy of that market estimate is a function of the firm's choice of strategy and financial market effectiveness.[3]

An entrepreneur can influence the expected value of their project by pursuing either: i) a short horizon *Quick Win* (Q) strategy that produces a stronger intermediate signal of project quality and so increases the probability of success; or ii) a longer horizon *Innovation* (I) strategy that increases project payoff given success by taking an idea and processing that idea into a value increasing innovation. The economy's idea processing capacity is then equal to the proportion of firms that would choose an I strategy assuming that there is an idea available, and innovativity (Φ) is equal to the proportion that do choose an I strategy given the idea supply constraint. As market effectiveness increases, the relative advantage of the signaling focused Q strategy falls. Consequently, the proportion of firms that prefer the I strategy—and so idea processing capacity—increases with market effectiveness.

Q firms produce more precise signals of project type than I firms, and these signals affect firm price by influencing the probability of success. It follows that the return distribution of Q firms has a higher standard deviation than the return distribution of I firms. Consequently, the standard deviation of the firm return distribution is a function of the ratio of I to Q firms and so innovativity. This relationship implies that we can use the variable Δ, with Δ equal one minus the standard deviation of idiosyncratic firm returns, to track the evolution of innovativity. In particular, we show that Δ enables us to identify innovativity regimes.

[3]Simon (1989) and Pirrong (1995) show that financial regulation can improve market effectiveness (in the sense that we are using that term here) by improving the credibility of firm financial reporting and by reducing market manipulation. Choi, Choi, and Malik (2020) find that job seekers use firm financial information in their job searches, and Brogaard, Ringgenberg, and Sovich (2019) find that more accurate prices enable market participants to improve their productive decisions.

Using a sample of NYSE listed firms from 1850 to 2019, we identify three innovativity regimes: i) a *PreWar* regime of 1850/1941; ii) a *Peak* regime of 1946/1969; and iii) a *Post80* regime of 1980/2019. Relative to the *Low* state of average TFP growth in the *PreWar* regime, our analyisis predicts that average TFP growth will be in the *High* state in the *Peak* regime of 1951/1969 and will return to the *Low* state in the *Post80* regime. While this rise and fall pattern of average TFP growth is of course well known in an empirical sense, our innovativity approach enables us to predict this pattern—including the regime transition dates—without reference to the TFP data itself.

We find that innovativity is constant between 1850 and 1939 despite the material exogenous shock to idea supply between 1870 and 1900 that is the Second Industrial Revolution (Gordon 2012). Obviously, if a constraint shifts up and the equilibrium does not change as a result, then that constraint is not binding. It follows that idea processing capacity and not idea supply is the binding constraint on innovativity in the *PreWar* regime. If idea processing capacity is the binding constraint, then an upward shift in that constraint will lead to an increase in innovativity. The financial market reform effort of the 1930s/1940s improved financial market effectiveness and so did lead to such a shift[4] And, as this analysis predicts, innovativity does increase to the *High* state in the *Peak* regime of 1946/1969. Our analysis suggests that the efficacy of the 1930s/1940s security market reforms gradually eroded in the 1970s, leading to a decline in idea processing capacity and so to a decline in innovativity. This low level of innovativity has resulted in the low average TFP growth performance of the US economy since 1980.[5]

Our analysis therefore suggests that the US is now in a *Low* innovativity regime because ineffective financial markets are adversely affecting the economy's idea processing capacity rather than because ideas are inevitably getting harder to find. Since policy reforms in the past have produced significant improvements in financial market effectiveness, policy initiatives aimed at increasing the economy's idea processing capacity offer a promising (and low cost) avenue of attack on the critical problem of low

[4]See Seligman (2003) for a history of securities market regulation. Field (2022) shows that this increase was not due to WW2.

[5]Market effectiveness is not the same thing as price informativeness (Bai, Philippon, and Savov 2015). Price informativeness is an endogenous variable that is a function of market effectiveness and the strategies that firms choose given market effectiveness. Our analysis predicts that price informativeness will increase as market effectiveness declines because firms shift from long horizon I strategies to short horizon Q strategies.

innovativity.[6]

Strategies and Idea Processing

Our analysis rests upon two building blocks: i) firms pursue either a Q or an I strategy; and ii) an I strategy creates the capacity to process an idea and produce an innovation. While both of these building blocks are of course abstractions, we believe that they capture key aspects of the innovation process.

Bhattacharya and Packalen (2020) provide a particularly clear illustration of the Q/I distinction in the context of innovation in science. As do the firms in our model, scientists wish to innovate but also need to attract a specific investment by an outside party in order to succeed (a faculty position, grants, etc.). To attract this investment, they must signal their quality. Bhattacharya and Packalen (2020) find that (to use our terminology) scientists choose between a Q strategy that focuses upon signaling by pursuing less innovative/incremental science with more immediate and certain results and a higher risk/longer horizon I strategy that aims at producing scientific innovations. They show that the Q strategy has recently come to predominate, and that this change has created an equilibrium in which "science stagnated". Similarly, we find that as firms switch from an I to a Q strategy, innovativity stagnates.

Arora, Belenzon, and Patacconi (2015) and Arora, Belenzon, Patacconi, and Suh (2019) examine scientific idea processing. Arora et al. (2019) argue that while university research does increase idea supply, "university research [requires] additional integration and transformation to become economically useful". Creating a fundamental innovation entails putting into place the capacity to take an idea and "access significant resources...integrate multiple knowledge streams...and direct their research toward solving specific practical problems". Or, as we would put it, idea processing requires an I strategy.

Thus, we think that the strategic choices that firms make and the impact of those choices on the economy's idea processing capacity do matter for innovativity and TFP growth.

Innovativity and Endogenous Growth Theory

As Bloom et al. (2020) observe, the unifying thread of the various strands of EGT developed by Romer (1986, 1990), Lucas (1988), Aghion and Howitt (1992), and Jones (1995) is that "economic growth

[6] As in Acemoglu, Moscona, and Robinson (2016), then, we too find that "the institutional environment has a key impact on technological progress".

arises from people creating ideas". Our analysis suggests that innovativity rather than idea supply alone drives TFP growth, and innovativity is determined by idea processing capacity as well as idea supply.[7] We owe the idea of idea processing to Weitzman (1998), and our modeling strategy for innovativity (with the Q and I sectors) is inspired by Lucas's (1988) two-sector growth model. In this initial effort to explore the role of idea processing capacity in productivity growth building upon the ideas of Schumpeter and Weitzman, we are aware that we abstract away from important features of the growth process that EGT has illuminated. We plan to incorporate more of the insights of EGT in future work.

While financial markets do not play a central role in many strands of EGT, the Schumpeterian strand developed by Aghion and Howitt (2006, 2008) on the theoretical side and King and Levine (1993) on the empirical side is an exception.[8] This literature focuses upon the role of financial markets in ameliorating credit constraints, which is not the aspect of the financial system that we think drives idea processing capacity. Following from this credit constraint focus, empirical research related to this strand of the literature examines the relationship between measures of financial system capacity such as Private Sector Credit/GDP (King and Levine 1993) or financial market development (Kim and Loayza 2019) and growth. These financial market capacity measures have generally been increasing in the US over our sample period and so cannot explain either the Low/High/Low pattern of US innovativity or the timing of the regime switches.[9] So, we think that our innovativity framework offers a more fruitful method of integrating financial markets into a growth model (at least for an economy on the innovation frontier).

In the remainder of this paper, we first derive the equilibrium level of innovativity (Φ) and then discuss our identification strategy. We next: i) identify innovativity regimes; ii) analyze the evolution of innovativity; and iii) identify the binding constraint on innovativity. Concluding remarks follow.

[7] One implication of this framework is that the TFP growth process is a function of innovativity rather than of idea supply directly. Consequently, factors affecting idea supply such as R&D spending and education (etc.) affect the TFP growth process only through their impact upon equilibrium innovativity. It follows that analyses that do attempt to measure the direct impact of idea supply factors upon the TFP growth process may be misspecified.

[8] See Aghion, Howitt and Levine (2018) and Popov (2018) for recent surveys.

[9] We note that this literature focuses upon explaining cross-country patterns in TFP growth (which we do not explore) rather than on the time-series variation of TFP growth within countries.

I. Ideas, Idea Processing, and Innovativity

We posit that the long run average rate of TFP growth $\bar{\gamma}$ is function of innovativity Φ, with

$$\frac{\partial \bar{\gamma}}{\partial \Phi} > 0. \tag{1}$$

We define innovativity as the proportion of firms that produce innovations. We assume that: i) a firm produces an innovation by taking an available idea and processing it; and ii) only firms that choose an I strategy can process ideas. We denote the proportion of firms that can choose an idea if they wish by η_S (the idea supply constraint) and the proportion of firms that would choose an I strategy assuming that there is an idea to choose by η_ρ (the idea processing constraint). In each period T, then,

$$\Phi_T = \text{Min}\left[\eta_{S,T}, \eta_{\rho,T}\left[M_T\right]\right]. \tag{2}$$

We treat idea supply as exogenous and idea processing capacity as a function of financial market effectiveness M.

After setting out the assumptions of our model, we derive η_ρ and Φ.

A. Set-Up and Assumptions

We analyze innovativity in the context of a model consisting of entrepreneurs, investors, and workers. In each period T, $T = \{1, \ldots, \infty\}$, a continuum of mass one of ex ante identical risk-neutral and profit-maximizing entrepreneurs enter the market. Each entrepreneur Z creates a single share firm consisting of a base project β_Z and chooses a strategy ψ, $\psi \in \{Q, I\}$, to develop their project in the way that maximizes its IPO price $P_{IPO,\psi,Z}$ (this will be equivalent to maximizing the project's expected value.) Entrepreneurs then sell their one share to investors in an IPO, and shares later trade in the secondary market. In order for the project to produce revenue the firm must be a commercial success, and to be a commercial success the firm must attract a worker who makes a specific investment.[10]

[10] Investors and workers enter the model in a very reduced form fashion: investors buy IPO shares and trade shares in the secondary market at the market price, and workers do or do not make a specific investment.

Since each entrepreneur is ex ante identical, all random variable realizations are iid, and each period is independent, we will generally drop the T and Z subscripts unless needed for clarity.

Each period T consists of 6 phases t_1 to t_6, as follows:

- t_1 — Project Creation: Each entrepreneur chooses a base project β_Z from a pool of projects. Each project is of an unobservable type τ^*, with $\tau \in \left\{Good(G), Bad(B)\right\}$ (an "*" indicates a specific value of a parameter or a realization of a random variable). A project in the pool is of type G (B) with probability 1/2, and each project comes endowed with one signal of project type $\kappa 1 [\beta]$, with $\kappa \in \{g, b\}$. An entrepreneur selects a project with a g signal;

- t_2 — Strategy Choice: Each entrepreneur learns the observable value that an innovation will create for their project (α) and chooses an observable strategy ψ, $\psi \in \{Q, I\}$ to develop it (with the proportion that can pursue I subject to the idea supply constraint);

- t_3 — Due Diligence and IPO: The market verifies $\kappa 1$ and α (if the firm chooses I), and firms sell their one share at $P_{IPO:\psi}$;

- t_4 — Secondary Market (SM): An project produces signal $\kappa 2 [\psi]$ of project type, with the precision of the signal depending upon the firm's strategy. An I project also produces an innovation. The firm's price adjusts from $P_{IPO:\psi}$ to $P_{SM:\psi,\kappa 2}$;

- t_5 — Specific Investment: The firm hires a worker of unobservable type W, with $W \in \{Y, \neg Y\}$. Only a Y worker makes a specific investment, and that specific investment is unobservable and non-contractable;

- t_6 — Revenue: The firm produces revenue of π_ψ if it is a commercial success; a firm is a commercial success if it has a G project and if it hires a Y worker. If the firm is not a commercial success, it produces a revenue of 0. The firm then winds up.

An entrepreneur chooses ψ to maximize the IPO price of their firm. Consequently,

$$\psi^* = \psi : P_{IPO:\psi} = \text{Max}\left[P_{IPO:Q}, P_{IPO:I}\right]. \tag{3}$$

The investors to whom entrepreneurs sell IPO shares and whom trade shares in the secondary market are risk neutral and do not discount future revenue. It follows that

$$P_{j:\iota} = \Pi_{j:\iota}, \tag{4}$$

where $P_{j:\iota}$ is the firm's price in phase j given market information ι and $\Pi_{j:\iota}$ is the firm's expected revenue evaluated in j conditional upon ι. Hence, entrepreneurs choose ψ to maximize expected project revenue.

When choosing ψ, an entrepreneur begins with a base project β of unobservable type τ^*. A β project is endowed with a signal $\kappa 1$ of its type in the project creation phase (t_1) which is verified at the IPO phase. The precision of a base project signal is a function of market effectiveness M, with

$$\kappa 1 \left[\beta\right] = \begin{cases} \tau^* & \text{w.p.} \quad M, \\ \neg\tau^* & \text{w.p.} \quad 1 - M, \end{cases} \tag{5}$$

with $0.76 < M \leq 1$.[11] A β project produces $\pi_\beta = 1$ if it is a commercial success.

In t_2 the entrepreneur chooses a strategy ψ to develop the β project in a way that maximizes the firm's expected revenue and so its IPO price. The entrepreneur can increase project revenue by either: i) choosing an I strategy that produces additional revenue α if the project is a commercial success; or ii) choosing a Q strategy that increases the probability that the project is a commercial success by improving the precision of the SM signal.

So, if the entrepreneur chooses I, then

$$\pi_I^* = \pi_\beta + \alpha^*, \tag{6}$$

with $\alpha \sim V$ on $\{0, \infty\}$. An I project uses the β signalling technology and so produces $\kappa 2 \left[\beta\right]$ in the SM phase.

[11] We could instead assume that $1/2 < M \leq 1$ while adding additional technical assumptions that specify how quickly firms switch from a Q strategy to an I strategy as M increases. These additional assumptions complicate the analysis without adding any insight, so we chose the simpler approach.

If the entrepreneur chooses Q, then the firm produces a secondary market signal $\kappa 2\,[Q]$ instead of $\kappa 2\,[\beta]$. For simplicity we assume that $\kappa 2\,[Q]$ is perfectly precise, implying that

$$\kappa 2\,[Q] = \begin{cases} \tau^* & \text{w.p.} \quad 1, \\ \neg\tau^* & \text{w.p.} \quad 0. \end{cases} \tag{7}$$

A Q strategy does not produce an innovation and does not increase project revenue conditional upon success, so $\pi_Q = \pi_\beta = 1$.

A firm is a commercial success if it has a G project and hires a Y worker who makes an unobservable and non-contractable specific investment. We assume that the probability that the firm hires a Y worker increases with the market's estimate of the probability that the firm has a G project. So, denote the probability that the firm is a commercial success at the end of the SM phase by $\theta_{C,SM:\psi,\kappa 2}$ and the probability that it has a G project given its approach and $\kappa 2$ by $\theta_{G:\psi,\kappa 2}$ (recall that all selected projects begin with $\kappa 1 = g$). The probability that the firm hires a Y worker in t_4 conditional upon SM information is $\theta_{Y:\psi,\kappa 2}$. To build in a smooth transition from Q to I as a function of market effectiveness, we assume that

$$\theta_{Y:\psi,\kappa 2} = \theta_{G:\psi,\kappa 2}^{\frac{1}{2}}.$$

It follows that

$$\theta_{C,SM:\psi,\kappa 2} = \theta_{G:\psi,\kappa 2}\,\theta_{Y:\psi,\kappa 2} = \theta_{G:\psi,\kappa 2}^{\frac{3}{2}}. \tag{8}$$

B. The Idea Processing Constraint

The Idea processing constraint (η_ρ) is equal to the proportion of entrepreneurs that would choose I to develop their projects assuming that there is an available idea, and entrepreneurs choose I if it maximizes their IPO price. It follows that

$$\eta_\rho = \text{Prob}\big|_{@t_1}\left[P_{IPO:I} > P_{IPO:Q}\right]. \tag{9}$$

We therefore begin our analysis of innovativity by examining IPO prices.

A firm's IPO price is equal to its expected secondary market price. A firm receives either a g or a b signal in the secondary market, implying that

$$P_{IPO,\psi} = \theta_{g,\psi}\, P_{SM:\psi,g} + \theta_{b,\psi}\, P_{SM:\psi,b}, \tag{10}$$

where $\theta_{\kappa 2,\psi}$ is the probability that the firm produces a secondary market signal of κ given its strategy ψ, and $P_{SM:\psi,\kappa 2}$ is the share price given ψ and $\kappa 2$. A secondary market price in turn equals the firm's expected revenue given ψ and $\kappa 2$, with (from equation 8)

$$P_{SM:\psi,\kappa 2} = \pi_\psi\, \theta_{C,SM:\psi,\kappa 2} = \pi_\psi\, \theta^{3/2}_{G:\psi,\kappa 2}. \tag{11}$$

Hence (from equation 10),

$$P_{IPO:\psi} = \pi_\psi\, \theta_{g,\psi}\, \theta^{3/2}_{G:\psi,g} + \pi_\psi\, \theta_{b,\psi}\, \theta^{3/2}_{G:\psi,b}. \tag{12}$$

Consider $P_{IPO:Q}$ and $P_{IPO:I}$ in turn.

If the entrepreneur chooses Q, then $\kappa 2$ reveals project type perfectly. Since $\theta_{G,IPO} = M$ and $\theta_{B,IPO} = 1 - M$ (from equation 5), it follows that $\theta_{g,Q} = M$, $\theta_{b,Q} = 1 - M$, $\theta_{G:Q,g} = 1$, and $\theta_{G:Q,b} = 0$. Consequently (from equation 12),

$$P_{IPO:Q} = \pi_\beta\, M = M. \tag{13}$$

If the entrepreneur chooses I, then $\kappa 2$ equals (does not equal) τ^* with probability M $(1 - M)$. So, given $\theta_{G,IPO}$ and $\theta_{B,IPO}$, it follows that

$$\theta_{g,I} = \theta_{G,IPO}\, M_T + \theta_{B,IPO}\, (1 - M_T) = 1 + 2(M_T)^2 - 2M, \tag{14}$$

and that

$$\theta_{b,I} = \theta_{G,IPO}\, (1 - M_T) + \theta_{B,IPO}\, M_T = 2\, M_T(1 - M_T). \tag{15}$$

$\theta_{G:I,g}$ equals the probability that an I entrepreneur with a G project receives a g signal divided by unconditional probability that an I entrepreneur receives a g signal, and so equals

$$\theta_{G:I,g} = \frac{M^2}{1+2(M)^2-2M}. \tag{16}$$

Similarly,

$$\theta_{G:I,b} = \frac{(1-M)\,M}{2\,(1-M)\,M} = \frac{1}{2}. \tag{17}$$

Substituting the results of equations 14, 15, 16, and 17 into equation 12 yields

$$P_{IPO:I} = (1+\alpha)\left(\frac{M^3}{\sqrt{2M^2-2M+1}} + \frac{(1-M)M}{\sqrt{2}}\right). \tag{18}$$

Consequently, an entrepreneur chooses $\psi = I$ if $NetI = P_{IPO:I} - P_{IPO:Q} > 0$, with (from equations 13 and 18)

$$NetI = (1+\alpha)\left(\frac{M^3}{\sqrt{2M^2-2M+1}} - \frac{(M-1)M}{\sqrt{2}}\right) - M. \tag{19}$$

Obviously, $NetI$ increases with α, implying that there exists an α_{Crit} such that

$$\psi = \begin{cases} I & \text{if } \alpha > \alpha_{Crit}\,[M]\,, \text{ and} \\ Q & \text{otherwise.} \end{cases} \tag{20}$$

Solving for $\alpha_{Crit}\,[M]$ by setting $NetI$ equal to 0 yields

$$\alpha_{Crit} = \frac{-2\,M\sqrt{\frac{M^2}{2M^2-2M+1}} + \sqrt{2}\,M - \sqrt{2} + 2}{2\,M\sqrt{\frac{M^2}{2M^2-2M+1}} - \sqrt{2}\,M + \sqrt{2}}. \tag{21}$$

Plotting α_{Crit} (Figure 1) reveals that it decreases as M increases (we confirm this observation with numerical analysis).

A firm chooses I if $\alpha > \alpha_{Crit}\,[M]$, implying that

$$\eta_\rho\,[M] = \text{Prob}\big|_{t_1}\left[\alpha > \alpha_{Crit}\,[M]\right]. \tag{22}$$

Since $\alpha_{Crit}[M]$ decreases with M, it follows that

$$\frac{\partial \eta_\rho}{\partial M} > 0. \tag{23}$$

That is, the economy's idea processing capacity increases with market effectiveness.

The intuition for this result is straight forward. Since the signaling advantage that the Q strategy provides declines as market effectiveness increases, the minimum revenue boost (α^*) that a firm needs from an innovation to offset the Q signaling advantage also declines as market effectiveness increases.

C. Equilibrium Innovativity

Having established the relationship between η_ρ and M, we are now in a position to analyze the equilibrium level of innovativity Φ, with (from equation 2) $\Phi = \text{Min}\left[\eta_S, \eta_\rho[M]\right]$. We plot equation 2 in Figure 2.

The comparative statics implied by equation 23 are straightforward, with

$$\frac{\partial \Phi}{\partial M}\begin{cases} > 0 & \text{if} \quad \eta_\rho[M] < \eta_S, \\ = 0 & \text{if} \quad \eta_\rho[M] \geq \eta_S, \end{cases} \tag{24}$$

and with

$$\frac{\partial \Phi}{\partial \eta_S}\begin{cases} > 0 & \text{if} \quad \eta_S < \eta_\rho[M], \\ = 0 & \text{if} \quad \eta_S[M] \geq \eta_\rho[M]. \end{cases} \tag{25}$$

II. Identifying the Binding Constraint on Innovativity

We cannot directly observe Φ or the binding constraint on Φ, but we know that Φ is a function of the relative proportions of Q and I firms. We also know that: i) a Q strategy provides a stronger signal of project type than an I strategy; and ii) signals affect secondary market prices and so firm returns (where returns are calculated from a firm's IPO price to its secondary market price). It follows that the standard deviation of (idiosyncratic) returns for Q firms will be higher than that for I firms. In this case, an increase in the proportion of firms choosing I will lead to a decrease in the fundamental component of the standard deviation of idiosyncratic firm returns for the market as a whole (σ_F), where σ_F can be estimated. We therefore conjecture that a combination of restrictions imposed by our theory, exogenous shocks to η_S and η_ρ, and (for expositional convenience) Δ, with

$$\Delta = 1 - \sigma_F, \tag{26}$$

will enable us to identify the state of Φ and the binding constraint on Φ. In this section we develop this conjecture.

A. The Relationship Between Δ, M, η_S, and Φ

A firm's IPO to Secondary Market return given ψ and $\kappa 2$ is $R_{\psi,\kappa 2}$, with

$$R_{\psi,\kappa 2} = \frac{P_{SM:\psi,\kappa 2} - P_{IPO:\psi}}{P_{IPO:\psi}}. \tag{27}$$

Recalling that a firm's expected return equals 0 for both strategies, the standard deviation of returns for firms choosing ψ is σ_ψ, with

$$\sigma_\psi = \sqrt{\theta_{g:\psi}\, R^2_{\psi,g} + \theta_{b:\psi}\, R^2_{\psi,b}}. \tag{28}$$

We note that σ_ψ is independent of Φ as it is the standard deviation of returns for firms given ψ while Φ determines the proportion of firms that choose ψ. It follows that

$$\Delta = 1 - \sigma_F = 1 - \sqrt{\Phi\left[\eta_\rho\left[M\right], \eta_S\right]\ \sigma^2_I\left[M\right] + \left(1 - \Phi\left[M, \eta_S\right]\right)\sigma^2_Q\left[M\right]}. \tag{29}$$

So, Δ is a function of Φ, σ^2_I, and σ^2_Q. We know how Φ behaves from equations 24 and 25. Turning to σ^2_I, and σ^2_Q, we note that the full expressions for these parameters are too complex and unintuitive to work with analytically even in our simple model of prices and signaling. We therefore calculate $\sigma^2_I\left[M\right]$ and $\sigma^2_Q\left[M\right]$ numerically (from equations 27 and 28) and plot them in Figure 3.[12] Inspecting Figure 3, we find

[12]We do the calculations and plotting in *Mathematica*, details available upon request.

that: i) $\sigma_Q^2 > \sigma_I^2$ for a given M (as we conjectured); ii) $\partial\sigma_Q^2/\partial M < 0$; and iii) $\partial\sigma_I^2/\partial M < 0$.

The relationship between Δ, η_S, and M is then straightforward. To begin with η_S, this term affects Δ only through its impact upon Φ. Since an increase in Φ shifts weight from the higher σ Q strategy to the lower σ I strategy, it follows from equation 25 that

$$\frac{\partial\Delta}{\partial\eta_S}\begin{cases} > 0 & \text{if} \quad \eta_S < \eta_\rho\left[M\right], \\ = 0 & \text{if} \quad \eta_S \geq \eta_\rho\left[M\right]. \end{cases} \tag{30}$$

Turning now to M, recall that Φ is non-decreasing in M (from equation 24), which implies that the weight of the lower σ I strategy remains constant or increases with M. Since an increase in M also decreases both σ_I^2 and σ_Q^2, it then follows that

$$\frac{\partial\Delta}{\partial M} > 0. \tag{31}$$

Combining our analysis of Φ (equations 24 and 25) and Δ (equations 30 and 31), we find that

$$\frac{\partial\Phi\left[M\right]}{\partial M} > 0 \text{ and } \frac{\partial\Delta\left[M\right]}{\partial M} > 0 \text{ if } M \leq M^*, \tag{32}$$

and that

$$\frac{\partial\Phi\left[M\right]}{\partial M} = 0 \text{ and } \frac{\partial\Delta\left[M\right]}{\partial M} > 0 \text{ if } M > M^*, \tag{33}$$

where

$$M^* = M : \eta_\rho\left[M^*\right] = \eta_S.$$

We plot the relationship between Φ and Δ implied by equations 32 and 33 in Figure 4. The $\Phi\left[M\right]/\Delta\left[M\right]$ line slopes up for $M \leq M^*$ and then becomes vertical for $M > M^*$.

Combining our results for Φ, M, and η_S with those for Δ, M, and η_S, we find that:

Proposition 1: A positive exogenous shock to M or η_S has the following impact upon Φ and Δ (Figure 5):

- A shock to M when η_ρ is the binding constraint on Φ increases Φ and Δ:
- A shock to M when η_S is the binding constraint on Φ does not increase Φ but does increase Δ;

- A shock to η_S when it is the binding constraint on Φ increases Φ and Δ; and

- A shock to η_S when it is not the binding constraint on Φ does not increase either Φ or Δ.

Proof: These results follow immediately from equations 32 and 33.□

Having established the relationships between Φ, Δ, M, and η_S, we can now investigate how to use these relationships to identify Φ and the binding constraint on Φ.

B. Identifying Φ and the Binding Constraint on Φ

We assume that $\partial\bar{\gamma}/\partial\Phi > 0$, where $\bar{\gamma}$ is average TFP growth. Consider two innovativity regimes J and K, where an innovativity regime is a period of time in which innovativity is constant. In then follows that

$$\Phi_J \begin{cases} > \Phi_K & \text{if } \bar{\gamma}_J > \bar{\gamma}_K, \\ = \Phi_K & \text{if } \bar{\gamma}_J = \bar{\gamma}_K, \text{ and} \\ < \Phi_K & \text{if } \bar{\gamma}_J < \bar{\gamma}_K. \end{cases} \tag{34}$$

In order to carry out the test in equation 34, we must first identify two innovativity regimes (since we need to know the dates of a regime before computing average TFP growth during that regime, it is impossible to identify an innovativity regime from the TFP data directly). Fortunately, we can identify innovativity regimes from Δ (assuming that shocks to M and η_S that have exactly off-setting effects on Δ do not occur simultaneously). We can then identify the relative state of Φ in each regime using equation 34.

Proposition 2: If $\Delta_T = \Delta_{T+1} = \cdots = \Delta_{T+N}$, then $\Phi_T = \Phi_{T+1} = \cdots = \Phi_{T+N}$. The period from T to $T+N$ is an innovativity regime χ.

Proof: Equations 30 and 31 imply that $\Delta_T = \Delta_{T+1}$ if: i) $M_T = M_{T+1}$ if η_ρ is binding; or ii) $M_T = M_{T+1}$ and $\eta_{S,T} = \eta_{S,T+1}$ if η_S is binding. In either case, it follows from equations 24 and 25 that $\Phi_T = \Phi_{T+1}$. □

Now assume that we can identify regimes J and K, that J and K are continguous, and that a shock to either η_S or M occurs at the end of J. We can then identify the binding constraint on innovativity in J as follows (see Figure 5).

Proposition 3: If idea supply is (is not) the binding constraint on innovativity in J, then an exogenous increase in idea supply implies that $\Delta_J < \Delta_K$ and that $\Phi_J < \Phi_K$ ($\Delta_J = \Delta_K$ and $\Phi_J = \Phi_K$).

Proof: This result follows from Proposition 1.□

Proposition 4: If idea processing capacity is (is not) the binding constraint on innovativity in J, then an exogenous increase in M implies that $\Phi_K > \Phi_J$ and $\Delta_K > \Delta_J$ ($\Phi_K = \Phi_J$ and $\Delta_K > \Delta_J$).

Proof: This result follows from Proposition 1.□

While it is impossible in general to identify the binding constraint on Φ in the absence of an exogenous shock to M or η_S, the following special case is an exception (see Figure 6).

Proposition 5: Consider (possibly discontinguous) innovativity regimes J and K. If $\Delta_J = \Delta_K$ and if $\eta_\rho [M_J]$ is the binding constraint in J, then:

$$\Phi_K \begin{cases} = \Phi_J & \text{if } \eta_\rho [M_K] \text{ is the binding constraint in } K, \\ < \Phi_J & \text{if } \eta_S \text{ is the binding constraint in } K. \end{cases} \tag{35}$$

Proof: Suppose first that $\eta_\rho [M_K]$ is the binding constraint in K. In this case $\Phi_K \left[\eta_\rho [M_K], \eta_{S,K}\right] = \Phi_K \left[\eta_\rho [M_K]\right]$. In then follows from $\Delta_J = \Delta_K$ and equation 29 that:

$$\Delta_J \left[\Phi_J [M_J], \sigma_I^2 [M_J], \sigma_Q^2 [M_J]\right] = \Delta_K \left[\Phi_K [M_K], \sigma_I^2 [M_K], \sigma_Q^2 [M_K]\right],$$

which implies that $M_J = M_K$ and hence that $\Phi_K = \Phi_J$.

Now suppose that $\eta_{S,K}$ is the binding constraint in K, in which case $\eta_\rho [M_K] > \eta_{\rho,K}$. If $\eta_\rho [M_K] > \eta_{S,K} > \eta_\rho [M_K]$, then $\Phi_K \left[\eta_{S,K}\right] > \Phi_J \left[\eta_\rho [M_J]\right]$, $\sigma_I^2 [M_K] < \sigma_I^2 [M_J]$, and $\sigma_Q^2 [M_K] < \sigma_Q^2 [M_J]$. In this case, equation 29 implies that $\Delta_K > \Delta_J$, which contradicts our assumption. Hence, if $\Delta_K = \Delta_J$ and $\eta_{S,K}$ is the binding constraint in K, it must be the case that $\Phi_K \left[\eta_{S,K}\right] < \Phi_J \left[\eta_\rho [M_J]\right]$ and $M_K > M_J$. □

So, we have show that we can: i) identify innovativity regimes on the basis of Δ; ii) identify the state of Φ given an innovativity regime; and iii) identify the binding constraint on Φ in a given innovativity regime on the basis of exogenous shocks to M and η_S and restrictions imposed by our theory. Consider (i), (ii), and (iii) in turn.

III. Innovativity Regimes: 1850 to 2019

An innovativity regime is a period of time for which Δ is constant (Proposition 2). To estimate Δ, we assume that

$$\Lambda_T = Constant + \Delta_{Start/End} + \beta_{Bull}\, Bull_T + \beta_{Bear}\, Bear_T + TShocks_T + \epsilon_T, \tag{36}$$

with

$$\Lambda_T = 1 - \sigma_{Market,T}, \tag{37}$$

and where $\sigma_{Market,T}$ is the observed standard deviation of idiosyncratic firm returns, $\Delta_{Start/End}$ is a set of time specific indicator variables that span our sample period, *Bull* (*Bear*) is a dummy variable which equals 1 when the equal weighted average return in T is in its upper (lower) decile, *TShocks* captures the impact of transitory shocks, and ϵ_T is the error term. We then track the evolution of Δ with the $\Delta_{Start/End}$ indicator variables.

We first discuss the sample and variables we use in our analysis, and we then present our results.

A. Sample and Variables

Our sample consists of NYSE listed common shares from 1850 to 2019. We construct this sample by combining data from the Yale School of Management's Old New York Stock Exchange Project (1850 to 1925) and CRSP (1926 to 2019).[13] The Old NYSE (ONY) data is available at a monthly frequency, so we also use monthly data for the CRSP period.[14]

We include an ONY firm/month observation in the sample if we have a return for that firm in that month, and we include a CRSP firm/month observation in the sample if we have a return, a price, a trading volume, shares outstanding, and a 2 digit SIC Code for that month. We sort firms into industries

[13]The Old NYSE data is available on the Yale School of Management's website. See Goetzmann, Ibbotson, and Peng (2001) for a description of the data.

[14]To restrict the sample to common shares, we drop: i) Preferred and Scrip shares for the ONY period; and ii) all non-Common shares, Asset Backed Securities (SIC 6189), and REITS (SIC 6798) for the CRSP period.

on the basis of their 2-digit SIC code (Johnson, Moorman, and Sorescu 2007). Due to limited observations, we assume that all ONY observations are in a single industry.

The ONY dataset consists of end of month prices but does not include dividend adjusted holding period returns. We therefore calculate the return R of firm j in month T on the basis of end of month price changes, with $R_{j,T} = \text{Ln}\left[{}^{P_{j,T}}/{}_{P_{j,T-1}}\right]$. We winsorize ONY returns at the 0.01 and 0.99 quantiles (-38.30% and 37.20%). For the CRSP period, $R_{j,T} = \text{Ln}\left[1 + \textit{Holding Period Return}_{j,T}\right]$. We winsorize these returns at -38.30% and 37.20% as well to be consistent with the ONY data (the 0.003 and 0.992 quantiles of the return distribution).

We set a firm j's idiosyncratic return equal to its net of 2 digit SIC industry return, where we set industry return equal to the median return in j's industry.[15]

In our theoretical analysis we assume that all firms are ex ante identical, but in practice the standard deviation of returns for large firms will generally be lower than that of small firms. To test to see if this phenomenon drives our results, we construct the variable Λ_{Norm} as follows. We sort firms for the CRSP sample into market cap quartiles each month and compute the standard deviation of idiosyncratic returns for each quartile ($\sigma_{Quar,T}$) as above. We normalize each quartile's $\sigma_{Quar,T}$ series by dividing it by the mean of that series. We set $\sigma_{Norm,T}$ equal to the average of the $\sigma_{Quar,T}$ for T and compute $\Lambda_{Norm,T}$ as in equation 37 using $\sigma_{Norm,T}$ instead of $\sigma_{Market,T}$.

We assume that the mix of Q and I firms evolves slowly. We therefore capture the evolution of Δ with a series of indictor variables of the form $\Delta_{Start/End}$. For our analysis of the CRSP period, we begin with indicator variables for: i) 1926/1929; ii) the Great Depression (1930/1941); iii) WW2 (1942/1945); iv) 1946/1949; and v) one for every 5 year period for the rest of the sample period. For the joint ONY/CRSP sample, we divide Pre-1930 data into periods relative to the Second Industrial Revolution (IR2). Gordon (2012) dates IR2 to the years 1870/1900. We therefore define a *PreIR2* period for the years 1850/1869, an *IR2* period for the years 1870/1900, and a *PostIR2* period of 1901/1929.

We summarize variable and period definitions in Table 1 and we present summary statistics for the

[15] We use the median rather than the mean industry return to reduce the influence of outliers. Aside from that change, we compute idiosyncratic returns using the method of Campbell, Lettau, Malkiel, and Xu (2002). This approach yields essentially identical results to the more elaborate market model method of Ang, Hodrick, Xing, and Zhang (2006).

ONY and the CRSP samples in Table 2.

B. Analysis

We begin our analysis of Δ's evolution by estimating equation 36 for the CRSP period alone as the CRSP data is of higher quality than the ONY data. In each regression, we control for market conditions with *Bull* and *Bear* dummies, which are statistically significant and have the expected sign. We control for transitory shocks by using a Garch(1,1)/AR(24) model.[16] This model yields white-noise residuals (using the Q-test) in each regression.

We begin by estimating equation 36 will the full set of Δ dummies (Table 3). In Specification 1 we use the CRSP sample with Λ_T as the dependent variable, and in Specification 2 use $\Lambda_{Norm,T}$ as the dependent variable. We exclude $\Delta_{2010/2014}$ and $\Delta_{2015/2019}$ to provide the constant term. We find that Δ is: i) insignificant between 1926 and 1941; ii) positive, statistically significant, and essentially constant between 1946 to 1969; iii) positive but statistically insignificant between 1970 and 1979; and iv) statistically insignificant from 1980 to 2019 (we will generally ignore the WW2 period in our discussion due to the extensive government control of the economy during that time).

In Specification 3 we estimate 36 for the entire 1850/2019 sample period. We find that Δ is insignificant for the entire *PreWar* period, and that the results of this specification match those of Specifications 1 and 2 for the CRSP period.

We assume that two adjacent periods J and K are in the same innovativity regime χ if either: i) Δ_J and Δ_K are significantly greater than 0 and if we do not reject $\Delta_J = \Delta_K$; or ii) Δ_J and Δ_K are not siginificanlty greater than 0 and we do not reject $\Delta_J = \Delta_K$. On this basis, we form three innovativity regimes: i) a *PreWar* regime of 1926/1941; ii) a *Peak* regime of 1946/1969; and iii) a *Post80* regime of 1980/2019. We also define two transition periods, namely a WW2 period of 1942/1945 and a 1970s period.

In Table 4 we estimate equation 36 for the CRSP period (Specification 1) and the 1850/2019 period (Specification 2), dropping the *Post80* regime for the constant term. Both specifications yield consistent

[16]The unreported transitory shock effects are highly significant. In the case of the Λ_{Norm} specification, we use a Garch(1,1)/AR(30) model.

results, with: i) $\Delta_{PreWar} = 0$; ii) $\Delta_{Peak} > 0$ at the 1% level; and iii) $\Delta_{Peak} > \Delta_{PreWar}$ at the 1% level.

We plot the evolution of Δ by period (Table 3, Specification 3) and by regime (Table 4, Specification 2) in Figure 7.

Δ and Idiosyncratic Volatility

Our Δ measure is related to idiosyncratic volatility. So, it could be the case that factors that drive idiosyncratic volatility also drive our estimates of Δ. We explore this possibility now.

Examining the path of idiosyncratic volatility, Campbell, Lettau, Malkiel, and Xu (2000) find a general upward trend between 1962 and 1997 and Brandt, Brav, Graham, and Kumar (2010) find that this trend reverses itself in the early 2000s (we note that this is not the pattern we find for innovativity). Brandt et al. (2010) observe that the long run trend variables that seem to explain the 1962/1997 increase in idiosyncratic volatility cannot also explain its post-1997 fall.[17] They argue instead that the rise and fall pattern of idiosyncratic volatility is driven by the behavior of retail investors investing in low price stocks.

To see if this retail investor effect also drives the evolution of Δ, we estimate equation 36 for the CRSP sample while dropping low price stocks, where a low price stock is one in the bottom 3 deciles of stocks each month sorted by start of month price (Table 4, Specification 3). We find the same pattern as above, with: i) $\Delta_{PreWar} = 0$; and ii) $\Delta_{Peak} > 0$ at the 1% level (we exclude Δ_{Post80} for the intercept). We conclude that the evolution of Δ that we observe is not due to retail investor trading in low priced stocks.[18]

Reverse Causality?

Thus far we have been assuming that we can identify innovativity regimes (using Δ) in a manner that is independent of the TFP data itself. An alternative hypothesis is that TFP growth (γ) somehow determines Δ. It may then appear that Δ enables us to identify innovativity regimes when in reality we are just capturing a correlation between Δ and γ.

[17] Among these explanations are: a rise in institutional ownership (Bennett, Sias, and Starks 2003), more volatile or opaque firm fundamentals (Wei and Zhang 2006, Rajgopal and Venkatachalam 2006), and product markets becoming more competitive (Irvine and Pontiff 2009).

[18] In unreported regressions, we also found that dropping the lower 3 deciles of stocks sorted by market cap did not alter the results.

However, we note that the economy can experience periods of high TFP growth during a low Δ regime. As we show below, for example, TFP growth is high during the DotCom boom of 1995/2004 and is low during the remainder of the *Post80* regime while Δ is constant over the entire *Post80* regime (Table 3). We therefore reject the reverse causality hypothesis.

Innovativity Regimes

Our analysis of the evolution of Δ yields a striking result: over the entire 1850 to 2019 period, the US has had three innovativity regimes. These regimes are a *PreWar* regime of 1850/1941, a *Peak* regime of 1946/1969, and a *Post80* regime of 1980/2019. Having identified innovativity regimes, we now turn to estimating Φ during those regimes.

IV. Innovativity: 1899 to 2019

We assume that average TFP growth in regime χ, $\bar{\gamma}_\chi$, is a random variable with

$$\bar{\gamma}_\chi \sim \Gamma\left[\Omega_\chi\left[\Phi_\chi\right], Y_\chi\right], \tag{38}$$

where Ω_χ is the TFP generating process given Φ_χ and Y_χ is the length of χ (in years). For any two innovativity regimes J and K, we posit that: i) $\Phi_J > \Phi_K$ if $\bar{\gamma}_J > \bar{\gamma}_K$; and that ii) $\Phi_J = \Phi_K$ if $\bar{\gamma}_J = \bar{\gamma}_K$ (equation 34), where $\bar{\gamma}_\chi$ is average TFP growth in regime χ.

We can observe the realization of $\bar{\gamma}$ ($\bar{\gamma}^*$) for all regimes, and we have sufficient data to estimate Ω_{Post80}. However, we lack the data to estimate Ω_{PreWar} and the observations to estimate Ω_{Peak}. We therefore examine the evolution of innovativity by taking as our Null hypothesis the proposition that the state of innovativity is constant across regimes. Our Null is then that

$$\bar{\gamma}_{Test,Null} \sim \Gamma_{Test}\left[\Omega_{Post80}, Y_{Test}\right], \tag{39}$$

with $Test \in \{PreWar, Peak\}$. We accept the Null if

$$\Gamma_{Test,2.5} < \bar{\gamma}^*_{Test} < \Gamma_{Test,97.5} \tag{40}$$

and reject it otherwise, where $\Gamma_{Test,Z}$ is the Z^{th} quantile of $\Gamma_{Test}[\Omega_{Post80}, Y_{Test}]$. To eliminate any possible bias introduced by the immediate PostWar boom, we start the *Peak* regime in 1951 for this analysis.

A. Data

We obtain our TFP growth data from two sources. For the 1951/2019 period we use TFP data from the San Francisco Federal Reserve, setting TFP growth in year T equal to the natural log of the utilization adjusted annual rate of total factor productivity growth (dftp_util).[19] In the absence of an annual TFP growth series for the *PreWar* period, we use the long run average TFP growth estimates from Bakker, Crafts, and Woltjer (2019). This data covers the period 1899/1941.[20]

We summarize our variable definitions in Table 5 and we report summary statistics in Table 6. We plot TFP growth by innovativity regime in Figure 8.

B. Analysis

To carry out the test in equation 40, we first estimate Γ_{Test}. And to do that, we must estimate Ω_{Post80}.

We model Ω_{Post80} as a two state Markov process (French 2001) as the evolution of TFP growth in the *Post80* period suggests that γ alternates between periods in which it is generally low and periods in which it is generally high (e.g., the DotCom Boom). We assume that

$$\Omega_{Post80} = \left\{ \{\gamma_U, \gamma_D\}, \epsilon_{Dis}, \Xi \right\}, \tag{41}$$

[19] Fernald (2014) describes this data series.

[20] As we discuss below, TFP growth during the Great Depression was very high. The Great Depression was also characterized by a substantial fall in real output (Cole and Ohanian 1999). Hannah and Temin (2010) argue that these circumstances may bias TFP growth figures from this period. We note this possibility, but to err on the side of caution we include the Great Depression in our *PreWar* regime.

where γ_U and γ_D are the states, ϵ_{Dis} is the error distribution, and Ξ is the transition matrix, with $\Xi = \{\theta_{DD}, \theta_{DU}, \theta_{UD}, \theta_{UU}\}$. We assume that $\gamma_U > \gamma_D \geq 0$, and that observed TFP growth in T given the state of ν, $\nu \in \{U, D\}$, is $\gamma_T[\nu]$, with

$$\gamma_T[\nu] = \gamma_\nu + \epsilon_T, \tag{42}$$

where ϵ_T is an iid draw from ϵ_{Dis}.

Factors that affect either the supply of ideas (such as R&D spending and the cost of finding ideas) or idea processing capacity do not affect the TFP growth process directly—they only affect that process through their impact upon the state of innovativity. Within a regime χ, however, the state of innovativity is constant. It follows that the TFP growth process is constant as well. Consequently, we do not include any controls for any such factors when estimating Ω_{Post80}. One implication of this approach is that there will not be any trend in Ω_{Post80}, and we test this implication below.

We estimate Ω_{Post80} and report the results in Table 7. All specifications yield white-noise residuals. In Specification 1 we estimate equation 41 using a Dynamic model and find that the point estimate of γ_U is 1.84 (significant at the 1% level) and that the point estimate of γ_D is negative and insignificant. In Specification 2 we estimate equation 41 including an AR(1) term, and find that the AR(1) term in insignificant. In Specification 3 we revert to the Dynamic model and impose the constraint that $\gamma_D = 0$ and find (unsurprisingly) that the point estimate and significance level of γ_U do not change materially. In Specification 4 we include a time trend and find that it too is insignificant. So, as our analysis predicts, there is no trend in the TFP growth process within the *Post80* regime.[21]

Specification 3 therefore provides out best estimate of Ω_{Post80}. Consequently, we assume that Ω_{Post80} has the following form:

- $\gamma_D = 0$;
- $\gamma_U \sim$ Normal Distribution $[1.86, 0.23]$;
- $\theta_{DD} \sim$ Normal Distribution $[0.94, 0.62]$;
- $\theta_{DU} = 1 - \theta_{DD}$;

[21] In unreported analysis we also reject a three state model and a model with lagged GDP growth (as in Gordon 2010).

- $\theta_{UD} \sim$ Normal Distribution $[-0.64, 0.58]$;

- $\theta_{UU} = 1 - \theta_{UD}$; and

- ϵ_{Dis} = the residuals from Specification 3,

with the θ_{DD} and θ_{UD} distributions in logit form.[22]

Given Ω_{Post80}, we next estimate the distribution of Γ_{Test} with a bootstrap consisting of 100,000 trials.

In each trial J we first specify Ξ_J by making iid draws for the values of $\gamma_{U,J}$, $\theta_{DD,J}$, and $\theta_{UD,J}$. Given Ξ_J, we simulate the evolution of the state of γ for Y_{Test} periods, with the initial state determined by a random draw from the stationary state distribution implied by Ξ_J. The simulation yields the number of years that the economy is in γ_U $(N_{U,J})$ and in γ_D $(N_{D,J})$ in each trial. The average rate of TFP growth in J is then $\bar{\gamma}_{Test,Null,J}$, where

$$\bar{\gamma}_{Test,Null,J} = \frac{(N_{D,J} \times 0) + (N_{U,J} \times \gamma_{U,J}) + \bar{\epsilon}_J}{Y_J}, \tag{43}$$

with $\bar{\epsilon}_J$ equal to the mean of Y_{Test} iid draws from ϵ_{Dis}. It follows that

$$\Gamma_{Test} = \left\{ \bar{\gamma}_{Test,Null,1}, \ldots, \bar{\gamma}_{Test,Null,100\,000} \right\}. \tag{44}$$

Equipped with Γ_{Test}, we can test our predictions. We report these tests in Table 8. To begin with the *Peak* case, we find that

$$\bar{\gamma}^*_{Peak51} > \Gamma_{Peak51,97.5}$$

and therefore reject the Null that $\Phi_{Peak} = \Phi_{Post80}$.

Turning to the *PreWar* case, we find that

$$\Gamma_{PreWar,2.5} < \bar{\gamma}^*_{PreWar} < \Gamma_{PreWar,97.5}.$$

[22] The 95% confidence interval for θ_{DD} (θ_{UD}) expressed in probabilities is: $\{0.43, 0.90\}$ $(\{0.14, 0.63\})$.

In this case, then, we accept the Null that $\Phi_{PreWar} = \Phi_{Post80}$.[23]

The Evolution of Φ

We find that innovativity follows a distinct low/high/low pattern over the 1899/2019 period, with $\Phi_{PreWar} = \Phi_{Post80}$ and $\Phi_{Peak} > \Phi_{Post80}$. Consequently, we refer to the state of Φ as *Low* in the *PreWar* and *Post80* regimes and as *High* in the *Peak* regime. We now examine the causes of this pattern.

V. Are We Running Out of Ideas?

The dominant narrative for the *Low/High/Low* pattern of US innovativity over the last 120 years presumes that it is driven by idea supply. It is easy to see how this presumption arises. To focus on the *Peak* to *Post80* decline, the fact that average TFP growth has fallen significantly while resources (apparently) expended on finding ideas has been increasing (Bloom et al. 2020) naturally leads one to think that TFP growth is slowing because the US is running out of ideas. Building upon this presumption: i) Gordon (2012, 2014) provides a narrative to explain why we are running out of ideas (the Second Industrial Revolution is over); ii) Bloom et al. (2020) calibrate exactly how fast we must be running out of ideas to reconcile increasing R&D spending with lower TFP growth (research productivity is declining at 5% per year); and iii) recent developments in endogenous growth theory provide a logical framework that can be parameterized such that ideas become harder to find (Jones 2019). This combination of narrative, empirical findings, and theory create a strong prima facie case for the hypothesis that idea supply is the binding constraint on TFP growth and that this constraint is shifting down over time.

Yet neither a narrative nor a calibration is a test of the hypothesis that idea supply is the binding constraint on TFP growth. The fact that TFP growth is declining while R&D spending is increasing is not in itself a test of this hypothesis as the TFP growth decline we observe could be due to either a decline in idea supply or a decline in idea processing capacity. So, in this section we use our innovativity framework

[23] We note that the plausible range of $\bar{\gamma}$ is wide for each regime. This result arises from the Markov nature of the growth process. Absent a theory that enables one to predict ex ante when TFP booms will occur and how long they will last, it is not possible to make precise estimates for average TFP growth. One inference that we draw from this analysis is that there may be a tendency in the growth literature to over-interpret small differences in TFP growth rates.

and the empirical results above to identify: i) the binding constraint on innovativity within each innovativity regime; and ii) the causes of the innovativity regime shifts. Consider each regime in turn.

A. The PreWar Regime

To identify the binding constraint on innovativity in the *PreWar* regime, we begin by observing that (from Table 4)

$$\Delta_{PreIR2}\left[\eta^*_{S,PreIR2}, \eta^*_{\rho,PreIR2}\left[M^*_{PreIR2}\right]\right] = \Delta_{PostIR2}\left[\eta^*_{S,PostIR2}, \eta^*_{\rho,PostIR2}\left[M^*_{PostIR2}\right]\right]. \tag{45}$$

Consider M and η_S in turn.

Before the Federal financial market reforms of the mid to late 1930s/early 1940s, the NYSE was largely self-regulated and its rules were in practice generally more binding than the completely ineffectual state securities laws (Seligman 1995).[24] As Pirrong (1995) establishes for the case of commodities exchanges, self-regulated exchanges exploit their control over their rules to benefit their members at the expense of the public. We therefore assume that market effectiveness in the *PreWar* period was set by NYSE members at its privately optimal level M^*_{PO}, and hence that

$$M^*_{PreIR2} = M^*_{PostIR2} = M^*_{PO}. \tag{46}$$

Turning now to idea supply, we note that the Second Industrial Revolution happens between 1870 and 1900, that is, in between the *PreIR2* period (1850/1869) and the *PostIR2* period (1901/1929). As Gordon (2014) observes, "within three months in the year 1879 three of the most fundamental 'general purpose technologies' were invented that spun off scores of inventions that changed the world." We interpret Gordon's argument to mean that IR2 shifted η_S up by a material amount, implying that

$$\eta^*_{S,PostIR2} = \eta^*_{S,PreIR2} + K. \tag{47}$$

[24] Seligman (1995) reports that the Investment Banking Association informed its members that they could safely ignore state securities laws by making offerings across state lines through the mail.

Consequently,

$$\Delta_{PreIR2}\left[\eta^*_{S,PreIR2}, \eta^*_\rho\left[M^*_{PO}\right]\right] = \Delta_{PostIR2}\left[\eta^*_{S,PreIR2} + K, \eta^*_\rho\left[M^*_{PO}\right]\right]. \tag{48}$$

As we demonstrated above in Proposition 3 and Figure 5 (Panels (a) and (b)), if the idea supply constraint shifts up and Δ does not increase, then the idea supply constraint is not binding. Our analysis therefore suggests that the economy's idea processing capacity is the binding constraint on innovativity in the *PreWar* regime.

B. The Peak Regime

If idea processing capacity is the binding constraint on US innovativity in the *PreWar* regime, then that regime will end if market effectiveness increases. The stock market crash of 1929 sparked a deep and wide-ranging reform effort aimed at doing precisely that (Seligman 1995). Our analysis therefore predicts (from Proposition 4 and Figure 5) that

$$\Delta_{PostReform} > \Delta_{PreWar} \quad \text{and} \quad \Phi_{PostReform} > \Phi_{PreWar}, \tag{49}$$

where the *PostReform* period indicates the period in which the reforms take effect.[25] Consistent with these predictions, we find that Δ (Figure 7) increases and that Φ (Table 8) enters its *High* state after the 1930s/1940s financial market reforms. This transition creates the *Peak* innovativity regime.

Strictly speaking, we cannot identify the binding constraint on equilibrium innovativity in the *Peak* period because we have no way of independently measuring the idea supply constraint. So, we don't know for certain if $\eta_{S,Peak} > \eta_{\rho,Peak}$. That said, we do know that idea processing capacity is the binding constraint on innovativity between Φ_{PreWar} and Φ_{Peak}, so we will refer to η_ρ as the binding constraint on innovativity in the *Peak* regime with this proviso.

[25] Following Bhattacharya and Daouk (2002), we expect a slight lag between when the reforms are legally put into place and when they take effect as it takes time to develop the capacity to effectively enforce the new rules.

The 1930s/1940s Reforms and M

Our prediction that the reform effort of the 1930s/1940s leads to an increase in idea processing capacity (and so innovativity) hinges upon the premise that these reforms did increase M. To assess the plausibility of this premise, consider just one strand of this effort: the evolution the financial reporting regime for NYSE listed firms.[26]

Prior to the 1933 and 1934 Securities Acts, there was no uniform system of financial accounting or disclosures for either firms seeking a listing on an exchange through an IPO or already listed firms (Seligman 1995). The Securities Acts of 1933 and 1934 together with the creation of the SEC to enforce them marked the beginning of a financial reporting regime that emphasized "comparability, full disclosure, and transparency (Zeff 2005)". In response to this new framework, the accounting profession and the SEC developed a standardized set of generally accepted accounting principles (that is, GAAP), and in 1939 the American Institute of Accounting recommends that auditor reports state that the accounts are prepared "in conformity with generally accepted accounting principles" (Zeff 2005). Reviewing the impact of this new financial reporting regime, Simon (1989) finds that these reforms led to "improvements in the quantity and quality of financial information" for NYSE listed firms. So, we infer from this evidence that this reform effort did improve financial market effectiveness.

C. The Post80 Regime

The question of why innovativity falls from its *High* state in the *Peak* regime to the *Low* state in the *Post80* regime is one of the central puzzles of PostWar US economic performance because there is no sharp exogenous event such as IR2 or the financial market reforms of the 1930s to cause it. Consequently, this shift could be due to a gradual decline in either market effectiveness (and so idea processing capacity) or idea supply.

We resolve this puzzle as follows. First, we note that $\Delta_{PreWar} = \Delta_{Post80}$ (Table 4), that $\Phi_{Post80} = \Phi_{PreWar}$ (Table 8), and (from above) that $\eta_{\rho,PreWar}\left[M^*_{PO}\right]$ is the binding constraint on Φ_{PreWar}.

[26] This effort also involved, for example, extensive reforms of the Federal Reserve and the banking system (https://www.federalreservehistory.org/essays/great-depression).

In then follows from Proposition 5 that η_ρ is also the binding constraint on innovativity in the *Post80* regime (see Figure 6). This result implies that

$$\eta_{\rho, PreWar} = \eta_{\rho, Post80} = \eta_\rho \left[M^*_{PO}\right].$$

These results suggest that innovativity in the US is now in its *Low* state now because ideas are getting harder to find, but because idea processing capacity has declined. The decline in idea processing in turn is due to market effectiveness falling from the high level brought about by the financial market reforms of the 1930s/1940s to its lower privately optimal level of the *PreWar* regime. Obviously, the regulatory structure that the reforms put into place is still there and still enforced. However, our analysis implies the that financial regulatory structure now in place has lost its efficacy. We therefore conjecture that the market has evolved resistance to the financial regulatory regime (much like harmful bacteria have evolved resistance to one of the other miracles of the 1930s/1940s, penicillin) and that the financial regulation has not kept up. This conjecture may merit further investigation.

D. Innovativity, Idea Processing, and Idea Supply

Our innovativity theory yields a method that enables us to identify innovativity regimes on an ex ante basis. This theory, in combination with exogenous shocks to idea supply and financial market effectiveness, also enables us to successfully predict how average TFP growth will vary across these regimes. To the best of our knowledge, no alternative analysis of TFP growth enables one to make ex ante predictions for how TFP growth in the US evolved over the last 120 years.

Our analysis further implies that the binding constraint on innovativity over our sample period is idea processing capacity rather than idea supply. That is, the US is now in a *Low* innovativity regime due to constraints on the economy's idea processing capacity rather than because ideas are getting harder to find.

We emphasize that this analysis is exploratory and that these results are far from definitive. In particular, our finding that idea processing capacity is the binding constraint on innovativity in the *Post80* regime rests upon our not rejecting the null that $\Phi_{PreWar} = \Phi_{Post80}$. Clearly, it could still be the case that $\Phi_{PreWar} > \Phi_{Post80}$. If this were the case, then our analysis would imply that idea supply rather than idea processing capacity is the binding constraint on innovativity in the *Post80* regime.

That said, we find no evidence that idea supply has ever been the binding constraint on innovativity and considerable evidence that idea processing capacity is the binding constraint on innovativity.

VI. Concluding Remarks

An innovation requires both an exploitable idea and an entrepreneur who transforms that exploitable idea into a new product or process. Innovativity—the economy's ability to create the innovations that drive TFP growth—is therefore determined by both idea supply and idea processing capacity rather than by idea supply alone. Examining US innovativity over the last 120 years, we find that it is plausibly the case that idea processing capacity is now and has been the binding constraint on US TFP growth.

Our innovativity framework offers a new perspective on the debate over the future of economic growth by calling the neo-Malthusian analysis of Gordan (2012, 2014) into question. Starting from the premise that ideas drive TFP growth and the observation that TFP growth is falling while the resources devoted to finding ideas is increasing, Gordon reaches the seemingly inescapable conclusion that TFP growth is declining because we are running out of ideas. And, if we are running out of ideas, it inevitably follows that "future economic growth may gradually sputter out"(Gordon 2012). Needless to say, the end of growth would have profound and terrible consequences for all aspects of economic, political, and social life.

Our analysis offers a way out of this pessimistic conclusion. We find that the poor TFP growth performance of the US economy since 1980 is not due a lack of ideas but to a lack of idea processing capacity. Our analysis further suggests that the economy's idea processing capacity can be (and has been) influenced by policy, and in particular by policies that improve financial market effectiveness. Consequently, the poor TFP growth performance of the US economy in recent decades may be due to correctable policy failings rather than to a brute fact of nature that we must simply accept and deal with as best we can.[27]

So, while our analysis here is exploratory, it does support Weitzman's (1998) conjecture that the limits to growth lie not in idea supply but in idea processing capacity. We therefore conclude that the role of idea processing capacity in the growth process merits further investigation.

[27] Bloom et al. (2020) argue that the US will need to double R&D spending over the next 12 years just to keep TFP growth where it is, let alone improve it. Since the US spends $667 billion/year on R&D now (according to the latest figures from the NSF), increasing TFP growth by increasing idea supply will be expensive. A major effort to improve financial market effectiveness and other aspects of the economy that impact idea processing capacity (which is, after all, the binding constraint on innovativity) will cost rather less than that.

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Table 1
Innovativity Regime Analysis: Variable and Period Definitions

Λ_T	$(1 - \sigma_{Market,T}) \times 100$.
$\Lambda_{Norm,T}$	$(1 - \sigma_{Norm,T}) \times 100$.
$\Lambda_{CRSP:HP,T}$	$(1 - \sigma_{HP,T}) \times 100$.
Bull (Bear)	A dummy variable equal to 1 if the unweighted average of share returns in month T is in the upper (lower) decile of sample returns.
$\Delta_{Start/End}$	The fundamental component of Λ for period *Start/End*.
PreIR2	1850/1869 (the period before the Second Industrial Revolution (IR2)).
IR2	1870/1900 (the Second Industrial Revolution (Gordon 2012)).
PostIR2	1901/1929.
GreatD	The Great Depression, 1930/1941.
PreWar	Before 1942.
Pre-Great Depression	Before 1930.
WW2	1942/1945.
Peak (Peak51)	1946/1969 (1951/1969) .
1970s	1970/1979.
Post80	1980/2019.
DotCom	The DotCom Boom of 1995/2004.
Post80ExDC	The Post80 period excluding the DotCom Boom.
ONY	Old New York Stock Exchange observations, 1850/1925.
CRSP	NYSE observations, 1926/2019.
CRSP:HP	CRSP observations for a sample consisting of the top 7 deciles of stocks each month, sorted by price.

Notes: The sample consists of NYSE listed common shares from 1850 to 2019. The sample is formed by combining monthly data from the Yale School of Management's (SOM) Old New York Stock Exchange project (available on the SOM's website) for the period of 1850 to 1925 and monthly data from CRSP for 1926 to 2019. We include a firm/month observation from the ONY period if we have a return for that month, and we include a firm/month observation from the CRSP period if we have a return, a price, a trading volume, shares outstanding, and a 2 digit SIC code. σ_T is the standard deviation of idiosyncratic firm returns in T, where a firm's idiosyncratic return equals its observed return minus the median return of the firms in its 2-digit industry (we assume that all ONY firms are in a single industry). $\sigma_{Norm,T}$ is the normalized standard deviation of idiosyncratic firm returns for T. To compute $\sigma_{Norm,T}$, we: i) sort firms into market cap quartiles for each month; ii) calculate the standard deviation of idiosyncratic firm returns for each quartile for each month; iii) normalize each quartile/month standard deviation by dividing it by the its mean value for the sample period; and iv) averaging the 4 normalized quartile standard deviations for each month. $\sigma_{CRSP:HP,T}$ is the standard deviation of idiosyncratic returns for firms with a share price in the top 7 share price deciles in T.

Table 2

Λ: Summary Statistics

	Mean	StDev
Λ_{CRSP}	91.51	2.19
Λ_{Norm}	0.00	25.50
$\Lambda_{ONY/CRSP}$	91.44	2.41
$\Lambda_{CRSP:HP}$	92.92	1.81
Observations/Month: ONY	54.00	22.91
Observations/Month: CRSP	1112.28	319.16

Notes: See Table 1 for variable definitions and sample information.

Sources: CRSP and the Yale School of Management's Old New York Stock Exchange project.

Table 3
The Evolution of Δ

Specification	(1)		(2)		(3)	
Sample	CRSP		CRSP		ONY/CRSP	
Dependent Variable	Λ		Λ_{Norm}		Λ	
	Point	StDev	Point	StDev	Point	StDev
Intercept	91.12*	0.73	0.00*	7.65	0.00	0.00
Bull	−0.34 *	0.07	−3.57 *	0.84	−5.63 *	0.07
Bear	0.52*	0.12	−6.72 *	0.74	−6.75 *	0.06
Δ_{PreIR2}					0.70	0.79
Δ_{IR2}					0.10	0.83
$\Delta_{PostIR2}$					−0.21	0.74
$\Delta_{1926/1929}$	−0.13	0.92	−5.02	10.95		
Δ_{GreatD}	0.99	1.42	8.23	10.91	0.47	0.86
Δ_{WW2}	2.84**	1.28	25.21**	10.44	2.42*	0.86
$\Delta_{1946/1949}$	2.69*	0.93	30.76*	9.91	2.75*	0.81
$\Delta_{1950/1954}$	2.37*	0.87	25.63*	9.59	2.55*	0.76
$\Delta_{1955/1959}$	2.47*	0.80	21.23**	10.04	2.46*	0.74
$\Delta_{1960/1964}$	2.87*	0.85	26.88*	9.74	2.58*	0.72
$\Delta_{1965/1969}$	2.49*	0.94	20.19**	10.19	2.14*	0.74
$\Delta_{1970/1974}$	1.70	1.05	10.17	10.11	1.28	0.79
$\Delta_{1975/1979}$	1.86	1.07	14.20	9.93	1.57**	0.78
$\Delta_{1980/1984}$	0.45	0.96	−0.39	9.78	0.19	0.75
$\Delta_{1985/1989}$	0.87	0.92	4.75	9.84	0.61	0.75
$\Delta_{1990/1994}$	0.16	0.89	−1.01	9.55	−0.21	0.75
$\Delta_{1995/1999}$	0.26	0.84	−1.10	9.52	−0.17	0.74
$\Delta_{2000/2004}$	−0.84	0.62	−11.04	10.94	−1.14	0.88
$\Delta_{2005/2009}$	−0.53	0.60	−4.19	10.37	−0.83	0.85
$\Delta_{2010/2019}$	Omitted		Omitted		Omitted	

Notes: In this table we estimate Δ by period. Δ is the fundamental component of Λ, with $\Lambda = (1 - \sigma_{Market}) * 100$ and $\Lambda_{Norm} = (1 - \sigma_{Norm}) * 100$, where σ (σ_{Norm}) is the standard deviation of idiosyncratic firm returns (the normalized standard deviation of idiosyncratic firm returns). See Table 1 for sample information and variable definitions. Specifications 1 and 3 are estimated with a Garch(1,1)/AR24 model, and Specification 2 is estimated with a Garch(1,1)/AR30 model. All specifications yield white-noise residuals (using the Q test). Δ in each period is measured relative to the Intercept (the omitted period). A "*" ("**") indicates statistical significance at the 1% (5%) level.

Table 4
The Evolution of Δ By Innovativity Regime

Specification	(1)		(2)		(3)	
Sample	CRSP		ONY/CRSP		CRSP:HP	
Dependent Variable	Λ		Λ		$\Lambda_{CRSP:HP}$	
	Point	StDev	Point	StDev	Point	StDev
Intercept	91.45*	0.28	91.41*	0.24	93.13*	0.25
Bull	−0.33 *	0.07	−0.55 *	0.07	−0.31 *	0.06
Bear	−0.52 *	0.06	−0.68 *	0.06	−0.59 *	0.06
Δ_{PreWar}	−0.66	0.58	−0.19	0.36	−0.43	0.46
Δ_{WW2}	2.21*	0.40	2.04*	0.47	1.15**	0.51
Δ_{Peak}	2.25*	0.40	2.33*	0.34	1.36*	0.37
Δ_{1970s}	1.36*	0.35	1.38*	0.32	0.60***	0.33
Δ_{Post80}	Omitted		Omitted		Omitted	

Notes: In this table we estimate Δ by innovativity regime, where an innovativity regime is a continuous period for which Δ is constant. We form these regimes on the basis to Table 3. Δ is the fundamental component of Λ, with $\Lambda = (1 - \sigma_{Market}) * 100$ and $\Lambda = (1 - \sigma_{CRSP:HP}) * 100$, where σ_{Market} ($\sigma_{CRSP:HP}$) is equal to the standard deviation of idiosyncratic firm returns (idiosyncratic returns of firms with a price in the top 7 deciles of firm prices). See Table 1 for sample information and variable definitions. We estimate each specification with a Garch(1,1)/AR24 model, and all specifications yield white-noise residuals (using the Q test). Δ in each period is measured relative to the Intercept (the omitted period). A "*" ("**")("***") indicates statistical significance at the 1% (5%) (10%) level.

Table 5
TFP Analysis: Sample and Variable Definitions

γ	The natural log of TFP growth.
$\bar{\gamma}^*_\chi$	Observed value of average TFP growth in regime χ.
Ω_{Post80}	The TFP growth process in the Post80 regime.
$\Gamma_\chi\left[\Omega_{Post80,Y_\chi}\right]$	The distribution of $\bar{\gamma}_\chi$ under the Null hypothesis that the TFP growth process in χ is equal to the TFP growth process in the *Post80* regime, where Y_χ is the length of χ in years.
$\Gamma_{\chi,Z}$	The Z^{th} percentile of Γ_χ.
g_D (g_U)	TFP growth in state D (U) in our two-state Markov model of TFP growth.
θ_{ij}	The transition probability from State i to j in our two-state Markov model of TFP growth.

Notes: We model the TFP growth process for the *Post80* regime (1980/2019) as a two sate Markov process Ω_{Post80} using annual data, with TFP growth in year Y equal to the natural log of capacity adjusted TFP growth from the San Francisco Federal Reserve TFP growth series (Fernald 2014).

Table 6
TFP Growth: Summary Statistics

Period	Mean	StDev
PreWar	1.29	—
Peak51	1.87	1.43
1970s	1.29	1.44
Post80	0.79	1.30
DotCom	1.92	0.58
Post80ExDC	0.38	1.26

Notes: In this table we report summary statistics by innovativity regime (*PreWar*, *Peak51*, and *Post80*). We also split the *Post80* regime into a *DotCom* period and a *Post80ExDC* period. See Table 1 for period definitions. We obtain our TFP data from Bakker, Crafts, and Woltjer (2019) for the PreWar period and from the San Francisco Federal Reserve for the PostWar period.

Table 7
The TFP Growth Process in the Post80 Regime

Specification Dependent Variable	(1) γ	(2) γ	(3) γ	(4) γ
g_D	-0.13	-0.21	0.00	0.00
	0.24	0.25	Constrained	
g_U	1.84*	1.88*	1.86*	1.84*
	0.28	0.31	0.28	0.35
AR(1)		0.11		
		0.21		
Trend				0.00
				0.01
θ_{DD}	0.70	0.67	0.72	0.72
	$\{0.39, 0.89\}$	$\{0.36, 0.88\}$	$\{0.43, 0.90\}$	$\{0.42, 0.90\}$
θ_{DU}	0.30	0.33	0.28	0.28
	$\{0.11, 0.61\}$	$\{0.12, 0.64\}$	$\{0.10, 0.57\}$	$\{0.10, 0.58\}$
θ_{UD}	0.34	0.35	0.35	0.35
	$\{0.14.0.61\}$	$\{0.15, 0.61\}$	$\{0.14, 0.63\}$	$\{0.14, 0.63\}$
θ_{UU}	0.66	0.65	0.65	0.65
	$\{0.39, 0.86\}$	$\{0.39, 0.85\}$	$\{0.37, 0.86\}$	$0.37, 0.86$

Notes: We estimate the TFP growth process for the *Post80* regime Ω_{Post80} with a two state Markov process, using the annual capacity-adjusted TFP growth series from the San Francisco Federal Reserve (Fernald 2014). See Table 5 for variable definitions and Table 6 for summary statistics on γ. This model yields white-noise residuals (using the Q test). Our theory implies that the TFP growth process is determined by state of innovativity. It follows that factors such as R&D spending or the supply of STEM labor do not affect the TFP growth process directly but only through their impact upon innovativity. In the Post80 regime, innovativity is constant (Table 3). Consequently, we do not include any controls for such factors in this model.

Table 8
Innovativity and TFP Growth

Null Hypothesis	$\bar{\gamma}^*$	Test Critical Value	Reject Null?
$\bar{\gamma}^*_{\text{Peak51}} \in \left\{\Gamma_{Peak51,2.5}, \Gamma_{Peak51,97.5}\right\}$	1.87	$\{-0.14, 1.84\}$	Yes
$\bar{\gamma}^*_{\text{PreWar}} \in \left\{\Gamma_{PreWar,2.5}, \Gamma_{PreWar,97.5}\right\}$	1.29	$\{0.07, 1.64\}$	No

Notes: We test the hypothesis that Φ in a *Test* regime equals that in the *Post80* regime by comparing observed TFP growth in the *Test* regime ($\bar{\gamma}^*_{Test}$) to the distribution of $\bar{\gamma}_{Test}$ under the Null hypothesis that the TFP growth process in the *Test* regime equals that of the *Post80* regime (Γ_{Test}). We accept the Null if $\bar{\gamma}^*_{\text{Test}} \in \left\{\Gamma_{Test,2.5}, \Gamma_{Test,97.5}\right\}$, where $\Gamma_{Test,Z}$ is the Z^{th} percentile of Γ_{Test}. We compute Γ_{Test} with a bootstrap consisting of 100,000 trials. In each trial j we: i) draw a set of parameters for the *Post80* TFP growth process from Table 7, Specification 3; ii) set the initial state equal to a random draw from the stationary state distribution implied by that draw; iii) simulate TFP growth in the *Test* period; and iv) calculate $\bar{\gamma}^*_{Null,j}$. We then set Γ_{Test} equal to $\left\{\bar{\gamma}^*_{Null,1}, \ldots, \bar{\gamma}^*_{Null,100,000}\right\}$.

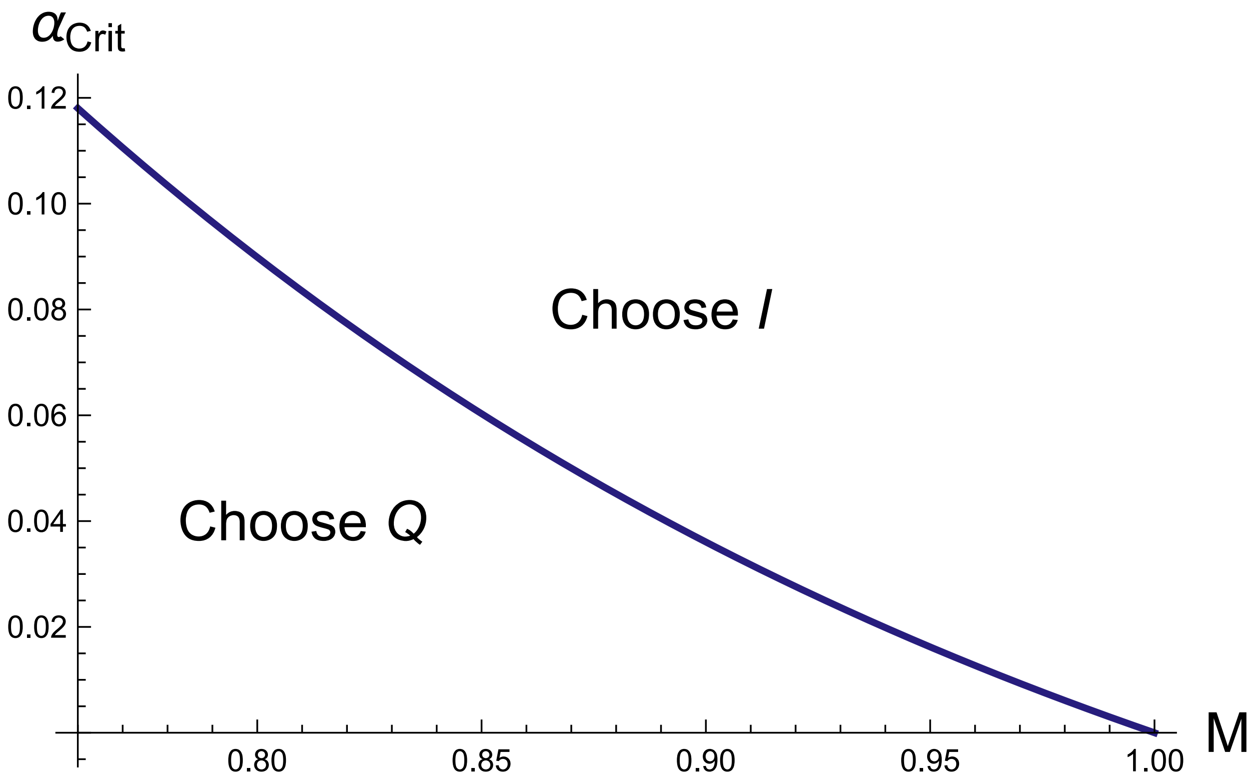

Figure 1: Strategy Choice and Market Effectiveness

Notes: We plot the minimum amount (α_{Crit}) that an *Innovation* (I) strategy must add to the payoff of a commercially successful project in order for the entrepreneur to choose I rather than the *Quick-Win* strategy Q as a function of market effectiveness M. This plot shows that the proportion of entrepreneurs who prefer I increases with M.

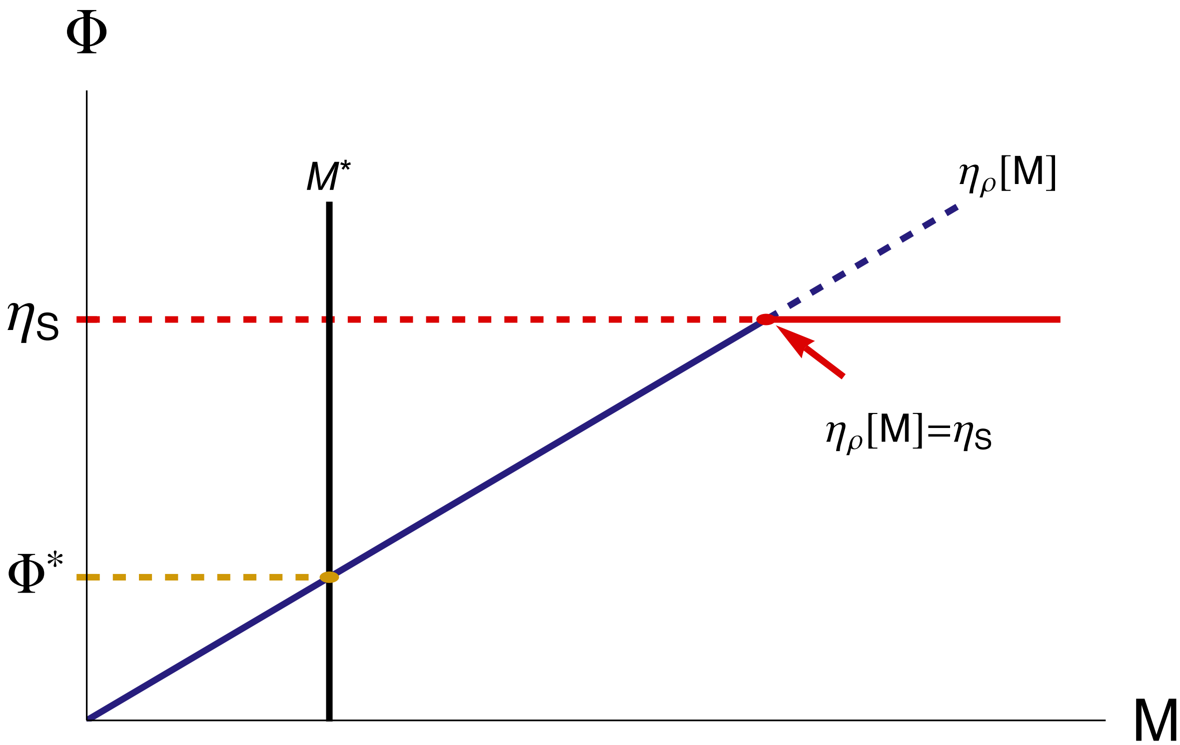

Figure 2: Equilibrium Innovativity

Notes: We plot the relationship between equilibrium *Innovativity* (Φ^*), *Market Effectiveness* (M), and *Idea Supply* (η_S). Φ equals the proportion of firms that do choose the *Innovation* (I) strategy. This proportion is equal to the minimum of: i) the proportion that could choose an idea to process (given by the exogenous idea supply constraint η_S indicated by the red line); and ii) the proportion that would choose an I strategy assuming that there is an idea available (the idea processing constraint $\eta_\rho[M]$ indicated by the blue line). Idea processing capacity increases with M. Hence, Φ^* is determined by the intersection of M^* and the lower of the blue and red lines, where η_ρ (η_S) is the binding constraint on Φ to the left (right) of the point where $\eta_\rho[M] = \eta_S$.

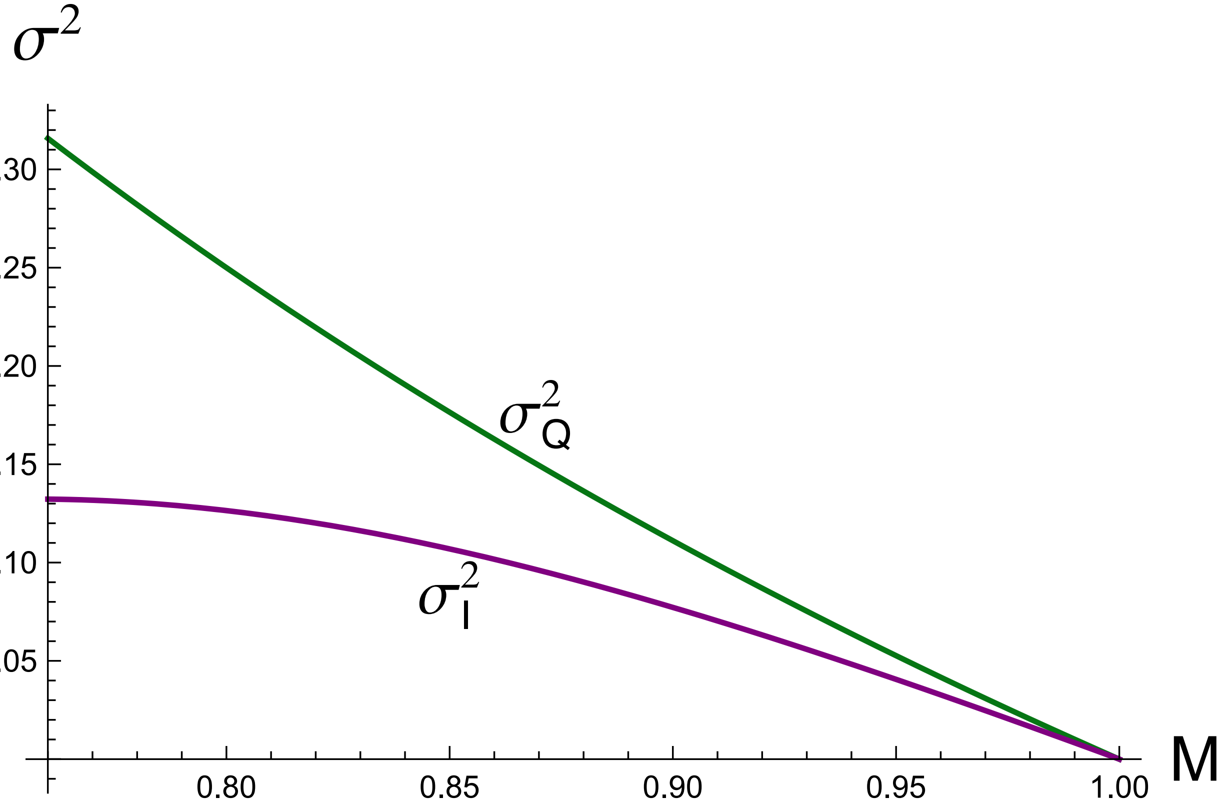

Figure 3: Variance of Returns by Strategy

Notes: We plot the variance of returns (IPO price to Secondary Market price) for firms pursuing an I (σ^2_I, in green) strategy or a Q strategy (σ^2_Q, in purple) as a function of market effectiveness M. The figure shows that: i) $\partial\sigma^2_Q/\partial M < 0$; ii) $\partial\sigma^2_I/\partial M < 0$; and iii) $\sigma^2_Q|_{M=M^*} > \sigma^2_Q|_{M=M^*}$.

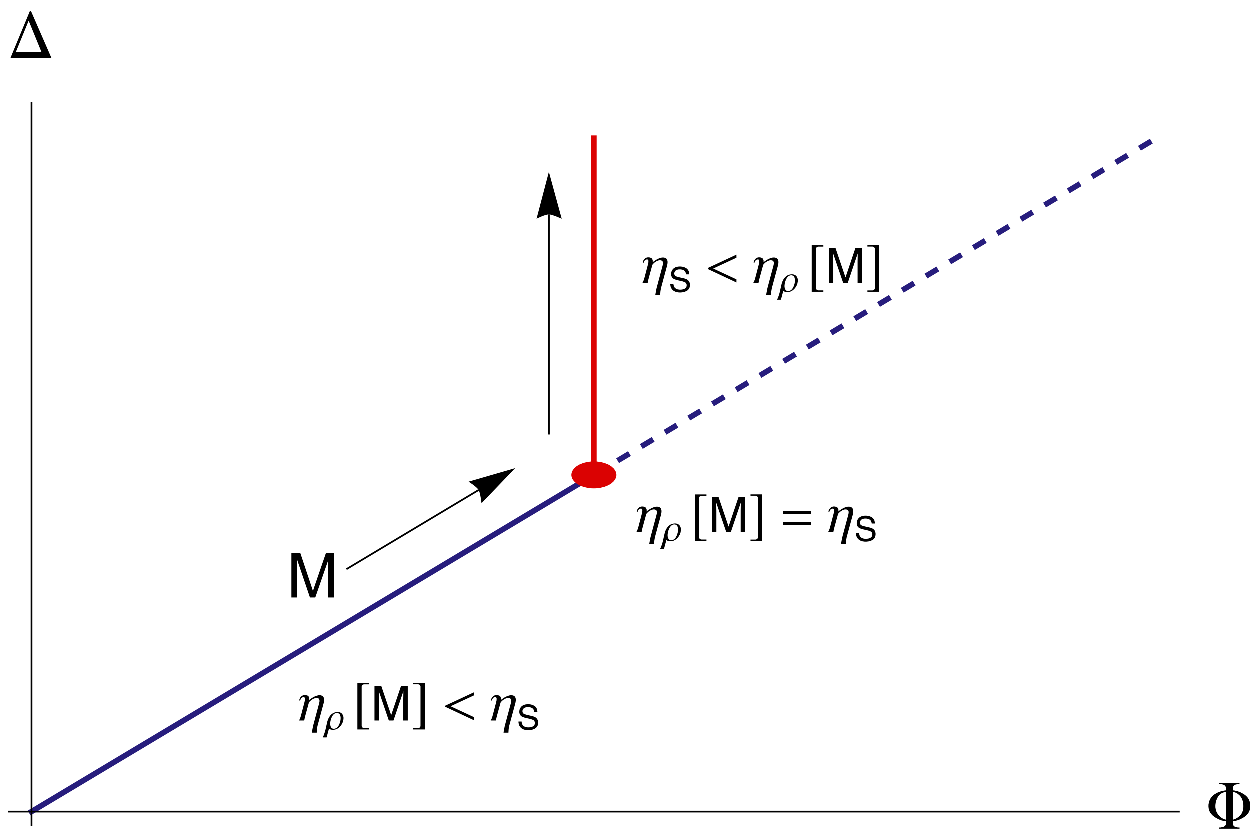

Figure 4: The Relationship Between Φ, Δ, M, and η_S

Notes: In this figure we plot the relationship between Innovativity (Φ), the fundamental component of the standard deviation of idiosyncratic firm returns (Δ), market effectiveness (M), and the idea supply constraint η_S. Idea processing capacity ($\eta_\rho [M]$) increases with M. So, for low values of M, η_ρ is the binding constraint on Φ. In this case, both Φ (Figure 2) and Δ increase with M (the blue line). η_S becomes the binding constraint on Φ once $\eta_\rho [M] = \eta_S$ (the red circle). In this case, an increase in M increases Δ but not Φ.

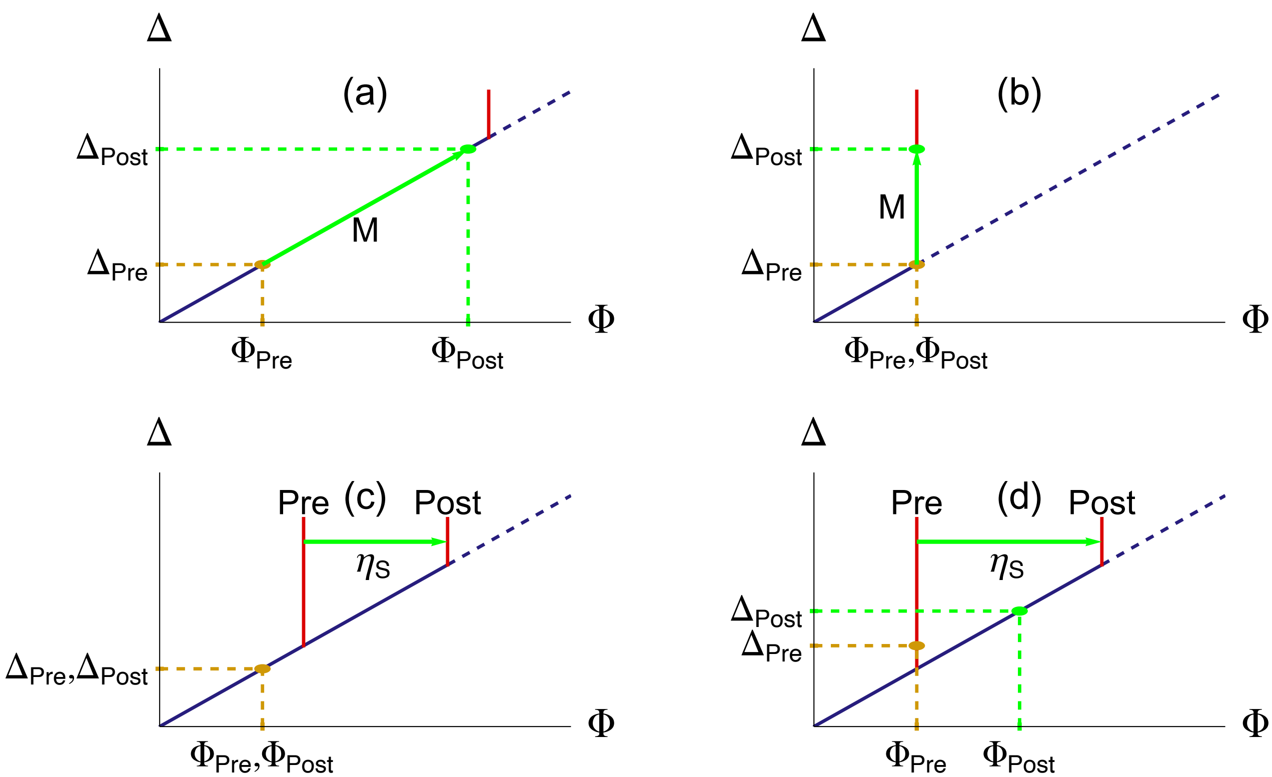

Figure 5: The Impact of Shocks on Φ and Δ

Notes: In this figure we examine the impact of shocks to market effectiveness (M) or idea supply (η_S) on equilibrium innovativity (Φ) and 1 minus the fundamental component of the standard deviation of idiosyncratic returns (Δ). See Figure 4 for a description of the diagram. In each panel, the PreShock equilibrium is indicated by the yellow dashed lines, the PostShock equilibrium (if different) by the green dashed lines, and the shock itself by the green arrow. Panel (a) (Panel (b)) shows the impact of a shock to M when idea processing capacity ($\eta_\rho [M]$) is (is not) the binding constraint on Φ, and Panel (c) (Panel (d)) shows the impact of a shock to η_S when it is (is not) the binding constraint on Φ.

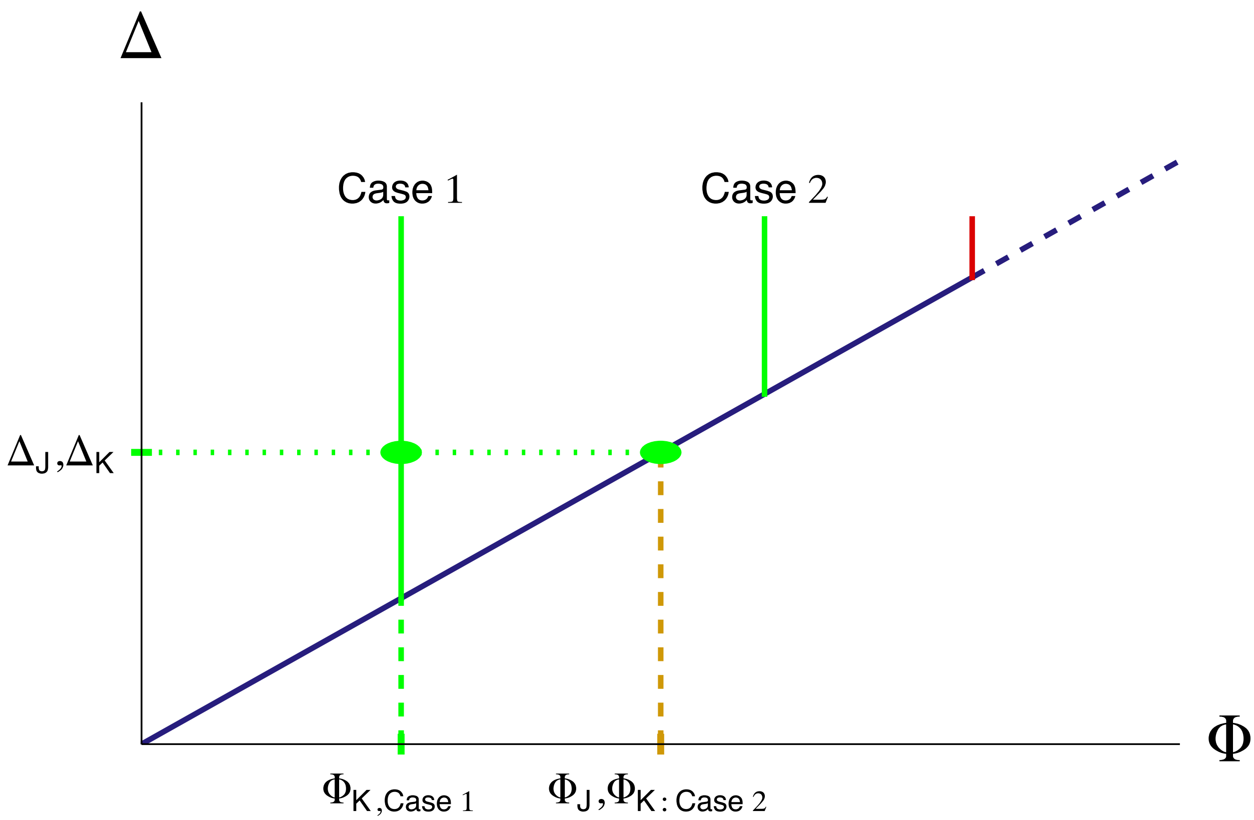

Figure 6: Innovativity Across Regimes When Δ Is Constant

Notes: In this figure we investigate what we can infer about innovativity in regime K given that $\Delta_K = \Delta_J$ and that $\eta_{\rho,J}$ is the binding constraint on Φ_J. In this case, $\Delta_J = \Delta_K$ implies that $\{\Phi_K, \Delta_K\}$ will be on the dotted green line, with: i) $\Phi_K < \Phi_J$ if $\eta_{S,K}$ is the binding constraint on Φ_K (Case 1); and ii) $\Phi_K = \Phi_J$ if $\eta_{S,K}$ is not the binding constraint on Φ_K (Case 2).

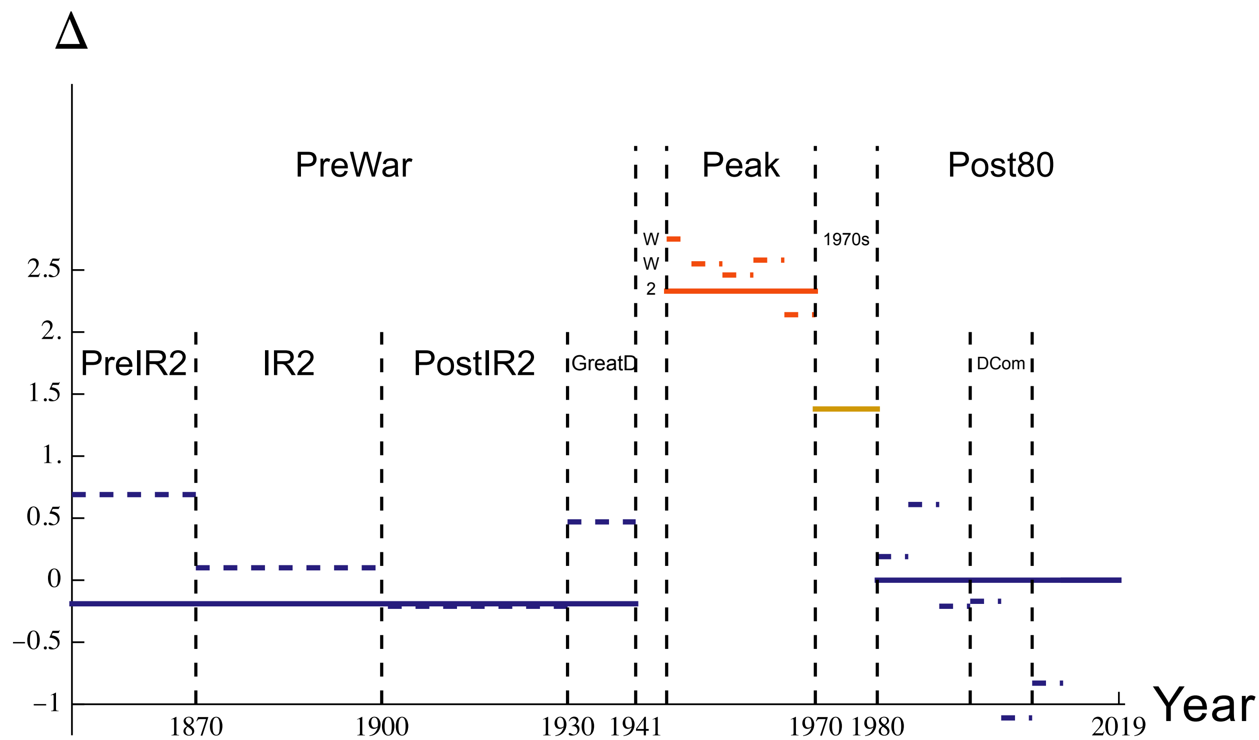

Figure 7: Innovativity Regimes

Notes: In this figure we plot Δ and identify innovativity regimes over our 1850 to 2019 sample period from the estimates in Table 3 (Specification 3) and Table 4 (Specification 2). An innovativity regime is a continuous period of time for which Δ (and so innovativity Φ) is constant. We identify three innovativity regimes: i) a *PreWar* regime of 1850/1941; ii) a *Peak* regime of 1946/1969; and iii) a *Post80* regime of 1980/2019. A solid line indicates estimated Δ for each regime, while a dashed line indicates estimated Δ for shorter periods of time. An orange (blue) line indicates that Δ is (is not) statistically significantly greater than 0. The yellow line indicates the 1970s transition period between the *Peak* and *Post80* regimes, with $\Delta_{Peak} > \Delta_{1970s} > 0$.

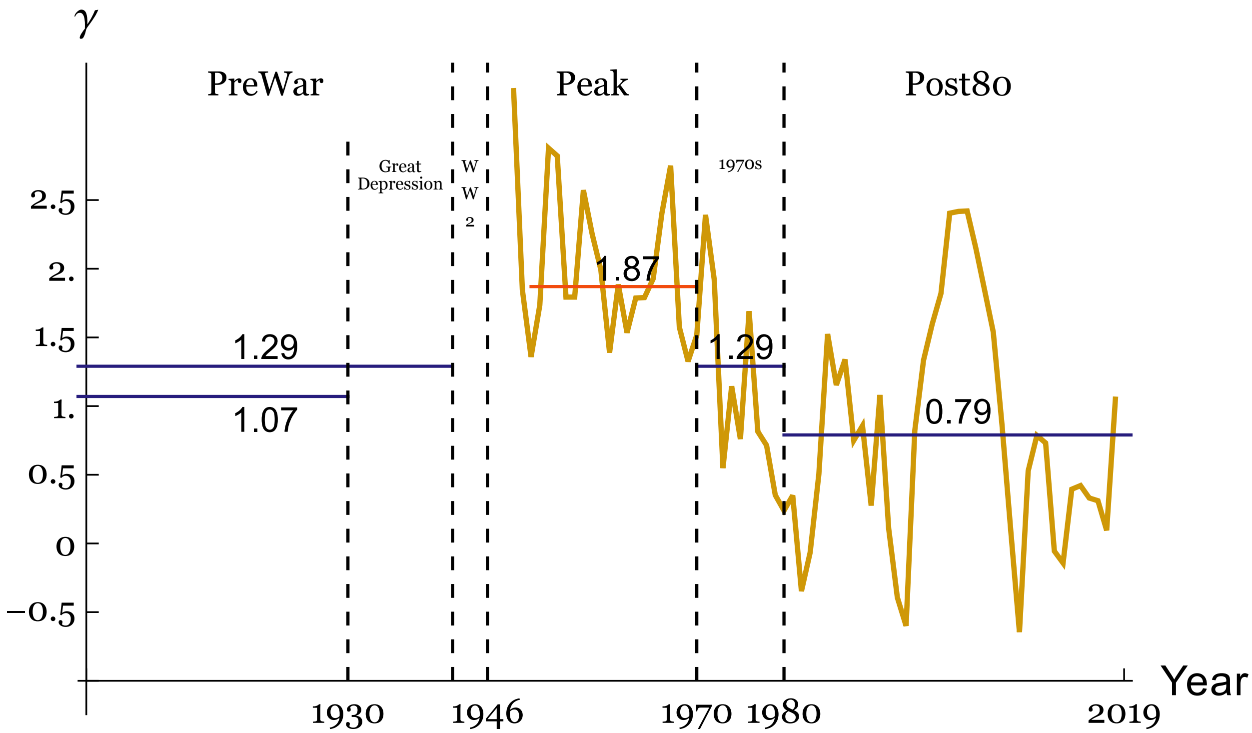

Figure 8: Innovativity and TFP Growth

Notes: We plot the evolution of average TFP growth over the 1899/2019 period by innovativity regime (Figure 7), with average TFP growth indicated by a blue (orange) line denotes that it is statistically significantly greater than average TFP growth in the *Post80* regime (Table 8). The yellow line shows the three year moving average of TFP growth for the PostWar period. Our PreWar TFP data is from Bakker, Crafts, and Woltjer (2019) and our PostWar data is from the San Francisco Federal Reserve's Annual Capacity Adjusted TFP Growth Series (Fernald 2014).

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