Ideas, Idea Processing, and US TFP Growth: Testing the Weitzman Conjecture

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Abstract

Innovativity—an economy's ability to produce the innovations that drive TFP growth—requires ideas and the ability to process those ideas into new products. We model innovativity as a function of endogenous idea processing capacity subject to an exogenous idea supply constraint and derive a method to identify 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) TFP growth fell after 1970 due to 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 test this conjecture 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 posit that: i) innovativity is a function of idea supply (the proportion of firms with access to an exploitable idea) and the economy's idea processing capacity (the proportion of firms that would choose a strategy that enables them to process an idea given that one is available); 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 that, in particular 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.[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]

To model innovativity, we assume that idea supply shifts in response to exogenous general purpose technology (GPT) shocks and that idea processing capacity is endogenously determined by the strategies that profit-maximizing 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

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

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

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. 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 the economy's 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 overall 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.

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.[4] 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 and that it 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

[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.

[4] We will generally drop the WW2 period from out analysis due to the extensive government controls over the economy at that time, and the 1970s is the transition period between the *Peak* and *Post80* innovativity regimes.

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 1941 despite the material exogenous GPT shock to idea supply between 1870 and 1900 that is the Second Industrial Revolution (Gordon 2012, 2014). Obviously, if a constraint shifts out 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 outward 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.[5] And, as this analysis predicts, innovativity does increase to the *High* state in the *Peak* regime of 1946/1969.

Innovativity falls again in 1970s despite another positive GPT shock to idea supply in the form of a permanent increase in the rate of change of the cost of computing (Nordhaus 2007). Our analysis therefore suggests that this fall is due decline in the economy's idea processing capacity brought about by a decline in efficacy of the 1930s/1940s security market reforms.[6]

So, our analysis implies 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 innovativity.[7]

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

[6] 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.

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

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 a scientific idea 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.[8]

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

[8] Kalyani (2022) supports the idea that firm strategy plays a critical role in innovation, finding that: i) patents can be either *creative* or *derivative*; ii) only creative patents drive TFP growth; and iii) the ratio of creative to derivative patents changes over time.

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.[9] 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 common with the Schumpeterian strand of EGT (see, for example, Aghion and Howitt (2006, 2008), King and Levine (1993), Aghion, Howitt and Levine (2018), and Popov (2018)) our analysis emphasizes the importance of financial markets. The Schumpeterian strand 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 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.[10] 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).

The EGT literature is vast, and there is much that we do not incorporate into this initial analysis of the idea processing/idea supply framework that we develop here. For example, while our analysis predicts that higher R&D spending in the post-1980 period will not increase TFP growth, we do not model the path of R&D spending itself. We also assume that firms do not strategically interact, so we do not examine the relationship between competition and innovation that is the focus of much of the Schumpeterian strand of the EGT literature. Furthermore, we do not embed our framework in a dynamic general equilibrium model. Our aim here is to test the Weitzman conjecture that idea processing capacity is the binding constraint on TFP growth using the simplest model possible. We plan to extend our analysis

[9] 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.

[10] 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.

to incorporate more aspects of EGT in future work.

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) show that innovativity determines average TFP growth; and iii) identify the binding constraint on innovativity. Concluding remarks follow.

I. Ideas, Idea Processing, and Innovativity

We hypothesize 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 exploit an idea to produce an innovation. To exploit an idea, a firm must: i) begin with a project with an exploitable idea; and ii) choose a long-horizon *Innovation* (I) strategy (rather than a short-horizon *Quick Win* (Q) strategy) to process that idea. We denote the proportion of firms with access to an exploitable idea by the economy's idea supply constraint χ_S, with $0 < \chi_S \leq 1$, and we denote the proportion of firms that will choose to process an idea assuming that one is available by the economy's idea processing capacity χ_ρ, with $0 < \chi_\rho \leq 1$. If $\chi_S < 1$ ($\chi_\rho < 1$), then the economy's idea supply constraint (idea processing capacity) is binding. Hence,

$$\Phi_T = \chi_{S,T}\left[W_T\right]\, \chi_{\rho,T}\left[M_T\right], \tag{2}$$

where W denotes the state of the economy's idea pool, M denotes the state of market effectiveness, and T denotes the time period.

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

A. Set-Up and Assumptions

We analyze innovativity in the context of a model consisting of firms and investors. In each period T, $T = \{1, \ldots, \infty\}$, a continuum of mass one of ex ante identical risk-neutral and profit-maximizing single share firms enter the market. Since each firm is ex ante identical, all random variable realizations are iid, and each period is independent, we will generally drop the T and F subscripts unless needed for clarity.

Each firm begins by selecting a promising project of type τ^*, $\tau \in \left\{Good(G), Bad(B)\right\}$ (an "*" denotes a specific value of a parameter or a realization of a random variable). While project type is unobservable, projects do produce signals of their type.

A firm produces a profit only if it is a commercial success, and to be a commercial success the firm must: i) have a G project; and ii) attract a specific investment by an outside party. The probability that the firm attracts the outside investment increases with the market's estimate of the probability that the firm has a G project.

A firm chooses an observable strategy ψ^*, $\psi \in \{I, Q\}$ to develop its project. A Q (*Quick-Win*) strategy produces a stronger signal of project type, while a I (*Innovation*) strategy produces a higher profit if the firm is a commercial success (and an innovation that improves the economy's TFP). A firm therefore faces the following trade-off when choosing its strategy: A Q strategy produces a stronger signal of project type and so increases the probability of commercial success, while an I strategy increases the firm's profit conditional upon success. The firm chooses its strategy to maximize its profit in light of this trade-off.

Sequence of Play

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

- t_1 — Project Creation: Each firm chooses a promising base project β_F of unobservable type τ^*, $\tau \in G, B$. Each project comes endowed with one signal of project type $\kappa 1$, $\kappa \in \{g, b\}$, and a promising project is one with a g signal. A promising project contains an exploitable idea with probability χ_S;

- t_2 — Strategy Choice: The firm learns whether or not its project contains an exploitable idea, and, if so, the observable net value α_F that processing that idea into an innovation will create for its project. The firm then chooses an observable strategy ψ, $\psi \in \{Q, I\}$ to develop its project;

- t_3 — Due Diligence and IPO: The market verifies firm information, and firms sell their one share at $P_{IPO,F}$;
- t_4 — Secondary Market (SM): A project produces a signal $\kappa 2$ of project type, with the precision of the signal depending upon the firm's strategy. The firm's price adjusts from P_{IPO} to P_{SM};
- t_5 — Specific Investment: An outside party decides whether or not to make a specific investment in the project as a function of market information on project type;
- t_6 — Revenue: The firm produces revenue of $\pi_{F,\psi}$ if it is a commercial success and revenue of 0 if not. The firm then winds up.

Projects, Firms, and Strategies

Since each firm sells its one share at P_{IPO}, it follows that a firm chooses its strategy ψ to maximize its IPO price. Consequently,

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

The investors to whom firms sell IPO shares and whom trade shares in the secondary market are (for simplicity) risk neutral and do not discount future revenue, so the price an investor pays for a share equals the expected profit that the firm produces. Consequently, firms choose ψ to maximize expected profit.

When choosing ψ, a firm begins with a base project β of unobservable type τ^*, where the unconditional probability that a project is of type G (B) equals $1/2$. Each β project is also endowed with an observable signal of project type $\kappa 1$, $\kappa 1 \in \{g, b\}$ which is verified in the *IPO* phase. Each firm therefore selects a promising project, that is, a project with a g signal.

The precision of a base project signal is a function of market effectiveness M, with

$$\kappa 1\left[\beta\right] = \begin{cases} \tau^* & \text{w.p.} \quad M, \\ \neg\tau^* & \text{w.p.} \quad 1 - M, \end{cases} \tag{4}$$

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

In t_2 the firm chooses a strategy ψ to develop the β project in a way that maximizes the firm's expected revenue and so its IPO price. A firm with an exploitable idea can increase project revenue by either: i) choosing an I strategy to process that idea, thereby producing additional net 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. A firm lacking an exploitable idea must choose the Q strategy.

So, if a firm with an exploitable idea chooses I, then

$$\pi_I^* = \pi_\beta + \alpha^*, \tag{5}$$

with

$$\alpha \sim V \text{ on } \{0, \infty\}. \tag{6}$$

An I project uses the β signalling technology and so produces $\kappa 2\,[\beta]$ in the SM phase.[12]

If the firm 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 if it attracts a specific investment by an outside party. We assume that the probability that the firm attracts the investment increases with the

[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.

[12] For simplicity, we assume that V remains constant over time. We can interpret $\eta_S\,[W]$ as the supply of ideas worth exploiting (all else equal), so factors that shift V enter the model through their impact upon η_S.

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 $\theta_{C,SM:\psi,\kappa1,\kappa2}$ and the probability that it has a G project given its strategy and $\kappa2$ by $\theta_{G:\psi,\kappa1,\kappa2}$. The probability that the firm attracts the specific investment conditional upon SM information is $\theta_{Y:\psi,\kappa1,\kappa2}$. To build in a smooth transition from Q to I as a function of market effectiveness, we assume that

$$\theta_{Y:\psi,\kappa1,\kappa2} = \theta_{G:\psi,\kappa1,\kappa2}^{\frac{1}{2}}. \tag{8}$$

It follows that

$$\theta_{C,SM:\psi,\kappa1,\kappa2} = \theta_{G:\psi,\kappa1,\kappa2}\,\theta_{Y:\psi,\kappa1,\kappa2} = \theta_{G:\psi,\kappa1,\kappa2}^{\frac{3}{2}}. \tag{9}$$

B. Idea Processing Capacity

The economy's idea processing capacity χ_ρ is equal to the proportion of firms that would choose an I strategy to develop their projects assuming that they have access to an exploitable idea, and firms choose I if it maximizes their IPO price. It follows that

$$\chi_\rho = \text{Prob}\big|_{@t_1}\left[P_{IPO:I} > P_{IPO:Q}\right]. \tag{10}$$

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

A firm's IPO price is equal to its expected secondary market price. Firms select projects with a g signal in t_1, and a firm receives either a g or a b signal in the secondary market, implying that

$$P_{IPO,\psi} = \theta_{g,g:\psi}\,P_{SM:\psi,g,g} + \theta_{g,b:\psi}\,P_{SM:\psi,g,b}, \tag{11}$$

where $\theta_{\kappa1,\kappa2:\psi}$ is the probability that the firm produces a secondary market signal of $\kappa2$ given its strategy ψ, and $P_{SM:\psi,\kappa1,\kappa2}$ is the share price given ψ, $\kappa1$, and $\kappa2$. A secondary market price in turn equals the firm's expected profit given ψ, $\kappa 1$, and $\kappa 2$, and so equals (from equation 9)

$$P_{SM:\psi,\kappa 1,\kappa 2} = \pi_\psi \, \theta_{C,SM:\psi,\kappa 1,\kappa 2} = \pi_\psi \, \theta^{3/2}_{G:\psi,\kappa 1,\kappa 2}. \tag{12}$$

Hence (from equation 11),

$$P_{IPO:\psi} = \pi_\psi \, \theta_{g,g:\psi} \, \theta^{3/2}_{G:\psi,g,g} + \pi_\psi \, \theta_{g,b:\psi} \, \theta^{3/2}_{G:\psi,g,b}. \tag{13}$$

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

If the firm chooses Q, then $\kappa 2$ reveals project type perfectly. Since the probability that a promising project is indeed a G (B) project is M (1 - M) given that $\kappa 1 = g$ (from equation 4), it follows that $\theta_{g,g:Q} = M$, $\theta_{g,b:Q} = 1 - M$, $\theta_{G:Q,g,g} = 1$, and $\theta_{G:Q,g,b} = 0$. Consequently (from equation 13),

$$P_{IPO:Q} = \pi_\beta \, M = M. \tag{14}$$

If the entrepreneur chooses I, then $\kappa 2$ equals (does not equal) τ^* with probability M $(1 - M)$. So, recalling that the firm starts with a promising project, it follows that

$$\theta_{g,g:I} = MM + (1 - M)(1 - M) = 1 + 2M^2 - 2M, \tag{15}$$

and that

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

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

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

Similarly,

$$\theta_{G:I,g,b} = \frac{(1 - M)\, M}{2\,(1 - M)\, M} = \frac{1}{2}. \tag{18}$$

Substituting the results of equations 15, 16, 17, and 18 into equation 13 yields

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

Consequently, an entrepreneur chooses $\psi = I$ if $\eta = P_{IPO:I} - P_{IPO:Q} > 0$, with (from equations 14 and 19)

$$\eta = (1+\alpha)\left(\frac{M^3}{\sqrt{2M^2-2M+1}} - \frac{(M-1)M}{\sqrt{2}}\right) - M. \tag{20}$$

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

$$\psi = \begin{cases} I & \text{if } \alpha > \alpha_{Crit}[M], \text{ and} \\ Q & \text{otherwise.} \end{cases} \tag{21}$$

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

$$\alpha_{Crit} = \frac{-2\,M\sqrt{\frac{M^2}{2M^2-2M+1}} + \sqrt{2}\,M - \sqrt{2} + 2}{2\,M\sqrt{\frac{M^2}{2M^2-2M+1}} - \sqrt{2}\,M + \sqrt{2}}. \tag{22}$$

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

So, firm chooses I if $\alpha > \alpha_{Crit}[M]$, which implies that

$$\chi_\rho[M] = \text{Prob}\big|_{@t_1}\left[\alpha > \alpha_{Crit}[M]\right]. \tag{23}$$

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

$$\frac{\partial \chi_\rho}{\partial M} > 0. \tag{24}$$

That is, the economy's idea processing capacity increases with market effectiveness. The intuition for this relationship between idea processing capacity and market effectiveness is straightforward. Since the signaling advantage that the Q strategy provides declines as market effectiveness increases, the minimum revenue boost α_{Crit} that a firm needs from an innovation to offset the Q signaling advantage also declines as market effectiveness increases.

C. Equilibrium Innovativity

Innovativity is equal to the proportion of firms that pursue an I strategy, and so (from equations 2 and 23)

$$\Phi = \chi_S \, \chi_\rho = \chi_S \, [W] \left(\text{Prob}\big|_{@t_1} \left[\alpha > \alpha_{Crit} \, [M] \right] \right). \tag{25}$$

Innovativity therefore evolves in response to shocks to W and M.

We assume that the state of the idea pool evolves in response to shocks to general purpose technology (GPT). Denote such a shock by ζ_{GPT}, with $\zeta_{GPT} \in \{Negative, 0, Positive\}$. Consequently,

$$\chi_{S,T+1} \, [W_{T+1}] = \chi_S \left[W_T + \zeta_{GPT,T+1} \right], \tag{26}$$

with $\partial \chi_S / \partial W \geq 0$ and with $\chi_S \, [W] : W > W^{**} = 1$. We assume that GPT shocks are independent over time.

Turning to market effectiveness, we assume that M evolves in response to the struggle between financial market participants and regulators. Market participants want M to be at the privately optimal level of $M_{Private}$ while regulators aim to move M to the socially optimal level of M_{Social}, with $M_{Social} > M_{Private}$ (Pirrong 1995). Consequently,

$$M_{T+1} = M_T + \zeta_{M,T+1} \tag{27}$$

and

$$M_{Private} \leq M \leq M_{Social}, \tag{28}$$

with $\zeta_{M,T} \in \{Negative, 0, Positive\}$ and with $\chi_\rho \, [M_{Social}] \leq 1$. We assume that M shocks are negatively correlated over time, with a positive M shock in T leading to a market reaction that increases the probability that the next M shock is negative.

The comparative statics of Φ in response to shocks to the economy's pool of ideas and market effectiveness are then straightforward:

$$\chi_{S,T+1}\left[\zeta_{GPT,T+1}\right] > \chi_{S,T} \implies \Phi_{T+1} > \Phi_{T}. \tag{29}$$

and

$$M_{T+1}\left[\zeta_{M,T+1}\right] > M_{S,T} \implies \Phi_{T+1} > \Phi_{T}. \tag{30}$$

We note that if the idea supply constraint is not binding (if $W > W^{**}$), then a positive ζ_{GPT} will not increase χ_S. In this case, the shock will have no effect upon Φ. Along the same lines, a positive ζ_M will not affect Φ if χ_ρ is not binding.

To test the relationships we derive between Φ, idea supply, and idea processing, we need an empirical measure of Φ. We turn to developing such a measure now.

II. Measuring Innovativity

We assume that the long run average rate of TFP growth $\bar{\gamma}$ is a function of Φ, but we cannot infer Φ from a TFP growth series alone because we cannot observe the period over which to calculate $\bar{\gamma}$. For example, it is impossible to tell from the TFP growth series itself whether the DotCom Boom is a transitory period of high TFP growth in a low innovativity regime or if it is a separate regime of high innovativity of its own.

However, we know that: i) Φ is a function of the relative proportions of Q and I firms; ii) the short-horizon Q strategy provides a stronger signal of project type than the long-horizon I strategy; and iii) 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 fundamental component of the standard deviation of (idiosyncratic) returns for Q firms (σ_Q) will be higher than that for I firms (σ_I). 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_{MarFun}), where σ_{MarFun}

can be estimated. We therefore conjecture that Δ, with

$$\Delta = 1 - \sigma_{MarFun}, \tag{31}$$

will provide a useful and non-circular empirical measure of Φ in that it will track Φ while being independent of TFP outcomes that are a function of Φ. In this section we develop this conjecture.

A. Constructing Δ

A firm's IPO to Secondary Market return given ψ, $\kappa 1$, and $\kappa 2$ is $R_{\psi,\kappa 1,\kappa 2}$, with

$$R_{\psi,\kappa 1,\kappa 2}\left[M\right] = \frac{P_{SM:\psi,\kappa 1,\kappa 2} - P_{IPO:\psi}}{P_{IPO:\psi}}, \tag{32}$$

where (from equation 12)

$$P_{SM:I,g,g} = (1+\alpha)\left(\frac{M^2}{1-2M+2M^2}\right)^{3/2},$$

$$P_{SM:I,g,b} = (1+\alpha)\left(\frac{1}{2\sqrt{2}}\right), \tag{33}$$

$$P_{SM:Q,g,g} = 1, \text{ and}$$

$$P_{SM:Q,g,b} = 0.$$

It then follows from equation 33 and IPO prices for Q and I firms (equations 14 and 19) that $R_{\psi,\kappa 1,\kappa 2}$ is a function of M (or a constant) alone and not χ_S.[13]

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

$$\sigma_\psi\left[M\right] = \sqrt{\theta_{g,g:\psi}\left[M\right]\, R^2_{\psi,g,g}\left[M\right] + \theta_{g,b:\psi}\left[M\right]\, R^2_{\psi,g,b}\left[M\right]}, \tag{34}$$

[13] In the case of I firms, the $(1+\alpha)$ term cancels out.

where $\theta_{\kappa 1,\kappa 2:\psi}$ is also a function of M but not χ_S. Consequently,

$$\Delta = 1 - \sigma_{MarFun} = 1 - \sqrt{\Phi\left[\chi_S, \chi_\rho\left[M\right]\right]\ \sigma_I^2\left[M\right] + \left(1 - \Phi\left[\chi_S, \chi_\rho\left[M\right]\right]\right)\sigma_Q^2\left[M\right]}. \tag{35}$$

So, Δ is a function of Φ, σ_I^2, and σ_Q^2. We know how Φ behaves from the analysis above. Turning to $\sigma_I^2\left[M\right]$ and $\sigma_Q^2\ \left[M\right]$, 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 $\sigma_I^2\left[M\right]$ and $\sigma_Q^2\left[M\right]$ numerically (from equations 32 and 34) and plot them in Figure 2.[14] Inspecting Figure 2, we find that: i) $\sigma_Q^2\big|_{M=M^*} > \sigma_I^2\big|_{M=M^*}$; ii) ${\partial\sigma_Q^2}/{\partial M} < 0$; and iii) ${\partial\sigma_I^2}/{\partial M} < 0$.

B. The Relationship between Δ and Φ

We now demonstrate that Δ is a useful measure of Φ by showing that: i) Δ tracks the directional impact of a shock to Φ; ii) Δ enables us to identify innovativity regimes (that is, periods of constant innovativity); and iii) Δ tracks the level of Φ in specific plausible cases (if not in general). Consider each proposition in turn.

Proposition 1: Δ tracks the directional impact of a shock to Φ.

Proof: Φ responds to positive (or negative) shocks to χ_S and M. Consider the impact of each of these shocks on Φ and Δ (we only explicitly examine the impact of positive shocks here, but the analysis extends directly to negative shocks).

We begin with idea supply. If χ_S is binding, then $\zeta_{GPT} = \mathit{Positive}$ implies that $\chi_{S,T+1}\left[\zeta_{GPT,T+1}\right] > \chi_S$. It follows that $\Phi_{T+1} > \Phi_T$ and $\sigma^2_{\psi,T+1}\left[M\right] = \sigma^2_{\psi,T}\left[M\right]$. Hence, from the Δ definition in equation 35, a positive shock to idea supply when χ_S is binding shifts weight from the higher $\sigma^2\ Q$ strategy to the lower $\sigma^2\ I$ strategy and so reduces σ_{MarFun}. However, if χ_S isn't binding, then a positive supply shock implies that $\chi_{S,T+1}\left[\zeta_{GPT,T+1}\right] = \chi_S$, $\Phi_{T+1} = \Phi_T$, and $\sigma^2_{\psi,T+1}\left[M\right] = \sigma^2_{\psi,T}\left[M\right]$. In this case, the shock has no effect upon either the Q/I split or σ^2_ψ and so does not effect σ_{Market}.

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

Consequently,

$$\begin{aligned}\chi_{S,T+1}\left[\zeta_{GPT,T+1}\right] > \chi_{S,T} &\implies (\Phi_{T+1} > \Phi_T) \text{ and } (\Delta_{T+1} > \Delta_T), \text{ and} \\ \chi_{S,T+1}\left[\zeta_{GPT,T+1}\right] = \chi_{S,T} &\implies (\Phi_{T+1} = \Phi_T) \text{ and } (\Delta_{T+1} = \Delta_T).\end{aligned} \tag{36}$$

Turn now to a shock to M. If $M_{T+1}\left[\zeta_{M,T+1}\right] > M_T$, then $\Phi_{T+1} > \Phi_T$ and (from Figure 2) $\sigma_{\psi,T+1}\left[M_{T+1}\right] < \sigma_{\psi,T}\left[M_T\right]$. Hence, a shock to M has two effects: i) it lowers σ_{MarFun} holding the Q/I split constant; and ii) it shifts weight from the higher σ^2 Q strategy to the lower σ^2 I strategy. Since both effects push in the same direction, it follows that

$$\chi_{\rho,T+1}\left[M_{T+1}\left[\zeta_{M,T+1}\right]\right] > \chi_{\rho,T} \implies (\Phi_{T+1} > \Phi_T) \text{ and } (\Delta_{T+1} > \Delta_T). \tag{37}$$

Thus, any *Positive* or *Negative* shock ζ_{GPT} or ζ_M either shifts Φ_T and Δ_T in the same direction or leave both Φ_T and Δ_T unchanged. $\square$

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 then an innovativity regime Ω in which Φ is constant.

Proof: In Proposition 1 we established that any shock ζ that shifts Φ also shifts Δ in the same direction. Hence, if $\Delta_T = \Delta_{T+1}$, then there is no shock in $T+1$ that shifts Φ, implying that $\Phi_T = \Phi_{T+1}$ (we assume here that multiple exactly off-setting shocks do not occur in the same period).

$\square$

Proposition 3: Consider two innovativity regimes J and K. If $\chi_{S,J} = \chi_{S,K}$, then $\Delta_J > (=)(<)\Delta_K$ implies that $\Phi_J > (=)(<)\Phi_K$.

Proof: If $\chi_{S,J} = \chi_{S,K}$, then it follows from the definition of Φ in equation 25 and the definition of Δ in equation 35 that both Φ and Δ are monotonically increasing functions of M.

$\square$

We assume for now that Proposition 3 holds. We shall show below that this is plausibly the case.

So, while we cannot directly measure Φ, our indirect measure Δ enables us to: i) identify innovativity regimes and innovativity regime shifts; ii) predict the directional impact of an innovativity regime shift on average TFP growth in all cases and to predict the relative level of average TFP growth across regimes in at least some cases; and iii) deduce (in combination with a set of exogenous shocks) whether it is shocks to idea supply and/or market effectiveness that drive the evolution of US innovativity over the 1899/2019 period. In the rest of the paper we consider (i), (ii), and (iii) in turn.

III. Innovativity Regimes and Regime Transitions: 1850 to 2019

An innovativity regime is a period of time for which Δ is constant (Proposition 2), and a regime transition occurs when Δ shifts from one stable value to another as a result of a shock to idea supply or market effectiveness (Proposition 1). The evoloution of Δ therefore enables us to track regimes and to identify regime shifts.

To estimate Δ, we assume that

$$O_T = 1 - \sigma_{MarO,T} = Constant + \Delta_{Start/End} + \beta_{Bull}\, Bull_T + \beta_{Bear}\, Bear_T + TShocks_T + \epsilon_T, \qquad (38)$$

where $\sigma_{MarO,T}$ 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).[15] The Old NYSE (ONY) data is available at a monthly frequency, so we

[15]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.

also use monthly data for the CRSP period.[16]

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 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.[17]

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 $\sigma_{MarO,Norm}$ 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 ($\sigma_{Quart,T}$) as above. We normalize each quartile's $\sigma_{Quart,T}$ series by dividing it by the mean of that series. We set $\sigma_{MarO,Norm,T}$ equal to the average of the $\sigma_{Quart,T}$ for T and then replace $\sigma_{MarO,T}$ with $\sigma_{NormO,T}$ in equation 38.

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

[16]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.

[17]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).

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 ONY and the CRSP samples in Table 2.

B. Analysis

We begin our analysis of Δ's evolution by estimating equation 38 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.[18] This model yields white-noise residuals (using the Q-test) in each regression.

We begin by estimating equation 38 will the full set of Δ dummies (Table 3). In Specification 1 we use the CRSP sample with O as the dependent variable, and in Specification 2 use O_{Norm} as the dependent variable. We exclude $\Delta_{2010/2014}$ and $\Delta_{2015/2019}$ to provide the constant term. In both specifications 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.

In Specification 3 we estimate 38 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 Ω 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

[18]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.

significantly 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 38 for innovativity regimes. In Specification 1 we examine the CRSP period and in Specification 2 we examine the 1850/2019 period, dropping the *Post80* regime for the constant term. Both specifications yield consistent 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 3.

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.[19] 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 38 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.[20]

[19] 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).

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

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.

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.

The Evolution of Innovativity

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 Λ and two regime transitions. These regimes are a *PreWar* regime of 1850/1941, a *Peak* regime of 1946/1969, and a *Post80* regime of 1980/2019. The regime transitions occur in the 1930s/40s and in the 1970s. Furthermore, since $\Delta_{PreWar} = \Delta_{Post80}$ and $\Delta_{Peak} > \Delta_{Post80}$, it follows that (assuming Proposition 3 holds) Φ itself is in one of two states: *High* or *Low*, with $\Phi_{Peak} = \Phi_{High}$ and $\Phi_{PreWar} = \Phi_{Post80} = \Phi_{Low}$.

We now turn to exploring the relationship between innovativity and TFP growth.

IV. Innovativity and TFP Growth: 1899 to 2019

The innovativity hypothesis posits that long run average TFP growth $\bar{\gamma}$ is a function of innovativity. Consequently, our analysis of innovativity regimes above predicts that (from Proposition 2)

$$\bar{\gamma}_{Peak}\left[\Phi_{High}\right] > \bar{\gamma}_{Post80}\left[\Phi_{Low}\right] \tag{39}$$

and (from Propositions 2 and 3) that

$$\bar{\gamma}_{Post80}\left[\Phi_{Low}\right] = \bar{\gamma}_{PreWar}\left[\Phi_{Low}\right]. \tag{40}$$

In this section we test these predictions.

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

$$\bar{\gamma}_\Lambda \sim \Gamma\left[\Omega_\Lambda\left[\Phi_\Lambda\right], Y_\Lambda\right], \tag{41}$$

where Ω_Λ is the TFP generating process given Φ_Λ and Y_Λ is the length of Λ (in years).

We can observe the realization of $\bar{\gamma}$ ($\bar{\gamma}^*$) for all regimes given that we have identified them via Δ, 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 take as our Null hypothesis the proposition that the state of innovativity is constant across regimes. Our Null is then that

$$\bar{\gamma}_{Test,Null} \sim \Gamma_{Test}\left[\Omega_{Post80}, Y_{Test}\right], \tag{42}$$

with $Test \in \{PreWar, Peak\}$. We accept the Null that $\bar{\gamma}_{Peak} = \bar{\gamma}_{Post80}$ if

$$\bar{\gamma}^*_{Peak} < \Gamma_{Test,95} \tag{43}$$

and we accept the Null that $\bar{\gamma}_{PreWar} = \bar{\gamma}_{Post80}$ if

$$\Gamma_{Test,2.5} < \bar{\gamma}^*_{PreWar} < \Gamma_{Test,97.5} \tag{44}$$

and reject the Null otherwise, where $\Gamma_{Test,Z}$ is the Z^{th} quantile of $\Gamma_{Test}\left[\Omega_{Post80}, Y_{Test}\right]$.

A. Data

We obtain our TFP growth data from two sources. The San Francisco Federal Reserve produces an annual TFP growth series for the years 1948/2019. For this period, we set TFP growth in year T equal to the natural log of the utilization adjusted annual rate of total factor productivity growth (dftp_util).[21] We

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

aware of no comparable data for the *PreWar* period. Instead, we use the long run average TFP growth estimates from Bakker, Crafts, and Woltjer (2019). This data covers the period 1899/1941.[22]

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 4.

B. Analysis

To carry out the tests in equations 43 and 44, 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

$$\Omega_{Post80} = \left\{ \{\gamma_U, \gamma_D\}, \epsilon_{Dis}, \Xi \right\}, \tag{45}$$

where γ_ν, $\nu \in U, D$ is expected TFP growth in state ν, 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 is $\gamma_T[\nu]$, with

$$\gamma_T[\nu] = \gamma_\nu + \epsilon_T, \tag{46}$$

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

Factors that affect either idea supply (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 Λ, 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}. Indeed, any estimate of the TFP growth process

[22] 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.

that does directly include such variables is mis-specified. 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 45 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 -0.13 and insignificant. In Specification 2 we estimate equation 45 including a time trend and find that the trend term is insignificant.[23] So, as our analysis predicts, there is no trend in the TFP growth process within the *Post80* regime.

From Specification 1, we assume that Ω_{Post80} has the following form:

- $\gamma_D \sim$ Normal Distribution $[-0.13, 0.24]$
- $\gamma_U \sim$ Normal Distribution $[1.86, 0.23]$;
- $\theta_{DD} \sim$ Normal Distribution $[0.83, 0.63]$;
- $\theta_{DU} = 1 - \theta_{DD}$;
- $\theta_{UD} \sim$ Normal Distribution $[-0.66, 0.62]$;
- $\theta_{UU} = 1 - \theta_{UD}$; and
- ϵ_{Dis} = the residuals from Specification 1,

with the θ_{DD} and θ_{UD} distributions in logit form.[24]

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

[23] Without imposing the constraint that $\gamma_D = 0$, outliers influence the regression and produce an unrealistic estimate of $\gamma_D = -2.22$.

[24] The 95% confidence interval for θ_{DD} (θ_{UD}) expressed in probabilities is: $\{0.39, 0.89\}$ ($\{0.14, 0.61\}$).

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

$$\bar{\gamma}_{Test,Null,J} = \frac{(N_{D,J} \times \gamma_{D,J}) + (N_{U,J} \times \gamma_{U,J}) + \bar{\epsilon}_J}{Y_J}, \tag{47}$$

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

$$\Gamma_{Test} = \left\{\bar{\gamma}_{Test,Null,1}, \ldots, \bar{\gamma}_{Test,Null,100\,000}\right\}. \tag{48}$$

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

$$\bar{\gamma}^*_{Peak} > \Gamma_{Peak,95}$$

and therefore reject the Null that $\Phi_{Peak} = \Phi_{Post80}$.[25]

Turning to the *PreWar* case, we find that

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

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

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.

Given that $\Phi_{PreWar} = \Phi_{Post80} = \Phi_{Low}$, we would ideally estimate Ω_{Low} using the combined

[25]To control for the possibility that this result is driven by the immediate PostWar boom, we also ran this test with $\bar{\gamma}^*_{Peak}$ measured for the 1951/1969 period rather than the 1948/1969 period. This change did not alter the result.

PreWar and *Post80* data and test the Null hypothesis that $\bar{\gamma}_{Peak} = \bar{\gamma}_{Low}$ with

$$\bar{\gamma}^*_{Peak} < \Gamma_{Low,95}\left[\Omega_{Low}, Y_{Peak}\right].$$

As we noted above, though, we do not have the annual TFP data for the *PreWar* period that would enable us to do so. To approximate this test, we modify our Null to

$$\bar{\gamma}^*_{Peak} < \frac{\bar{\gamma}^*_{PreWar} + \bar{\gamma}^*_{Post80}}{2} + (\Gamma_{Post80,95} - \bar{\gamma}^*_{Post80}). \tag{49}$$

We reject this Null as well. It follows that $\Omega_{High}\left[\Phi_{High}\right] > \Omega_{Low}\left[\Phi_{Low}\right]$.

The Rise and Fall of US TFP Growth

The innovativity hypothesis predicts that average TFP growth will track innovativity, and we find that our measure of innovativity Δ does correctly predict both the pattern and the timing of the rise and fall of average TFP growth in the US over the last 120 years. This analysis therefore suggests both that our empirical measure of innovativity does track Φ and that Φ does drive TFP growth.

V. The Rise and Fall of US Innovativity: 1850 - 2019

The rise and fall of US innovativity over the 1850/2019 period could in principle be due to either variation in the supply of exploitable ideas (arising from *GPT* shocks) and/or to variation in the economy's idea processing capacity (arising from *M* shocks). In this section we seek to identify which of these factors does drive the innovativity regime shifts that we observe.[26]

We do so as follows. Recall from above that in our analysis of the impact of shocks on Φ and Δ (Propositions 1, 2, and 3) we show that: i) a *Positive* shock to idea supply/idea processing capacity will cause an innovativity regime shift only if that constraint is binding; and ii) that regime shift will cause a shift in Δ in the same direction. So, if an *M* (*GPT*) shock occurs and Δ changes state shortly thereafter,

[26] Of course, if neither *GPT* shocks nor *M* shocks provide a satisfactory explanation of innovativity regime shifts, our analysis would then suggest some other type of shock is responsible.

we infer that χ_ρ (χ_S) is binding and that the M shock (GPT shock) caused innovativity to transition from one state to another. If, on the other hand, an M (GPT) shock occurs and Δ does not shift, we infer that χ_ρ (χ_S) is not binding.

To carry out this analysis, we begin by identifying shocks.

A. Shocks

We assume that GPT shocks affect idea supply and that M shocks affect idea processing capacity. Consider GPT and M shocks in turn.

GPT Shocks

The first GPT shock in our sample period is the Second Industrial Revolution (*IR2*) of 1870/1900. 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." In the context of our model, we interpret Gordon (2014) to mean that *IR2* created a *Positive GPT* shock $\zeta_{GPT,IR2}$.

For the remainder of our sample period, we identify GPT shocks on the basis of Nordhaus's (2007) analysis of productivity growth in computing. Nordhaus (Table 8) identifies two positive and statistically significant shocks (where a shock is a permanent change to the speed of improvement in computing), one in 1945 and one in 1985. Denote these two shocks by $\zeta_{GPT,1945}$ and $\zeta_{GPT,1985}$.

Market Effectiveness Shocks

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) reports, for example, 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. 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 of $M_{Private}$.

A general consensus that the ineffective financial markets of the *PreWar* regime caused the stock market crash of 1929 sparked a deep and wide-ranging reform effort aimed precisely at pushing M towards M_{Social} (Seligman 1995). Consider just one strand of this effort: the evolution the financial reporting regime for NYSE listed firms.[27]

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.

On the basis of this evidence, we assume that this reform effort created a positive M shock $\zeta_{M,Reform}$ in the later 1930s/early 1940s.[28]

While *GPT* shocks will not create a natural and influential constituency to push back against them, M shocks are a different story since they can benefit the economy in general while adversely affecting the influential financial services sector. Thus, an M shock will naturally lead to attempts by financial market participants to work around the reforms, which could lead to a deterioration in M once those efforts become successful (and if the regulators do not keep up with market developments). This *Response* shock may not be a sharp event. We therefore postulate that a *Negative M* shock $\zeta_{M,Response}$ will

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

[28]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.

occur at some point after $\zeta_{M,Reform}$.[29]

While we identify only one *Positive M* shock over our sample period, it is obviously the case that financial regulation has undergone numerous changes since the 1930s/1940s reforms. In our view, these subsequent changes have not been on the same scale as the more fundamental transformation of the regulatory regime in the 1930s/1940s. Thus, we do not count these more minor regulatory adjustments as "shocks". It would of course be useful to develop a more quantitative method to assess the impact of regulatory change on financial market effectiveness.

Shocks: 1850 to 2019

So, we identify three *Positive GPT* shocks: $\zeta_{GPT,IR2}$ in 1870/1900, $\zeta_{GPT,1945}$ in around 1945, and $\zeta_{GPT,1985}$ in around 1985. We also identify two M shocks: a *Positive M* shock $\zeta_{M,Reform}$ in around 1940 and a *Negative* shock $\zeta_{M,Response}$ at a later but unspecified date.

We plot these shocks against Δ (from Table 3) in Figure 5, and we now turn to investigating this relationship.

B. Innovativity Regimes: Shocks and Transitions

At the start of our sample period, we assume that $\chi_{\rho,PreWar} = \chi_{\rho}[M_{Private}] < 1$ given the absence of effective financial regulation. Consequently, χ_{ρ} is initially a binding constraint on Φ. We have no information on the state of idea supply W, so we do not assume a value for χ_S. Consequently, we do not know whether χ_S is also binding. Consider now the impact of GPT and M shocks on innovativity regimes and regime transisitons.

The Second Industrial Revolution

The first shock in our sample period is the *Positive IR2* shock $\zeta_{GPT,IR2}$ to χ_S in 1870/1900. Inspecting Figure 5, we find that $\zeta_{GPT,IR2}$ did not affect Δ as $\Delta_{PreIR2} = \Delta_{IR2} = \Delta_{PostIR2}$ (Table 4). It then follows from Proposition 1 that $\zeta_{GPT,IR2}$ did not affect Φ either. The only way that a *Postive* shock

[29] If we do detect $\zeta_{M,Response}$, then our analysis implies that will be evidence of a decline in the effectiveness of financial market regulation. While carrying out the analysis required to test this implication is outside the scope of this paper, we plan to investigate this implication in future work.

to χ_S will not increase Δ (and therefore Φ) is if the idea supply constraint is not binding. So, we infer that the idea supply is not a binding constraint on Φ in the *PreWar* period.

The Shocks of the 1930s/1940s

Since χ_ρ is binding, our analysis predicts that a *Positive* shock to M will increase the economy's idea processing capacity and will therefore lead to increases in Δ and Φ. $\zeta_{M,Reform}$ is such a shock. Our analysis therefore predicts that $\zeta_{M,Reform}$ will increase Δ. Inspecting Figure 5, we find precisely that: Δ increases significantly following $\zeta_{M,Reform}$.

Our analysis therefore implies that the economy's transition from the *Low* Φ *PreWar* regime to the *High* Φ *Peak* regime is the result of an increase in the economy's idea processing capacity brought about by an improvement in financial market effectiveness.

We also observe a *Positive GPT* shock $\zeta_{GPT,1945}$ at around the same time as $\zeta_{M,Reform}$. In theory, this shock too could increase Δ and Φ. However, we established above that χ_S is not binding. Since a *Positive* shock to a non-binding constraint will not have any effect, we conclude that it is the M shock $\zeta_{M,Reform}$ to the economy's idea processing capacity rather than the *GPT* shock $\zeta_{GPT,1945}$ to idea supply that caused the innovativity regime shift.

The Peak to Post80 Transition

The economy's shift from the *High* Φ *Peak* regime to the *Low* Φ *Post80* regime is one of the central puzzles of US PostWar economic performance because there is no clear sharp event that could have brought it about.

Since this decline occurs despite a *Positive* $\zeta_{GPT,1985}$ that would either improve innovativity or at least leave it unchanged, our analysis suggests that this decline cannot be due to a decline in the supply of exploitable ideas (as Gordon 2014 conjectures). Instead, our analysis implies that this regime transition is due to a *Negative* $\zeta_{M,Response}$ that decreased the economy's idea processing capacity. Our argument in favor of this conjecture consists of three pieces of evidence.

First, given that $\zeta_{GPT,1985}$ is *Positive* and (from above) $\chi_{S,Peak}$ is not binding, our analysis suggests that $\chi_{S,Post80}$ is also not binding. In this case, only a *Negative M* shock could bring about the decline in Δ that we observe. We believe that the *Positive M* shock $\zeta_{M,Reform}$ will induce a *Negative M* shock in response, so we find the idea that such a shock exists plausible.

Second, given that $\chi_{S,Peak}$ is not binding, in follows that Φ and Δ are monotonic functions of M. Consequently, since $\Delta_{PreWar} = \Delta_{Post80}$ (Table 4), our analysis then predicts from Proposition 3 that $\Phi_{PreWar}\left[M_{PreWar}\right] = \Phi_{Post80}\left[M_{Post80}\right]$.[30] We confirmed this prediction above (Table 8). This result implies that $M_{PreWar} = M_{Post80}$ and hence that a *Negative M* shock after 1970 caused M to fall from M_{Peak} to M_{Post80}.

And third, we established above that $M_{PreWar} = M_{Private}$, and we know that $M \geq M_{Private}$. Assuming again that Δ is a monotonic function of M due to χ_S not being binding, our analysis then predicts that $\Delta_{Post80}\left[M_{Post80}\right] \geq \Delta_{PreWar}\left[M_{PreWar}\right]$. We find that $\Delta_{Post80} = \Delta_{PreWar}$, confirming this prediction (Table 4). This result in turn suggests that the level of M in the *Post80* regime has fallen back to its pre-reform level.

So, while this evidence in favor of the hypothesis that the *Post80* decline in US innovativity is due to fall in financial market effectiveness that reduced the economy's idea processing capacity is not definitive, we think that the evidence does establish that this hypothesis is plausible.

C. Innovativity, Idea Processing, and Idea Supply

The dominant narrative for the *Low/High/Low* pattern of US innovativity over the last 120 years presumes that it is driven by soley by shocks to 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

[30] To be sure, our test of this prediction is not that powerful because our estimate of the plausible range of $\bar{\gamma}_{PreWar}$ under the Null is wide.

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 empirical result 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.

Our innovativity analysis does provide a way to test the idea supply hypothesis. Since Δ tracks innovativity and since idea supply shocks will cause an innovativity regime shift if the economy's idea supply constraint is binding, the idea supply hypothesis predicts that the timing of idea supply shocks will explain the evolution of US innovativity. Yet this is not the case: the *Positive IR2* shock did not increase Δ, the *Positive GPT:1945* shock occurs at the same time as the *Positive Reform* shock to M, and the *Positive GPT:1985* shock occurs when innovativity falls from its *High* state in the *Peak* regime to its *Low* state in the *Post80* regime. So, while it is of course impossible to rule the idea supply hypothesis out,[31] the evolution of innovativity and the timing of shocks over the 1850/2019 period provide very little reason to rule it in.

The Weitzman conjecture that it is the economy's idea processing capacity rather than the idea supply constraint that determines the level of innovativity does a better job of explaining how innovativity evolves. This hypothesis predicts that innovativity will increase following an increase in M, and we observe that innovativity does shift from its *Low* state in the textitPreWar regime to its *High* state in the *Peak* regime following the financial market reforms of the 1930s/40s. Furthermore, our analysis suggests that M declined in the 1970s, causing the economy to transition from the *High* innovativity *Peak* regime to the *Low* innovativity *Post80* regime. Thus, our analysis suggests that the Weitzman conjecture is plausibly correct.

[31] For example, perhaps *GPT* shocks do not influence idea supply.

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.[32]

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.

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[32]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

O_T	$(1 - \sigma_{MarO,T}) \times 100$.
$O_{Norm,T}$	$(1 - \sigma_{NormO,T}) \times 100$.
$O_{CRSP:HP,T}$	$(1 - \sigma_{HP,T}) \times 100$.
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	1946/1969 (TFP data for 1948/1969) .
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. $\sigma_{MarO,T}$ is the observed 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). $\sigma_{NormO,T}$ is the normalized standard deviation of idiosyncratic firm returns for T. To compute $\sigma_{NormO,T}$, 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
O_{CRSP}	91.51	2.19
Λ_{Norm}	0.00	25.50
$O_{ONY/CRSP}$	91.44	2.41
$O_{CRSP:HP}$	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	O		O_{Norm}		Oa	
	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 O, with $O = (1 - \sigma_{MarO}) * 100$ and $O_{Norm} = (1 - \sigma_{NormO}) * 100$, where σ_{MarO} (σ_{NormO}) 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	O		O		$O_{CRSP:HP}$	
	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.
$\bar{\gamma}_{\Lambda}^{*}$	Observed value of average TFP growth in regime Λ.
Ω_{Post80}	The TFP growth process in the Post80 regime.
$\Gamma_{\Lambda}\left[\Omega_{Post80}, Y_{\Lambda}\right]$	The distribution of $\bar{\gamma}_{\Lambda}$ under the Null hypothesis that the TFP growth process in Λ is equal to the TFP growth process in the *Post80* regime, where Y_{Λ} is the length of Λ in years.
$\Gamma_{\Lambda,Z}$	The Z^{th} percentile of Γ_{Λ}.
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	—
Peak	2.06	1.47
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*, *Peak*, 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
g_D	-0.13	0.00
	0.23	Constrained
g_U	1.84*	1.84*
	0.28	0.34
Trend		0.00
		0.01
θ_{DD}	0.70	0.72
	$\{0.39, 0.89\}$	$\{0.42, 0.90\}$
θ_{DU}	0.30	0.28
	$\{0.11, 0.61\}$	$\{0.10, 0.58\}$
θ_{UD}	0.34	0.35
	$\{0.14.0.61\}$	$\{0.14, 0.63\}$
θ_{UU}	0.66	0.65
	$\{0.39, 0.86\}$	$\{0.37, 0.86\}$

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?
$\bar{\gamma}^*_{\text{Peak}} < \Gamma_{Post80,95}$	2.06	1.66	Yes
$\bar{\gamma}^*_{\text{PreWar}} \in \left\{\Gamma_{Post80,2.5}, \Gamma_{Post80,97.5}\right\}$	1.29	{-0.05, 1.68}	No
$\bar{\gamma}^*_{Peak} < \Gamma_{Low,95}$	2.06	1.91	Yes

Notes: To compare innovativity across regimes, we assume that $\bar{\gamma}_{Test} \sim \Gamma_{Null}$, where Γ_{Null} is the distribution of $\bar{\gamma}_{Test}$ under the Null hypothesis. We consider two Nulls: i) the TFP growth process in the *Test* regime equals that in the *Post80* regime; and ii) the TFP process in the *Test* regime equals that of the combined *Low* innovitivity *PreWar* and *Post80* regimes. We compute Γ_{Post80} 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 1; 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 $\bar{\gamma}^*_{Post80,j}$. We then set Γ_{Post80} equal to $\left\{\bar{\gamma}^*_{Post80,1}, \ldots, \bar{\gamma}^*_{Post80,100{,}000}\right\}$. We lack the data required to estimate Γ_{PreWar}, so to approximate Γ_{Low} we center Γ_{Post80} on $(\bar{\gamma}^*_{Post80} + \bar{\gamma}^*_{PreWar})/2$.

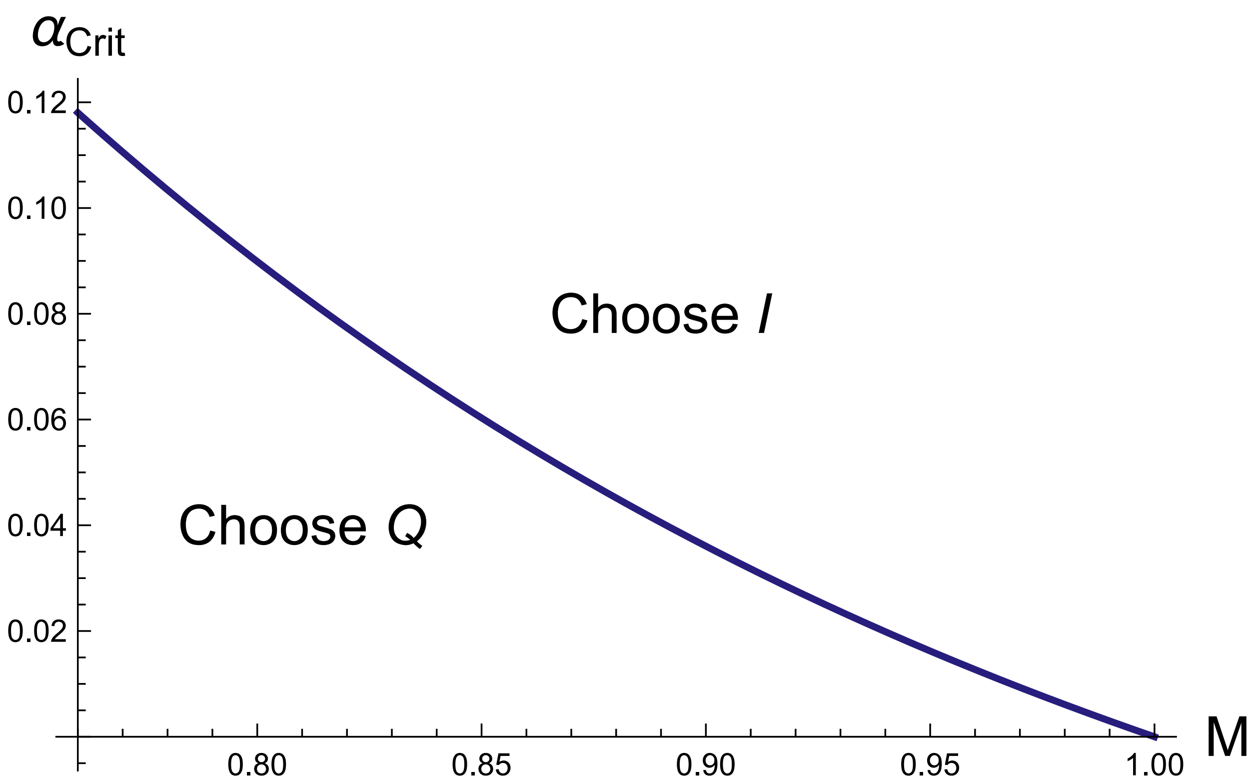

Figure 1: Strategy Choice and Market Effectiveness

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.

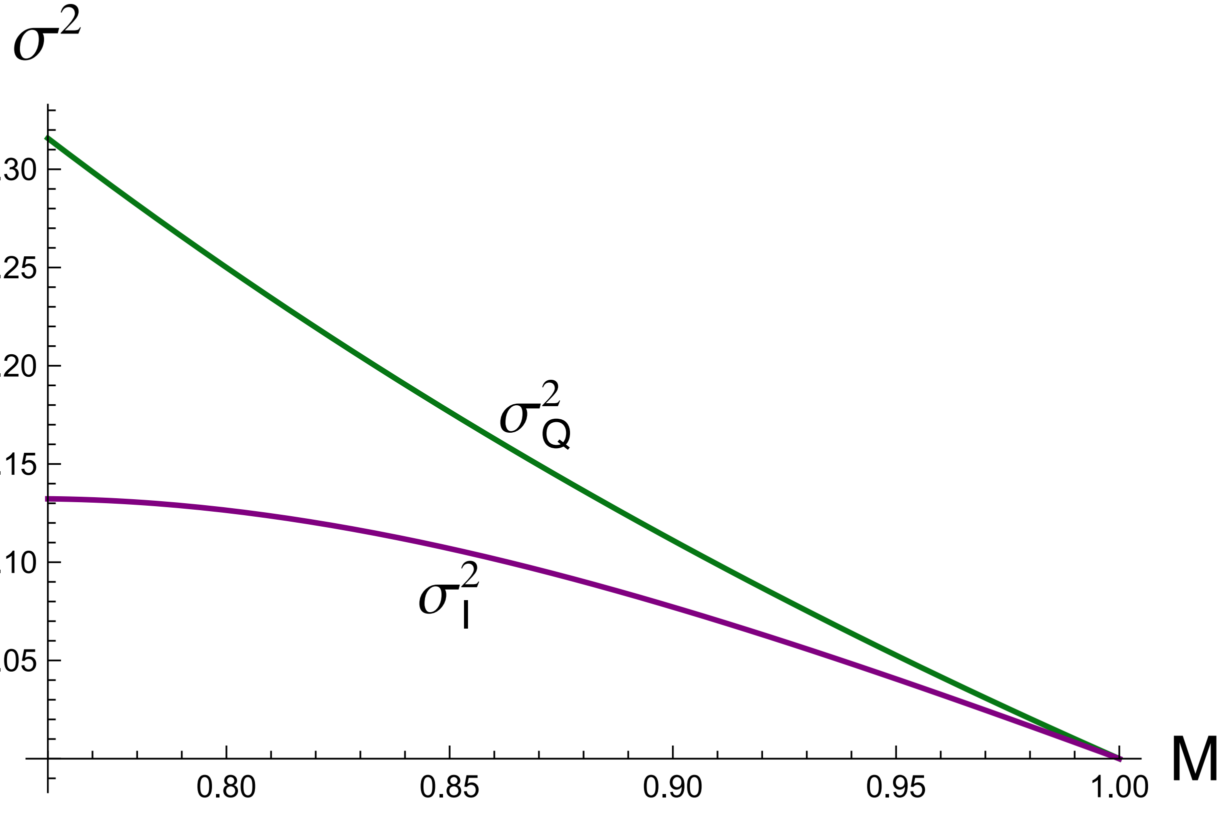

Figure 2: Variance of Returns by Strategy

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

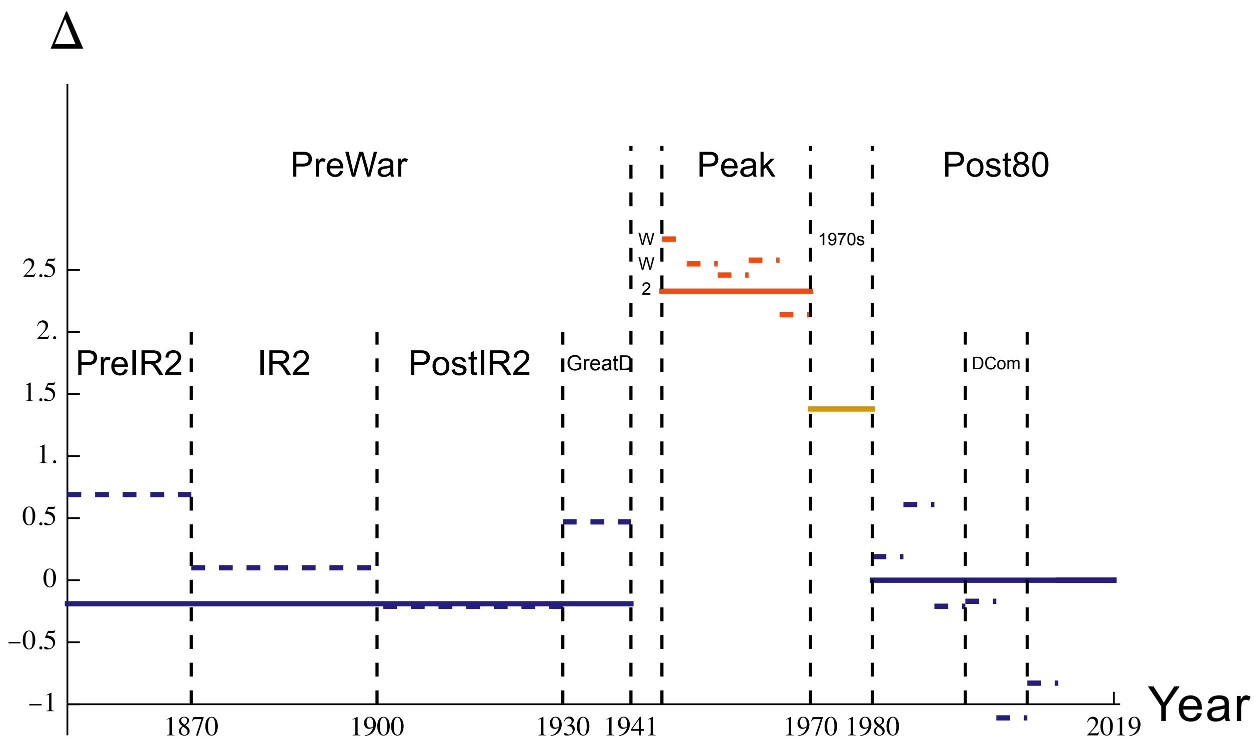

Figure 3: Innovativity Regimes

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 $\Delta_{Peak} > \Delta_{1970s} > 0$.

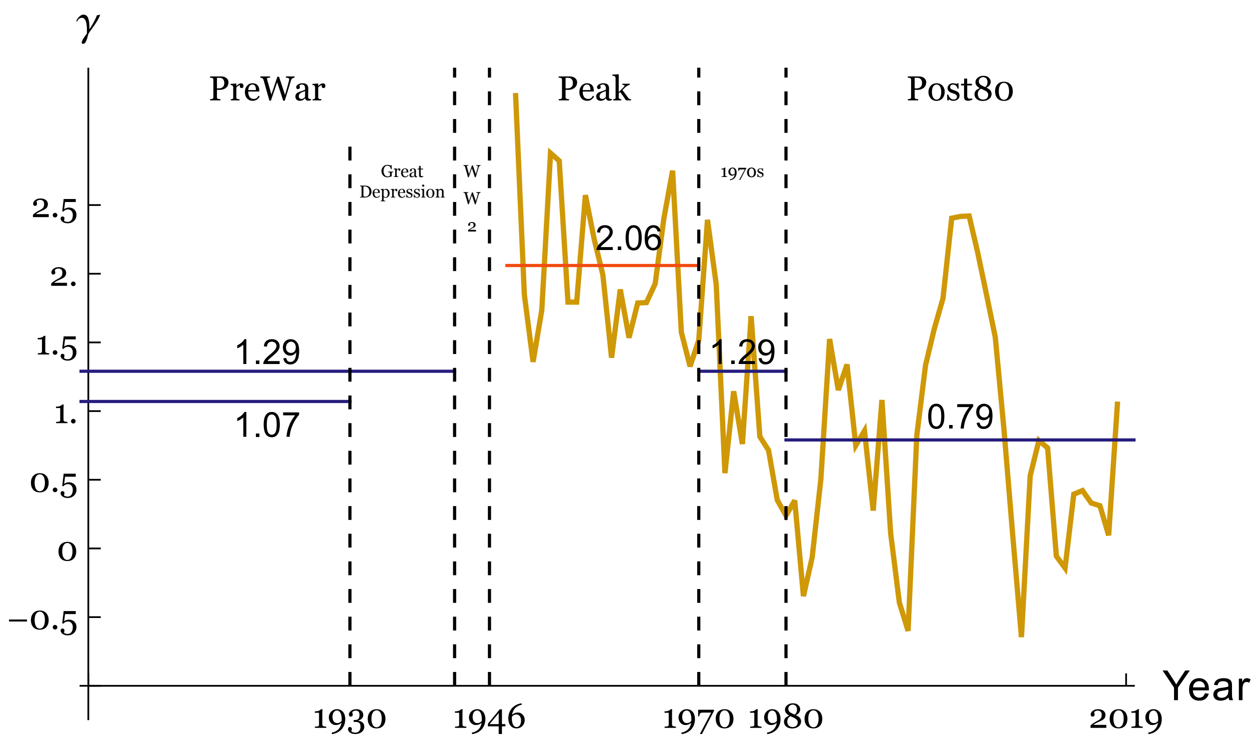

Figure 4: Innovativity and TFP Growth

Notes: We plot the evolution of average TFP growth over the 1899/2019 period by innovativity regime (Figure 3), 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).

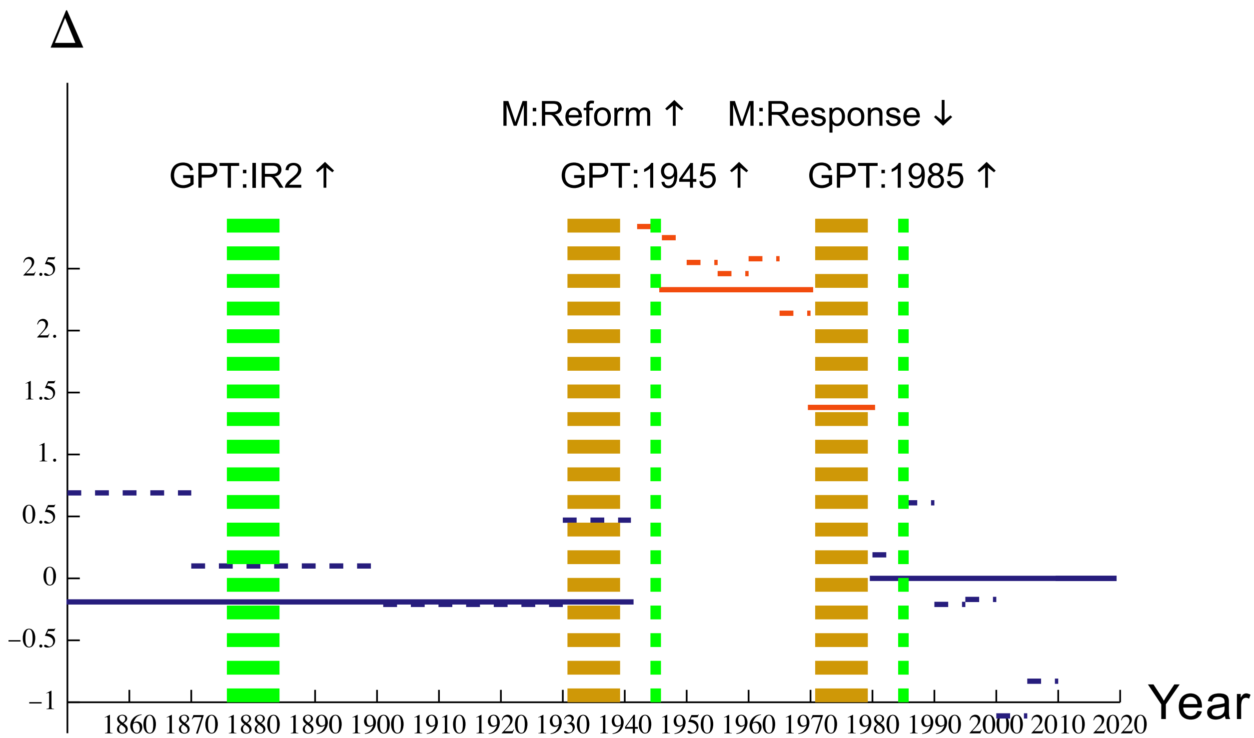

Figure 5: Shocks and Innovativity Regimes

Notes: We plot the evolution of Δ (from Figure 3) against general purpose technology (*GPT*) shocks to idea supply (in green) and market effectiveness (*M*) shocks to idea processing capacity (in yellow), with the direction of the shock indicated by an up or down arrow. We identify three positive GPT shocks: the Second Industrial Revolution (*IR2*) shock (Gordon 2012) of 1880, the *GPT:1945* cost of computing shock (Nordhaus 2007), and the *GPT:1985* cost of computing shock (Nordhaus 2007). We identify one positive *M* shock: the 1930s/1940s financial market reforms triggered by the Great Depression (Seligman 1995). We conjecture that the positive *Reform* shock induced a negative *Reaction* shock as financial market participants found ways around the restrictions imposed by the reformed regulatory regime.