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Economic
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Research Council

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SRC Discussion Paper No 121
July 2022



Systemic Risk Centre

Discussion Paper Series

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

This paper is published as part of the Systemic Risk Centre's Discussion Paper Series. The support of the Economic and Social Research Council (ESRC) in funding the SRC is gratefully acknowledged [grant number ES/R009724/1].

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Published by
Systemic Risk Centre
The London School of Economics and Political Science
Houghton Street
London WC2A 2AE

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Ideas, Idea Processing, and TFP Growth in the US: 1899 to 2019

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July 11, 2022

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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 capability 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 capability is the binding constraint on innovativity; and iii) average TFP growth declined after 1970 due to a constraints on idea processing capability, 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 capability 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 capability; and ii) the TFP growth process is a function of innovativity. We solve for equilibrium innovativity and derive the empirical measure of innovativity the theory implies (this measure is independent of the TFP data itself). Exploiting exogenous shocks to idea supply and idea processing capability together with restrictions imposed by our theory, we establish that: i) measured innovativity predicts the evolution of average US TFP growth over the last 120 years;¹ and ii) idea processing capability (rather than idea supply) is the binding constraint on innovativity. 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 deserves further

¹We also show that high TFP growth does not reverse cause high measured innovativity.

examination.²

One implication of our analysis is that the post-1970 decline in US TFP growth did not happen because ideas are getting harder to find—contrary to Gordon’s (2012, 2014) highly influential conjecture that the growth slowdown arose because “the main ideas of [the Second Industrial Revolution] had by and large been implemented by then”.³ Consequently, an effective policy response to the critical problem of low TFP growth should incorporate measures aimed at enhancing the economy’s idea processing capability in addition to the current set of measures which aim almost exclusively at shifting up the (in our view) non-binding idea supply constraint (see, for example, Bloom, Van Reenan, and Williams 2019). In particular, our analysis finds that financial market effectiveness plays a critical role in determining idea processing capability. Hence, policies aimed at improving financial market effectiveness may offer a promising (and inexpensive) path to improve US TFP growth.

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) in a tractable reduced form fashion.

We contribute to EGT by endogenizing idea processing capability. We begin with the premise that the economy’s idea processing capability is determined by the strategies

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

³See also Cowen (2011) and Bloom, Jones, Van Reenan, and Webb (2020). The *FT* article “Productivity and innovation stagnation, past and future: an epic compendium of recent views” by Cardiff Garcia (11 March 2016) provides an extensive set of links to the wide-ranging debate inspired by Gordon’s analysis.

that profit-maximizing entrepreneurs (or firms) choose to develop their projects (Arora, Belenzon, Patacconi, and Suh 2019).

A project produces a payoff if it is a commercial success and a project is a commercial success if its type is *Good* (rather than *Bad*) 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.⁴

An entrepreneur can influence the expected value of their project by pursuing either: i) a short horizon *Quick Win* (*Q*) strategy that increases the probability of commercial success by producing a stronger intermediate signal of project quality; 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 capability 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 capability—increases with market effectiveness.

⁴Simon (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.

Since Q firms produce more precise signals of project type than I firms and since those signals affect firm price by influencing the probability of commercial success, the return distribution of Q firms has a higher standard deviation than the return distribution of I firms. As the proportion of I firms (and so innovativity) increases, then, the standard deviation of the return distribution of all firms falls. Our empirical measure of innovativity ($\tilde{\Phi}$) is therefore based upon one minus the fundamental component of the standard deviation of idiosyncratic firm returns.⁵

We use $\tilde{\Phi}$ to identify innovativity regimes, that is, continuous periods of time in which $\tilde{\Phi}$ is constant. Identifying innovativity regimes is important for three reasons.

First, we show that true innovativity Φ is also constant within an innovativity regime. So, given a regime, we can then measure Φ itself on the basis of the TFP growth process within that regime. One cannot identify an innovativity regime on the basis of the TFP data directly because one must first identify a period in which Φ is constant before estimating the TFP process that is a function of Φ . For example, it is impossible to tell on an ex ante basis if a period of high TFP growth such as the DotCom boom of 1995/2004 is a transitory period of high TFP growth within a low innovativity regime or a separate high innovativity regime of its own.

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

⁵This measure of innovativity is inspired by Simon (1989), who finds that the market effectiveness improving 1933 Securities Act lowered the standard deviation of IPO returns.

measure the direct impact of idea supply factors upon the TFP growth process may be misspecified (especially given our finding that idea supply is not the binding constraint on innovativity in the US over the 1899/2019 period).⁶

Second, given an innovativity regime, we can identify the binding constraint on innovativity in that regime on the basis of exogenous shocks to idea supply or idea processing capability.

And third, we show that Φ and $\tilde{\Phi}$ can respond differently to shocks to idea supply and idea processing capability depending upon which constraint is binding. So, comparing the evolution of Φ and $\tilde{\Phi}$ will enable us to identify the binding constraint on innovativity in certain cases even in the absence of a clear exogenous shock. In particular, we show that if Φ and $\tilde{\Phi}$ are each in the same state in two innovativity regimes, then the binding constraint upon innovativity is also the same in those two 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 1980/2019.⁷ We find that $\tilde{\Phi}$ is in a *Low* state in the *PreWar* and *Post80* regimes and in a *High* state in the *Peak* regime.

Using a combination of exogenous shocks and restrictions imposed by our theory, we predict that true innovativity (and so average TFP growth) will track measured innovativity. Examining Φ on the basis of these regimes, we find that this is so. While this

⁶Bakker, Crafts, and Woltjer (2019) make a related observation in their discussion of Bloom et al. (2020).

⁷While our measure of innovativity is related to idiosyncratic volatility, we show that the trading behavior of retail investors in low-priced stocks that drives the time-series variation in idiosyncratic volatility (Brandt, Brav, Graham, and Kumar 2009) is not driving the time series variation in innovativity.

rise and fall pattern of average TFP growth is of course well known in an empirical sense, our innovativity approach is the first (to the best of our knowledge) to predict this pattern—including the regime transition dates—without reference to the TFP data itself.

The principal contribution of our innovativity framework is that it enables us to examine the causes of innovativity’s rise and fall by identifying the binding constraint on innovativity over time. To begin with the *PreWar* regime, 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 capability is the binding constraint on innovativity in the *PreWar* regime.

If idea processing capability is the binding constraint on innovativity, then an upward shift in idea processing capability will lead to an increase in innovativity. The financial market reform effort of the 1930s/1940s did lead to an increase in financial market effectiveness and so to such an upward shift. And, as we predict, both $\tilde{\Phi}$ and Φ do increase to the *High* state in the *Peak* regime of 1946/1969.⁸

The *High* innovativity *Peak* regime ends in 1969 and the US then transitions into the *Low* innovativity *Post80* regime. The cause of this shift is one of the central puzzles of PostWar US economic performance as there is no sharp exogenous event that explains it. Consequently, this decline could be due to either a gradual deterioration in financial market effectiveness that decreases idea processing capability or to a gradual downward shift in the idea supply constraint due to, for example, ideas getting harder to find.

⁸See Seligman (2003) for a history of securities market regulation.

To resolve this puzzle, we note that both $\tilde{\Phi}$ and Φ are in the same *Low* state in the *PreWar* and *Post80* regimes. In this case, our analysis shows that the binding constraint on innovativity must be the same in each regime as well. Since we find that the binding constraint on innovativity in the *PreWar* regime is idea processing capability, it follows that idea processing capability is also the binding constraint on innovativity in the *Post80* regime.

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 capability 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 capability offer a promising avenue of attack on the critical problem of low innovativity.⁹

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 capability 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 innovative 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

⁹As in Acemoglu, Moscona, and Robinson (2016), then, we too find that “the institutional environment has a key impact on technological progress”.

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 capability 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 capability 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 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 capability as well as idea supply. 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 capability 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.¹⁰ 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 capability. 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 1990) 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.¹¹ 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).

¹⁰See Aghion, Howitt and Levine (2018) and Popov (2018) for recent surveys.

¹¹We 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.

In the remainder of this paper, we first derive the equilibrium level of innovativity (Φ) and the empirical measure of innovativity that this analysis implies ($\tilde{\Phi}$). We next use these measures to: i) identify innovativity regimes on the basis of $\tilde{\Phi}$; ii) identify Φ for each regime; and iii) predict the evolution of Φ across regimes and identify the binding constraint on Φ in each regime. Conclusions follow.

I. Innovativity: Theory and Measurement

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

$$(1) \quad \frac{\partial \bar{\gamma}}{\partial \Phi} > 0.$$

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 capability constraint). In each period T , then,

$$(2) \quad \Phi_T = \text{Min} [\eta_{S,T}, \eta_{\rho,T} [M_T]].$$

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

After setting out the assumptions of our model, we derive η_ρ and Φ . We then derive $\tilde{\Phi}$, the empirical measure of Φ that this analysis implies. We conclude this section by establishing that a combination of $\tilde{\Phi}$ and restrictions imposed by our theory enable us to both measure Φ itself and to identify the binding constraint on Φ empirically.

A. Set-Up and Assumptions

We analyze innovativity in the context of a model consisting of entrepreneurs, investors, and workers. In each period T , $T = \{1, \dots, \infty\}$, 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 specific investment by a worker.¹²

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 of an unobservable type τ^* , with $\tau \in \{Good(G), Bad(B)\}$, each with probability $1/2$ (an “*” indicates a

¹²Investors 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.

specific value of a parameter or a realization of a random variable). Each project comes endowed with one signal of project quality $\kappa_{\beta, IPO}$, with $\kappa \in \{g, b\}$, and entrepreneurs select projects with a g signal;

- t_2 – Strategy Choice: Each entrepreneur learns the observable value that an innovation will create for their project (Δ) 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 $\kappa_{\beta, IPO}$ and Δ (if the firm chooses I), and firms sell their one share at $P_{IPO, \psi}$;
- t_4 – Secondary Market (SM): Both Q and I projects produce a signal of project type $\kappa_{SM, \psi}$, 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 $P_{SM, \psi, \kappa}$;
- t_5 – Specific Investment: The firm hires a worker. The worker is in state W , with $W = Y$ (N) if that worker makes (does not make) an unobservable and non-contractable specific investment in the firm;
- t_6 – Revenue: The firm produces revenue of $\pi_{\psi, Z}$ if it is a commercial success; a firm is a commercial success if it has a G project and if its worker makes the specific investment. 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,

$$(3) \quad \psi^* = \psi : P_{IPO,\psi} = \text{Max} \{P_{IPO,Q}, P_{IPO,I}\}.$$

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

$$(4) \quad P_{j,\iota} = \Pi_{@j:\iota},$$

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 (we use the “@ j ” notation to indicate the value of a parameter in phase j). Hence, entrepreneurs choose ψ to maximize expected project revenue.

When choosing ψ , all entrepreneurs begin with a base project of unobservable type τ^* . A base project is endowed with a signal $\kappa_{\beta,IPO}$ of its type in the project creation phase (t_1) which is verified at the IPO phase. A base project also produces a signal $\kappa_{\beta,SM}$ of its type in the secondary market (t_4) and revenue π_β of 1 in t_6 if the project is commercially successful. An entrepreneur selects a project with a g signal, and so the output of the β project is then β_{Out} , with $\beta_{Out} = \left\{ g_\beta, \kappa_{\beta,SM}, \{ \pi_\beta, 0 \} \right\}$.

The precision of a base project signal at both the project creation and the

secondary market phase is a function of market effectiveness M , with

$$(5) \quad \kappa_\beta = \begin{cases} \tau^* & \text{w.p. } M, \\ \neg\tau^* & \text{w.p. } 1 - M, \end{cases}$$

with $1/2 < M \leq 1$.

In t_2 the entrepreneur chooses a strategy ψ to develop the base 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 increases the revenue the project produces if it 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

$$(6) \quad \pi_I^* = \pi_\beta + \Delta^*,$$

with $\Delta \sim V$ on $\{0, \infty\}$. Consequently, the firm's output becomes I_{Out} , with

$$I_{Out} = \left\{ g_\beta, \kappa_{\beta, SM}, \{ \pi_\beta + \Delta^*, 0 \} \right\}.$$

If the entrepreneur chooses Q , then the firm produces a secondary market signal $\kappa_{Q, SM}$ instead of $\kappa_{\beta, SM}$. For simplicity we assume that $\kappa_{Q, SM}$ is perfectly precise, implying

that

$$(7) \quad \kappa_{Q,SM} = \begin{cases} \tau^* & \text{w.p. } 1, \\ \neg\tau^* & \text{w.p. } 0. \end{cases}$$

The firm's output if the entrepreneur chooses Q is then Q_{Out} , with

$$Q_{Out} = \left\{ g_\beta, \kappa_{Q,SM}, \{ \pi_\beta, 0 \} \right\}.$$

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

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

It follows that

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

B. Idea Processing Capability

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

$$(9) \quad \eta_\rho = \text{Prob}@t_1 [P_{IPO,I} > P_{IPO,Q}].$$

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

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

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

$$(11) \quad P_{SM:\psi,\kappa} = \pi_\psi \theta_{C@SM:\psi,\kappa} = \pi_\psi \theta_{G:\psi,\kappa}^{3/2}.$$

Hence (from equation 10),

$$(12) \quad P_{IPO,\psi} = \pi_\psi \theta_{g:\psi} \theta_{G:\psi,g}^{3/2} + \pi_\psi \theta_{b:\psi} \theta_{G:\psi,b}^{3/2}.$$

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

If the entrepreneur chooses Q , then κ_Q 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),

$$(13) \quad P_{IPO,Q} = \pi_\beta M = M.$$

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

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

and that

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

$\theta_{G:I,g}$ 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

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

Similarly,

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

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

$$(18) \quad P_{IPO,I} = (1 + \Delta) \left(\frac{M^3}{\sqrt{2M^2 - 2M + 1}} + \frac{(1 - M)M}{\sqrt{2}} \right).$$

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

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

Obviously, $NetI$ increases with Δ , implying that there exists a Δ_{Crit} such that

$$(20) \quad \psi = \begin{cases} I & \text{if } \Delta > \Delta_{Crit} [M], \text{ and} \\ Q & \text{otherwise.} \end{cases}$$

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

$$(21) \quad \Delta_{Crit} = \frac{-2M \sqrt{\frac{M^2}{2M^2 - 2M + 1}} + \sqrt{2}M - \sqrt{2} + 2}{2M \sqrt{\frac{M^2}{2M^2 - 2M + 1}} - \sqrt{2}M + \sqrt{2}}.$$

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

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

$$(22) \quad \eta_\rho [M] = \text{Prob}@t_1 [\Delta > \Delta_{Crit} [M]].$$

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

$$(23) \quad \frac{\partial \eta_\rho}{\partial M} > 0.$$

That is, the economy's idea processing capability 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 (Δ^*) that a firm needs from an innovation to offset the Q signaling advantage also declines as market effectiveness increases.

C. Innovativity in Equilibrium

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)

$$(24) \quad \Phi = \text{Min} [\eta_S, \eta_\rho [M]].$$

We assume that if $\eta_\rho [M^*] > \eta_S^*$, the proportion of firms that can pursue I are selected at random. We plot equation 24 in Figure 2.

The comparative statics implied by equation 24 are straightforward, with

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

and with

$$(26) \quad \frac{\partial \Phi}{\partial \eta_S} \begin{cases} > 0 & \text{if } \eta_S < \eta_\rho [M], \\ = 0 & \text{if } \eta_S [M] \geq \eta_\rho [M]. \end{cases}$$

We now turn to deriving a measure of Φ that we can estimate empirically.

D. An Empirical Measure of Innovativity

Since Φ equals the proportion of firms that do choose an I strategy given η_S , $\tilde{\Phi}$ should track that proportion. To find such a measure, we begin by observing 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). This observation suggests 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 standard deviation of idiosyncratic firm returns for the market as a whole (σ_{Fun}). We therefore conjecture that $\tilde{\Phi}$, with

$$(27) \quad \tilde{\Phi} = 1 - \sigma_{Fun},$$

will provide a good measure of Φ . In this section we develop this conjecture.

To analyze $\tilde{\Phi}$, we begin by noting that a firm's IPO to Secondary Market return

given ψ and κ is $R_{\psi,\kappa}$, with

$$(28) \quad R_{\psi,\kappa} = \frac{P_{SM:\psi,\kappa} - P_{IPO,\psi}}{P_{IPO,\psi}}.$$

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

$$(29) \quad \sigma_\psi = \sqrt{\theta_{g:\psi} R_{\psi,g}^2 + \theta_{b:\psi} R_{\psi,b}^2}.$$

Since the proportion of firms that pursue I equals Φ , it follows that

$$(30) \quad \tilde{\Phi} = 1 - \sigma_{Fun} = 1 - \sqrt{\Phi [M, \eta_S] \sigma_I^2 [M] + (1 - \Phi [M, \eta_S]) \sigma_Q^2 [M]}.$$

So, $\tilde{\Phi}$ is a function of Φ , σ_I^2 , and σ_Q^2 . We know how Φ behaves from equation 24. Turning to σ_I^2 , and σ_Q^2 , 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 $\sigma_I^2 [M]$ and $\sigma_Q^2 [M]$ numerically (from equations 28 and 29) and plot them in Figure 3.¹³

Inspecting Figure 3, we note 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) $\partial\sigma_I^2/\partial M > 0$ if $M < 0.76$ and $\partial\sigma_I^2/\partial M < 0$ if $M \geq 0.76$. So, the weighted average of σ_I^2 and σ_Q^2 for a given I/Q split falls with M if either $M > 0.76$ or if less than 75% of entrepreneurs choose I when $M < 0.76$ (given the numerical values of $\sigma_Q^2 [M]$ and $\sigma_I^2 [M]$ that we compute above). Since our analysis would not be very empirically relevant

¹³We do the calculations and plotting in *Mathematica*, details available upon request.

if a high proportion of entrepreneurs choose I when markets are very ineffective, we assume that less than 75% of entrepreneurs do choose I when $M < 0.76$ (or that $M > 0.76$). It follows that the weighted average of σ_Q^2 and σ_I^2 falls with M (holding the I/Q split constant).

Given equation 30 and these assumptions, we can examine the comparative statics of $\tilde{\Phi}$. To begin with an increase in M , we find that:

$$(31) \quad \frac{\partial \tilde{\Phi}}{\partial M} \begin{cases} > 0 & \text{if } \eta_\rho[M] < \eta_S, \\ > 0 & \text{if } \eta_\rho[M] \geq \eta_S. \end{cases}$$

An increase in M when η_S is not binding leads to: i) a decrease in the Φ weighted average of σ_Q^2 and σ_I^2 holding Φ constant; and ii) a shift in firms from Q to I . Since both effects push in the same direction, it follows that an increase in M in this case leads to an increase in $\tilde{\Phi}$. If η_S is binding, then an increase in M does not increase Φ as firms cannot shift from Q to I . However, the Φ weighted average of σ_Q^2 and σ_I^2 decreases, implying that $\tilde{\Phi}$ increases in this case as well.

Turning to an increase in η_S , we find that

$$(32) \quad \frac{\partial \tilde{\Phi}}{\partial \eta_S} \begin{cases} > 0 & \text{if } \eta_S < \eta_\rho[M], \\ = 0 & \text{if } \eta_S \geq \eta_\rho[M]. \end{cases}$$

The intuition for equation 32 is straightforward: i) an increase in η_S when η_S is binding shifts firms from Q to I and so leads to an increase $\tilde{\Phi}$; and ii) an increase in η_S when η_S is

not binding does not affect either Φ , σ_I^2 , or σ_Q^2 , and so does not affect $\tilde{\Phi}$.

Examining the comparative statics of Φ (equations 25 and 26) with those of $\tilde{\Phi}$ (equations 32 and 31), we find that Φ does not necessarily vary monotonically with $\tilde{\Phi}$. For example, consider the case in which η_S is the binding constraint on Φ in periods J and K while $\eta_{S,J} < \eta_{S,K}$ and $\eta_\rho[M_J] > \eta_\rho[M_K]$. We know that $\Phi_J < \Phi_K$, but since $\tilde{\Phi}$ increases with M whether or not $\eta_\rho[M]$ is binding, it could also be the case that $\tilde{\Phi}_J > \tilde{\Phi}_K$. Consequently, we cannot infer the state of Φ from $\tilde{\Phi}$ alone.

We now show how we can use $\tilde{\Phi}$ and restrictions imposed by our theory to identify the state of Φ and the binding constraint on Φ empirically given this quirk in $\tilde{\Phi}$.

E. Identifying Φ and the Binding Constraint on Φ

We denote a period of time over which Φ is constant as an innovativity regime Λ , and assume that

$$(33) \quad \begin{aligned} \bar{\gamma}_J > \bar{\gamma}_K &\implies \Phi_J > \Phi_K, \text{ and} \\ \bar{\gamma}_J = \bar{\gamma}_K &\implies \Phi_J = \Phi_K \end{aligned}$$

for two innovativity regimes J and K . However, we cannot estimate Φ directly from the TFP data itself because we do not know the period (regime) over which to estimate $\bar{\gamma}$ ex ante.¹⁴ Fortunately, we can identify an innovativity regime on the basis of $\tilde{\Phi}$. Given a regime Λ , we can then estimate Φ_Λ from $\bar{\gamma}_\Lambda$.

Proposition 1: If $\tilde{\Phi}_j = \tilde{\Phi}_{j+1} = \dots = \tilde{\Phi}_{j+N}$, then $\Phi_j = \Phi_{j+1} = \Phi_{j+N}$. The period from j to

¹⁴For example, a period of high TFP growth such as the DotCom boom could be either a transient phase of high TFP growth in a low innovativity regime or a separate regime of high innovativity.

$j + N$ is an innovativity regime Λ .

Proof: From equations 31 and 32, $\tilde{\Phi}_j = \tilde{\Phi}_{j+1}$ if: i) $\eta_\rho [M_j] = \eta_\rho [M_{j+1}]$, $\eta_{S,j} > \eta_\rho [M_j]$, and $\eta_{S,j+1} > \eta_\rho [M_{j+1}]$ when η_ρ is the binding constraint in j ; and ii) $\eta_{S,j} = \eta_{S,j+1}$ and $\eta_\rho [M_j] = \eta_\rho [M_{j+1}]$ when η_S is the binding constraint in j .¹⁵ That is, $\tilde{\Phi}$ remains constant only if the binding constraint on Φ remains constant. If the the binding constraint on Φ remains constant then Φ is also constant. \square

Given an innovativity regime Λ , we can identify the binding constraint on Φ_Λ by using a combination of two methods. The first is to examine the impact of an exogenous shock to either η_S or η_ρ on Φ and $\tilde{\Phi}$. The second is to exploit restrictions that our theory places on the identify of the binding constraint. Consider each in turn.

Identifying the impact of a shock to η_S or η_ρ on Φ and $\tilde{\Phi}$ is straightforward given the comparative statics analysis above. We therefore list these impacts in Table 1 without further discussion.

Our theory places two important restrictions upon the identity of the binding constraint, as we show in the following propositions.

Proposition 2: Consider two innovativity regimes J and K . If $\tilde{\Phi}_J = \tilde{\Phi}_K$ and if $\Phi_J = \Phi_K$, then the binding constraint on Φ_J is also the binding constraint on Φ_K .

Proof: The binding constraint on Φ_J is either $\eta_{S,J}$ or $\eta_{\rho,J}$. Suppose that it is $\eta_{S,J}$. The binding constraint in K is either $\eta_{S,K}$ or $\eta_{\rho,K}$. Suppose that it is $\eta_{\rho,K}$. In this case,

$$\eta_{\rho,K} = \eta_{S,J}, \quad \eta_{\rho,K} = \eta_{\rho,J} - X, \quad \text{and} \quad \eta_{S,K} = \eta_{S,J} + Z,$$

¹⁵We assume here that η_S and η_ρ do not both change in exactly offsetting directions in a single period.

with $X > 0$ and $Z > 0$. Since: i) neither Φ or $\tilde{\Phi}$ increase with η_S when it is not binding; and ii) $\eta_{S,K}$ is not binding, we can set $Z \approx 0$. It follows that

$$(34) \quad \tilde{\Phi}_J [\eta_{\rho,J}, \eta_{S,K}] > \tilde{\Phi}_K [\eta_{\rho,J} - X, \eta_{S,K}],$$

because $\tilde{\Phi}$ does increase with η_ρ whether or not it is the binding constraint. This contradicts our premise that $\tilde{\Phi}_J = \tilde{\Phi}_K$. Hence, if η_S is the binding constraint in J , then η_S is also the binding constraint in K (and $\eta_{\rho,J} = \eta_{\rho,K}$).

Now suppose that $\eta_{\rho,J}$ is the binding constraint on Φ_J . If $\eta_{S,K}$ is the binding constraint on Φ_K , then

$$\eta_{\rho,J} = \eta_{S,K}, \quad \eta_{\rho,K} = \eta_{\rho,J} + X, \quad \text{and} \quad \eta_{S,K} = \eta_{S,J} - Z,$$

with $X > 0$ and $Z > 0$. As above, we can set $Z \approx 0$, implying that

$$(35) \quad \tilde{\Phi}_J [\eta_{\rho,J}, \eta_{S,K}] < \tilde{\Phi}_K [\eta_{\rho,J} + X, \eta_{S,K}].$$

This contradicts our premise that $\tilde{\Phi}_J = \tilde{\Phi}_K$. Hence, if η_ρ is the binding constraint in J , then η_ρ is also the binding constraint in K . In this situation, the only inference we can draw about η_S is that it is not binding in either J or K . \square

While Φ and $\tilde{\Phi}$ do not necessarily vary monotonically, our analysis does imply that a decline in $\tilde{\Phi}$ predicts a decline in Φ in the following case:

Proposition 3: Consider three innovativity regimes X , Y , and Z . If: i) $\eta_{\rho,X} [M_X]$ is the binding constraint on Φ in X ; ii) $\tilde{\Phi}_X < \tilde{\Phi}_Y$; iii) $\Phi_X < \Phi_Y$; and iv) $\tilde{\Phi}_X = \tilde{\Phi}_Z$, then $\Phi_Z < \Phi_Y$.

Proof: If $\eta_{\rho,X} [M_X]$ is the binding constraint on Φ_X and if $\Phi_Y > \Phi_X$, then $\text{Min} [\eta_{S,Y}, \eta_{\rho,Y}] = \zeta_Y^* > \eta_{\rho,X}$. In this case, it follows from equations 31 and 32 that

$$(36) \quad \text{Min} [\tilde{\Phi}_Y] = \tilde{\Phi}_Y : \eta_{S,Y} \geq \zeta_Y^* \text{ and } \eta_{\rho,Y} = \zeta_Y^*.$$

Consequently, $\tilde{\Phi}_Z < \tilde{\Phi}_Y$ if and only if $\eta_{S,Z} < \zeta_Y^*$ and/or $\eta_{\rho,Z} < \zeta_Y^*$. In either case, $\Phi_Z < \Phi_Y$. \square

So, given an innovativity regime, we can identify the state of innovativity in that regime from $\bar{\gamma}$ and we have tools to identify a regime's binding constraint. Our analysis also yields predictions for how Φ will evolve across regimes. We therefore begin our empirical analysis by identifying innovativity regimes.

II. Innovativity Regimes: 1850 to 2019

Since an innovativity regime Λ is a continuous period of time in which $\tilde{\Phi}$ is constant, we identify innovativity regimes by estimating $\tilde{\Phi}$. We assume that $\tilde{\Phi}_T = 1 - \sigma_{Fun,T}$, where $\sigma_{Fun,T}$ is the fundamental component of the standard deviation of idiosyncratic firm returns in T . We observe $O_{\sigma,T}$, with $O_{\sigma,T} = 1 - \sigma_T$ and where σ_T is the observed value of the standard deviation of idiosyncratic firm returns in T . To estimate $\tilde{\Phi}$, then, we assume that

$$(37) \quad O_{\sigma,T} = \text{Constant} + \tilde{\Phi}_{Start/End} + \beta_{Bull} Bull_T + \beta_{Bear} Bear_T + Shocks_T + \epsilon_T,$$

where $\tilde{\Phi}_{Start/End}$ 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, *Shocks* captures the impact of transitory shocks, and ϵ_T is the error term. We then track the evolution of $\tilde{\Phi}$ with the $\tilde{\Phi}_{Start/End}$ 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).¹⁶ The Old NYSE (ONY) data is available at a monthly frequency, so we also use monthly data for the CRSP period.¹⁷

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, 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 $R_{J,T} = \text{Ln} [P_{J,T}/P_{J,T-1}]$. We winsorize ONY

¹⁶The 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.

¹⁷To 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.

returns at the 0.01 and 0.99 quantiles (-38.30% and 37.20%). For the CRSP period, $R_{J,T} = \text{Ln} \left[1 + \text{Holding Period Return}_{J,T} \right]$. 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's idiosyncratic return $NetR_{J,T}$ equal to its net of industry return, where we set industry return equal to the median return in J 's industry.¹⁸ Hence,

$$(38) \quad O_{\sigma,T} = 1 - \text{Standard Deviation} \left[\overrightarrow{NetR}_T \right]$$

where \overrightarrow{NetR}_T is the set of idiosyncratic firm returns for T .

We assume that equilibrium innovativity evolves slowly. We therefore capture the evolution of innovativity with a series of indicator variables of the form $\tilde{\Phi}_{Start/End}^*$ with $\tilde{\Phi}_{Start/End} = 1$ if $Start \leq T \leq End$ and 0 otherwise. 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 2 and we present summary

¹⁸We 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).

statistics for the ONY and the CRSP samples in Table 3.

B. Analysis

We begin our analysis of $\tilde{\Phi}$'s evolution by estimating equation 37 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.¹⁹ This model yields white-noise residuals (using the Q-test) in each regression. We report our initial results in Table 4.

In Specification 1 we estimate equation 37 with the full set of $\tilde{\Phi}$ dummies, excluding $\tilde{\Phi}_{2010/2014}$ and $\tilde{\Phi}_{2015/2019}$ to provide the constant term. We find that $\tilde{\Phi}$ is: i) insignificant between 1926 and 1939; 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).

We extend our analysis to the full 1850/2019 sample period in Specification 2 (again dropping $\tilde{\Phi}_{2010/2014}$ and $\tilde{\Phi}_{2015/2019}$ for the intercept). We find that $\tilde{\Phi}$ is insignificant for the entire 1850/1941 period, and that the results of this specification are consistent with those of the CRSP only specification for the CRSP period (with the exception of $\tilde{\Phi}_{1975/1979}$, which now becomes significant at the 5% level). We plot the evolution of innovativity on

¹⁹The unreported transitory shock effects are highly significant.

the basis of this specification in Figure 4.

In Table 5, Specification 1, we combine adjacent periods of constant innovativity into innovativity regimes, namely: i) a *PreWar* regime of 1850/1941; ii) a *Peak* regime of 1946/1969; and iii) a *Post80* regime of 1980/2019 (which we omit for the intercept). We include two transition periods, namely a *WW2* period of 1942/1945 and a *1970s* period. The results of this specification are consistent with the results of the previous specifications, with: i) $\tilde{\Phi}_{PreWar} = 0$; ii) $\tilde{\Phi}_{Peak} > 0$ at the 1% level; iii) $\tilde{\Phi}_{Peak} > \tilde{\Phi}_{1970s}$ at the 1% level; and iv) $\tilde{\Phi}_{1970s} > 0$ at the 5% level.

Innovativity and Idiosyncratic Volatility

Our measure of innovativity is related to idiosyncratic volatility. So, it could be the case that factors that drive idiosyncratic volatility also drive our estimates or $\tilde{\Phi}$. 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.²⁰ 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.

²⁰Among 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).

To see if this retail investor effect also drives the evolution of innovativity, we estimate equation 37 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 5, Specification 2). We find the same pattern as above: $\tilde{\Phi}$ equals 0 between 1926 and 1939 and $\tilde{\Phi}_{Peak} > 0$ at the 1% level (we exclude $\tilde{\Phi}_{Post80}$ for the intercept). We conclude that the evolution of innovativity that we observe is not due to retail investor trading in low priced stocks.

The Evolution of $\tilde{\Phi}$

This analysis of innovativity yields a striking result: over the entire 1850 to 2019 period, $\tilde{\Phi}$ in the US has been in one of two persistent states (with brief transition periods). In light of these results, we divide our sample period into three innovativity regimes Λ , with $\Lambda \in \{PreWar, Peak, Post80\}$. We denote the state of $\tilde{\Phi}$ in Λ by $\tilde{\phi}_\Lambda$, with $\tilde{\phi} \in \{High(H), Low(L)\}$. Our results then imply that i) $\tilde{\phi}_{PreWar} = L$; ii) $\tilde{\phi}_{Peak} = H$; and iii) $\tilde{\phi}_{Post80} = L$.

Having identified innovativity regimes, we now turn to estimating equilibrium Φ .

III. Innovativity: 1899 to 2019

We assume that average TFP growth in a given regime Λ , $\bar{\gamma}_\Lambda$, is a random variable that is a function of the state of innovativity in that regime, with

$$(39) \quad \bar{\gamma}_\Lambda \sim \Gamma [\Omega[\phi_\Lambda], Y_\Lambda],$$

where ϕ_Λ is the state of Φ in Λ , $\Omega[\phi_\Lambda]$ is the TFP generating process given the state of Φ , and Y_Λ is the length of Λ (in years).

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 for the *PreWar* regime and the observations to estimate Ω for the *Peak* regime. We therefore test to see if ϕ is constant across regimes by: i) using the *Post80* regime as our *Control* case and the *PreWar* and *Peak* regimes as *Test* cases; and ii) taking as our Null hypothesis the proposition that the state of innovativity is constant across regimes. Our Null is then that

$$(40) \quad \bar{\gamma}_{Test,Null} \sim \Gamma_{Test}[\Omega_{Post80}, Y_{Test}].$$

We accept the Null if

$$(41) \quad \Gamma_{Test,2.5} < \bar{\gamma}_{Test}^* < \Gamma_{Test,97.5}$$

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

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 (Fernald (2014) describes this data series), setting TFP growth in year T equal to the natural log of the utilization adjusted annual rate of total factor productivity growth (dftp_util). 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.

We summarize our variable definitions in Table 6 and we report summary statistics in Table 7. We plot TFP growth by innovativity regime in Figure 5.

B. Analysis

To carry out the test in equation 41, 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

$$(42) \quad \Omega_{Post80} = \left\{ \left\{ \gamma_U, \gamma_D \right\}, \epsilon_{Dis}, \Xi \right\},$$

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

$$(43) \quad \gamma_T[\nu] = \gamma_\nu + \epsilon_T,$$

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 capability 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} . 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 8. All specifications yield white-noise residuals. In Specification 1 we estimate equation 42 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 42 including an AR(1) term, and find that the AR(1) term is 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 our best estimate of Ω_{Post80} . Consequently, we assume that Ω_{Post80} has the following form:

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

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

- $\theta_{DU} = 1 - \theta_{DD}$;
- $\theta_{UD} \sim \text{Normal Distribution } [-0.64, 0.58]$;
- $\theta_{UU} = 1 - \theta_{UD}$; and
- ϵ_{Dis} = the residuals from Specification 2,

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 ($Q_{D,J}$) in each trial. The average rate of TFP growth in J is then $\bar{\gamma}_{Test,Null,J}$, where

$$(44) \quad \bar{\gamma}_{Test,Null,J} = (N_{D,J} \times 0) + (N_{U,J} \times \gamma_{U,J}) + \bar{\epsilon}_J,$$

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

$$(45) \quad \Gamma_{Test} = \{\bar{\gamma}_{Test,Null,1}, \dots, \bar{\gamma}_{Test,Null,100\,000}\}.$$

Equipped with Γ_{Test} , we can test our predictions. We report these tests in Table 9. To begin with the *Peak* case, we note that the *Peak* regime begins with the boom that

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

immediately follows the end of WW2. To eliminate the possibility that the early post-war years create an upward bias in $\bar{\gamma}$, we drop the first 5 observations from the *Peak* regime and so start the analysis in 1951 (*Peak51*). 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

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

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

Reverse Causality?

Thus far we have been assuming that innovativity determines the TFP growth process, but of course it is possible that γ determines our measure of innovativity instead. We note that γ is highly volatile and that the economy can experience transitory TFP booms in the midst of what we classify as a *Low* innovativity regime. So, if γ determines innovativity, then we would expect to observe that innovativity is in the *High* state during such transitory TFP booms. We therefore test the reverse causality hypothesis by seeing if

²³We 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.

this is so (focusing upon the CRSP period due to superior data).

We identify two TFP booms in *Low* innovativity periods: i) the DotCom Boom of 1995/2004; and ii) the 1930s (see Table 7).²⁴ Average TFP growth in these two periods (1.92% and 1.86%) is the same as that during the 1951/1969 *Peak* period (1.87%). We combine these two periods into a single *Transitory TFP Boom (TTB)* period and estimate innovativity (Table 5, Specification 3) as above, excluding the non-DotCom Boom years of the *Post80* regime to provide the intercept (average TFP growth: 0.37%). We find that innovativity in the *TTB* period is not statistically significant and therefore reject the reverse causality hypothesis.

The Evolution of Φ

We find that state of innovativity follows the same low/high/low pattern as $\tilde{\phi}$, with innovativity in the *Low* state in both the *PreWar* and *Post80* regimes and in the *High* state in the *Peak* regime. We now examine the causes of this pattern.

IV. Are We Running Out of Ideas?

The fact that average TFP growth in the US has been declining while resources expended on finding ideas has been increasing (Bloom et al. 2020) naturally creates the presumption 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)

²⁴Field (2006) and Bakker, Crafts, and Woltjer (2019) examine TFP growth during the Depression. We use the Bakker, Crafts, and Woltjer TFP figures here.

calibrate exactly how fast we are running out of ideas (research productivity is declining at 5% per year); and iii) recent developments in EGT 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 resources (apparently) expended on finding ideas 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 capability. So, in this section we use our innovativity framework 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.

The PreWar Regime

To identify the binding constraint on innovativity in the *PreWar* regime, we begin by observing that $\tilde{\Phi}$ is in the *Low* state for that entire period (Figure 4). Focusing on the periods before and after the Second Industrial Revolution, it then follows that

$$(46) \quad \tilde{\phi}_{PreIR2}^* \left[\eta_{S,PreIR2}^*, \eta_{\rho,PreIR2}^* [M_{PreIR2}^*] \right] = \tilde{\phi}_{PostIR2}^* \left[\eta_{S,PostIR2}^*, \eta_{\rho,PostIR2}^* [M_{PostIR2}^*] \right]$$

Consider M and η_ψ 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).²⁵ 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

$$(47) \quad M_{PreIR2}^* = M_{PostIR2}^* = M_{PO}^*.$$

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

$$(48) \quad \eta_{S,PostIR2}^* = \eta_{S,PreIR2}^* + K.$$

Consequently,

$$(49) \quad \tilde{\phi}_{PreIR2}^* \left[\eta_{S,PreIR2}^*, \eta_{\rho,PreIR2}^* [M_{PO}^*] \right] = \tilde{\phi}_{PostIR2}^* \left[\eta_{S,PreIR2}^* + K, \eta_{\rho,PostIR2}^* [M_{PO}^*] \right].$$

²⁵Seligman (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.

As we demonstrated above (equation 32), if the idea supply constraint shifts up and $\tilde{\Phi}$ does not increase, then the idea supply constraint is not binding. Our analysis therefore suggests that the economy's idea processing capability is the binding constraint on innovativity in the *PreWar* regime.

The Peak Regime

If idea processing capability 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 equations 25 and 31) that

$$(50) \quad \phi_{PostReform}^* > \phi_{PreWar}^* \quad \text{and} \quad \tilde{\phi}_{PostReform}^* > \tilde{\phi}_{PreWar}^*$$

where the *PostReform* period indicates the period in which the reforms take effect.²⁶

Consistent with these predictions, we find that both $\tilde{\phi}$ (Figure 4) and ϕ (Table 9) do shift from the *Low* state to the *High* state after the 1930s financial market reforms.

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 capability is the binding constraint on innovativity between ϕ_L

²⁶Following 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 capability to effectively enforce the new rules.

and ϕ_H , so we will refer to η_ρ as the binding constraint on innovativity in the *Peak* regime with this proviso.

Our prediction that the reform effort of the 1930s leads to an increase in idea processing capability (and so innovativity) hinges upon the premise that these reforms 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.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. So, we infer from this evidence that this reform effort did improve financial market effectiveness.

The Post80 Regime

The state of $\tilde{\Phi}$ declines from H in the *Peak* regime to L in the *Post80* regime.

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

Given that $\tilde{\phi}_{PreWar} = L$ as well, this $L/H/L$ pattern of $\tilde{\phi}$ together with the empirical results above imply from Proposition 3 that $\phi_{Post80} = L$. As predicted, we find the state of innovativity does decline from H in the *Peak* regime to L in the *Post80* regime. Of course, the empirical fact that the TFP growth process is in the L state in the *Post80* period is well known. But, this result is a genuine prediction as our measure of $\tilde{\Phi}$ does not depend upon the TFP data itself.

The question of why the state of innovativity declines in the *Post80* period is one of the central puzzles of PostWar US economic performance. This shift is a puzzle in part because there is no sharp exogenous event such as IR2 or the financial market reforms of the 1930s to cause this shift. Consequently, the shift could be due to a gradual decline in either market effectiveness or idea supply.

In Proposition 2 above we demonstrate that if $\phi_J^* = \phi_K^*$ and if $\tilde{\phi}_J^* = \tilde{\phi}_K^*$ for two innovativity regimes J and K , then the binding constraint on innovativity in J is also the binding constraint on innovativity in K . We show in Section III that $\tilde{\phi}_{PreWar}^* = \tilde{\phi}_{Post80}^*$, and we show in Section IV that $\phi_{PreWar}^* = \phi_{Post80}^*$. In our discussion of the binding constraint on innovativity in the *PreWar* regime in this section we establish that it is idea processing capability. It follows that idea processing capability and not idea supply is the binding constraint on innovativity in the *Post80* regime.

Innovativity, Idea Processing, and Idea Supply

Our innovativity theory yields an empirical measure of innovativity 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 capability rather than idea supply. That is, the US is now in a *Low* innovativity regime due to constraints on the economy's idea processing capability rather than because ideas are getting harder to find. In short, Weitzman's (1998) conjecture that the limits to growth lie not in idea supply but in idea processing capability is plausibly correct.

V. Conclusion

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 capability 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 capability is now and has been the binding constraint on US TFP growth. This finding therefore suggests that idea processing capability plays a central role in the growth process and merits further investigation.

Our innovativity framework creates 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 has fallen since the *Peak* regime of 1946/1969, 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 dismal 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 capability. Our analysis further suggests that the economy’s idea processing capability can be (and has been) influenced by policy, and in particular by policies that affect financial market effectiveness. Consequently, the poor TFP growth performance of the US economy may be due to (cheaply) correctable policy failings rather than to a brute fact of nature that we must simply accept and deal with as best we can.²⁸

Our analysis here is exploratory. We focus upon endogenizing idea processing capability in a TFP growth model in which both idea processing capability and idea supply play a central role. To do that, we abstract away from important features of endogenous growth theory. We aim to more fully incorporate these features in future work. It may happen that doing so alters some of the conclusions we reach here. But, given the stakes in the future of growth debate, we should find out.

²⁸Bloom 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 capability (which is, after all, the binding constraint on innovativity) will cost rather less than that.

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Table 1
Identifying the Binding Constraint on Innovativity from Shocks

Observed Shock	$\tilde{\Phi}$	Φ	Binding Constraint
$\eta_S \uparrow (\downarrow)$	No Change	No Change	η_ρ
$\eta_S \uparrow$	\uparrow	\uparrow	η_S
$\eta_S \downarrow$	\downarrow	\downarrow	Insufficient Info
$\eta_\rho [M] \uparrow (\downarrow)$	$\uparrow (\downarrow)$	No Change	η_S
$\eta_\rho [M] \uparrow$	\uparrow	\uparrow	η_ρ
$\eta_\rho [M] \downarrow$	\downarrow	\downarrow	Insufficient Info

Notes: The impact of an observed exogenous shock to: i) idea supply (η_S) or ii) idea processing capability (η_ρ) via a shock to market effectiveness (M) on observed innovativity ($\tilde{\Phi}$) and true innovativity (Φ) may indicate the identity of the binding constraint on Φ in the pre-shock equilibrium.

Table 2
Innovativity Regime Analysis: Variable and Period Definitions

$O_{\sigma,T}$	(1 - the standard deviation of idiosyncratic share returns in month 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.
$\tilde{\Phi}_Z$	A dummy variable for period Z , used as an estimate of innovativity in Z .
Y_1/Y_2	The period of Y_1 to Y_2 .
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	1850/1941 for innovativity analysis, 1899/1941 for TFP analysis.
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.
HSB	The high TFP growth periods of the Great Depression and 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, and a 2 digit SIC code. A firm's idiosyncratic return equals its observed return minus the median return of the firms in its 2-digit industry, and we count all ONY firms as being in a single industry.

Table 3
The Standard Deviation of Idiosyncratic Firm Returns:
Summary Statistics

	Mean	StDev
O_σ : ONY	91.34	2.65
O_σ : CRSP	91.51	2.19
O_σ : CRSP:HP	92.92	1.81
Observations/Month: ONY	54.00	22.91
Observations/Month: CRSP	1112.28	319.16

Notes: $O_{\sigma,T}$ equals $(1 - \text{the standard deviation of idiosyncratic share returns in month } T) \times 100$. See Table 1 for variable definitions and sample information.
Sources: CRSP and the Yale School of Management's (SOM) Old New York Stock Exchange project (available on the SOM website).

Table 4
Measured Innovativity: Estimates

Specification	(1)		(2)	
Sample	CRSP		ONY/CRSP	
Dependent Variable	O_σ		O_σ	
Intercept	91.12*	0.73	91.28*	0.53
Bull	-0.34 *	0.07	-0.56 *	0.08
Bear	0.52*	0.12	-0.68 *	0.11
$\tilde{\Phi}_{\text{PreIR2}}$			0.69	0.95
$\tilde{\Phi}_{\text{IR2}}$			0.10	0.93
$\tilde{\Phi}_{1901/1929}$			-0.21	0.76
$\tilde{\Phi}_{1926/1929}$	-0.13	0.92		
$\tilde{\Phi}_{\text{GreatD}}$	0.99	1.42	0.47	0.98
$\tilde{\Phi}_{\text{WW2}}$	2.84**	1.28	2.42**	1.00
$\tilde{\Phi}_{1946/1949}$	2.69*	0.93	2.75*	0.71
$\tilde{\Phi}_{1950/1954}$	2.37*	0.87	2.55*	0.65
$\tilde{\Phi}_{1955/1959}$	2.47*	0.80	2.46*	0.62
$\tilde{\Phi}_{1960/1964}$	2.87*	0.85	2.58*	0.67
$\tilde{\Phi}_{1965/1969}$	2.49*	0.94	2.14*	0.70
$\tilde{\Phi}_{1970/1974}$	1.70	1.05	1.29	0.74
$\tilde{\Phi}_{1975/1979}$	1.86	1.07	1.56**	0.80
$\tilde{\Phi}_{1980/1984}$	0.45	0.96	0.19	0.68
$\tilde{\Phi}_{1985/1989}$	0.87	0.92	0.61	0.64
$\tilde{\Phi}_{1990/1994}$	0.16	0.89	-0.21	0.62
$\tilde{\Phi}_{1995/1999}$	0.26	0.84	-0.17	0.62
$\tilde{\Phi}_{2000/2004}$	-0.84	0.62	-1.11	0.61
$\tilde{\Phi}_{2005/2009}$	-0.53	0.60	-0.83	0.55
$\tilde{\Phi}_{2010/2019}$	Omitted		Omitted	
Time Series Effects	Garch(1,1)/AR24			

Notes: Each specification is estimated with a Garch(1,1)/AR24 model that yields white-noise residuals (using the Q test). Measured innovativity ($\tilde{\Phi}$) in each period is measured relative to the Intercept (the omitted period). A “*” (“**”) indicates statistical significance at the 1% (5%) level. See Table 2 for variable definitions and sample information.

Table 5
Innovativity Regimes and Robustness Tests

Specification	(1)		(2)		(3)	
Sample	ONY/CRSP		CRSP:HP		CRSP	
Dependent Variable	O_σ		O_σ		O_σ	
	Point	StDev	Point	StDev	Point	StDev
Intercept	91.41*	0.29	93.13*	0.27	91.48*	0.34
Bull	-0.55 *	0.08	-0.31 *	0.07	-0.33 *	0.07
Bear	-0.68 *	0.12	-0.59 *	0.11	-0.52 *	0.12
$\tilde{\Phi}_{1926/1929}$					-0.72	0.45
$\tilde{\Phi}_{PreWar}$	-0.19	0.46	-0.43	0.78		
$\tilde{\Phi}_{WW2}$	2.04**	0.86	1.15	0.67	2.21**	1.09
$\tilde{\Phi}_{Peak}$	2.33*	0.41	1.36*	0.41	2.23*	0.49
$\tilde{\Phi}_{1970s}$	1.38*	0.48	0.60	0.57	1.36*	0.50
$\tilde{\Phi}_{Post80}$	Omitted		Omitted			
$\tilde{\Phi}_{HSB}$					-0.16	0.18
$\tilde{\Phi}_{Post80ExDC}$					Omitted	
Time Series Effects	Garch(1,1)/AR24					

Notes: Each specification is estimated with a Garch(1,1)/AR24 model that yields white-noise residuals (using the Q test). Innovativity ($\tilde{\Phi}$) in each period is measured relative to the Intercept (the omitted period). A “*” (“**”) indicates statistical significance at the 1% (5%) level. See Table 2 for variable definitions and sample information.

Table 6
TFP Analysis: 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.
$\Gamma_\Lambda [\Omega_{Post80, Y_\Lambda}]$	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 <i>Post80</i> regime.
$\Gamma_{\Lambda, Z}$	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.

Table 7
TFP Growth: Summary Statistics

Period	Mean	StDev
1899/1929	1.07	—
GreatD	1.86	—
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: See Table 2 for period definitions.

Sources: Bakker, Crafts, and Woltjer (2019) for the PreWar period; San Francisco Federal Reserve data for the PostWar period.

Table 8
The TFP Growth Process in the Post80 Regime

Specification	(1)	(2)	(3)	(4)
Dependent Variable	γ	γ	γ	γ
g_D	-0.13 0.24	-0.21 0.25	0 Constrained	0
g_U	1.84* 0.28	1.88* 0.31	1.86* 0.28	1.84* 0.35
AR(1)		0.11 0.21		
Trend				0.00 0.01
θ_{DD}	0.70 {0.39, 0.89}	0.67 {0.36, 0.88}	0.72 {0.43, 0.90}	0.72 {0.42, 0.90}
θ_{DU}	0.30 {0.11, 0.61}	0.33 {0.12, 0.64}	0.28 {0.10, 0.57}	0.28 {0.10, 0.58}
θ_{UD}	0.34 {0.14, 0.61}	0.35 {0.15, 0.61}	0.35 {0.14, 0.63}	0.35 {0.14, 0.63}
θ_{UU}	0.66 {0.39, 0.86}	0.65 {0.39, 0.85}	0.65 {0.37, 0.86}	0.65 {0.37, 0.86}

Notes: We use a two-state Markov model to estimate Ω_{Post80} using the annual capacity-adjusted TFP growth series described in Fernald (2014). See Table 6 for variable definitions and Table 7 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 4). Consequently, we do not include any controls for such factors in this model.

Source: The TFP data is from the San Francisco Federal Reserve.

Table 9
Innovativity and TFP Growth

Null Hypothesis	$\bar{\gamma}^*$	Test Critical Value	Reject Null?
$\bar{\gamma}_{Peak51}^* \in \{\Gamma_{Peak51,2.5}, \Gamma_{Peak51,97.5}\}$	1.87	$\{-0.14, 1.84\}$	Yes
$\bar{\gamma}_{PreWar}^* \in \{\Gamma_{PreWar,2.5}, \Gamma_{PreWar,97.5}\}$	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 $\bar{\gamma}_{Test}^* \in \{\Gamma_{Test,2.5}, \Gamma_{Test,97.5}\}$, 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 8, 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 $\{\bar{\gamma}_{Null,1}^*, \dots, \bar{\gamma}_{Null,100,000}^*\}$.

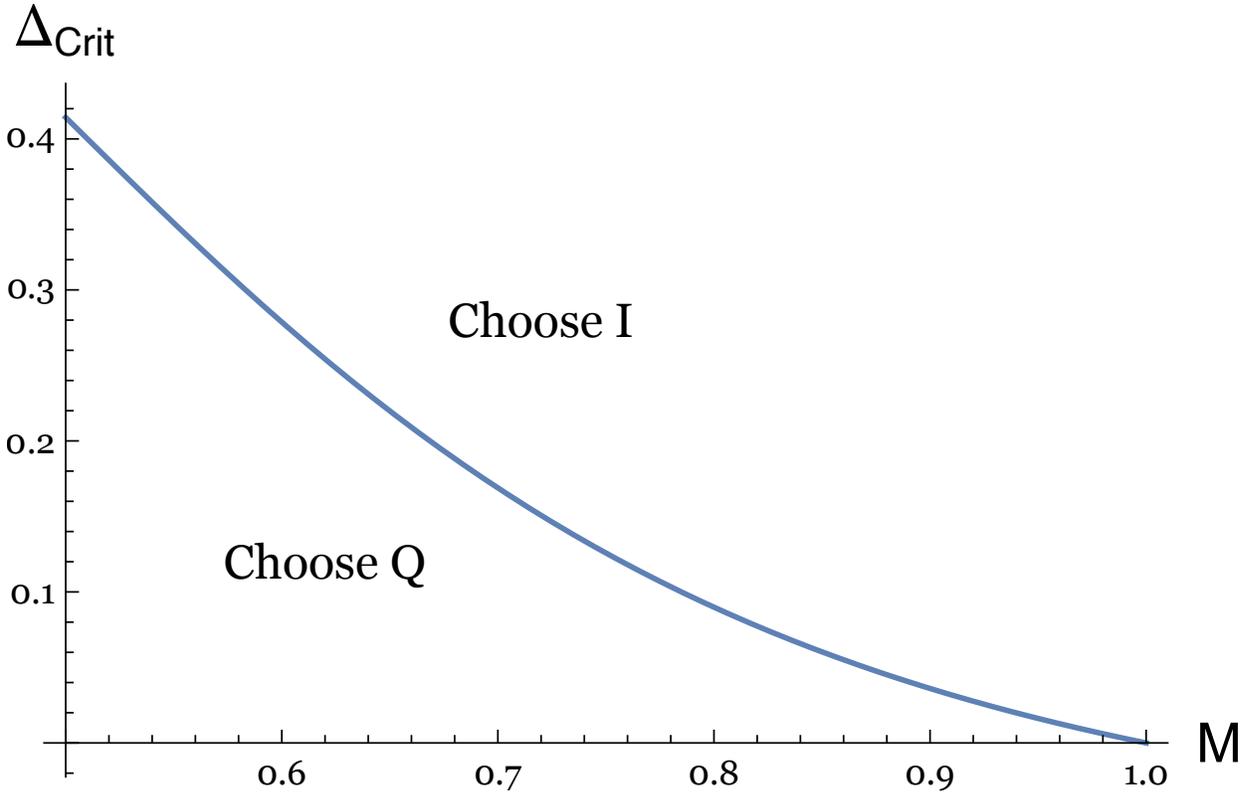


Figure 1: Strategic Approach and Market Effectiveness

Notes: We plot the value of Δ_{Crit} as a function of market effectiveness M . If the value of the innovation that an I approach creates for a commercially successful project (Δ) exceeds Δ_{Crit} , then the entrepreneur chooses an I strategic approach rather than an Q strategic approach. This plot shows that the proportion of entrepreneurs who prefer I increases with M .

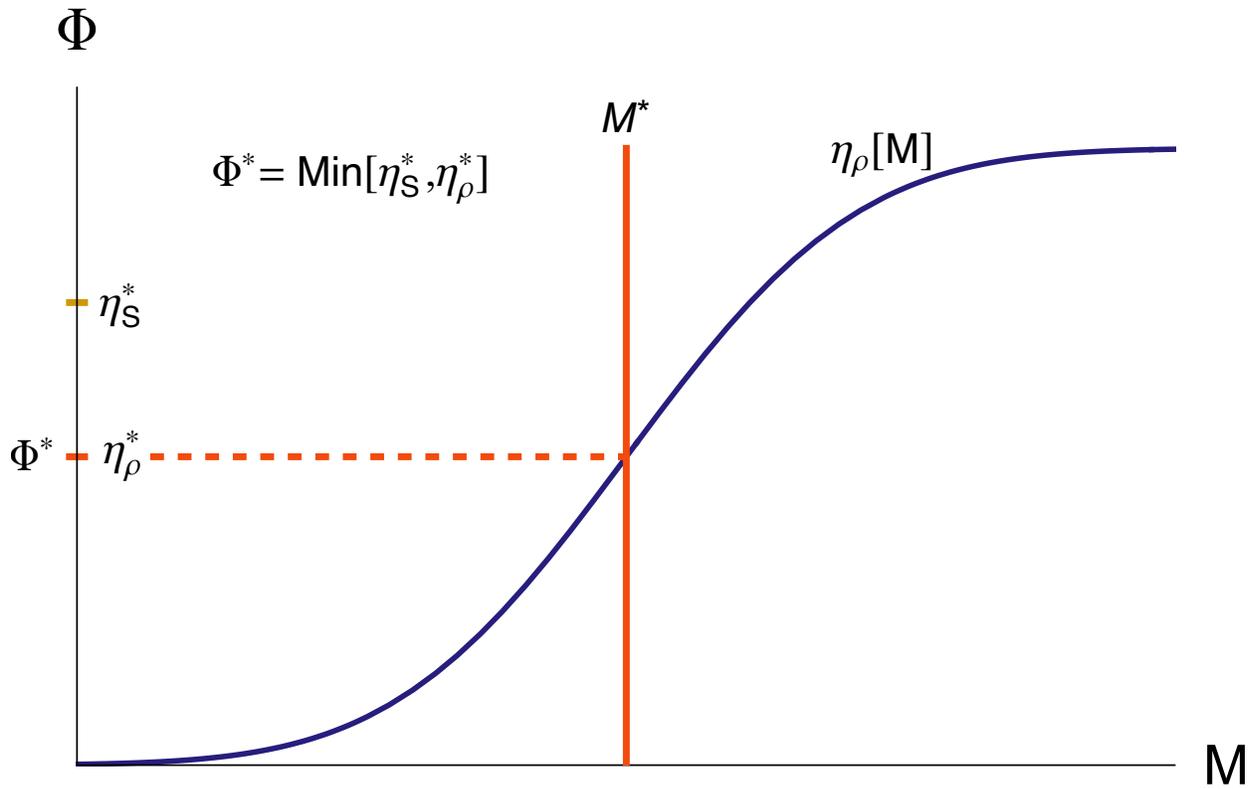


Figure 2: Equilibrium Innovativity

Notes: Equilibrium innovativity Φ^* (on the vertical axis) equals the minimum of exogenous idea supply η_S^* and endogenous idea processing capability $\eta_\rho^*[M]$. Idea processing capability equals the proportion of entrepreneurs who prefer an *I* strategic approach, with η_ρ determined by the intersection of market effectiveness (the orange line M^*) with the $\eta_\rho[M]$ curve.

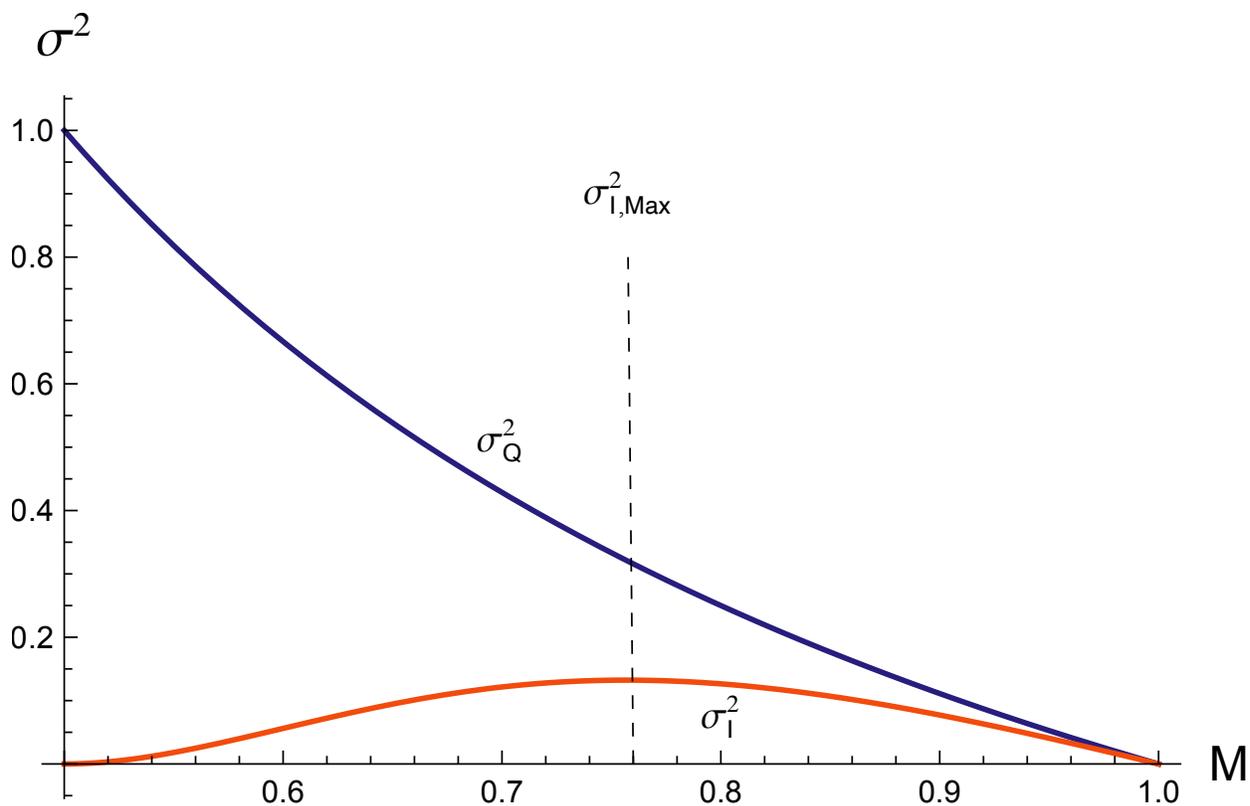


Figure 3: Variance of Returns by Strategic Approach

Notes: We plot the variance of returns for firms pursuing an I (σ_S^2) and a Q (σ_F^2) strategic approach as a function of market effectiveness M . We note that: i) $\partial\sigma_Q^2/\partial M < 0 \forall M$; ii) $\partial\sigma_I^2/\partial M > 0$ if $\sigma_I^2 < \sigma_{I,Max}^2$; and iii) $\partial\sigma_I^2/\partial M < 0$ if $\sigma_I^2 > \sigma_{I,Max}^2$, with $\sigma_{I,Max}^2$ occurring at $M \approx 0.76$ (indicated by the black dashed line).

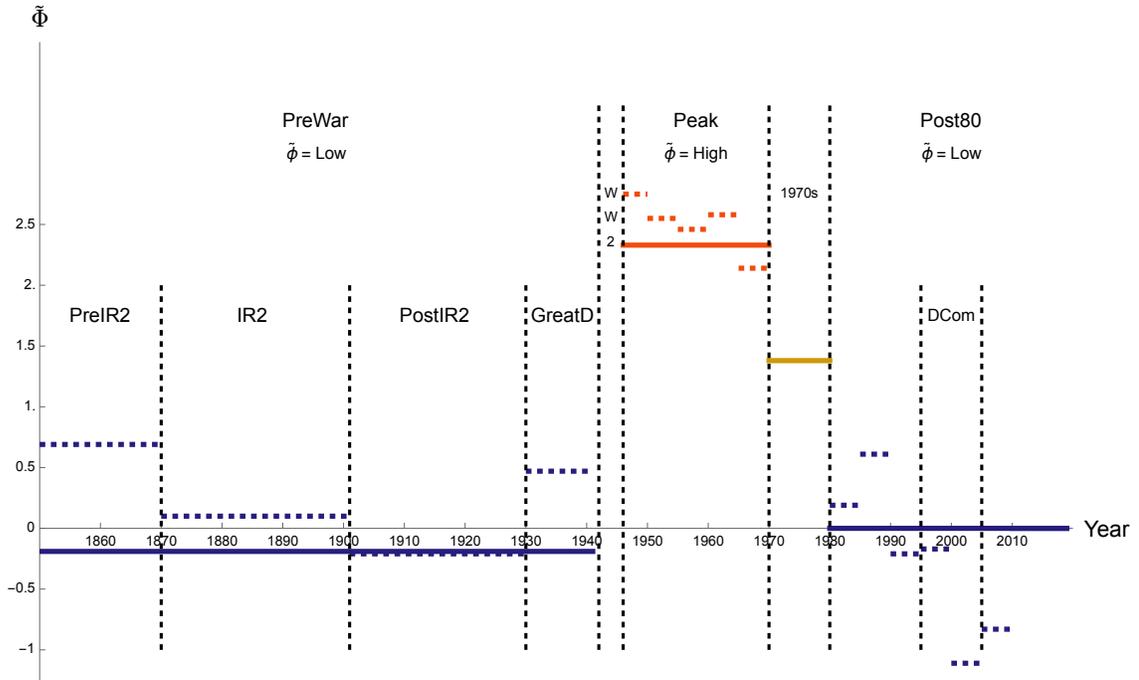


Figure 4: Innovativity Regimes

Notes: We plot measured innovativity ($\tilde{\Phi}$) and the state of measured innovativity ($\tilde{\phi}$) over our 1850 to 2019 sample period from the estimates in Table 4 (Specification 2) and Table 5 (Specification 1). We identify three innovativity regimes, where a regime is a continuous period in which $\tilde{\Phi}$ is constant: 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 $\tilde{\Phi}$ for each regime, while a dashed line indicates estimated $\tilde{\Phi}$ for shorter periods of time (see Table 2). An orange (blue) line indicates that $\tilde{\Phi}$ is *High (Low)*, where $\tilde{\phi} = High (Low)$ if $\tilde{\Phi} > (=) 0$. The *1970s* period is a transition between the *Peak* and *Post80* regimes, with $\tilde{\Phi}_{Peak} > \tilde{\Phi}_{1970s} > \tilde{\Phi}_{Post80}$.

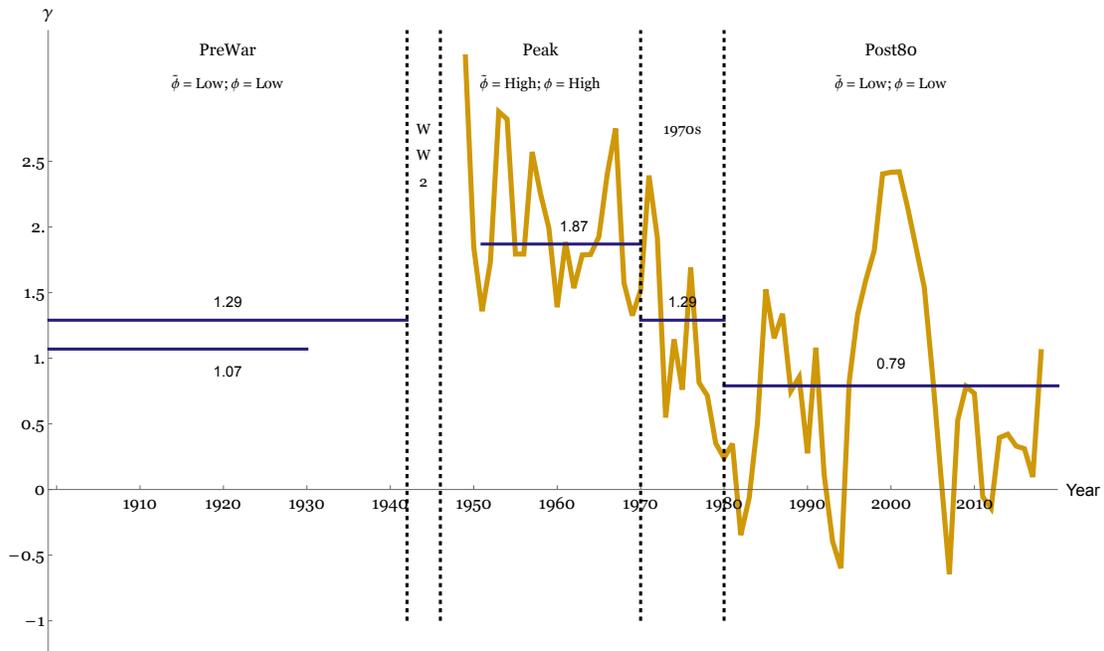


Figure 5: Innovativity and TFP Growth

Notes: We plot the evolution of average TFP growth over the 1899/2019 period by innovativity regime (Figure 4), with the state of measured innovativity ($\tilde{\phi}$) and true innovativity (ϕ) indicated for each regime. The blue lines show average TFP growth in a period, and the yellow line shows the three year moving average of TFP growth for the PostWar period (for which annual data exists).

Sources: PreWar: Bakker, Crafts, and Woltjer (2019) ; PostWar: San Francisco Federal Reserve, Annual Capacity Adjusted TFP Growth Series



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