Measuring the Average Period of Production*

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PRELIMINARY AND INCOMPLETE

Abstract

The importance of time in production was emphasized by Classical economists and was at the core of the Austrian capital theory proposed by Böhm-Bawerk and further elaborated by Wicksell, Hicks, Dorfman, and many others. A central concept in this literature is the existence of an 'average period of production' which governs the demand for circulating capital associated with a production process. Building on Böhm-Bawerk (1889), we propose a measure of the average period of production as a (weighted) average temporal distance between the time at which a firm employs its inputs and the time at which these inputs deliver finished goods that are sold to consumers. We show that, under stationarity conditions, this measure corresponds to the ratio of a firm's stock of inventories to the cost of the goods it sells in a given period. Using data from publicly traded companies worldwide, we compute this measure for various industries and countries, and show that, consistently with theory, this measure is lower, the higher is the cost of capital faced by firms.

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1 Introduction

Production takes time. From the extraction and preparation of raw materials to the design, manufacturing, assembly, and distribution of finished goods, each step entails a distinct duration influenced by technological and economic factors. The importance of time in production was emphasized by Classical economists, including David Ricardo and Karl Marx, and was at the core of the capital theory proposed by Böhm-Bawerk (1889). This 'Austrian' capital theory was somewhat anticipated by Jevons (1871), and was further elaborated by Wicksell (1934), Hicks (1939) and Dorfman (1959), among many others. A central concept in this literature is the existence of an 'average period of production' which governs the demand for circulating capital associated with a production process.

This old literature invoked several examples to illustrate the benefits of longer, more working-capital-intensive production processes. Jevons (1871) and Wicksell (1934) describe the problem of a tree planter who needs to decide when to harvest a forest to maximize returns. If the trees are cut down too early, they yield little timber and profit. If left to grow longer, the trees increase in size, and their economic value rises—but the planter must wait longer for the returns. Similarly, Böhm-Bawerk (1889) mentioned wine aging to demonstrate how time adds value to goods through production processes that are inherently dependent on waiting. These examples highlight the trade-off between immediate returns and the gains from a longer production process. These examples also hint at a natural connection between production length and interest rates, as the tree planter and wine producer must weigh the time value of money against the increased output from waiting.

The benefits of longer production processes are not limited to these stylized examples. In modern manufacturing processes, the need for care and precision often leads to tradeoffs in which longer production processes are favored despite the higher associated working capital needs. Beyond manufacturing, time is crucial for research and development. The pharmaceutical production process often spans 10 or 15 years for a single drug, involving discovery, preclinical testing, and multiple phases of clinical trials. Each phase is designed to ensure the drug's safety and efficacy, but the long duration highlights the enormous time investment required before market approval. Time impacts costs significantly: estimates suggest that, in the biopharmaceutical industry, over $1 billion is required to bring a new compound to market, with much of the expense tied to sustaining operations during prolonged R&D efforts (DiMasi and Grabowski, 2007).

Building on the work of Böhm-Bawerk (1889) and Hicks (1939), in this paper we propose a measure of the average period of production defined as a weighted average temporal distance between the time at which a firm employs its inputs and the time at which these inputs deliver finished goods that are sold to consumers. In section 2, we develop the theoretical underpinnings of this measure and show how it is shaped by the cost of capital faced by firms. In section 3, we develop specific examples that connect with prior theoretical work on the topic. In section 4, we show that, under stationarity conditions, this measure corresponds to the ratio of a firm's stock of inventories to the cost of the goods it sells in a given period, opening the door for empirical explorations of the average period of production in a wide swath of sectors.

Using data from publicly traded companies worldwide, in sections 5 and 6, we compute this measure for firms and industries in several countries, and we show that, consistent with theory, this measure increases as the cost of capital faced by firms decreases. We also find that the ranking of industries by their average period of production is quite stable across countries. This suggests that there are important technological determinants of production length that shape the temporal dimension of certain production processes regardless of where they are conducted, a feature that is reminiscent of the absence of factor intensity reversals in neoclassical trade theory. Furthermore, we find that industries with longer production processes tend to feature higher skill intensity but lower physical capital intensity, pointing at an interesting dichotomy between physical capital intensity and working capital intensity.

2 A Conceptual Measure of the Average Period of Production

Consider a production process taking place in continuous time over a potentially endogenous time interval $[0, T]$. We will refer to T as the *length* of the production process. The mapping between inputs and output is governed by the production function

$$Y(\boldsymbol{L}) = Z(\boldsymbol{L}) F(\boldsymbol{L}), \tag{1}$$

where $\boldsymbol{L}$ is the infinitely-dimensional vector of inputs employed along the production process, i.e., $\boldsymbol{L} = \{\ell(t)\}_{t\in[0,T]}$. We think of the input vector as encompassing both labor and materials but we will simplify the exposition by often referring to it as labor, with an associated wage rate w. Firms treat w and the price p of the good as given, and for simplicity we assume, for the time being, that these prices are time invariant.

The function $F(\boldsymbol{L})$ captures a production technology mapping labor $\boldsymbol{L}$ into output, and we assume it is homogenous of degree one in the vector $\boldsymbol{L}$. The function $Z(\boldsymbol{L})$ is interpreted as a measure of productivity which is also potentially affected by the path of labor used in production. Specifically, we assume that $Z(\boldsymbol{L})$ is homogeneous of degree 0 in $\boldsymbol{L}$ (to avoid introducing scale effects), and we define the vector $\boldsymbol{\lambda} = \{\ell(t)/L\}_{t\in[0,T]}$, where $L = \int_0^T \ell(t)\,dt$ is total labor use along the whole production process. Thus, $\lambda(t)$ captures the distribution of labor expenditures along the production process.

Given a path of labor used along the production process, we define the 'average period of production' or APP as

$$\mathcal{APP}(\boldsymbol{\lambda}) = \int_0^T (T - t)\,\lambda(t)\,dt. \tag{2}$$

This measure represents a weighted average temporal distance between the time $t \in [0, T]$ when inputs are utilized and the time T marking the completion of the process and the sale of the good. The weights are determined by the shares of employment $\lambda(t)$ at different points in time. While this definition is closely related to the one proposed by Böhm-Bawerk (1889), his formulation was developed it in discrete time.

Böhm-Bawerk (1889) famously posited that more 'roundabout' production processes – featuring a disproportionately large share of input expenditures happening far from the completion and sale of the product – tend to be associated with disproportionately higher labor efficiency. In his own words:

> A greater result is obtained by producing goods in roundabout ways than by producing them directly. Where a good can be produced in either way, we have the fact that, by the indirect way, a greater product can be got with equal labour, or the same product with less labour. [...] That roundabout methods lead to greater results than direct methods is one of the most important and fundamental propositions in the whole theory of production." Böhm-Bawerk (1889, p. 19-20).

According to this view, it may be sensible to posit that the function $Z(\boldsymbol{L})$ depends on $\boldsymbol{L}$ in a way that makes Z increasing in the average period of production, or $Z(\boldsymbol{L}) = Z(\mathcal{APP})$, with $Z'(\mathcal{APP}) > 0$.

If the wage rate is time invariant, it is clear that $\mathcal{APP}(\boldsymbol{\lambda})$ also captures a weighted distance of labor *expenditures* from the collection of final-good sale revenue. Such an expenditure-based alternative measure of the $\mathcal{APP}$ can easily be amended to allow for time-varying wages by instead defining $\boldsymbol{\lambda} = \{w(t)\,\ell(t)\,/E_L\}_{t\in[0,T]}$, where $E_L = \int_0^T w(t)\,\ell(t)\,dt$ is total input spending along the whole production process. Hicks (1939, Chapter XVII) proposed an expenditure-based definition of the average period of production, but instead advocated applying a discount factor for input expenditures at different dates.[1] Hicks' adjustment is definitely appropriate when computing the circulating capital demands associated with a production process, but it is less obviously suitable when studying the effect of the average period of production on productivity. We will return to this point in section 4.

[1]Specifically, $\mathcal{APP}_{Hicks}$ is given by (2) with $\boldsymbol{\lambda}_{Hicks} = \left\{w(t)\,\ell(t)\,e^{-rt}/\int_0^T w(t)\,\ell(t)\,e^{-rt}dt\right\}$, where r is the relevant discount rate (e.g., the interest rate).

Note that the average period of production in (2) is naturally bounded below by 0 and bounded above by T. For a given production length T, the average period of production is higher, the higher the share of inputs used in relatively earlier phases of production. The average period of production will also typically be increasing in T, though this will not necessarily be the case for *any* possible path of $\lambda(t)$. For instance, if $\ell(t)$ is disproportionately large for values of t close to T, the $\mathcal{APP}$ may well be reduced by an increase in T, as this may tilt *average* input expenditures closer to the completion of the good. In Appendix A.1 we show, however, that $\mathcal{APP}$ in equation (2) is necessarily increasing in T whenever (i) $\ell(T)$ is no larger than the average input use (i.e., L/T) along the chain, or (ii) $\ell(t)$ and $\lambda(t)$ grow along the chain but at no more than a constant exponential rate.

We next consider the endogenous determination of the average period of production with the ultimate aim of illustrating the existence of a negative relationship between $\mathcal{APP}$ – as defined in equation (2) – and the cost of capital faced by firms. For simplicity, we focus on an environment with frictionless and perfectly competitive capital markets, in which firms can borrow and lend at a time-invariant interest rate r. Consider then the problem of a firm deciding on input choices along the production process. The firm chooses the labor input vector $\boldsymbol{L}$ and the length of the interval $[0,T]$, to maximize profits when evaluated at the beginning of the production process (or $t=0$), or

$$\max_{\boldsymbol{L},T}\ \pi = pZ(\boldsymbol{L})\,F(\boldsymbol{L})\,e^{-rT} - w\int_0^T \ell(t)\,e^{-rt}dt, \tag{3}$$

Although we have assumed that firms treat p and w as given, in equilibrium w/p will be such that the firm makes zero profits, since $F(\boldsymbol{L}) = Z(\boldsymbol{L})\,F(\boldsymbol{L})$ is necessarily homogeneous of degree one in $\boldsymbol{L}$, given our assumptions. Because sale revenue only accrues an interval T from the initial period 0, sale revenue is discounted with the compound interest term e^{-rT}. Similarly, the effective cost of labor hired at date t incorporates the discount factor e^{-rt}.

Whenever the functions $Z(\boldsymbol{L})$ and $F(\boldsymbol{L})$ are continuously differentiable, we can express the first-order condition for the choice of $\ell(t)$ as

$$\frac{\partial Z(\boldsymbol{L})\,F(\boldsymbol{L})}{\partial \ell(t)} = \frac{w}{p}e^{r(T-t)}.$$

Given two labor inputs at two different points in time, say $t_H > t_L$, we have that

$$\frac{\ell(t_H)}{\ell(t_L)} = \frac{\varepsilon_{Y,\ell(t_H)}}{\varepsilon_{Y,\ell(t_L)}}e^{r(t_H-t_L)}, \tag{4}$$

where $\varepsilon_{Y,\ell(t)}$ is the elasticity of output Y with respect to $\ell(t)$. Equation (4) indicates that labor is allocated throughout the production process in a way that prioritizes 'stages' of production with disproportionately large impacts on output. In Böhm-Bawerk's theory, such stages with a disproportionately large impact on value are expected to be those further removed from the completion of the good (thereby capturing a benefit of 'roundaboutness'). For uniform output elasticities along the production chain, however, equation (4) indicates that a disproportionate desire to backload input expenditures closer to the end of the process, and more so the higher the interest rate r. This will be one of the key forces generating a negative relationship between interest rates and the average period of production, as further demonstrated in the next section.

Turning to the first-order condition with respect to T, we can express it as

$$p\frac{\partial\left(Z\left(\boldsymbol{L}\right)F\left(\boldsymbol{L}\right)\right)}{\partial T}=w\ell\left(T\right)+rpZ\left(\boldsymbol{L}\right)F\left(\boldsymbol{L}\right). \tag{5}$$

Importantly, given the envelope theorem, the term $\partial\left(Z\left(\boldsymbol{L}\right)F\left(\boldsymbol{L}\right)\right)/\partial T$ is a partial derivative that holds $\boldsymbol{L}$ fixed, and captures the direct positive impact of T on productivity $Z\left(\boldsymbol{L}\right)$ (e.g., via a higher degree of 'roundaboutness') and on physical output $F\left(\boldsymbol{L}\right)$ (via a higher amount of input use). The two right-hand-side terms reflect the costs of extending the production process. The first one is the direct cost of the extra inputs added to production, while the second term captures the financial costs associated with delaying the collection of final-good revenue. This second term is naturally increasing in the interest rate r and in sale revenue. Overall, the above first-order condition (5) can be succinctly expressed as

$$T=\frac{\varepsilon_{Y,T}}{\alpha_{T}+r}, \tag{6}$$

where $\varepsilon_{Y,T}$ is the elasticity of output with respect to T (holding the vector $\boldsymbol{L}$ fixed) and where α_T is the ratio of input expenditure at T relative to total sale revenue, or $\alpha_T = w\ell\left(T\right)/\left(pZ\left(\boldsymbol{L}\right)F\left(\boldsymbol{L}\right)\right)$. Equation (6) hints at a negative relationship between T and r, which in turn suggests an additional channel via which higher interest rates negatively impact average production periods.

Despite the above intuitive effects of the interest rate r on $\boldsymbol{L}$ and T, it is hard to formally show this relationship for a general production function $Y\left(\boldsymbol{L}\right)=Z\left(\boldsymbol{L}\right)F\left(\boldsymbol{L}\right)$ even when assuming, as we have, that it is homogeneous of degree one. To make more progress, in the next section we turn to three specific examples, which have been focal in the 'Austrian' literature on the temporal dimension of production.

3 Three Examples

In this section, we consider three specific formulations of the function $Y\left(\boldsymbol{L}\right)=Z\left(\boldsymbol{L}\right)F\left(\boldsymbol{L}\right)$ with the goal of further sharpening the characterization of how interest rates r shape the average period of production $\mathcal{APP}$.

3.1 Point-Input Point-Output

Suppose that the production technology $F(\boldsymbol{L})$ is such that inputs are only needed at the very beginning of production, i.e., $t = 0$, and thus an interval T before completion. This corresponds to the point-input point-output model of Wicksell (1934), Metzler (1950), Cass (1973) and Findlay (1978), among others. It maps particularly closely to the production of lumber, in which trees are planted by labor at some initial instant, and one need only wait for trees to grow, with no further labor input needed (this literature often ignores the labor needed to chop off the tree). Böhm-Bawerk (1889) invoked the similarly suitable example of wine production, which may also benefit from a process of maturation.

In terms of the more general specification in the last section, this point-input point-output formulation boils down to assuming that $\ell(t)$ only has mass at $t = 0$, and thus $\ell(0) = L$, $\lambda(0) = 1$ and $\ell(t) = \lambda(t) = 0$ for $t > 0$. Given our constant returns to scale assumption, we must necessarily have $F(\boldsymbol{L}) = \kappa\ell(0) = \kappa L$, for some constant κ, which we normalize to 1 without loss of generality. According to the definition of the average period of production in equation (2), this immediately delivers $\mathcal{APP} = T$: the average period of production thus coincides with the interval of time over which production takes place. This extreme version of the 'Austrian' model of production is typically coupled with the assumption that the technology function $Z(\boldsymbol{L})$ is increasing and concave in the average period of production, thereby capturing the benefits of 'maturation' (e.g., growth of trees or maturation of wine). More formally, we specify $Z(\boldsymbol{L}) = Z(\mathcal{APP}) = Z(T)$, with $Z'(T)$ and $Z''(T) < 0$.

Turning to the general optimization problem in (3), in this case the firm does not really optimize over the choice of $\boldsymbol{L}$ as we exogenously impose that labor is only employed at $t = 0$. With constant returns to scale, the level of $\ell(0) = L$ is indeterminate at the firm level. The problem in (3) then reduces to choosing T to solve:

$$\max_{T} \ \pi = pZ(T)\,Le^{-rT} - wL.$$

Regardless of the choice of $\ell(0) = L$, the first-order condition associated with the choice of T is given by

$$\frac{Z'(T)}{Z(T)} = r. \tag{7}$$

Equation (7) is a well-known formula in Austrian models of capital, though it was first derived by Jevons (1871, p. 245). It indicates that, at the optimal production length, the growth of labor productivity is equated to the interest rate. Given the concavity of the function $Z(T)$, it immediately follows that:

Proposition 1. In the point-input point-output model, the average period of production $\mathcal{APP}$ is equal to the production length T, and the $\mathcal{APP}$ is decreasing in the interest rate r.

3.2 Uniform Input Use

Suppose now that inputs are used at a constant rate along the whole production process so that $\ell(t) = L/T$ and $\lambda(t) = 1/T$ for all t. Such a constant input flow would be optimal, for instance, if the production technology is given by $F(\boldsymbol{L}) = \min\{\ell(t)\}_{t\in[0,T]}$. Production processes with a uniform input use have been studied as far back as Jevons (1871, Chapter VII) or Böhm-Bawerk (1889, p. 89).

Given that $\lambda(t) = 1/T$ and our definition of the average period of production in (2), one can easily show that

$$\mathcal{APP} = \int_0^T (T-t)\,\frac{1}{T}dt = \frac{1}{2}T.$$

Therefore, the average period of production is equal to one-half the time interval over which production occurs. In 'Austrian' models, this specific formulation of the path of labor used in production is also typically coupled with a productivity function $Z(\boldsymbol{L})$ that is increasing and concave in the the average period of production, or $Z(\boldsymbol{L}) = Z(\mathcal{APP})$, with $Z'(\mathcal{APP})$ and $Z''(\mathcal{APP}) < 0$.

Given constant returns to scale, the function $F(\boldsymbol{L})$ must necessarily be linear in the constant labor use $\ell = L/T$, so we have $F(\boldsymbol{L}) = \kappa L/T$, where again we can safely set $\kappa = 1$. The problem in (3) then simplifies to choosing T to solve:

$$\max_T \;\pi = pZ\left(\frac{1}{2}T\right)\frac{L}{T}e^{-rT} - w\frac{L}{T}\int_0^T e^{-rt}dt,$$

The first-order condition of this problem (after imposing zero profits) can be rewritten as

$$\frac{1}{2}\frac{Z'\left(\frac{1}{2}T\right)}{Z\left(\frac{1}{2}T\right)} = \frac{r}{1-e^{-rT}}, \tag{8}$$

which is a slightly modified version of the 'Jevons' equation in (7).[2] Differentiating with respect to r and using the fact that $e^x - x - 1 \geqslant 0$ for all x, one can verify that the right-hand-side of this equality is increasing in the interest rate r, and thus the marginal cost of lengthening production is again increasing in the interest rate. A subtle aspect of equation (8) is that its right-hand-side is now also decreasing in T, thereby seemingly complicating the characterization of the impact of r on T. Nevertheless, this turns out to be a dominated effect, and in Appendix

[2] Note also that equation (8) is a special case of the more general optimality condition (6), given that $\varepsilon_{Y,T} = \frac{1}{2}Z'\left(\frac{1}{2}T\right)T/Z\left(\frac{1}{2}T\right)$ and that (imposing zero profits) $\alpha_T = e^{-rT}/\int_0^T e^{-rt}dt$.

A.2 we show that:

Proposition 2. In the uniform input use model, the average period of production $\mathcal{APP}$ is equal to half of the production length T, and the $\mathcal{APP}$ is decreasing in the interest rate r.

3.3 Time-Separable Technology

Finally, suppose that input choices are endogenously determined with some positive amount of substitution across stages. We maintain the assumption that $F(\boldsymbol{L})$ is homogeneous of degree one and thus homothetic. Furthermore, as is typical in intertemporal problems, to avoid time-inconsistency issues, we assume that $F(\boldsymbol{L})$ can be written in the following explicitly separable manner

$$F(\boldsymbol{L}) = H\left(\int_0^T h(a(t), \ell(t))\, dt\right), \tag{9}$$

for some functions H, h, and a. As is well known since Bergson (1936), the only *homothetic* production technology of the separable type in (9) is a constant elasticity of substitution production technology, which for the case of a homogeneous-of-degree-one technology, we can write as

$$F(\boldsymbol{L}) = \left(\int_0^T a(t)(\ell(t))^{(\sigma-1)/\sigma}\, dt\right)^{\sigma/(\sigma-1)}, \tag{10}$$

for $\sigma > 0$.[3] As we will show below, with this production technology, the marginal rate of substitution between two input choices $\ell(t_L)$ and $\ell(t_H)$ will be a monotonic function of the ratio $\ell(t_L)/\ell(t_H)$, independently of the scale of production.

Turning to the productivity function $Z(\boldsymbol{L})$, we could in principle allow it to be a function of the allocation of labor $\boldsymbol{L}$ over time, but we will simplify matters by simply making it a function of the interval of production T, or $Z(\boldsymbol{L}) = Z(T)$, with $Z'(T) > 0$ and $Z''(T) < 0$, just as in the two cases studied above. Note, however, that the positive effect of 'roundaboutness' on productivity can additionally be captured by assuming that the function $a(t)$ is increasing in the distance $T - t$, thereby further incentivating the choice of labor allocations associated with higher average production periods.

The profit maximization problem in (3) now becomes

$$\max_{\boldsymbol{L},T}\ \pi = pZ(T)\left(\int_0^T a(t)(\ell(t))^{(\sigma-1)/\sigma}\, dt\right)^{\sigma/(\sigma-1)} e^{-rT} - w\int_0^T \ell(t)\, e^{-rt} dt. \tag{11}$$

[3] As shown by Berndt and Christensen (1973), the only homothetic production technology that features a cost function that is separable in the cost of the various inputs (in our case, input choices at various points along the production process) is also a constant elasticity of substitution production function.

The first order condition for the choice of $\ell(t)$ is

$$pZ(T)(F(\boldsymbol{L}))^{1/\sigma}a(t)\ell(t)^{-1/\sigma}e^{-rT}=we^{-rt}, \tag{12}$$

thus implying that for two input choices $\ell(t_L)$ and $\ell(t_H)$, we have

$$\frac{\ell(t_H)}{\ell(t_L)}=\left(\frac{a(t_H)}{a(t_L)}\right)^{\sigma}e^{r(t_H-t_L)\sigma}.$$

It is easily verified that this expression is a special case of our more general expression in (4), with the ratio of output elasticities $\varepsilon_{Y,\ell(t_H)}/\varepsilon_{Y,\ell(t_L)}$ being a simple function of the ratios $a(t_H)/a(t_L)$ and $\ell(t_H)/\ell(t_L)$. This allows us to formalize our previously anticipated insight that a higher interest rate r will enhance the attractiveness of backloading input expenditures, thereby leading to a lower average period of production. Specifically, note that holding T constant, a lower interest rate r increases the ratio $\ell(t_L)/\ell(t_H)$ for all $t_L<t_H$, thereby leading to disproportionately more labor being allocated furthest from completion. More formally, consider then two interest rates r and $\tilde{r}$ with $r>\tilde{r}$, and associated distributions of labor input $\boldsymbol{\lambda}$ and $\tilde{\boldsymbol{\lambda}}$, respectively. Because the lower interest rate $\tilde{r}$ is associated with a higher ratio $\ell(t_L)/\ell(t_H)$ for $t_L<t_H$, we can then conclude that

$$\frac{\tilde{\lambda}(t_L)}{\tilde{\lambda}(t_H)}>\frac{\lambda(t_L)}{\lambda(t_H)}$$

for $t_L<t_H$. It then follows that $\boldsymbol{\lambda}$ first-order stochastically dominates $\tilde{\boldsymbol{\lambda}}$ and thus

$$\mathcal{APP}\left(\tilde{\boldsymbol{\lambda}}\right)=\int_0^T(T-t)\tilde{\lambda}(t)\,dt>\int_0^T(T-t)\lambda(t)\,dt=\mathcal{APP}(\boldsymbol{\lambda}).$$

In sum, the average period of production $\mathcal{APP}$ is higher under the lower interest rate $\tilde{r}$.

Proposition 3. With time-separable technologies, holding the interval T constant, the average period of production $\mathcal{APP}$ is decreasing in the interest rate r.

Turning to the choice of T, the associated first order condition can be expressed, after some manipulations, as

$$\frac{Z'(T)}{Z(T)}=r-\frac{1}{\sigma-1}\frac{1}{\int_0^T\left(\frac{a(t)}{a(T)}\right)^{\sigma}e^{-(T-t)r(\sigma-1)}dt}, \tag{13}$$

which is a modified version of the Jevons-style equations (7) and (8). Given $Z''(T)<0$, this will tend to generate a negative relationship between T and r, but the second term in the left-hand-side complicates proving this result in full generality for any arbitrary path of the function $a(t)$. In addition, and as pointed out in section 2, even if T were to be decreasing in r, it is not clear that a lower T will be associated with a lower average production $\mathcal{APP}$ for any path of $a(t)$, as the expansion of production when $a(T)$ is disproportionately large can lead to a lower weighted average value of $\mathcal{APP}$. To make progress, let us assume that $a(t) = a_0 e^{g(T-t)}$, so that input demand $\ell(t)$ grows or falls at a constant rate along the production process. Specifically, from equation (12), we have that $\ell(t) = \ell_0 e^{(T-t)\sigma(g-r)}$ for some constants $\ell_0 > 0$ and g, and equation (13) reduces to

$$\frac{Z'(T)}{Z(T)} = r - \frac{1}{\sigma - 1}\frac{r(\sigma-1) - \sigma g}{1 - e^{-T(r(\sigma-1)-\sigma g)}}. \tag{14}$$

We then show in Appendix A.3 that, regardless of the sign of g:

Proposition 4. With the time-separable technology in (9) and $a(t) = a_0 e^{-gt}$, both the production length T and the average period of production $\mathcal{APP}$ are decreasing in the interest rate r.

4 An Empirical Measure of the Average Period of Production

In this section, we develop an empirical counterpart to our average period of production measure. For this purpose, we return to our general model in section 2 in which a production process is associated with the use of a sequence of labor inputs $\ell(t)$ at each instant t in an interval $[0, T]$. Focusing on a given process leading to the production of a good, note that the cumulated cost of the good in an initial interval $\left[0, \hat{t}\right]$ of production is given by

$$C\left(\hat{t}\right) = \int_0^{\hat{t}} w\ell(t)\, dt, \tag{15}$$

where L is the total amount of labor spending over the entire production process. Empirically, this will be recorded as inventories of materials or work-in-process inventories. This cumulated cost differs from the last term in the profit-maximization problem in (3) by the financial term e^{-rt}. We omit this term because standard practice is to measure inventories on a cost basis, and this cost does not include the financial costs associated with holding inventories.

Consider now a stationary equilibrium in which a firm simultaneously carries out various production processes of the type above, and these processes are at various phases of completion. For simplicity, we assume a uniform time-invariant distribution of production processes of different ages. More specifically, at each instant t, the firm begins the production of N goods, continues to add value to goods began in previous periods $t' \in (t-T, t)$, and also completes the production of N goods began at $t-T$. Total inventories in steady state are then

$$I = N\int_0^T C\left(\hat{t}\right) d\hat{t} = Nw\int_0^T \int_0^{\hat{t}} \ell\left(s\right) ds d\hat{t}, \tag{16}$$

regardless of initial conditions.

The total labor cost embodied in the goods completed at that instant is given by $C\left(T\right) = NwL$, where remember that $L = \int_0^T \ell\left(t\right) dt$ is total labor use along the whole production process. Empirically, this corresponds to the accounting concept of the costs of goods sold (or COGS), which typically excludes financing costs incurred during production, thereby justifying our omission of these terms as well.

With equation (16) at hand, we can thus express the ratio of inventories to the cost of goods sold as

$$\frac{I}{C(T)} = \int_0^T \int_0^{\hat{t}} \frac{\ell}{L}\ell\left(s\right) ds d\hat{t} = \int_0^T \int_0^{\hat{t}} \lambda\left(s\right) ds d\hat{t}.$$

Solving this double integral by parts delivers

$$\frac{I}{C(T)} = \int_0^T \int_0^{\hat{t}} \lambda\left(s\right) ds d\hat{t} = \left|\hat{t}\int_0^{\hat{t}} \lambda\left(s\right) ds\right|_0^T - \int_0^T \hat{t}\lambda\left(\hat{t}\right) d\hat{t} = \int_0^T \left(T-\hat{t}\right)\lambda\left(\hat{t}\right) d\hat{t} = \mathcal{APP}.$$

The ratio of inventories to the cost of goods sold $I/C\left(T\right)$ thus exactly corresponds to our conceptual measure of the average period of production $\mathcal{APP}$ in equation (2).

In sum, we have:

Proposition 5. The average period of production $\mathcal{APP}$ associated with a firm's production process can be computed as the ratio of the firm's inventories to its cost of goods sold (COGS).

To better grasp the meaning of this result, consider the case in which the quarterly balance sheets of a firm report a ratio of inventories to cost of goods sold equal to 2, thus indicating that the average period of production is two quarters. Of course, this does not mean that the production process takes two quarters to complete from beginning to end. Indeed, remember that $\mathcal{APP}$ is necessarily smaller than the production length T. Instead, $\mathcal{APP} = 2$ indicates that inputs were employed, on average, two quarters before the sale of the good.

Precedents Although the result in Proposition 5 is not well known in the literature, it is admittedly not new. More than sixty-five years ago, Dorfman (1959) studied the temporal dimension of production and related the stationary equilibrium of a firm's production processes to the so-called "bathtub theorem", which asserts that "in any reservoir of constant content, so that the rate of inflow equals the rate of outflow, the average period of detention equals the content of the reservoir divided by the rate of flow" (Dorfman, 1959, p. 353). In this bathtub analogy, the constant rate of water inflow corresponds to new labor expenditures at a point in time, while the water outflow are past labor expenditures embodied in the goods sold at point in time. Thus, the average "detention" of input expenditures (or average period of production) is the ratio of inventories to the cost of goods sold, as shown above.

Much more recently, Schwartzman (2014) has derived a link between what he refers as the "time to produce and distribute" (or time to produce, for short) and a firm's inventory over cost ratio. His derivation is however developed in discrete time, and is largely concerned with delineating how changes in interest rates affect output depending on the ratio of inventories to cost in various sectors. In the next sector, we will further comment on his empirical contribution.

Alternatives Before concluding this theoretical section, we briefly comment on two variants of our measure of the average production period. First, we have assumed that wages (or the price of inputs more broadly) are time invariant. If instead we allow wages to change over the production process, perhaps because different types of workers are used at different stages of production, we can alternatively define the average production length as

$$\mathcal{APP}_{Exp} = \int_0^T (T-t)\,\frac{w(t)\,\ell(t)}{\int_0^T w(t)\,\ell(t)\,dt}dt, \tag{17}$$

which now represents a weighted average temporal distance between the time when labor *expenditures* are incurred and the time when revenue is collected. Note, however, that we can define $\lambda(t) = w(t)\,\ell(t)/E_L$, where $E_L = \int_0^T w(t)\,\ell(t)\,dt$, so as long as the shares $\lambda(t)$ are stationary (e.g., because all wages grow at a common rate), then our main results in Propositions 3, 4 and 5 continue to apply in this case: $\mathcal{APP}_{Exp}$ can be computed as the ratio of a firm's inventories to its cost of goods sold (COGS), and it is expected to depend negatively on the cost of capital faced by a firm.

Next, we consider Hicks' preferred notion of the average period of production, which is closely related to concept of duration in finance (Macaulay, 1938). In particular, Hicks (1939) proposed to measure the average period of production as

$$\mathcal{APP}_{Hicks} = \int_0^T (T-t)\,\frac{w(t)\,\ell(t)\,e^{-rt}}{\int_0^T w(t)\,\ell(t)\,e^{-rt}dt}dt, \tag{18}$$

which is analogous to (18) except for the fact that it applies a discount factor for input expenditures at later dates (or, alternatively, it compounds the interest associated with input expenditures incurred early in production). This definition is appealing when attempting to compute the capital demands associated with a production process of a given length, but the inclusion of the discount factors e^{-rt} generates a *mechanical* positive impact of the interest rate

r on $\mathcal{APP}_{Hicks}$. Hicks (1939) was uncomfortable with this direct impact, so when considering the overall impact of the interest rate on the average period of production, he advocated ignoring this direct effect.[4] This naturally resulted in a negative relationship between $\mathcal{APP}_{Hicks}$ and r, as we have derived above. In a more recent piece, Malinvaud (2003) derived the same result, again purposefully ignoring the direct effect of interest rates on $\mathcal{APP}_{Hicks}$ working through the terms in e^{-rt}. Beyond these conceptual aspects, the fact that inventories are measured on a cost basis also implies that $\mathcal{APP}_{Hicks}$ will typically *not* map directly to the ratio of inventories to the cost of goods sold. This rationalizes our preference for the measure $\mathcal{APP}$ (or $\mathcal{APP}_{Exp}$) over $\mathcal{APP}_{Hicks}$.

5 The Average Period of Production in the US

Having discussed the conceptual underpinnings of our measure of the temporal dimension of production, we now turn to its measurement. This requires two key inputs: a measure of a firm's inventories and a measure of the costs embodied in the goods it sells. Fortunately, as discussed below, these inputs are readily available for publicly traded companies. In this section, we begin our analysis with data for U.S. companies, and in Section 6, we expand the analysis to a dataset of global publicly traded companies.

5.1 Data Sources and Variables Definition

We construct our proposed measure of the average period of production using annual financial reports from publicly traded U.S. firms for the period 1980–2018. This data is obtained from the Compustat North America database, maintained by Wharton Research Data Services. Financial reports provide detailed information on the cost of goods sold (COGS) and total inventories, which are in turn disaggregated into raw materials, work-in-process, and finished goods. Guided by the theoretical analysis, we calculate the *average period of production* for a given firm in a given year as the ratio of total inventories to COGS. We continue to refer to this measure as the $\mathcal{APP}$.

Compustat also allows us to estimate the cost of capital each firm faces as the ratio of interest expenses to the sum of long-term and short-term debt. In addition to financial fundamentals, Compustat provides time-varying information on a firm's industry classification, which we standardize to the 2012 vintage of the North American Industry Classification System (NAICS).

[4] In Hick's own words: "if the average period changes, without the rate of interest having changed, it must indicate a change in the stream; but if it changes, when the rate of interest changes, this need not indicate any change in the stream at all. Consequently, even when we are considering the effect of changes in the rate of interest on the production plan, we must not allow the rate of interest which we use in the calculation of the average period to be changed" (Hicks, 1939, p. 220).

More details on this concordance are provided in the Appendix.

Since information and communication technologies (ICT) are a key factor influencing inventory management (Kahn et al., 2002), we supplement the Compustat data with an industry-level measure of the stock of information processing capital equipment relative to sectoral output, obtained from the Bureau of Labor Statistics. This measure is available at the three- or four-digit NAICS levels. For brevity, we refer to this measure as “IT capital intensity.”

Finally, to examine the relationship between the average period of production ($\mathcal{APP}$) and other variables at the industry level, we use a broad range of industry-level variables (discussed below) obtained from the NBER-CES Manufacturing Industry Database (Becker et al., 2021).

In the main text, we focus on presenting results based on a sample of all firms in Compustat classified as belonging to the manufacturing sector (NAICS code 31–32–33). However, in an Appendix to be made available soon, we report results for all goods-producing industries (NAICS codes 11-21-22-23, in addition to the manufacturing). The exclusion of privately held firms from our sample is certainly a limitation of our study, but we lack systematic and reliable data on the cost of goods sold (COGS) for non-publicly traded firms. Nonetheless, we occasionally benchmark our results against imperfect proxies for the $\mathcal{APP}$, which can be constructed using larger samples that include privately held companies.

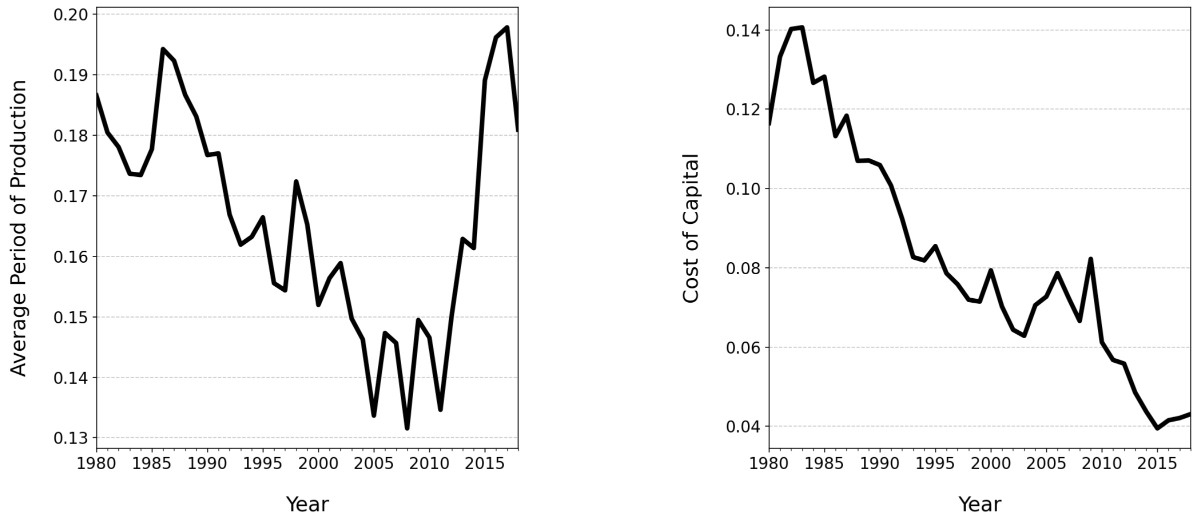
5.2 Aggregate Trends

Although our measure of the temporal length of production can be computed at both the firm and industry levels, we first present evidence of its evolution at the aggregate level for the period 1980–2018. We do so by computing a cost-weighted average of the $\mathcal{APP}$ for U.S. firms in the manufacturing sector, which naturally coincides with the ratio of the sum of their inventories to the sum of their COGS.

Panel (a) of Figure 1 illustrates the evolution of the cost-weighted average $\mathcal{APP}$. This measure fluctuated during the 1980s but then declined significantly in the 1990s and early 2000s, coinciding with the widespread adoption of IT capital in U.S. manufacturing, reaching a value of 0.13 in 2005. Starting in 2005, however, we observe a marked increase in the average $\mathcal{APP}$ in U.S. manufacturing, reaching a value of 0.20 in 2017 and 0.18 in 2018. This implies that in 2018, on average, inputs were employed $365 \times 0.18 = 66$ days before the sale of the goods in which they were used.[5]

[5]Data from the St. Louis Fed (http://fred.stlouisfed.org/series/MNFCTRIRSA) indicates that total monthly inventories relative to sales were around 1.36 months, or 0.11 years, in 2018. Naturally, sales are higher than the cost of goods sold (COGS), and this disparity has grown in recent years. De Loecker et al. (2020) use U.S. Census data, including non-publicly traded companies, to estimate that the average markup in U.S. manufacturing fluctuated between 1.60 and 1.85 from 1980 to 2012. For values closer to 1.80 in the later years of their sample, this implies a ratio of inventories to costs of $0.11 \times 1.80 = 0.20$, which is remarkably close to our estimates based on Compustat data.

Figure 1: The Average Production Period and the Cost of Capital in U.S Manufacturing.



(a) Cost-Weighted Average Period of Production

(b) Cost-Weighted Average Cost of Capital

Notes: The figure represents the cost-weighted annual averages of the average period of production (Panel (a)) and cost of capital (Panel (b)) for U.S. publicly traded companies in the manufacturing industry (2012 NAICS codes 31–32–33) for each year from 1980 to 2018. Both metrics are calculated using firm-level data from annual financial reports. The average period of production is calculated as the ratio of total inventories to COGS, and the cost of capital is calculated as the ratio of interest expenses to total debt. See the Appendix for the data preparation algorithm. Source: Compustat.

The recent increase in $\mathcal{APP}$ documented in Panel (a) of Figure 1 could, in part, be explained by a significant decline in the cost of capital faced by firms.[6] This trend is illustrated in Panel (b) of Figure 1, which shows that the average cost of capital for U.S. manufacturing firms fell from around 12 percent in 1980 to about 4 percent in 2018, with approximately half of this decline occurring after 2010.

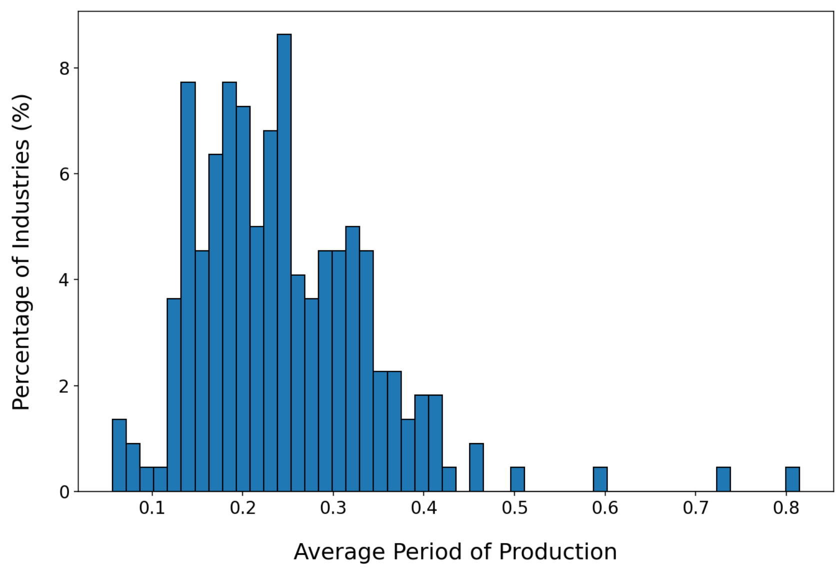
Was the decline in the cost of capital partly responsible for the observed increase in $\mathcal{APP}$ since 2005? We explore this possibility below by regressing our firm-level measure of $\mathcal{APP}$ on our firm-level measure of the cost of capital, while controlling for industry-level measures of IT capital intensity and other industry characteristics in some specifications. Before discussing these results, however, we document several interesting aspects of the cross-sectoral variation in $\mathcal{APP}$ within U.S. manufacturing.

[6]Carreras-Valle (2021) documents a parallel recent rise in the ratio of inventories *over sales* among U.S. firms and relates it to increased trade with China.

5.3 Variation in the Average Period of Production Across Industries

How much does the average period of production vary across U.S. manufacturing sectors when computed at the six-digit NAICS 2012 industry level? Figure 2 shows significant variation in $\mathcal{APP}$ within our sample, which includes 220 manufacturing sectors. We exclude sectors with fewer than 50 firm-year observations after data preparation (see the Appendix for details).

Figure 2: Distribution of the Average Production Period for U.S. Manufacturing Industries



Notes: The figure shows the distribution of industries (N = 220), defined as six-digit NAICS codes, based on an average of the firm-level average periods of production. For each industry, this measure is first calculated as a cost-weighted average across firms within each year and then as a simple average across years from 1980 to 2018. The average period of production is defined as the ratio of total inventories to COGS. The data covers U.S. publicly traded companies in the manufacturing sector (2012 NAICS codes 31–32–33). Industries with fewer than 50 firm-year observations are excluded. See the Appendix for the data preparation algorithm. Source: Compustat.

While most sectors exhibit $\mathcal{APP}$ values ranging from 0.1 to 0.4 (equivalent to 36.5 to 146 days), a small number of sectors display significantly higher $\mathcal{APP}$ values. The only previous paper we are aware of that computes the ratio of inventories to the cost of goods sold is Schwartzman (2014), which calculated this ratio for 26 fairly aggregated manufacturing sectors. The range of $\mathcal{APP}$ in that study is naturally somewhat narrower than ours, but the mean $\mathcal{APP}$ in their sample appears to be around 2.25 months, or 0.19 years, aligning with our estimates.

In Table 1, we present the top 10 manufacturing industries based on their average period of production. It is noteworthy that the 'lengthier' production processes – distilleries and wineries – coincide with two of the examples provided by the illustrious economists who discussed the benefits of aging in production. To some extent, maturation is also relevant for the fourth 'longest' production process, tobacco manufacturing, which involves leaf processing and aging. Other industries with high $\mathcal{APP}$ values are sectors that produce technically complex products, such as ophthalmic goods, pharmaceutical preparation, or electromedical instruments.

Table 1: Top 10 U.S. Industries based on the Average Period of Production

NAICS	Industry	Average Period of Production
312140	Distilleries	0.814
312130	Wineries	0.730
339115	Ophthalmic Goods Manuf.	0.594
312230	Tobacco Manuf.	0.511
333517	Machine Tool Manuf.	0.464
333132	Oil and Gas Field Machinery and Equipment Manuf.	0.458
316998	All Other Leather Good and Allied Product Manuf.	0.432
325412	Pharmaceutical Preparation Manuf.	0.418
332215	Metal Kitchen Cookware, Utensil, Cutlery, and Flatware Manuf.	0.415
334510	Electromedical and Electrotherapeutic Apparatus Manuf.	0.414

Notes: The table lists the top 10 U.S. manufacturing industries, defined as six-digit NAICS codes, based on an average of the firm-level average periods of production. For each industry, this measure is calculated first as a cost-weighted average across firms within each year and then as a simple average across years from 1980 to 2018. The average period of production is defined as the ratio of total inventories to COGS. The data includes U.S. publicly traded companies in the manufacturing sector (2012 NAICS codes 31–32–33). Industries with fewer than 50 firm-year observations are excluded. See the Appendix for the data preparation algorithm. Source: Compustat.

Table 2 instead reports the bottom 10 manufacturing industries based on the average period of production. Reassuringly, the list includes a combination of sectors that produce largely homogeneous goods (e.g., petroleum refineries, ethyl alcohol), perishable goods (e.g., fluid milk, baked goods, ice cream), and industries with relatively simple manufacturing processes (e.g., bottled water manufacturing or motor vehicle metal stamping).

We also explore how our measure of the average period of production correlates with other industry characteristics. We construct measures of the latter using the 2021a version of the NBER-CES Manufacturing Database (Becker et al., 2021). Table 3 reports the correlations between our $\mathcal{APP}$ variable and several industry variables, including measures that have been commonly used to capture skill and physical capital intensity. Specifically, we calculate the annual values for each industry variable, take the average across years from 1980 to 2018, and then compute the correlation with our $\mathcal{APP}$ measure.

As indicated in Table 3, $\mathcal{APP}$ is positively correlated with skill intensity, possibly reflecting the disproportionate need for care and precision in skill-intensive processes, while it is negatively correlated with physical capital intensity. This latter correlation highlights an interesting

Table 2: Bottom 10 U.S. Industries based on the Average Period of Production

NAICS	Industry	Average Period of Production
311511	Fluid Milk Manuf.	0.056
324110	Petroleum Refineries	0.068
311812	Commercial Bakeries	0.071
325193	Ethyl Alcohol Manuf.	0.073
336370	Motor Vehicle Metal Stamping	0.081
312112	Bottled Water Manuf.	0.096
327992	Ground or Treated Mineral and Earth Manuf.	0.112
311520	Ice Cream and Frozen Dessert Manuf.	0.118
327420	Gypsum Product Manuf.	0.119
327320	Ready-Mix Concrete Manuf.	0.119

Notes: The table lists the bottom 10 U.S. manufacturing industries, defined as 6-digit NAICS codes, based on an average of the firm-level average periods of production. For each industry, this measure is calculated first as a cost-weighted average across firms within each year and then as a simple average across years from 1980 to 2018. The average period of production is defined as the ratio of total inventories to COGS. The data includes U.S. publicly traded companies in the manufacturing sector (2012 NAICS codes 31–32–33). Industries with fewer than 50 firm-year observations are excluded. See the Appendix for the data preparation algorithm. Source: Compustat.

dichotomy between physical capital and working capital intensities, which, to the best of our knowledge, has not been previously noted in the literature. Both correlations between $\mathcal{APP}$ and skill and physical capital intensities are highly statistically significant (at the 1% level).

We also define three measures of 'inventory intensity' based on variables available from the NBER Manufacturing Database. First, we compute the simple ratio of inventories to sales, which shows a high correlation of 0.70 with our $\mathcal{APP}$ measure constructed from Compustat data. We then refine the denominator of this variable by approximating COGS as the sum of payroll, material costs, and energy costs. This refinement increases the correlation with $\mathcal{APP}$ to over 0.8. We have confirmed that this high correlation is not driven by outliers (see Figure A.1 in the Appendix). Finally, we further refine this measure by excluding non-production worker wages from total payroll (to better approximate the labor cost component of COGS), but this has minimal impact on the correlation, which remains above 0.8. These very high correlations alleviate concerns that our focus on publicly traded companies may bias our results.

In the bottom rows of Table 3, we correlate an industry's $\mathcal{APP}$ with two measures of productivity. In both cases, we find an essentially zero correlation of these productivity variables with the $\mathcal{APP}$, in contrast to the positive relationship posited by 'Austrian' theories. Nevertheless, this zero correlation appears to be partly explained by the fact that the $\mathcal{APP}$ is itself negatively correlated with physical capital intensity. In fact, a simple regression of log

Table 3: Correlation of Average Production Period with Other Industry Characteristics

Industry characteristic	Correlation with $\mathcal{APP}$	p-Value
Capital Intensity		
Log (Capital Stock / Total Workers)	−0.1855	0.0058
Log (Capital Expenditures / Payroll)	−0.1928	0.0041
Skill Intensity		
Log (Non-Production Workers / Total Workers)	0.2838	0.0000
Non-Production Payroll / Payroll	0.3589	0.0000
Inventory Intensity		
Inventories / Sales	0.7060	0.0000
Inventories / (Payroll + Material Costs + Energy Costs)	0.8062	0.0000
Inventories / (Prod. Worker Wages + Material Costs + Energy Costs)	0.8032	0.0000
Productivity		
Log (Value Added / Total Workers)	0.0413	0.5427
Total Factor Productivity	0.0269	0.6911

Notes: The table reports the correlations between the average period of production, constructed using Compustat data, and various industry characteristics, derived from the NBER-CES Manufacturing Database, for U.S. manufacturing industries defined as 6-digit NAICS codes (2012 NAICS codes 31–32–33). Annual values of industry characteristics are averaged across years from 1980 to 2018, and correlations are computed based on this cross-sectional data. Industries with fewer than 50 firm-year observations in the Compustat dataset are excluded. Pearson correlation coefficients are presented alongside their associated p-values. See the Appendix for the data preparation algorithm. Sources: Compustat and NBER-CES Manufacturing Database.

value added per worker on the $\mathcal{APP}$ and the log capital-labor ratio of the industry reveals a positive and highly statistically significant coefficient for the $\mathcal{APP}$ (t-stat = 4.66). See the partial correlation plot in Figure A.2 in the Appendix.

5.4 The Average Period of Production and the Cost of Capital

Propositions 3 and 4 predict that the average period of production is negatively associated with the cost of capital. In this section, we perform regression analyses to examine the empirical relationship between these two variables, using panel data on publicly traded firms in U.S. manufacturing during the period 1980–2018. Specifically, we estimate the following regression equation:

$$\mathcal{APP}_{it} = \beta R_{it} + \gamma \mathbf{Z}_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \tag{19}$$

where i and t denote firms and years, respectively, $\mathcal{APP}_{it}$ represents the average period of production of firm i in year t, R_{it} is the cost of capital faced by firm i in year t, $\mathbf{Z}_{it}$ is a vector of industry-level controls for the sector to which firm i belongs, and μ_i and λ_t are firm and year fixed effects. Table 4 presents summary statistics for the variables used in these regressions.

We can see that the empirical distributions of all these variables are skewed with their mean exceeding their median.

Table 4: Summary Statistics for Firms in U.S. Manufacturing Industry, 1980-2018

	Mean	Std. Dev.	P25	Median	P75	Count
Average Period of Production	0.311	0.245	0.161	0.254	0.389	56,850
Cost of Capital	0.109	0.085	0.065	0.091	0.123	56,850
IT Capital Intensity	0.048	0.050	0.014	0.023	0.074	43,875
Capital Intensity	167.0	264.3	48.20	83.77	163.3	51,069
Skill Intensity	0.367	0.141	0.244	0.362	0.478	52,408
Labor Productivity	151.4	174.9	61.35	97.71	178.3	52,408

Notes: The table reports summary statistics for firm-year observations of U.S. publicly traded companies in the manufacturing industry (2012 NAICS codes 31–32–33) for the period 1980–2018. Capital intensity and labor productivity are expressed in $1,000 per worker. See the Appendix for the data preparation algorithm. Sources: Bureau of Labor Statistics, Compustat, NBER-CES Manufacturing Database.

Table 5 presents the results of estimating equation (19). All variables are expressed in logarithms, allowing the regression coefficients to be interpreted as elasticities. Each regression includes firm and year fixed effects, with two-way clustered standard errors: at the firm and year levels in columns (1)–(3) and at the industry and year levels in column (4).

Table 5: The Average Period of Production and the Cost of Capital

Dependent Variable:	Average Period of Production			
	(1)	(2)	(3)	(4)
Cost of Capital	-0.090	-0.087	-0.088	-0.088
	(0.006)	(0.006)	(0.006)	(0.006)
IT Capital Intensity	–	0.018	0.022	0.022
	–	(0.013)	(0.015)	(0.014)
Capital Intensity	–	–	-0.030	-0.030
	–	–	(0.016)	(0.021)
Skill Intensity	–	–	0.037	0.037
	–	–	(0.039)	(0.035)
Labor Productivity	–	–	-0.038	-0.038
	–	–	(0.029)	(0.033)
R^2	0.760	0.781	0.780	0.780
Observations	56,133	43,007	39,076	39,076
Clustering	Firm-Year	Firm-Year	Firm-Year	NAICS 4-Year

Notes: The table presents the results of estimating equation (19) on a panel of U.S. publicly traded companies in the manufacturing industry (2012 NAICS codes 31–32–33) for the period 1980–2018. All variables are in logarithms, allowing the regression coefficients to be interpreted as elasticities. Each regression includes firm and year fixed effects. See the Appendix for details on the data preparation algorithm. Sources: Bureau of Labor Statistics, Compustat, NBER-CES Manufacturing Database.

Column (1) of Table 5 presents the results of the regression without industry controls. The coefficient of -0.090 reflects the elasticity of $\mathcal{APP}$ with respect to changes in the interest rates faced by firms. In our sample of manufacturing firms, it is evident that a higher firm-level cost of capital is associated with a shorter firm-level average period of production.

How large is this coefficient in economic terms? To gauge the magnitude of this effect, consider that between 2005 and 2018, the $\mathcal{APP}$ increased from 0.134 to 0.181, corresponding to a log change of 0.301. Over the same period, the cost of capital faced by firms declined from 0.073 to 0.043, a log change of -0.529. Based on our estimates, this would predict a log change in $\mathcal{APP}$ of $-0.529 \times -0.090 = 0.048$, which accounts for approximately 16% of the observed 0.301 log change in $\mathcal{APP}$ during this period. However, it is important to note that the regression in Table 5 captures only a partial correlation between these variables and does not establish a causal relationship. Future research should aim to identify how exogenous changes in the cost of capital influence firms' average period of production.

In the remaining columns of Table 5, we assess the robustness of our results by incorporating various industry-level controls. In column (2), we include an industry-level measure of IT intensity, and in column (3), we additionally include industry-level measures of capital intensity, skill intensity, and labor productivity. The inclusion of these variables has a negligible effect on the estimated elasticity of the $\mathcal{APP}$ with respect to the cost of capital. Finally, in column (4), we report results that cluster standard errors two-ways, at the four-digit NAICS level and at the year level. The negative coefficient on the cost of capital remains highly significant.[7]

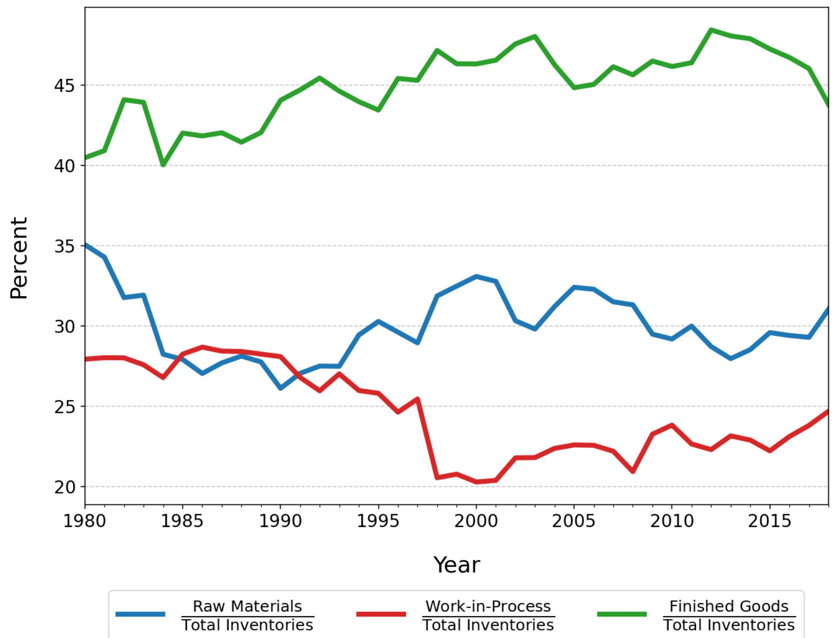
5.5 Disaggregation by Type of Inventory

We now turn to explore the extent to which our results in Table 5 are disproportionately driven by specific components of inventories. As mentioned above, firms' financial statements disaggregate inventories into those associated with raw materials, work-in-process, and finished goods. As shown in Figure 3, finished goods account for more than 40 percent of total inventories on average, work-in-process for less than 30 percent, and raw materials for about a third.

In Table 6, we estimate the regression equation (19) for the ratio of each of these types of inventories to the cost of goods sold, without including any industry-level controls. All variables are expressed in logarithms, allowing the regression coefficients to be interpreted as elasticities. Each regression includes firm and year fixed effects, with standard errors clustered at the firm and year levels. Unfortunately, only a subset of observations contains data on types of inventories, and we estimate each regression on that subset.

[7]The addition of industry-level variables reduces the sample size because such measures are not available for all industries. In the Appendix, we re-estimate all three specifications on the restricted subset of observations with non-missing values for all industry-level variables. The effect of restricting the sample on the estimated elasticity of the $\mathcal{APP}$ with respect to the cost of capital is negligible.

Figure 3: Cost-Weighted Average Shares of Total Inventories in U.S. Manufacturing



Notes: The figure represents the cost-weighted annual averages of raw materials (blue line), work-in-process (red line), and finished goods (green line) as shares of total inventory for U.S. publicly traded companies in the manufacturing industry (2012 NAICS codes 31–32–33) for each year from 1980 to 2018. These averages are calculated using firm-level data from annual financial reports. Source: Compustat.

Table 6: The Average Period of Production and the Cost of Capital by Inventory Type

	Total Inventories to COGS Ratio (1)	Raw Materials Inventories to COGS Ratio (2)	Work-in-Process Inventories to COGS Ratio (3)	Finished Goods Inventories to COGS Ratio (4)
Cost of Capital	-0.101	-0.100	-0.128	-0.108
	(0.006)	(0.008)	(0.012)	(0.009)
R^2	0.766	0.745	0.768	0.737
Observations	34,865	34,865	34,865	34,865

Notes: The table presents the results of estimating equation (19) on a panel of U.S. publicly traded companies in the manufacturing industry (2012 NAICS codes 31–32–33) for the period 1980–2018. The dependent variable in each column is the log of the ratio of total inventories (Column 1), raw material inventories (Column 2), work-in-process inventories (Column 3), or finished goods inventories (Column 4) to COGS. All variables are in logarithms, allowing the regression coefficients to be interpreted as elasticities. Each regression includes firm and year fixed effects. Standard errors are clustered at the firm and year levels. See the Appendix for details on the data preparation algorithm. Sources: Bureau of Labor Statistics, Compustat, NBER-CES Manufacturing Database.

As is clear from Table 6, a higher cost of capital is associated with lower values for all these ratios, and these negative relationships are characterized by remarkably similar elasticities. Thus, a higher cost of capital tends to reduce the average period of production by decreasing the stock of raw materials, work-in-process, and finished-goods inventories.

6 The Average Period of Production Worldwide

The Compustat database, maintained by Wharton Research Data Services, also provides data on a large sample of publicly traded firms worldwide. In this section, we use this data to construct our proposed measure of the average period of production for the period 1980-2018 for various countries and sectors (see the Appendix for more details on the data construction).

Because we lack cross-country industry-level data comparable to the U.S. NBER Manufacturing Database, we will only seek to compare our sectoral measures of production length across countries, and to revisit the link between the $\mathcal{APP}$ and the cost of capital faced by firms with a larger sample of firms worldwide.

6.1 Cross-Country Rank Correlation of Production Lengths

As we described in the last section, U.S. industries differ significantly in their average production length. How consistent are industry rankings of the $\mathcal{APP}$ across countries? In Table 7, we calculate Spearman rank correlations for the rankings of industries based on the average period of production across pairs of 10 countries. We arrived at this sample by restricting the analysis to country-industries with at least 50 observations in the period 1980-2018, and we only report rank correlations for pairs of countries with at least 10 overlapping six-digit NAICS codes. Reassuringly, all but one of the recorded rank correlations are positive, and many of those are both high and highly statistically significant. The U.S. ranking is particulary correlated with those for Germany (0.75), United Kingdom (0.74), and Canada (0.71), but all correlations are above 0.5, except for India (0.41) and Malaysia (-0.03). In the Appendix (see Table A.1) we relax a bit our criteria for inclusion, and present results for a larger set of country-pairs.

6.2 Pooled Regressions

We next return to the specification in (19) with our full sample of countries in the global Compustat database. We present the estimation results in Table 8. For comparison, we first replicate our results in column (1) of Table 5, when only the U.S. sample is used. Then, in column (2), we report the same results but with standard errors two-way clustered at the industry and year level. Our results with our global sample are in columns (3) and (4), which

Table 7: Rank Correlations of Industry Average Period of Production across Countries

Code	CAN	CHN	DEU	GBR	IND	JPN	KOR	MYS	TWN	USA
CAN	–	–	–	0.53^c	0.73^a	0.75^a	–	–	–	0.71^a
CHN	–	–	–	–	0.10	0.53^c	0.68^b	–	0.38	0.65^b
DEU	–	–	–	–	–	–	–	–	–	0.75^b
GBR	0.53^c	–	–	–	0.79^a	0.63^a	0.63^b	–	0.65^b	0.74^a
IND	0.73^a	0.10	–	0.79^a	–	0.47^a	0.55^a	0.37	0.20	0.41^a
JPN	0.75^a	0.53^c	–	0.63^a	0.47^a	–	0.75^a	0.15	0.38^b	0.58^a
KOR	–	0.68^b	–	0.63^b	0.55^a	0.75^a	–	–	0.52^b	0.67^a
MYS	–	–	–	–	0.37	0.15	–	–	–	-0.03
TWN	–	0.38	–	0.65^b	0.20	0.38^b	0.52^b	–	–	0.53^a
USA	0.71^a	0.65^b	0.75^b	0.74^a	0.41^a	0.58^a	0.67^a	-0.03	0.53^a	–

Notes: Spearman rank correlations are reported. Sample includes country-industries with at least 50 observations in the period 1980-2018 in the Compustat database. Rank correlations are reported only if two countries have at least 10 overlapping six-digit NAICS codes. Statistical significance at the 1%, 5% and 10% levels are denoted by subscripts *a*, *b* and *c*, respectively. Source: Compustat.

differ from each other only in the level at which standard errors are clustered. As is clear from the table, the results are qualitative and quantitatively very similar to those in our U.S. sample.

Table 8: The Average Period of Production and the Cost of Capital Worldwide

Dependent Variable:	Average Period of Production			
	(1)	(2)	(3)	(4)
	USA only	USA only	All Countries	All Countries
Cost of Capital	-0.090	-0.090	-0.078	-0.077
	(0.006)	(0.006)	(0.005)	(0.005)
R^2	0.760	0.760	0.765	0.770
Observations	56,133	55,207	209,606	189,914
Clustering	Firm-Year	NAICS 4-Year	Firm-Year	NAICS 4-Year

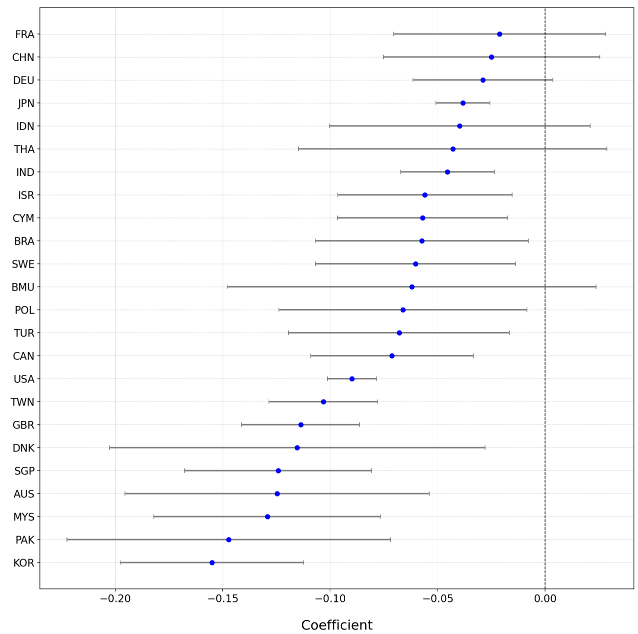
Notes: The table presents the results of estimating equation (19) on a panel of global publicly traded companies in the manufacturing industry (2012 NAICS codes 31–32–33) for the period 1980–2018. The first two columns are based on the data for U.S. firms, and the last two columns are for firms from all countries. The dependent variable in all columns is the log of the ratio of total inventories to COGS. All variables are in logarithms, allowing the regression coefficients to be interpreted as elasticities. Each regression includes firm and year fixed effects. Standard errors are clustered at the levels indicated in the table. See the Appendix for details on the data preparation algorithm. Source: Compustat

The elasticity we find in the pooled regressions is slightly smaller than in the U.S. sample (-0.078 vs -0.090). When computing the increase in the $\mathcal{APP}$ observed over the period 2005 to 2018 that our regressions would ascribe to the decline in the cost of capital faced by firms, the implied contribution is still economically meaningful. More specifically, the observed decline in the cost of capital faced by firms would have increased the $\mathcal{APP}$ by about 0.014 log points, which is about 10% of the observed increase over the period 2005 to 2018.[8]

6.3 Industry- and Country-Level Heterogeneity

Beyond the pooled regressions in Table 8, we have also experimented with running equation (19) country-by-country (with data for firms in various manufacturing sectors) and industry-by-industry (with data for firms in various countries). These regressions drop sectors or countries with less than 1,000 firm-year observations.

Figure 4: Average Production Period and Cost of Capital: Country Heterogeneity



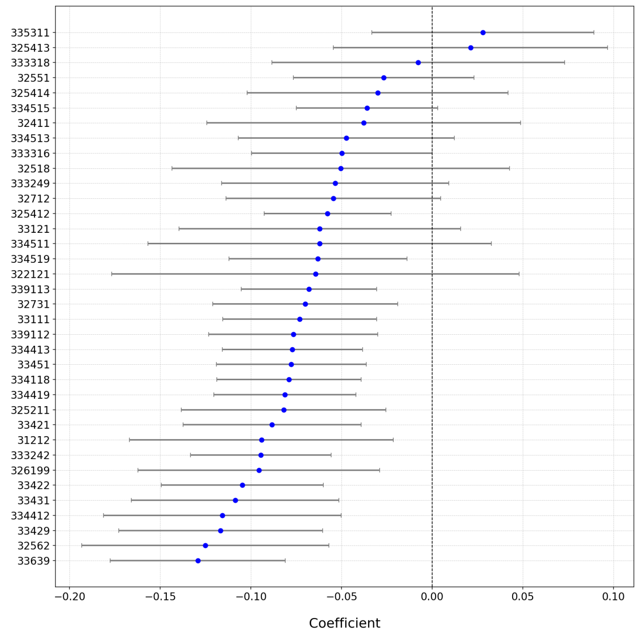
Notes: The plot displays the estimated coefficients and 95% confidence intervals from regressions run separately for each country on a panel of global publicly traded companies in the manufacturing industry (2012 NAICS codes 31–32–33) for the period 1980–2018. The dependent variable in all regressions is the log of the ratio of total inventories to COGS, while the independent variable is the log of the cost of capital. All variables are in logarithms, allowing the coefficients to be interpreted as elasticities. Each regression includes firm and year fixed effects. Standard errors are two-way clustered at the firm and year levels. See the Appendix for details on the data preparation algorithm. Source: Compustat.

The results of these exercises are plotted in Figures 4 and 5, and they demonstrate the robustness of the negative association between the $\mathcal{APP}$ and the cost of capital faced by firms. More specifically, the cost of capital is negatively correlated with the $\mathcal{APP}$ in all countries, with the results being significantly positive at the 5% level in 18 of the 24 countries. Similarly,

[8]For 2005, we compute an average cost of capital of 7.13% worldwide, while we estimate and average $\mathcal{APP}$ of 0.2868. In 2018, the average cost of capital was down to 5.95%, while the average $\mathcal{APP}$ in that year had gone up to 0.3291. These averages are computed by first taking the cost-weighted averages within country and industry pairs, and then taking the unweighted average of these.

we find a negative coefficient on the cost of capital in all but two sectors, with a statistically negative coefficient applying in the majority of sectors.

Figure 5: Average Production Period and Cost of Capital: Industry Heterogeneity



Notes: The plot displays the estimated coefficients and 95% confidence intervals from regressions run separately for each industry, defined by six-digit NAICS codes, on a panel of global publicly traded companies in the manufacturing industry (2012 NAICS codes 31–32–33) for the period 1980–2018. The dependent variable in all regressions is the log of the ratio of total inventories to COGS, while the independent variable is the log of the cost of capital. All variables are in logarithms, allowing the coefficients to be interpreted as elasticities. Each regression includes firm and year fixed effects. Standard errors are two-way clustered at the firm and year levels. See the Appendix for details on the data preparation algorithm. Source: Compustat.

7 Conclusions

In this paper, we have developed a measure to capture the temporal dimension of production, building on the Austrian capital theory of Böhm-Bawerk (1889). We define the average period of production as a weighted average temporal distance between the time a firm employs its inputs and the time these inputs deliver finished goods to consumers. Under stationarity conditions, this measure corresponds to the ratio of a firm's stock of inventories to the cost of goods it sells in a given period, making it readily computable using data from publicly traded companies worldwide. Consistent with theoretical predictions, we have demonstrated that firms facing higher capital costs tend to exhibit shorter average production periods.

Our ultimate aim is to foster further empirical research into how production length and interest rates shape industrial structure. Recent work by Antràs (2023a,b) has explored the theoretical connections between interest rates and comparative advantage in models of international trade and global value chains. The measure developed in this paper provides a foundation for empirically testing these 'Austrian' theories of international specialization. Moreover, we hope that our measure will find broader applications across fields, offering new insights into the interplay between production length, financial constraints, and industrial structure.

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A Appendix

A.1 A Change in T

From straightforward differentiation of equation (2), we have that

$$\begin{aligned}
\mathcal{APP}'(T) &= (T-T)\frac{\ell(T)}{L} + \int_0^T \left[\frac{\ell(t)}{L} - (T-t)\frac{\ell(t)}{L^2}\ell(T)\right] ds \\
&= 0 + 1 - \frac{\ell(T)}{L}\int_0^T \left[(T-t)\frac{\ell(t)}{L}\right] ds \\
&= 1 - \frac{\ell(T)}{L}\mathcal{APP}.
\end{aligned}$$

Note that if $\ell(t)$ stays constant or decreases along the production process, we then have $\ell(T)/L > 1/T$, and thus

$$\mathcal{APP}'(T) > 1 - \frac{\mathcal{APP}}{T} > 0,$$

where the last inequality follows from $\mathcal{APP}$ being bounded above by T. Next, consider the case in which $\ell(t)$ grows at some constant rate g. In such a case, note that

$$\ell(t) = \lambda e^{gt},$$

$$L = \lambda \int_0^T e^{gt} dt,$$

and

$$\mathcal{P} = \int_0^T (T-t)\frac{e^{gt}}{\int_0^T e^{gt} dt} dt.$$

We then obtain

$$\begin{aligned}
\mathcal{APP}'(T) &= 1 - \frac{\ell(T)}{L}\mathcal{APP} \\
&= 1 - \frac{e^{gT}}{\left(\int_0^T e^{gt} dt\right)^2}\int_0^T (T-t) e^{gt} dt \\
&= 1 - \frac{e^{gT}}{\left(\int_0^T e^{gt} dt\right)^2}\left(T\int_0^T e^{gt} dt - \int_0^T t e^{gt} dt\right) \\
&= 1 - \frac{e^{gT}}{\left(\frac{1}{g}\left(e^{gT}-1\right)\right)^2}\left(T\frac{1}{g}\left(e^{gT}-1\right) - \frac{1}{g^2}\left(e^{gT}(gT-1)+1\right)\right) \\
&= 1 - \frac{e^{gT}}{e^{gT}-1}\left(1 - \frac{gT}{e^{gT}-1}\right).
\end{aligned}$$

It is then straightforward to show that $\frac{e^x}{e^x-1}\left(1-\frac{x}{e^x-1}\right) \leqslant 1$ for any x, and thus $\mathcal{APP}'(T) > 0$.

On the other hand, if $\ell(t)$ grows more than exponentially, or is discontinuously higher for large values of t, it may well be possible for $\mathcal{APP}$ to fall when T is increased. As a simple illustration, consider a comparison of two production processes in discrete time. The first one lasts for $T = 10$ periods and all labor inputs occur at $t = 0$, so $\mathcal{APP} = 10$. The second process is exactly identical to the first one, except that it lasts for an additional period ($T = 11$) and half of the inputs are provided in that last period $t = 11$, with the remaining inputs being employed at $t = 0$. In that case, $\mathcal{APP} = 5.5 < 10$, and thus the $\mathcal{APP}$ is *lower* for the process with a higher T.

A.2 Proof of Effect of r on T in Uniform Input Model

Take equation (8) and rearrange it as

$$g(T, r) = \frac{1}{2}\frac{Z'\left(\frac{1}{2}T\right)}{Z\left(\frac{1}{2}T\right)}\left(1 - e^{-rT}\right) - r = 0.$$

Differentiating with respect to r, we have

$$\frac{\partial g(T, r)}{\partial r} = \frac{1}{2}\frac{Z'\left(\frac{1}{2}T\right)}{Z\left(\frac{1}{2}T\right)} T e^{-rT} - 1 = \frac{rTe^{-rT}}{1 - e^{-rT}} - 1 < 0,$$

because $xe^{-x} - 1 + e^{-x} < 0$ for all x.

Next, differentiate with respect to T to obtain, after a few manipulations

$$\begin{aligned}
\frac{\partial g(T, r)}{\partial T} &= \frac{1}{2}\left[\frac{Z''\left(\frac{1}{2}T\right)}{Z\left(\frac{1}{2}T\right)} - \left(\frac{Z'\left(\frac{1}{2}T\right)}{Z\left(\frac{1}{2}T\right)}\right)^2\right]\left(1 - e^{-rT}\right) + \frac{1}{2}\frac{Z'\left(\frac{1}{2}T\right)}{Z\left(\frac{1}{2}T\right)} r e^{-rT} \\
&= \frac{1}{2}\left[\frac{Z''\left(\frac{1}{2}T\right)}{Z\left(\frac{1}{2}T\right)} - \left(\frac{Z'\left(\frac{1}{2}T\right)}{Z\left(\frac{1}{2}T\right)}\right)^2\right] 2\frac{rZ\left(\frac{1}{2}T\right)}{Z'\left(\frac{1}{2}T\right)} + \frac{1}{2}\frac{Z'\left(\frac{1}{2}T\right)}{Z\left(\frac{1}{2}T\right)} r e^{-rT} \\
&= \frac{Z'\left(\frac{1}{2}T\right)}{Z\left(\frac{1}{2}T\right)} r \left[\frac{Z''\left(\frac{1}{2}T\right) Z\left(\frac{1}{2}T\right)}{\left(Z'\left(\frac{1}{2}T\right)\right)^2} - 1 + \frac{1}{2}e^{-rT}\right] < 0,
\end{aligned}$$

where the sign follows from $Z'' < 0$ and $e^{-rT} < 1$.

Thus $g(T, r)$ is decreasing in T and r, and thus invoking the implicit function theorem we can conclude that T is decreasing in r.

A.3 The Choice of T with Time-Separable Technology

Start from equation (14), and define

$$f(T,r) = \frac{Z'(T)}{Z(T)} - \left(r - \frac{1}{\sigma - 1}\frac{r(\sigma-1)-\sigma g}{1-e^{-T(r(\sigma-1)-\sigma g)}}\right),$$

so that T is such that $f(T,r) = 0$. Next note that

$$\frac{\partial f(T,r)}{\partial T} = \frac{Z''(T)}{Z(T)} - \frac{(Z'(T))^2}{Z(T)^2} - \frac{(r(\sigma-1)-\sigma g)^2 e^{-T(r(\sigma-1)-\sigma g)}}{\left(e^{-T(r(\sigma-1)-\sigma g)}-1\right)^2(\sigma-1)} < 0,$$

and thus $\partial f(T,r)/\partial T < 0$.

Taking the derivative of $f(T,r)$ with respect to r delivers

$$\frac{\partial f(T,r)}{\partial r} = e^{-T(r(\sigma-1)-\sigma g)}\frac{1-e^{-T(r(\sigma-1)-\sigma g)} - T(r(\sigma-1)-\sigma g)}{\left(e^{-T(r(\sigma-1)-\sigma g)}-1\right)^2} < 0,$$

where the sign follows from $1 - e^{-x} - x < 0$ for all $x \neq 0$. By the implicit function theorem, it thus follows that $\partial T/\partial r < 0$.

A.4 Data Preparation Algorithm

In this section, we outline the algorithm for preparing the data for empirical analysis.

1. We use the Wharton Research Data Services (WRDS) API to query data on annual firm fundamentals from WRDS. We apply the following filters, which are standard in the literature:

   (a) We require variables identifying the firm, fiscal year, reporting date, and country of incorporation to be non-empty. The Compustat database uses `gvkey`, `fyear`, `datadate`, and `fic` as codes for these variables, respectively.

   (b) We require the reporting date to be between January 1, 1979, and December 31, 2023.

   (c) On WRDS, the data for North American firms is stored at `comp_na_daily_all.funda`. When querying this dataset, we require the report to be consolidated (`consol = "C"`), in the industrial format (`indfmt = "INDL"`), the data format to be standardized (`datafmt = "STD"`), and the population source to be domestic (`popsrc = "D"`).

   (d) On WRDS, the data for Global firms is stored at `comp_global_daily.g_funda`. When querying this dataset, we require the report to be consolidated (`consol =

"C"), in the industrial format (`indfmt = "INDL"`), the data format to be standardized data collected from the company's original filing (`datafmt = "HIST_STD"`), and the population source to be international (`popsrc = "I"`).

(e) We require the following variables to be strictly greater than zero and non-empty: sales, COGS, interest expenses, long-term debt, short-term debt, and inventories. The Compustat database uses `sale, cogs, xint, dltt, dlc, invt` as codes for these variables, respectively.

(f) We require the following variables to be either missing or non-negative: raw materials inventories, work-in-progress inventories, and finished goods inventories. The compustat database uses `invrm, invwip, invfg` as codes for these variables, respectively.

In this way, we retrieve 178,924 firm-year observations from the North American dataset and 345,915 observations from the Global dataset. We pool North American and Global data. We then drop all duplicates based on firm and reporting date identifiers `gvkey` and `datadate`, unless duplicates are identical, in which case we keep the first occurrence.

2. We use the WRDS API to query data on the industry classification of firms from WRDS. On WRDS, the data on industry classification is stored at `comp_na_daily_all.co_industry` for North American firms and at `comp_global_daily.g_co_industry` for Global firms. The variable `naicsh` contains industry classification according to the current vintage at the fiscal year. For instance, if the fiscal year is 2003, then the code in `naicsh` is according to the 2002 vintage. We retrieve that variable, together with the firm and year identifiers, for observations whose reporting date is between January 1, 1979, and December 31, 2023.

   In this way, we retrieve 356,833 firm-year observations from the North American dataset, and 946,722 firm-year observations from the Global dataset. We pool the North American and Global data. We then drop all duplicates based on firm and reporting date identifiers `gvkey` and `datadate`, unless the `naicsh` codes are nested (in which case we keep one instance with the longest code) or have a common prefix (in which case we keep one instance and assign the longest common prefix to it).

3. We add, whenever possible, data on industry classification to the data on fundamentals, based on `gvkey` and `datadate`. We drop firms that have no NAICS code in any year. We conduct data imputation: whenever a group, defined as all observations having the same `gvkey` and NAICS vintage, has `naicsh` codes that are nested (e.g., codes 11 and 111), we assign the longest code to observations with non-missing NAICS in the group.

4. We obtain concordances between 6-digit NAICS codes from different vintages (1997,

2002, 2007, 2012, 2017, and 2022) provided by the United States Census Bureau. These concordances are not one-to-one. For example, a single 2002 NAICS code may map to multiple 2007 NAICS codes.

Additionally, the Census Bureau only provides concordances between consecutive vintages (e.g., 1997 to 2002, but not 1997 to 2007). To address this limitation, we construct a concordance that maps any vintage to the 2012 vintage while preserving all possible mappings in cases of ambiguity.

For instance, if a single 1997 code maps to two codes in 2002, and each of those maps to two further codes in 2012, we retain all four mappings for the original 1997 code.

5. We convert the historical NAICS codes to 2012 NAICS classification and impute missing values in the merged Compustat data as follows:

   (a) If the historical NAICS maps to a unique code in the 2012 classification, we assign that unique code. If the historical NAICS has no mapping in the 2012 classification, we do not assign a code.

   (b) If the historical NAICS has multiple mappings in the 2012 classification, we proceed as follows:

      i. If the firm has a unique NAICS in 2012, and this code is one of the possible mappings, we assign that code.

      ii. If not, we uniformly draw a random code from the possible options. We use the `hashlib` Python library to draw codes consistently for replicability.

   (c) For remaining observations with missing NAICS according to the 2012 classification, we assign the code from the closest same-firm observation that has a NAICS code.

6. We then perform the following steps:

   (a) Previously, we eliminated duplicate pairs of firms and reporting dates. However, it is still possible for a firm to have two observations for the same fiscal year. This occurs when there is a change in the fiscal year-end month, and both observations are usually correct. In such cases, we retain only the observation with the earliest reporting date.

   (b) We construct new variables, according to the definitions in the main text.

   (c) We identified extreme outliers, treated as data errors, and removed observations outside the 1st and 99th percentiles of these variables: the ratio of inventories to COGS, the ratio of sales to COGS, and the interest rate.

   (d) We create a new firm identifier by combining `gvkey` and the 2012 NAICS code.

(e) Fiscal years are restricted to the range 1980-2018.

7. We manually download annual industry-level data for the years 1987 to 2018 from the Bureau of Labor Statistics, based on the 2017 NAICS classification at the 3- or 4-digit level. This includes the value of productive capital stock for total information processing capital (in billions of 2017 dollars), sectoral output (in billions of current dollars), and the real sectoral output index (base year 2017 = 100). Using the real sectoral output index and sectoral output in current dollars, we calculate the real sectoral output in billions of 2017 dollars. Next, we convert the industry classification to the 2012 NAICS vintage using a concordance table constructed earlier. Finally, we compute IT capital intensity as the ratio of total information processing capital stock to sectoral output.

8. We manually download the NBER-CES Manufacturing Industry Database, which provides annual industry-level data from 1958 to 2018. This dataset includes information on output, employment, payroll, other input costs, investment, capital stocks, total factor productivity (TFP), and various industry-specific price indexes. We use the version classified according to the 2012 NAICS system at the 6-digit level.

A.5 Other Appendix Figures and Tables

In this section, we collect other Tables and Figures referenced in the main text.

Figure A.1: Distribution of the Average Production Period for U.S. Manufacturing Industries

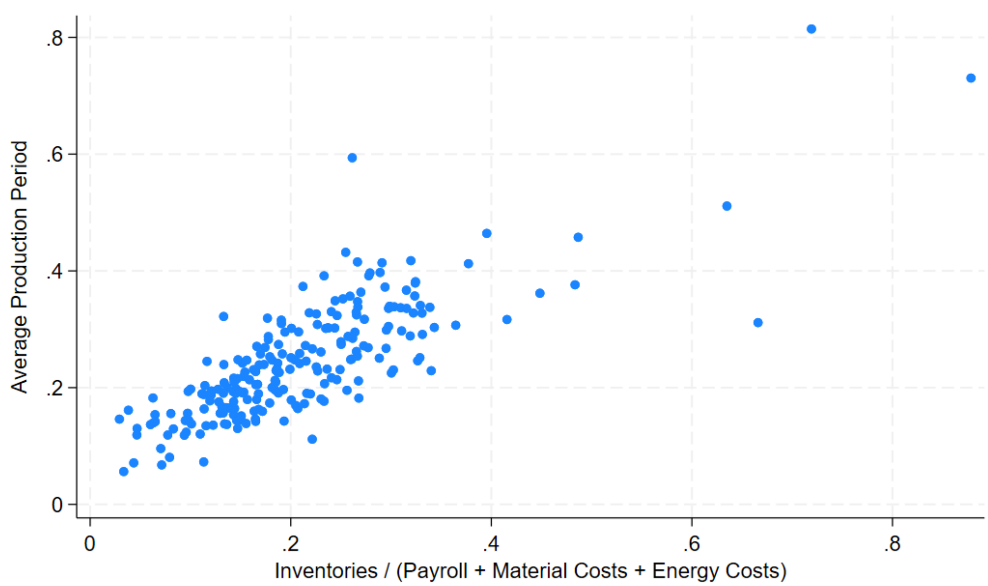

Figure A.2: Partial Effect of Average Production Length on Labor Productivity Industries

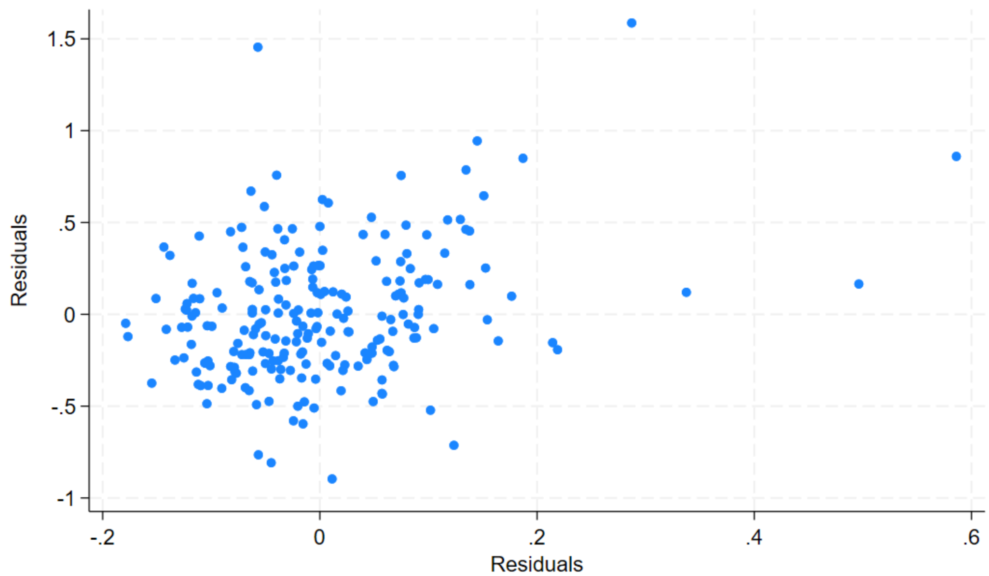

Table A.1: Rank Correlations of Industry Average Period of Production across Countries

Code	BMU	CAN	CHN	CYM	DEU	GBR	IND	JPN	KOR	MYS	SGP	SWE	TWN	USA
BMU	–	–	–	–	–	0.89^a	0.27	-0.06	0.39	–	–	–	–	0.69^a
CAN	–	–	0.52^b	–	–	0.39^b	0.29	0.56^a	0.54^a	-0.23	–	–	0.50^b	0.63^a
CHN	–	0.52^b	–	–	–	0.39	0.44^b	0.57^a	0.55^b	0.12	–	–	0.56^b	0.62^a
CYM	–	–	–	–	–	–	0.68^b	–	–	–	–	–	–	0.14
DEU	–	–	–	–	–	0.63^b	0.79^a	0.58^a	0.41	–	–	–	0.48^c	0.60^a
GBR	0.89^a	0.39^b	0.39	–	0.63^b	–	0.68^a	0.60^a	0.54^a	-0.02	–	0.49^c	0.62^a	0.70^a
IND	0.27	0.29	0.44^b	0.68^b	0.79^a	0.68^a	–	0.46^a	0.58^a	0.43^b	0.02	0.43	0.28^c	0.44^a
JPN	-0.06	0.56^a	0.57^a	–	0.58^a	0.60^a	0.46^a	–	0.68^a	0.17	0.45	0.66^b	0.39^a	0.56^a
KOR	0.39	0.54^a	0.55^b	–	0.41	0.54^a	0.58^a	0.68^a	–	0.29	–	–	0.70^a	0.67^a
MYS	–	-0.23	0.12	–	–	-0.02	0.43^b	0.17	0.29	–	–	–	0.28	-0.11
SGP	–	–	–	–	–	–	0.02	0.45	–	–	–	–	–	0.27
SWE	–	–	–	–	–	0.49^c	0.43	0.66^b	–	–	–	–	–	0.60^b
TWN	–	0.50^b	0.56^b	–	0.48^c	0.62^a	0.28^c	0.39^a	0.70^a	0.28	–	–	–	0.53^a
USA	0.69^a	0.63^a	0.62^a	0.14	0.60^a	0.70^a	0.44^a	0.56^a	0.67^a	-0.11	0.27	0.60^b	0.53^a	–

Notes: Spearman rank correlations are reported. Sample includes country-industries with at least 30 observations in the period 1980-2018 in the Compustat database. Rank correlations are reported only if two countries have at least 10 overlapping six-digit NAICS codes. Statistical significance at the 1%, 5%, and 10% levels are denoted by subscripts a, b and c, respectively. Source: Compustat.