NBER WORKING PAPER SERIES

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Working Paper 33499
http://www.nber.org/papers/w33499

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2025

We are grateful to Chenzi Xu for discussing our paper. Antràs thanks the Ferrante Fund at Harvard University for financial support. This paper was written for the invited session on "Inventories, Production Length and International Trade" at the 2025 AEA meetings in San Francisco. An abridged version of this paper is slated for publication in the 2025 AEA Papers and Proceedings. Wharton Research Data Services (WRDS) was used in preparing this paper. This service and the data available thereon constitute valuable intellectual property and trade secrets of WRDS and/or its third-party suppliers. The replication package for the paper is available at https://antras.scholars.harvard.edu/pages/data and https://github.com/vitaliitub/AverageProductionPeriod. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 33499
February 2025
JEL No. D2, E14, E22, F14, G31, L60

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 and validate this measure for various industries and countries, and show that, consistent with theory, this measure is lower, the higher the cost of capital faced by firms is.

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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 trade-offs 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 (or $\mathcal{APP}$), 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 study 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 range of sectors.

Using data from publicly traded companies, 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 to 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 infinite-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 homogeneous 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 the 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 $\mathcal{APP}$ 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 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 let the function $Z(\boldsymbol{L})$ depend on $\boldsymbol{L}$ in a way that makes Z increasing in the average period of production, or $Z(\boldsymbol{L}) = Z(\mathcal{APP})$, with $Z'(\mathcal{APP}) > 0$.

Because the cost of inputs w 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 the 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 that are used in 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, for continuous $l(t)$, $\mathcal{APP}$ 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) $\ell(t)$ grows along the chain at 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 the $\mathcal{APP}$—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 ($t = 0$), or

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

Because the sale revenue is realized T units of time after the initial date $t = 0$, it is discounted by the compound interest term e^{-rT}. Similarly, the effective cost of labor hired at date t incorporates the discount factor e^{-rt}.[2]

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

[2] 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 $Y(\boldsymbol{L}) = Z(\boldsymbol{L}) F(\boldsymbol{L})$ is homogeneous of degree one in $\boldsymbol{L}$, given our assumptions.

with disproportionately large impact on output. In Böhm-Bawerk's theory, such stages with 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 a desire to backload input expenditures closer to the end of the process, and more so the higher the interest rate r is. This will be one of the key forces generating a negative relationship between interest rates and the average period of production, as 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 first-order condition (5) above 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 α_T is the ratio of input expenditure at T relative to 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 these relationships 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 production 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 the interest rate r shapes 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 timber, in which trees are planted by labor at some initial instant, and one needs only wait for trees to grow, with no further labor input needed (this literature often ignores the labor needed to cut down 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 $\ell(t) = L\delta(t)$, where $\delta(t)$ is the Dirac delta function.[3] Then $\lambda(t) = \delta(t)$ and $\int_0^T \lambda(t)dt = 1$. 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. Given our constant returns to scale assumption, we must necessarily have $F(\boldsymbol{L}) = \kappa \int_0^T \ell(t)\, dt = \kappa L$, for some constant κ, which we normalize to 1 without loss of generality.

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 $Z'(T) > 0$ 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 for 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:

[3] A Dirac delta function is a function whose value is zero everywhere except at zero, and whose integral over the entire real line is equal to one.

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 $\lambda(t) = 1/T$ for all t. Such a constant input flow would be optimal, for instance, if the production technology is given by $F(\boldsymbol{L}) = \min_{t\in[0,T]} \{\ell(t)\}$. Production processes with a uniform input use have been studied as far back as Jevons (1871, Chapter VII) and Böhm-Bawerk (1889, p. 89).

Given $\lambda(t) = 1/T$ 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 the '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 average period of production, or $Z(\boldsymbol{L}) = Z(\mathcal{APP})$, with $Z'(\mathcal{APP}) > 0$ and $Z''(\mathcal{APP}) < 0$.

Given constant returns to scale, the time-invariant labor input level $\ell(t) = \bar{\ell}$ is indeterminate at the firm level, but the function F can be expressed as $F(\boldsymbol{L}) = \kappa\bar{\ell}$, where again we can safely set $\kappa = 1$. The problem in (3) then simplifies to choosing T to solve:

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

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).[4]

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 equation 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 A.2 we show that:

[4] 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) $\alpha_T = e^{-rT}/\int_0^T e^{-rt}dt$.

Proposition 2. In the uniform input use model, the average period of production ($\mathcal{APP}$) is equal to half 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

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

for some functions H, h, and a. As has been well known since Bergson (1936), the only *homothetic* production technology of the separable type as in (9) is a constant elasticity of substitution production technology, which, in the case of constant returns to scale, can be written as

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

for $\sigma > 0$.[5] 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 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 also be captured by assuming that the function $a(t)$ is increasing in the distance $T - t$, thereby further incentivizing the choice of labor allocations associated with higher average production periods.

The profit maximization problem in (3) now becomes

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

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

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

[5] As shown by Berndt and Christensen (1973), the only homothetic production technology that features a dual 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.

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 farther from completion. More formally, consider 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 technology, 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, applying the zero-profits condition, and using (12)—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, 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 in the later stages of production can lead to a lower weighted average value of $\mathcal{APP}$. To make progress, we assume that $a(t) = a_0 e^{gt}$ for some constants $g \in \mathbb{R}$ and $a_0 \in \mathbb{R}$, so that input demand $\ell(t)$ grows or falls at a constant rate along the production process. Specifically, from equation (12), $\ell(t) = \ell_0 e^{t\sigma(g+r)}$ for some constant $l_0 \in \mathbb{R}$. Equation (13) then reduces to

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

As long as the second-order condition for the choice of T is satisfied, we can show (see Appendix A.3) that regardless of the sign of g:

Proposition 4. Under the time-separable technology as in formula (9) with $a(t) = a_0 e^{gt}$, 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 measure of the average period of production. For this purpose, we return to the general model in Section 2, in which a production process is associated with the use of a sequence of labor inputs, $\{\ell(t)\}_{t \in [0,T]}$. Focusing on a given process leading to the production of a good, note that the cumulative cost of the good in an initial interval $[0, \hat{t}]$ of production is given by

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

Empirically, $C(\hat{t})$ will be recorded as a component of inventories. This cumulative cost differs from the last term in the profit-maximization problem in (3) by the financial term e^{-rt}. We omit this term because it is standard practice to measure inventories on a cost basis, which 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 begun in previous periods $t' \in (t - T, t)$, and also completes the production of N goods that begun 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 we recall that $L = \int_0^T \ell\left(t\right) dt$ is total labor use along the whole production process. Empirically, $C\left(T\right)$ corresponds to the accounting concept of the cost 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

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

Solving this double integral by changing the order of integration yields

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

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).[6]

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 a firm's annual financial report states that the ratio of inventories to the cost of goods sold equals to 0.5, thus indicating an average period of production of 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, $\mathcal{APP} = 0.5$ indicates that inputs were employed, on average, two quarters before the sale of the good.

[6]The older, less math-savvy co-author of this paper was mystified by the above derivation using a change in the order of integration, and suggested offering an alternative derivation based on integration by parts:

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

Precedents Although our sense is that the result in Proposition 5 is not well known in the literature, it is admittedly not new. The idea that, in a stationary equilibrium with a uniform distribution of production processes of different ages, the average period of production can be computed as the ratio of the stock of goods in process to the flow of goods sold can be traced back to Marschak (1934). In a highly illuminating piece, 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 input expenditures at a point in time, while the water outflow represents past input expenditures embodied in the goods sold at a 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.[7]

More recently, Schwartzman (2014) has derived a similar link between what he refers to as "time to produce and distribute" (or time to produce, for short) and a firm's inventory over cost ratio. However, his derivation is developed in discrete time, and primarily examines how changes in interest rates affect output depending on the ratio of inventories to cost in various sectors. We further discuss his empirical contribution in the next section.

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 an 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 if 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: $\mathcal{APP}_{Exp}$ can be computed as the ratio of a firm's inventories to its cost of goods sold, 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 the concept of duration in finance (Macaulay, 1938). In particular, Hicks

[7]There is also a close connection between this result and the so-called Little's law in queueing theory (see Little, 1961).

(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 (17) except that it applies a discount factor for input expenditures at later dates (or, alternatively, it accounts for interest compounding on early input expenditures). 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.[8] This naturally results 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 $\mathcal{APP}_{Hicks}$ arising from the discounting term 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 U.S.

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 Variable Definitions

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 (S&P Global, 2025). Financial reports provide detailed information on cost of goods sold (COGS) and total inventories, which are in turn disaggregated

[8] 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).

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 $\mathcal{APP}$.

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). More details on the data preparation algorithm are provided in Appendix A.4.

Since information and communication technologies (ICT) is a key factor influencing inventory management (Kahn, McConnell and Perez-Quiros, 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 BLS (Bureau of Labor Statistics, 2025). 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 $\mathcal{APP}$ 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, Gray and Marvakov, 2021).

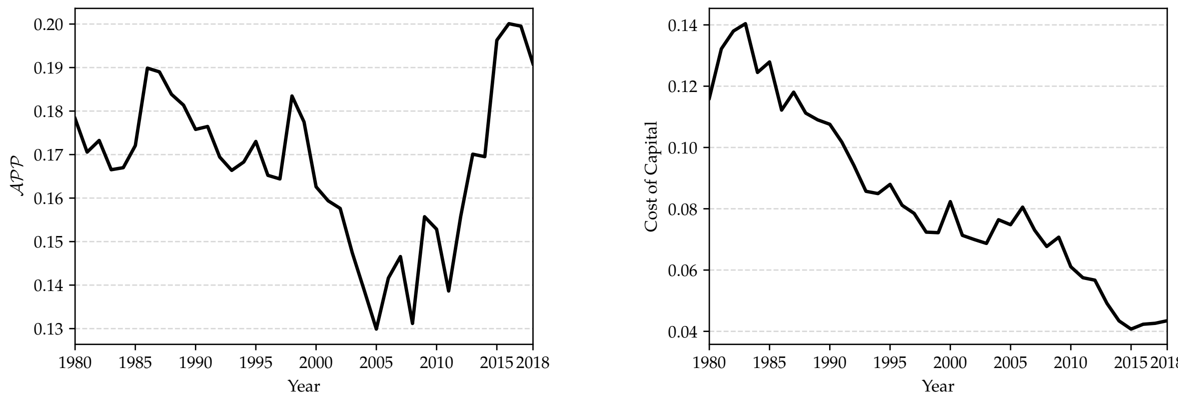
In the main text, we focus on presenting results based on the sample of all firms in Compustat classified as belonging to the manufacturing sector (NAICS codes 31–32–33). However, in Appendix A.5 we report results for all goods-producing industries (NAICS codes 11–21–22–23, in addition to the manufacturing). The exclusion of privately held firms from our sample is certainly a limitation of our study, but we lack systematic and reliable data on COGS for non-publicly traded firms. Nonetheless, we occasionally benchmark our results against imperfect proxies for $\mathcal{APP}$, which can be constructed using data that includes 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 $\mathcal{APP}$ 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 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 in U.S. manufacturing. Starting in the mid 2000s, we observe a marked increase in average $\mathcal{APP}$ in U.S. manufacturing, reaching 0.19 in 2018. In that year, inputs were employed for an average of $365 \times 0.19 = 69$ days before the sale

Figure 1: $\mathcal{APP}$ and Cost of Capital in U.S Manufacturing



(a) Cost-Weighted Average Period of Production **(b)** Cost-Weighted Average Cost of Capital

Notes: The figure shows the cost-weighted annual averages of $\mathcal{APP}$ and cost of capital for U.S. publicly traded companies in manufacturing industries from 1980 to 2018. $\mathcal{APP}$ represents the ratio of inventories to COGS, while cost of capital is the ratio of interest expenses to total debt (short- and long-term). Source: Compustat.

of the goods in which they were used.[9]

The recent increase in $\mathcal{APP}$ could, in part, be explained by the significant decline in the cost of capital faced by firms.[10] Indeed, Panel (b) of Figure 1 also shows that average cost of capital for U.S. manufacturing firms fell from around 12% in 1980 to about 4% in 2018, with more than half of this decline occurring after 2006.

Was the decline in cost of capital partly responsible for the observed increase in $\mathcal{APP}$ since 2006? We explore this possibility below by regressing our firm-level measure of $\mathcal{APP}$ on our firm-level measure of cost of capital, while controlling for the 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.

5.3 Variation in the Average Period of Production Across Industries

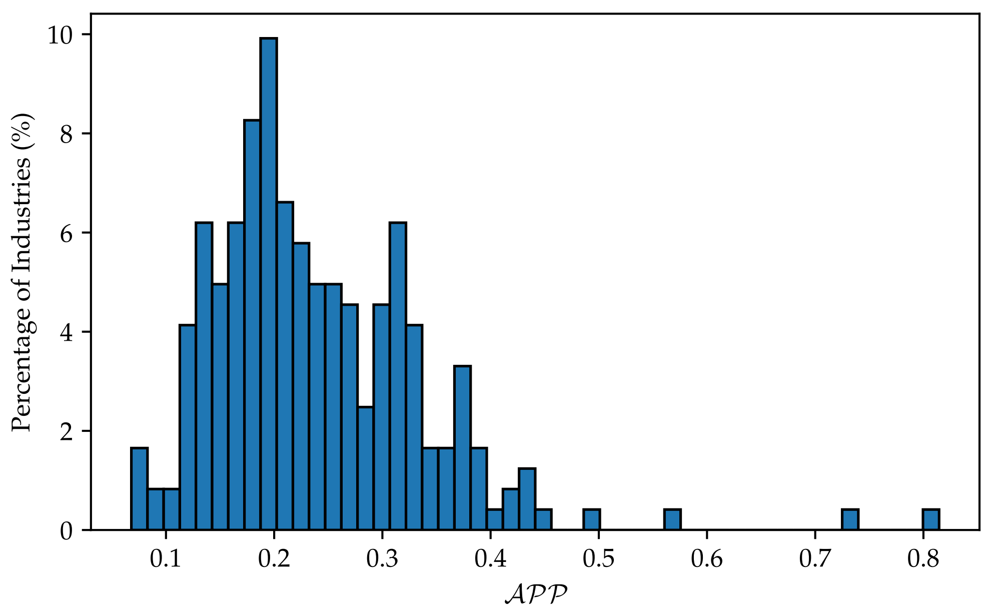
How much does the average period of production vary across U.S. manufacturing sectors when computed at the six-digit NAICS level? Figure 2 shows significant variation in $\mathcal{APP}$s within

[9]Data from the U.S. Census Bureau (U.S. Census Bureau, 2025) indicates that total monthly inventories relative to sales were around 1.36 months, or 0.11 years, in 2018. Naturally, sales are higher than COGS, and this disparity has grown in recent years. De Loecker, Eeckhout and Unger (2020) use U.S. Census data, including non-publicly traded companies, to estimate that 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.

[10]Carreras-Valle (2024) documents a parallel recent rise in the ratio of inventories *over sales* among U.S. firms and relates it to increased trade with China.

our sample, which includes 242 manufacturing sectors. We exclude sectors with fewer than 50 firm-year observations after the data preparation.[11]

Figure 2: Distribution of $\mathcal{APP}$ in U.S. Manufacturing



Notes: The figure shows the distribution of industries ($N = 242$) based on $\mathcal{APP}$. For each industry, defined as a six-digit NAICS code, $\mathcal{APP}$ is calculated as a cost-weighted average across firms within each year, then averaged across years from 1980 to 2018. The data covers U.S. publicly traded companies in manufacturing industries. Industries with fewer than 50 firm-year observations are excluded. 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.[12] The only previous paper we are aware of that computes the ratio of inventories to COGS is Schwartzman (2014), which calculated this ratio for 26 fairly aggregated manufacturing sectors. The range of $\mathcal{APP}$ values in his study is naturally somewhat narrower than ours, but the mean $\mathcal{APP}$ in his 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 the 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

[11]Our replication package includes a file containing these estimates of the average period of production for 269 six-digit NAICS U.S. goods-producing industries. The file can also be downloaded at `https://antras.scholars.harvard.edu/sites/g/files/omnuum5876/files/2025-02/complete_ranking_usa_goods.csv`.

[12]In addition to analyzing average $\mathcal{APP}$, Figure A.3 presents a histogram of the standard deviation of the log of $\mathcal{APP}$ within six-digit NAICS industries. The standard deviation pooled across industries (0.717) is significantly higher than the average within-industry standard deviation (0.531). This suggests that a large share of the total heterogeneity in $\mathcal{APP}$ arises from differences between industries, rather than within them. These differences likely reflect variations in production technology across industries.

'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 preparations, and electromedical instruments.

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, 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 NBER-CES Manufacturing Industry Database. Table 3 reports the correlations between $\mathcal{APP}$ and several industry variables, including measures that have been commonly used to capture the skill and physical capital intensities. Specifically, for each industry variable, we calculate the average from 1980 to 2018 and then calculate its correlation with $\mathcal{APP}$.

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 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 of $\mathcal{APP}$ with skill intensity and physical capital intensity are highly statistically significant (at the 1% level).

We also define three measures of *inventory intensity* based on variables available from the NBER-CES Manufacturing Industry Database. First, we compute the simple ratio of inventories to sales, which is highly correlated (0.703) with our $\mathcal{APP}$ measure derived 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 0.799. We have confirmed that this high correlation is not driven by outliers (see Figure A.4 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 a minimal impact on the correlation. 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 industry-level $\mathcal{APP}$ values with two industry-level measures of productivity. In both cases, the correlations are essentially zero, in contrast to the positive relationship posited by 'Austrian' theories. Nevertheless, this zero correlation appears to be partly explained by the fact that $\mathcal{APP}$ is itself negatively correlated with physical capital intensity. In fact, a simple regression of log value added per worker on $\mathcal{APP}$ and log capital-labor ratio reveals a positive and highly statistically significant coefficient for $\mathcal{APP}$ (t-stat = 3.11). See the partial correlation plot in Figure A.5 in the Appendix.

Table 1: The Top 10 U.S. Manufacturing Industries by $\mathcal{APP}$

NAICS	Industry	$\mathcal{APP}$
312140	Distilleries	0.814
312130	Wineries	0.737
339115	Ophthalmic Goods Manuf.	0.573
312230	Tobacco Manuf.	0.488
333997	Scale and Balance Manuf.	0.441
333132	Oil and Gas Field Machinery and Equipment Manuf.	0.439
316998	All Other Leather Good and Allied Product Manuf.	0.432
325412	Pharmaceutical Preparation Manuf.	0.430
334510	Electromedical and Electrotherapeutic Apparatus Manuf.	0.421
332215	Metal Kitchen Cookware, Utensil, Cutlery, and Flatware Manuf.	0.415

Notes: The table lists the top 10 U.S. manufacturing industries ranked by $\mathcal{APP}$. For each industry, defined as a six-digit NAICS code, $\mathcal{APP}$ is calculated as a cost-weighted average across firms within each year, then averaged from 1980 to 2018. Industries with fewer than 50 firm-year observations are excluded. Please refer to the replication package for the complete ranking. Source: Compustat.

Table 2: The Bottom 10 U.S. Manufacturing Industries by $\mathcal{APP}$

NAICS	Industry	$\mathcal{APP}$
324110	Petroleum Refineries	0.068
311511	Fluid Milk Manuf.	0.069
311812	Commercial Bakeries	0.071
325193	Ethyl Alcohol Manuf.	0.073
336370	Motor Vehicle Metal Stamping	0.083
312112	Bottled Water Manuf.	0.097
327992	Ground or Treated Mineral and Earth Manuf.	0.112
336350	Motor Vehicle Transmission and Power Train Parts Manuf.	0.112
337214	Office Furniture (except Wood) Manuf.	0.115
311520	Ice Cream and Frozen Dessert Manuf.	0.116

Notes: The table lists the bottom 10 U.S. manufacturing industries ranked by $\mathcal{APP}$. For each industry, defined as a six-digit NAICS code, $\mathcal{APP}$ is calculated as a cost-weighted average across firms within each year, then averaged from 1980 to 2018. Industries with fewer than 50 firm-year observations are excluded. Please refer to the replication package for the complete ranking. Source: Compustat.

Table 3: Correlation of $\mathcal{APP}$ with Industry Characteristics in U.S. Manufacturing

Characteristic	Correlation with $\mathcal{APP}$	p-Value
Capital Intensity		
Log (Real Capital Stock / Total Workers)	−0.197	0.002
Log (Capital Expenditures / Payroll)	−0.205	0.001
Skill Intensity		
Log (Non-Production Workers / Total Workers)	0.276	0.000
Non-Production Payroll / Payroll	0.355	0.000
Inventory Intensity		
Inventories / Sales	0.703	0.000
Inventories / (Payroll + Material Costs + Energy Costs)	0.799	0.000
Inventories / (Prod. Worker Wages + Material Costs + Energy Costs)	0.795	0.000
Productivity		
Log (Real Value Added / Total Workers)	0.003	0.962
Total Factor Productivity	−0.002	0.971

Notes: The table reports the Pearson correlations between $\mathcal{APP}$ and various industry characteristics for U.S. six-digit NAICS manufacturing industries ($N = 242$). The data was constructed by averaging annual values of variables from 1980 to 2018. Annual $\mathcal{APP}$ values were calculated as cost-weighted averages across firms within each industry. Industries with fewer than 50 firm-year observations in Compustat were excluded. Sources: Compustat, NBER-CES.

5.4 The Average Period of Production and the Cost of Capital

Our conceptual framework in Sections 2 and 3 predicts that the average period of production should be negatively associated with the cost of capital. In this section, we perform regression analyses to examine the empirical relationship between these two variables. 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 distributions of all these variables are skewed, with the mean exceeding the median for each variable.

Table 5 presents the results of estimating equation (19). All variables are expressed in logarithms, allowing the regression coefficients to be interpreted as elasticities. All regressions include firm and year fixed effects. The standard errors are clustered at the industry (six-digit NAICS codes) and year levels (two-way clustering).

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 cost of capital 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, note that between 2006 and 2018, $\mathcal{APP}$ increased from 0.142 to 0.191, corresponding to a log change of 0.296. Over the same period, cost of capital faced by firms declined from 0.081 to 0.043, a log change of -0.633. Based on our estimates, this predicts a log change in $\mathcal{APP}$ of $-0.633 \times -0.090 = 0.057$, which accounts for approximately 19% of the observed log change in $\mathcal{APP}$ during this period. However, it is important to note that the regression in Table 5 only captures the correlation between these variables and does not establish a causal relationship. Future research should aim to identify how exogenous changes in cost of capital influence firms' average period of production.

In the remaining columns of Table 5, we assess the robustness of our results to controlling for various industry-level characteristics. 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 (log of real capital stock per worker), skill intensity (share of non-production workers), and labor productivity (log of real value added per worker). The inclusion of these variables has a negligible effect on the estimated elasticity of $\mathcal{APP}$ with respect to cost of capital.[13]

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

	Mean	Std. Dev.	P25	Median	P75	N
Average Period of Production	0.310	0.243	0.161	0.251	0.388	57,800
Cost of Capital	0.106	0.082	0.064	0.090	0.121	57,800
IT Capital Intensity	0.048	0.049	0.014	0.022	0.072	46,135
Capital Intensity	166.4	257.9	49.15	85.58	163.5	56,273
Skill Intensity	0.362	0.140	0.242	0.356	0.470	57,791
Labor Productivity	193.9	272.0	81.03	121.5	203.9	57,791

Notes: The table reports summary statistics for a panel of U.S. manufacturing companies from 1980 to 2018. Capital intensity and labor productivity are in thousands of 2012 U.S. dollars. IT capital intensity, capital intensity, skill intensity, and labor productivity are industry-level variables that have been imputed to firm-level observations based on NAICS. Sources: BLS, Compustat, NBER-CES.

[13] The addition of industry-level variables reduces the sample size as these measures are not available for all industries. We re-estimate the specifications in columns (1) and (2) using the same 44,608 observations available in column (3), ensuring consistency across samples. We find that restricting the sample does not significantly affect the estimated elasticity of $\mathcal{APP}$ with respect to cost of capital.

Table 5: $\mathcal{APP}$ and Cost of Capital in U.S. Manufacturing

Dependent Variable:	Average Period of Production		
	(1)	(2)	(3)
Cost of Capital	-0.090^a	-0.088^a	-0.090^a
	(0.007)	(0.007)	(0.007)
IT Capital Intensity	–	0.006	0.005
	–	(0.020)	(0.019)
Capital Intensity	–	–	−0.030
	–	–	(0.028)
Skill Intensity	–	–	−0.046
	–	–	(0.049)
Labor Productivity	–	–	−0.045
	–	–	(0.047)
R^2	0.789	0.810	0.812
Observations	57,800	46,135	44,608

Notes: The table presents the results of estimating equation (19) on a panel of U.S. publicly traded manufacturing companies from 1980 to 2018. All variables are in logarithms. All regressions include firm and year fixed effects. The standard errors are clustered at the industry (six-digit NAICS codes) and year levels (two-way clustering). Statistical significance at the 1%, 5%, and 10% levels is denoted by superscripts a, b, and c, respectively. IT capital intensity, capital intensity, skill intensity, and labor productivity are industry-level variables that have been imputed to firm-level observations based on NAICS. Sources: BLS, Compustat, NBER-CES.

5.5 Disaggregation by the Type of Inventory

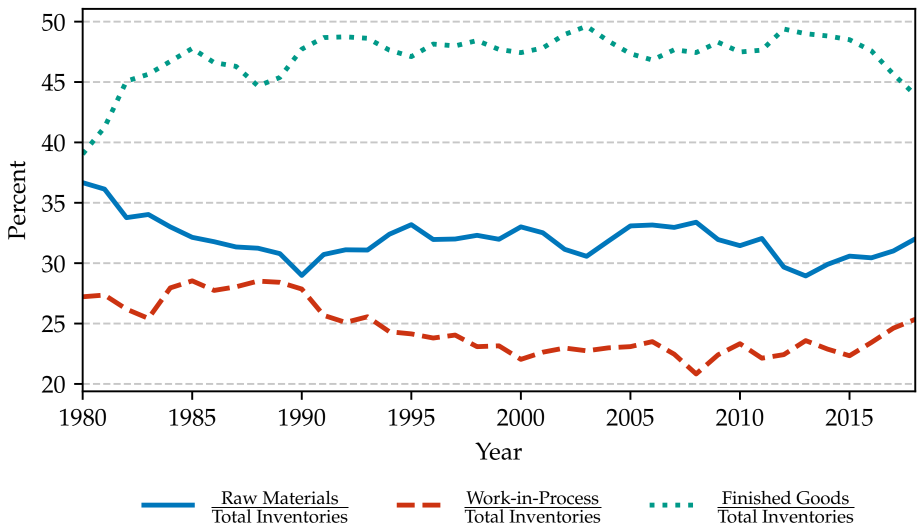
We now turn to exploring the extent to which our results in Table 5 are disproportionately driven by specific components of inventory. As mentioned in Section 5.1, firms' financial statements disaggregate inventories into raw materials, work-in-process, and finished goods. As shown in Figure 3, on average, finished goods account for more than 40 percent of total inventories, while work-in-process accounts 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 type of inventory to COGS, without including any industry-level controls[14]. All variables are expressed in logarithms, allowing the regression coefficients to be interpreted as elasticities. All regressions include firm and year fixed effects. The standard errors are clustered at the industry (six-digit NAICS codes) and year levels (two-way clustering). Only about two-thirds of the observations contain data disaggregated by types of inventory, and we estimate each regression on that subset.

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.

[14]We find that the results in Table 6 concerning the elasticity of $\mathcal{APP}$ with respect to cost of capital are robust to the inclusion of the industry-level control variables as in column (3) of Table 5.

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



Notes: The figure shows the cost-weighted annual averages of raw materials, work-in-process, and finished goods as shares of total inventories for U.S. publicly traded companies in manufacturing from 1980 to 2018. Source: Compustat.

Table 6: $\mathcal{APP}$ and Cost of Capital by Inventory Type in U.S. Manufacturing

	Total Inventories to COGS (1)	Raw Materials to COGS (2)	Work-in-Process to COGS (3)	Finished Goods to COGS (4)
Cost of Capital	-0.101^a	-0.100^a	-0.123^a	-0.107^a
	(0.006)	(0.009)	(0.011)	(0.010)
R^2	0.793	0.766	0.796	0.763
Observations	37,418	37,418	37,418	37,418

Notes: The table presents the results of estimating equation (19) on a panel of U.S. publicly traded companies in manufacturing from 1980 to 2018. The dependent variables are the ratios of certain types of inventory to COGS. We estimate each regression on the subset of observations that contain complete data on inventory types. All variables are in logarithms. All regressions include firm and year fixed effects. The standard errors are clustered at the industry (six-digit NAICS codes) and year levels (two-way clustering). Statistical significance at the 1%, 5%, and 10% levels is denoted by superscripts a, b, and c, respectively. Source: Compustat.

6 The Average Period of Production Worldwide

Compustat also contains data on a large sample of publicly traded firms worldwide. In this section, we use this data to calculate the average period of production for the years 1980–2018 across various countries and sectors, while restricting the analysis to manufacturing industries. Because we lack cross-country, industry-level data comparable to the NBER-CES Manufacturing Industry Database for the U.S., we will only compare our sectoral measures of production length across countries. Additionally, we revisit the link between the average period of production and the cost of capital faced by firms using a larger global sample.

6.1 Rank Correlations of Industries by the Average Period of Production Across Countries

As described in the previous sections, U.S. industries differ significantly in their $\mathcal{APP}$. How consistent are industry rankings of $\mathcal{APP}$s across countries? In Table 7, we present Spearman rank correlations for industry rankings, defined using six-digit NAICS codes, based on $\mathcal{APP}$ across pairs of countries. To construct the rankings, for each country-industry pair, we first calculate cost-weighted average of $\mathcal{APP}$ within each year from 1980 to 2018, and then compute the average across those years. We restrict the analysis to country-industry pairs with at least 50 observations during the period and report rank correlations only for pairs of countries with at least 10 overlapping industries. Table 7 includes 11 countries.[15]

Reassuringly, all rank correlations are positive, and many are both high and highly statistically significant. The U.S. ranking is particularly correlated with those of France (0.87), the UK (0.76), Canada (0.71), South Korea (0.69), China (0.64), and Germany (0.64), but all correlations are above 0.50, except for India (0.42) and Malaysia (0.05).

6.2 Pooled Regressions

We now return to the specification in (19) with the sample of global manufacturing companies. We present the estimation results in Table 8. For comparison, we first replicate the results from column (1) of Table 5 for U.S. firms only. The results in column (2) are for the sample of firms that includes all countries, and the results in column (3) exclude U.S. firms. All variables are expressed in logarithms, allowing the regression coefficients to be interpreted as elasticities. All regressions include firm and year fixed effects. The standard errors are clustered at the industry (six-digit NAICS codes) and year levels (two-way clustering).

[15] In Figure A.7 in the Appendix, we report the rank correlations calculated using an alternative criterion for the inclusion of country-industry pairs. Specifically, we include country-industry pairs with at least 30 observations during the period 1980–2018, resulting in a larger set of country pairs.

Table 7: Rank Correlations of Manufacturing Industries by $\mathcal{APP}$ Across Countries

	CAN	CHN	DEU	FRA	GBR	IND	JPN	KOR	MYS	TWN	USA
CAN	–	0.41	–	–	0.57^c	0.64^b	0.75^a	–	–	0.57^c	0.71^a
CHN	0.41	–	–	–	0.42	0.42^b	0.50^a	0.69^a	–	0.47^b	0.64^a
DEU	–	–	–	–	–	–	–	–	–	–	0.64^b
FRA	–	–	–	–	–	–	–	–	–	–	0.87^a
GBR	0.57^c	0.42	–	–	–	0.83^a	0.62^a	0.71^b	–	0.41	0.76^a
IND	0.64^b	0.42^b	–	–	0.83^a	–	0.43^a	0.45^b	0.38	0.29	0.42^a
JPN	0.75^a	0.50^a	–	–	0.62^a	0.43^a	–	0.73^a	0.21	0.34^b	0.57^a
KOR	–	0.69^a	–	–	0.71^b	0.45^b	0.73^a	–	–	0.58^a	0.69^a
MYS	–	–	–	–	–	0.38	0.21	–	–	–	0.05
TWN	0.57^c	0.47^b	–	–	0.41	0.29	0.34^b	0.58^a	–	–	0.61^a
USA	0.71^a	0.64^a	0.64^b	0.87^a	0.76^a	0.42^a	0.57^a	0.69^a	0.05	0.61^a	–

Notes: Spearman rank correlations are reported. To construct the rankings of industries (defined as six-digit NAICS codes) for each country, we first calculate the cost-weighted average of $\mathcal{APP}$ for each country-industry pair within each year from 1980 to 2018 and then compute the average of these values across those years. We limit the analysis to country-industry pairs with at least 50 observations during this period. Rank correlations are reported only for country pairs with at least 10 overlapping industries. The analysis is based on a panel of publicly traded manufacturing companies. Statistical significance at the 1%, 5%, and 10% levels is denoted by superscripts a, b, and c, respectively. Source: Compustat.

Table 8: $\mathcal{APP}$ and Cost of Capital Worldwide

Dependent Variable:	Average Period of Production		
	(1)	(2)	(3)
	U.S. only	All Countries	U.S. excluded
Cost of Capital	-0.090^a	-0.079^a	-0.071^a
	(0.007)	(0.005)	(0.005)
R^2	0.789	0.786	0.786
Observations	57,800	180,954	123,154

Notes: The table presents the results of estimating equation (19) on a panel of global publicly traded companies in manufacturing from 1980 to 2018. The first column uses data for U.S. firms, the second includes firms from all countries, and the last excludes U.S. firms. All variables are in logarithms. All regressions include firm and year fixed effects. The standard errors are clustered at the industry (six-digit NAICS codes) and year levels (two-way clustering). Statistical significance at the 1%, 5%, and 10% levels is denoted by superscripts a, b, and c, respectively. Source: Compustat.

As shown in Table 8, the results in all three columns are qualitatively and quantitatively very similar. The elasticity found in the pooled regressions is slightly smaller than in the U.S. sample (-0.078 vs. -0.090). However, when computing the 2006–2018 increase in $\mathcal{APP}$ that our regressions attribute to the decline in cost of capital faced by firms, the implied contribution remains economically meaningful.

Specifically, between 2006 and 2018, global average $\mathcal{APP}$ increased from 0.293 to 0.335, corresponding to a log change of 0.134. Over the same period, average cost of capital for global firms declined from 0.074 to 0.059, representing a log change of -0.227. Based on our estimates, this predicts a log change in $\mathcal{APP}$ of $-0.227 \times -0.079 = 0.018$, which accounts for approximately 13% of the observed log change in $\mathcal{APP}$ during this period.[16]

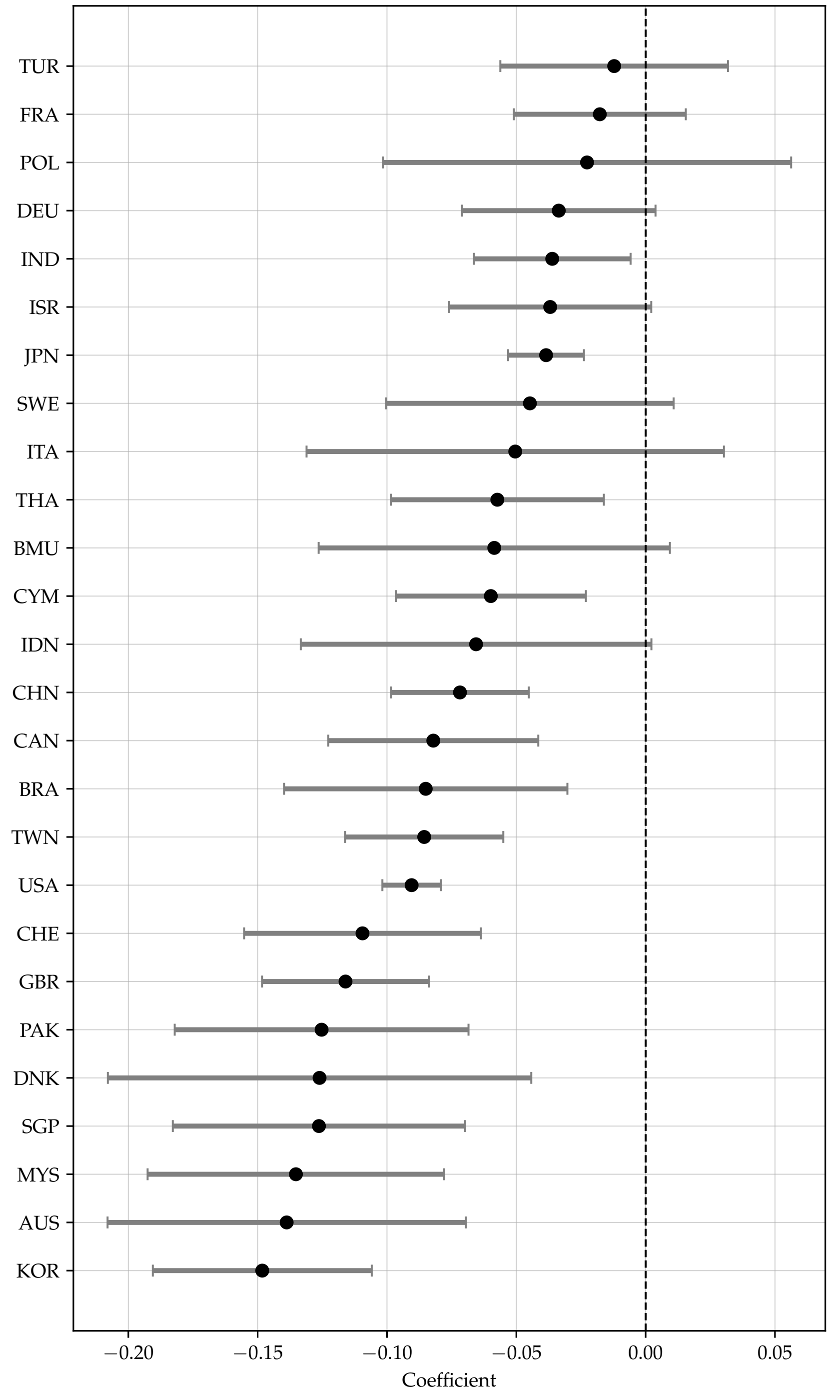
6.3 Heterogeneity at the Industry and Country Levels

Beyond the pooled regressions in Table 8, we also experimented with running equation (19) country-by-country (using data on manufacturers) and industry-by-industry (using global data). We exclude industries or countries with fewer than 750 firm-year observations each.

The results of these exercises are plotted in Figures 4 and 5, demonstrating the robustness of the negative relationship between $\mathcal{APP}$ and cost of capital. Specifically, cost of capital is negatively correlated with $\mathcal{APP}$ in all countries, with results significantly negative at the 5% level in 17 of 26 countries. Similarly, we find a negative coefficient on cost of capital in all but 4 of 69 manufacturing industries, with the coefficient significantly negative in most of them.

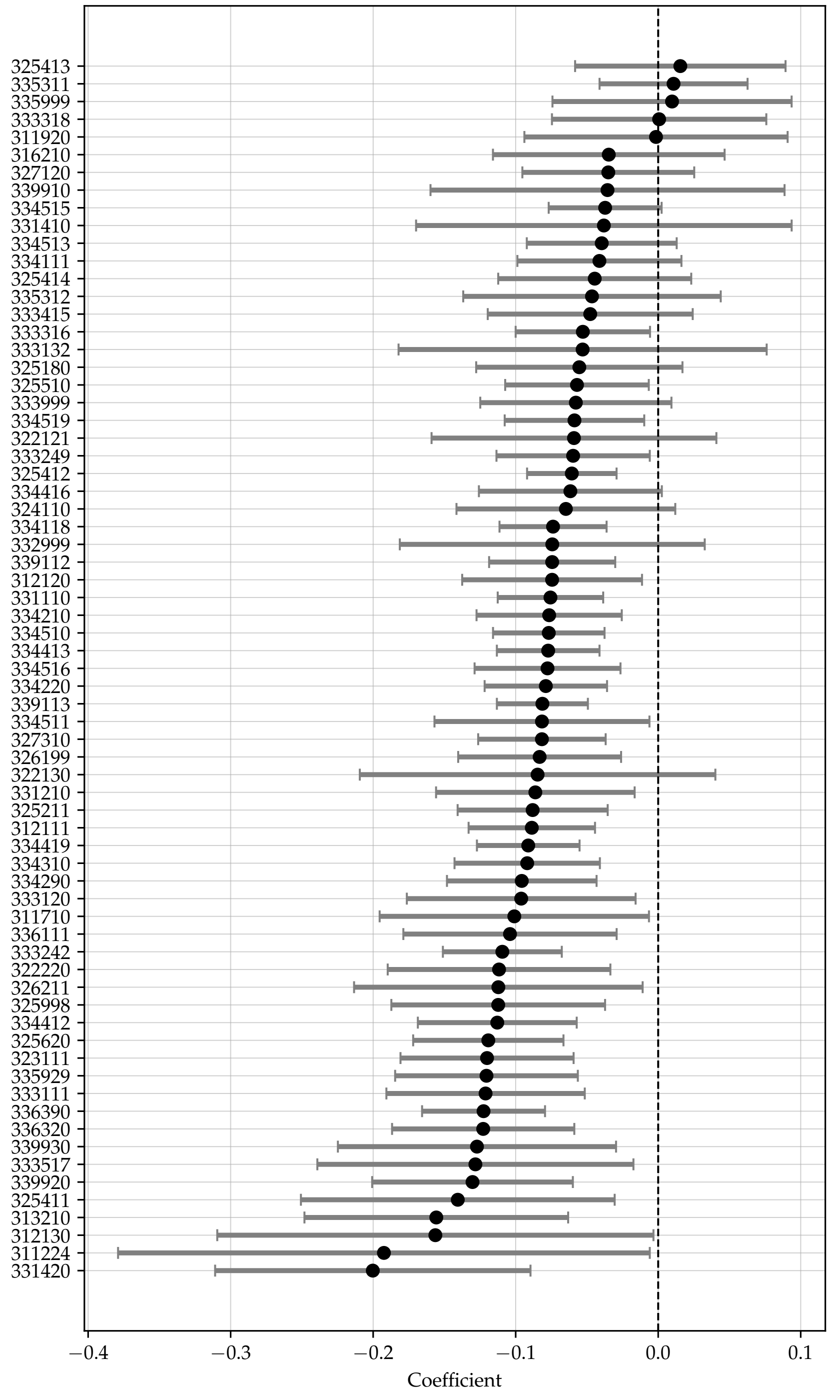
[16] Global averages are calculated by first taking cost-weighted averages within country-industry pairs and then computing the average across these pairs.

Figure 4: $\mathcal{APP}$ and Cost of Capital in Manufacturing: Country Heterogeneity



Notes: The plot displays the results of estimating regression (19) separately for each country. The estimated coefficients and 95% confidence intervals are reported. The data is a panel of global publicly traded companies in manufacturing from 1980 to 2018. All variables are in logarithms. All regressions include firm and year fixed effects. The standard errors are clustered at the firm and year levels (two-way clustering). Source: Compustat.

Figure 5: $\mathcal{APP}$ and Cost of Capital Worldwide: Industry Heterogeneity



Notes: The plot displays the results of estimating regression (19) separately for each six-digit NAICS industry. The estimated coefficients and 95% confidence intervals are reported. The data is a panel of global publicly traded companies from 1980 to 2018. All variables are in logarithms. All regressions include firm and year fixed effects. The standard errors are clustered at the firm and year levels (two-way clustering). 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 (2023*a*,*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. More generally, we hope that our measure will find broader applications across fields, offering new insights into the interplay between production length, financial conditions, and industrial structure.

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A Appendix

A.1 Effect of a Change in T on $\mathcal{APP}$

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

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

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

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

We then obtain

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

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, 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 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

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

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

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

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

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 Choice of T with Time-Separable Technology

Start from equation (14), and define

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

so that T is such that $f(T,r) = 0$. For the first-order condition (14) to be associated with a profit-maximizing choice of T, we need to impose $\partial f(T,r)/\partial T < 0$. Note that

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

so it is clear that as long as $\sigma > 1$, we will indeed necessarily have $\partial f(T,r)/\partial T < 0$.

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

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

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 Compustat.[17] We apply the following standard filters:

   (a) We require variables identifying the firm, fiscal year, reporting date, and country of incorporation (`gvkey`, `fyear`, `datadate`, and `fic`, respectively) to be non-empty.

   (b) We require the reporting date to be before December 31, 2023.

   (c) For North American firms, 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) For Global firms, 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"`).

   We pool North American and Global data. We then drop all duplicates based on firm and reporting date (`gvkey` and `datadate`), unless duplicates are identical, in which case we keep a single occurrence.

2. We use the WRDS API to query data on the industry classification of firms from Compustat. On WRDS, the data on industry classification is stored separately for North American and 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 before December 31, 2023. 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 `naicsh` in any year. We

[17] WRDS data is updated daily, with changes that may include additions, removals, or modifications of observations. While we did not find a way to access specific dated versions of the data, and the results are therefore not fully reproducible, such updates are unlikely to significantly affect the findings. The authors have preserved a copy of the data used in this paper on their local machines, retrieved on Jan 9, 2025, 10:31 PM EST.

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. When a firm has two observations for the same fiscal year, `fyear`, we retain only the observation with the earliest `datadate`.

4. We obtain concordances between NAICS vintages (1997, 2002, 2007, 2012, 2017, and 2022) from the United States Census Bureau. These concordances are not one-to-one.

5. We convert `naicsh` to 2012 NAICS and impute missing values as follows:

   (a) If `naicsh` maps to a unique 2012 NAICS code, we assign that unique code.

   (b) If `naicsh` maps to multiple 2012 NAICS codes:

      i. If the firm has a `naicsh` 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 mappings. We use the `hashlib` Python library to draw codes consistently for replicability.

   (c) For remaining observations, we assign the code from the closest same-`gvkey` observation that has a 2012 NAICS code.

6. We then perform the following data cleaning steps:

   (a) We drop observations with fiscal year outside of the range 1980–2018. In the paper analysis, *year* refers to the fiscal year.

   (b) We drop observations for which the following variables are negative or missing: sales, COGS, interest expenses, long-term debt, short-term debt, and total inventories (`sale, cogs, xint, dltt, dlc, invt`, respectively).

   (c) We drop observations outside the 1st and 99th percentiles of the following variables: the $\mathcal{APP}$, the cost of capital, and the ratio of sales to COGS.

   (d) In the paper analysis, a firm ID is the combination of `gvkey`, `fic`, and the six-digit 2012 NAICS code. We use the country of incorporation, `fic`, as a country ID.

   (e) We remove observations with an incomplete six-digit NAICS code.

7. We download annual industry-level data (based on the 2017 NAICS classification at the 3- or 4-digit level) for the years 1987 to 2018 from the Bureau of Labor Statistics website. We convert the industry classification to 2012 NAICS, and compute IT capital intensity as the ratio of total information processing capital stock to sectoral output.

8. We download the 2021a version (classified according to the six-digit level of 2012 NAICS) of the NBER-CES Manufacturing Industry Database, which provides annual industry-level data from 1958 to 2018, from the NBER website.

Table A.1 contains the number of firm-year observations after the implementation of the data preparation algorithm.

Table A.1: Number of Firm-Year Observations by Sample and NAICS Imputation

	Non-Imputed NAICS	Imputed NAICS	Total
U.S. Manufacturing Industries	46,511	11,289	57,800
U.S. All Goods-Producing Industries	53,284	14,051	67,335
Global Manufacturing Industries	151,831	29,123	180,954
Global All Goods-Producing Industries	171,432	35,754	207,186

Notes: The table presents the number of firm-year observations by sample (rows) and NAICS origin. "Non-imputed" refers to cases where the `naicsh` code was present for the given firm and year in the industry classification files and was unambiguously converted to the 2012 vintage of NAICS. All other observations are classified as "imputed NAICS". See Step 5 of the data preparation algorithm

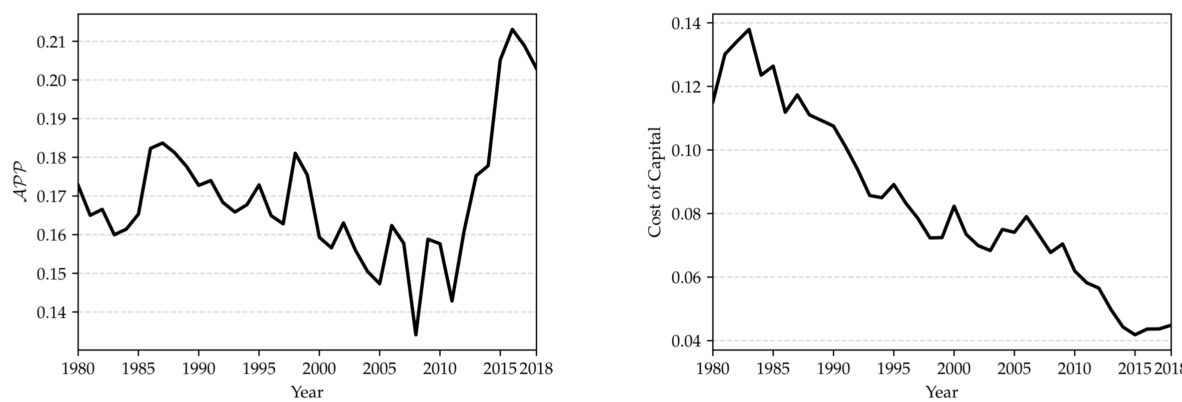
In Appendix A.7, we reproduce some results from the main text using the restricted sample of observations with non-imputed NAICS and demonstrate that the results remain qualitatively and quantitatively similar. This suggests that the findings in the main text are not driven by the data imputations.

A.5 Analysis Beyond Manufacturing: All Goods Producers

In the main text, we focus our analysis on data for manufacturing industries under NAICS codes 31–32–33. In this section, we extend the analysis to include all goods-producing industries, which encompass NAICS codes 11, 21, 22, and 23, in addition to manufacturing. This broader scope incorporates agriculture, forestry, fishing and hunting; mining, quarrying, and oil and gas extraction; utilities; and construction, alongside manufacturing.

Figure A.1 illustrates the evolution of cost-weighted average $\mathcal{APP}$ and cost of capital, similar to Figure 1 in the main text. Comparing the two figures reveals that the increase in $\mathcal{APP}$ from the mid-2000s to 2018 was more pronounced for goods-producing firms than for manufacturing firms, although the overall trends remain consistent.

Figure A.1: $\mathcal{APP}$ and Cost of Capital in U.S Goods-Producing Industries.



(a) Cost-Weighted Average Period of Production **(b)** Cost-Weighted Average Cost of Capital

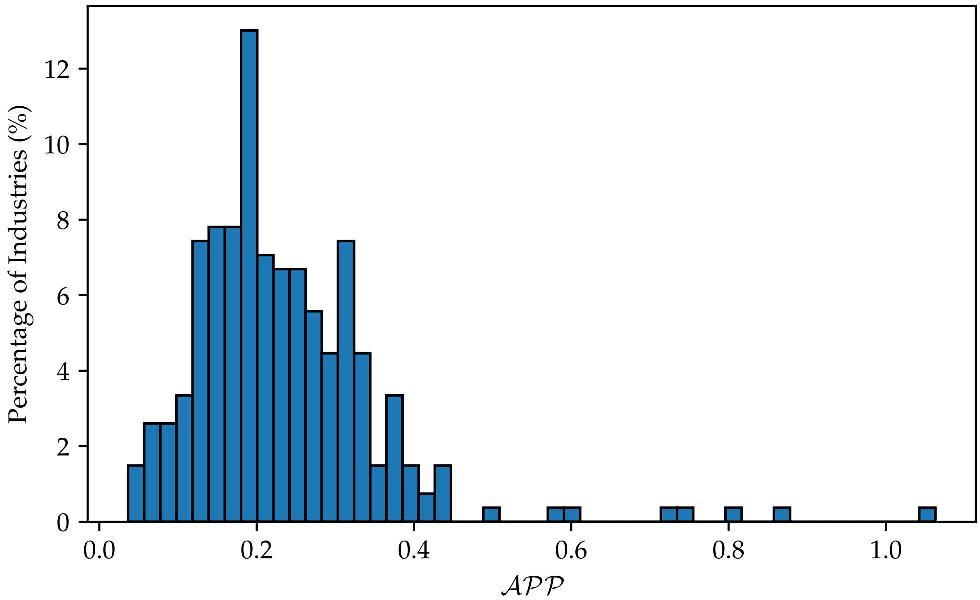
Notes: The figure shows the cost-weighted annual averages of $\mathcal{APP}$ and cost of capital for U.S. publicly traded companies in goods-producing industries from 1980 to 2018. $\mathcal{APP}$ represents the ratio of inventories to COGS, while cost of capital is the ratio of interest expenses to total debt (short- and long-term). Source: Compustat.

Figure A.2, similar to Figure 2, shows the distribution of goods-producing industries by $\mathcal{APP}$. With only 27 additional industries included, the two figures are very similar.

Table A.2 presents the top 20 industries by $\mathcal{APP}$. Compared to Table 1 in the main text, some non-manufacturing industries—land subdivision, housing construction, and residential remodeling—naturally enter Table A.2. These industries engage in projects with extended duration, requiring substantial working capital investments throughout the production length.

Table A.3 presents the bottom 20 industries ranked by $\mathcal{APP}$, similar to Table 2 in the main text. Interestingly, the six goods-producing industries with the shortest $\mathcal{APP}$ values are not manufacturers. The list naturally includes utilities (NAICS code 22), such as water, electricity, gas, and hydroelectric power, which operate through real-time production and delivery of services. It also includes coal, petroleum, and natural gas mining (NAICS code 21), as the

Figure A.2: Distribution of $\mathcal{APP}$ in U.S. Goods-Producing Industries



Notes: The figure shows the distribution of industries ($N = 269$) based on $\mathcal{APP}$. For each industry, defined as a six-digit NAICS code, $\mathcal{APP}$ is calculated as a cost-weighted average across firms within each year, then averaged across years from 1980 to 2018. The data covers U.S. publicly traded companies in goods-producing industries. Industries with fewer than 50 firm-year observations are excluded. Source: Compustat.

standardized mining process often involves the direct and continuous supply of resources to buyers. Conversely, the inclusion of certain construction industries (NAICS code 23) near the bottom is less intuitive and likely reflects differences in inventory accounting practices across industries rather than variations in actual production timelines.

Table A.4 presents summary statistics for firms in U.S. goods-producing industries from 1980 to 2018. These statistics are similar to those in Table 4 in the main text, which is expected, as manufacturing firms make up 86% of the sample.

We next return to the specification in (19) with the sample of U.S. goods-producing firms. Estimation findings are presented in Table A.5. For comparison, we first replicate the findings from column (1) of Table 5 for U.S. manufacturing firms only. Column (2) shows results for the sample that includes U.S. firms in all goods-producing industries, while column (3) excludes manufacturers. Table A.5 indicates that $\mathcal{APP}$ appears *more* sensitive to cost of capital for firms in goods-producing industries outside manufacturing than within manufacturing. We also find that the elasticity of $\mathcal{APP}$ with respect to cost of capital in Table A.5 is robust to the inclusion of IT capital intensity as a control variable, as shown in column (2) of Table 5.

In Table A.6, we present Spearman rank correlations for industry rankings based on $\mathcal{APP}$ across pairs of countries, similar to Table 7 in the main text. The resulting Table A.6 includes 11 countries, and the results overall are very similar to Table 7.

Table A.2: The Top 20 U.S. Goods-Producing Industries by $\mathcal{APP}$

NAICS	Industry	$\mathcal{APP}$
237210	Land Subdivision	1.063
236117	New Housing For-Sale Builders	0.870
312140	Distilleries	0.814
312130	Wineries	0.737
236115	New Single-Family Housing Construction (except For-Sale Builders)	0.716
236118	Residential Remodelers	0.601
339115	Ophthalmic Goods Manuf.	0.573
312230	Tobacco Manuf.	0.488
333997	Scale and Balance Manuf.	0.441
333132	Oil and Gas Field Machinery and Equipment Manuf.	0.439
316998	All Other Leather Good and Allied Product Manuf.	0.432
325412	Pharmaceutical Preparation Manuf.	0.430
334510	Electromedical and Electrotherapeutic Apparatus Manuf.	0.421
332215	Metal Kitchen Cookware, Utensil, Cutlery, and Flatware Manuf.	0.415
333131	Mining Machinery and Equipment Manuf.	0.404
339112	Surgical and Medical Instrument Manuf.	0.396
334516	Analytical Laboratory Instrument Manuf.	0.392
325620	Toilet Preparation Manuf.	0.388
315190	Other Apparel Knitting Mills	0.383
334519	Other Measuring and Controlling Device Manuf.	0.381

Notes: The table lists the top 20 U.S. goods-producing industries ranked by $\mathcal{APP}$. For each industry, defined as a six-digit NAICS code, $\mathcal{APP}$ is calculated as a cost-weighted average across firms within each year, then averaged from 1980 to 2018. Industries with fewer than 50 firm-year observations are excluded. Please refer to the replication package for the complete ranking. Source: Compustat.

Table A.3: The Bottom 20 U.S. Goods-Producing Industries by $\mathcal{APP}$

NAICS	Industry	$\mathcal{APP}$
221310	Water Supply and Irrigation Systems	0.036
237310	Highway, Street, and Bridge Construction	0.048
238210	Electrical Contractors and Other Wiring Installation Contractors	0.051
212112	Bituminous Coal Underground Mining	0.055
237130	Power and Communication Line and Related Structures Construction	0.061
221122	Electric Power Distribution	0.064
324110	Petroleum Refineries	0.068
311511	Fluid Milk Manuf.	0.069
311812	Commercial Bakeries	0.071
325193	Ethyl Alcohol Manuf.	0.073
237990	Other Heavy and Civil Engineering Construction	0.075
211111	Crude Petroleum and Natural Gas Extraction	0.079
237110	Water and Sewer Line and Related Structures Construction	0.081
336370	Motor Vehicle Metal Stamping	0.083
221210	Natural Gas Distribution	0.085
212111	Bituminous Coal and Lignite Surface Mining	0.089
238990	All Other Specialty Trade Contractors	0.093
312112	Bottled Water Manuf.	0.097
221111	Hydroelectric Power Generation	0.100
213111	Drilling Oil and Gas Wells	0.107

Notes: The table lists the bottom 20 U.S. goods-producing industries ranked by $\mathcal{APP}$. For each industry, defined as a six-digit NAICS code, $\mathcal{APP}$ is calculated as a cost-weighted average across firms within each year, then averaged from 1980 to 2018. Industries with fewer than 50 firm-year observations are excluded. Please refer to the replication package for the complete ranking. Source: Compustat.

Table A.4: Summary Statistics for Firms in U.S. Goods-Producing Industries, 1980–2018

	Mean	Std. Dev.	P25	Median	P75	N
Average Period of Production	0.299	0.267	0.136	0.232	0.376	67,335
Cost of Capital	0.104	0.079	0.064	0.088	0.119	67,335
IT Capital Intensity	0.047	0.047	0.014	0.024	0.067	53,452

Notes: The table reports summary statistics for a panel of U.S. companies in goods-producing industries from 1980 to 2018. IT capital intensity is an industry-level variable that has been imputed to firm-level observations based on NAICS classifications. Sources: BLS, Compustat.

Table A.5: $\mathcal{APP}$ and Cost of Capital in the U.S.

Dependent Variable:	Average Period of Production		
	(1) Manufacturing	(2) All Goods Prod.	(3) Manuf. Excluded
Cost of Capital	-0.090^a	-0.094^a	-0.125^a
	(0.007)	(0.006)	(0.024)
R^2	0.789	0.819	0.814
Observations	57,800	67,335	9,535

Notes: The table presents the results of estimating equation (19) on a panel of U.S. publicly traded companies in goods-producing industries from 1980 to 2018. The first column is based on data for firms in manufacturing, the second is based on data for all firms, and the last excludes manufacturing. All variables are in logarithms. All regressions include firm and year fixed effects. The standard errors are clustered at the industry (six-digit NAICS codes) and year levels (two-way clustering). Statistical significance at the 1%, 5%, and 10% levels is denoted by superscripts a, b, and c, respectively. Source: Compustat.

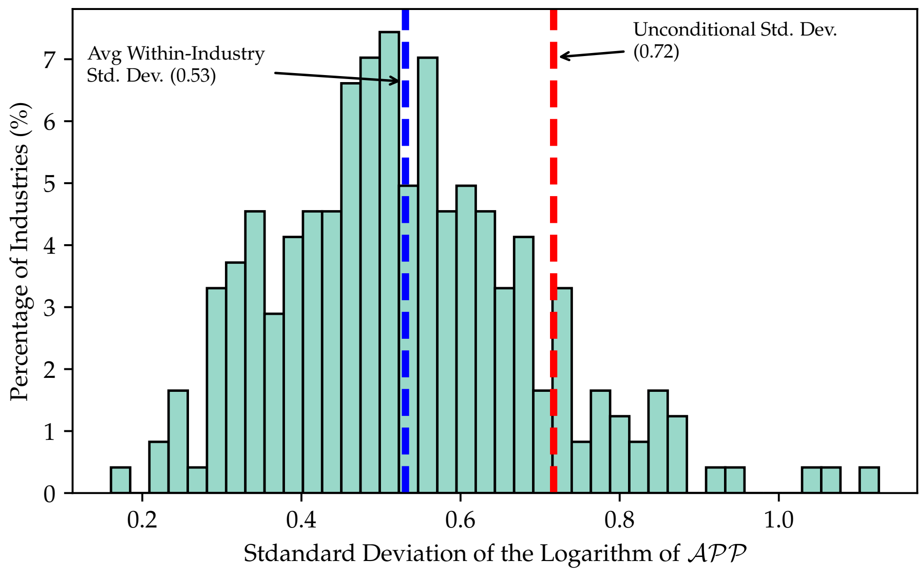
Table A.6: Rank Correlations of Goods-Producing Industries by $\mathcal{APP}$ Across Countries

	CAN	CHN	DEU	FRA	GBR	IND	JPN	KOR	MYS	TWN	USA
CAN	–	0.51^b	–	–	0.65^a	0.64^b	0.81^a	0.88^a	–	0.57^c	0.80^a
CHN	0.51^b	–	–	–	0.13	0.47^a	0.53^a	0.73^a	0.34	0.47^b	0.61^a
DEU	–	–	–	–	–	–	–	–	–	–	0.64^b
FRA	–	–	–	–	–	–	–	–	–	–	0.87^a
GBR	0.65^a	0.13	–	–	–	0.83^a	0.50^a	0.71^b	0.15	0.41	0.86^a
IND	0.64^b	0.47^a	–	–	0.83^a	–	0.46^a	0.45^b	0.54^c	0.29	0.47^a
JPN	0.81^a	0.53^a	–	–	0.50^a	0.46^a	–	0.75^a	0.35	0.34^b	0.57^a
KOR	0.88^a	0.73^a	–	–	0.71^b	0.45^b	0.75^a	–	–	0.58^a	0.72^a
MYS	–	0.34	–	–	0.15	0.54^c	0.35	–	–	–	0.27
TWN	0.57^c	0.47^b	–	–	0.41	0.29	0.34^b	0.58^a	–	–	0.61^a
USA	0.80^a	0.61^a	0.64^b	0.87^a	0.86^a	0.47^a	0.57^a	0.72^a	0.27	0.61^a	–

Notes: Spearman rank correlations are reported. To construct the rankings of industries (defined as six-digit NAICS codes) for each country, we first calculate the cost-weighted average of $\mathcal{APP}$ for each country-industry pair within each year from 1980 to 2018 and then compute the average of these values across those years. We limit the analysis to country-industry pairs with at least 50 observations during this period. Rank correlations are reported only for country pairs with at least 10 overlapping industries. The analysis is based on a panel of publicly traded goods-producing companies. Statistical significance at the 1%, 5%, and 10% levels is denoted by superscripts a, b, and c, respectively. Source: Compustat.

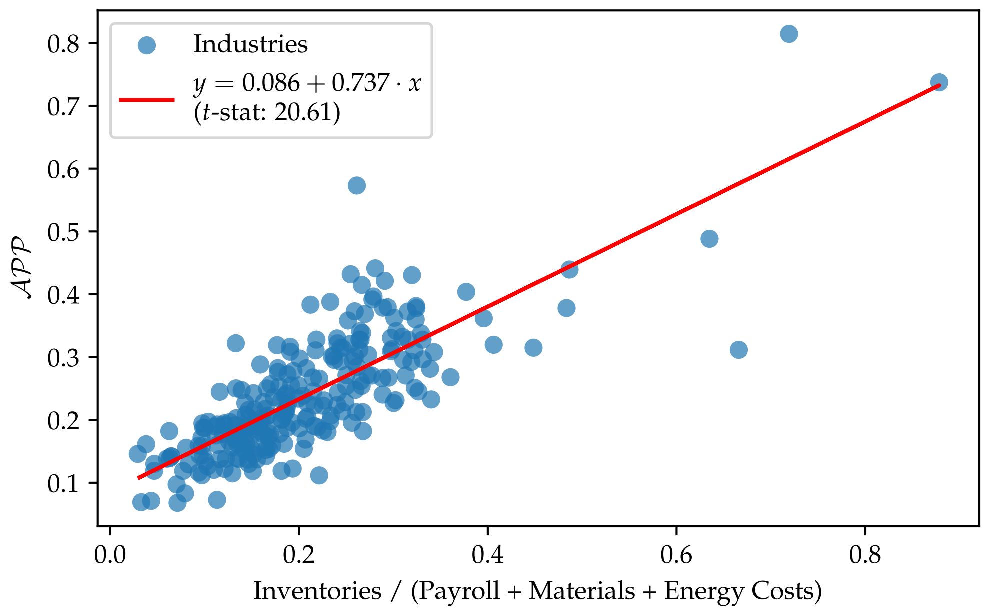
A.6 Figures and Tables Referenced in the Main Text

Figure A.3: Distribution of the Standard Deviation of $\mathcal{APP}$ in U.S. Manufacturing



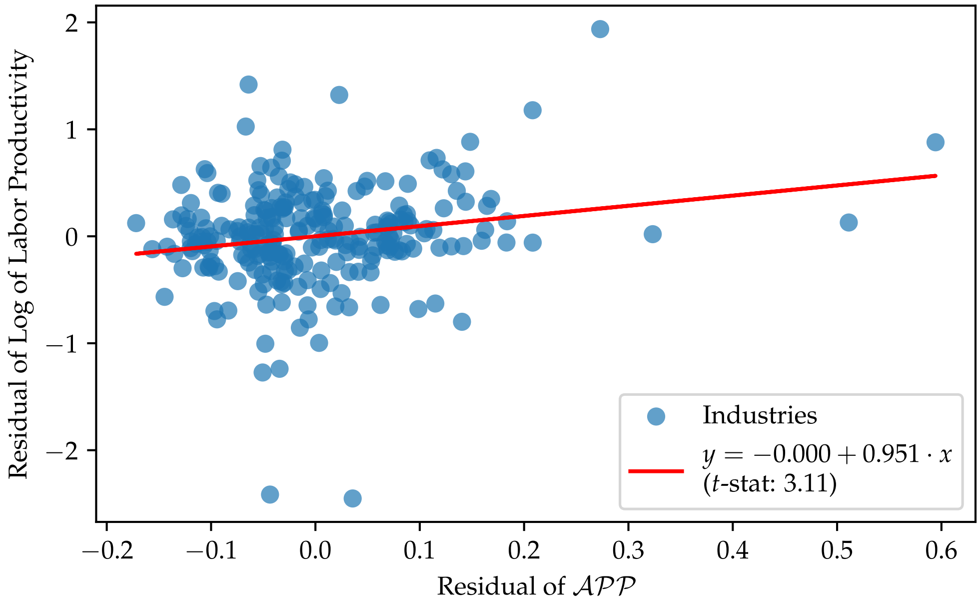
Notes: The figure shows the distribution of industries, defined as six-digit 2012 NAICS codes ($N = 242$), based on the standard deviation of the logarithm of $\mathcal{APP}$. The analysis is based on a panel of U.S. publicly traded manufacturing companies from 1980 to 2018. Industries with fewer than 50 observations are excluded. The red line represents the standard deviation constructed using the pooled sample, while the blue line represents the average of within-industry standard deviations. Source: Compustat.

Figure A.4: Inventory Intensity and $\mathcal{APP}$ in U.S. Manufacturing



Notes: The figure presents a scatterplot with *(X-axis)* representing the ratio of inventories to a measure of COGS and *(Y-axis)* representing $\mathcal{APP}$. Each point ($N = 242$) represents a U.S. manufacturing industry, defined by a six-digit NAICS code. The red line depicts the OLS regression. Annual values of variables were averaged from 1980 to 2018. For $\mathcal{APP}$, annual values were first obtained by taking cost-weighted averages across firms in each industry. Industries with fewer than 50 firm-year observations in Compustat were excluded. Sources: Compustat, NBER-CES.

Figure A.5: Partial Effect of $\mathcal{APP}$ on Labor Productivity in U.S. Manufacturing



Notes: The figure presents a scatterplot with *(X-axis)* residuals from the regression of $\mathcal{APP}$ on log cost of capital and *(Y-axis)* residuals from the regression of log labor productivity on log cost of capital. Each point ($N = 242$) represents a U.S. manufacturing industry, defined by a six-digit NAICS code. The red line depicts the OLS regression. Annual values of variables were averaged from 1980 to 2018. For $\mathcal{APP}$, annual values were first obtained by taking cost-weighted averages across firms in each industry. Industries with fewer than 50 firm-year observations in Compustat were excluded. Sources: Compustat, NBER-CES.

Table A.7: Rank Correlations of Manufacturing Industries by $\mathcal{APP}$ Across Countries

	AUS	BMU	BRA	CAN	CHN	CYM	DEU	FRA	GBR	IDN	IND	JPN	KOR	MYS	PAK	SGP	SWE	THA	TWN	USA
AUS	–	–	–	0.41	0.36	–	–	–	0.58^c	–	0.24	0.26	0.44	–	–	–	–	–	0.62^c	0.35
BMU	–	–	–	–	0.49^c	–	–	–	0.79^a	–	0.17	−0.13	0.47	–	–	–	–	–	–	0.62^b
BRA	–	–	–	–	–	–	–	–	–	–	–	0.25	–	–	–	–	–	–	–	0.42
CAN	0.41	–	–	–	0.49^a	0.51	0.15	0.58^b	0.49^a	–	0.31	0.55^a	0.59^a	−0.23	–	–	–	0.50	0.54^a	0.65^a
CHN	0.36	0.49^c	–	0.49^a	–	0.53^c	0.41	0.58^a	0.55^a	0.62^b	0.52^a	0.41^a	0.41^a	0.06	–	0.79^a	0.31	0.62^b	0.59^a	0.58^a
CYM	–	–	–	0.51	0.53^c	–	–	–	–	–	0.38	0.41	0.70^b	–	–	–	–	–	0.38	0.29
DEU	–	–	–	0.15	0.41	–	–	0.39	0.46^c	–	0.61^a	0.57^a	0.27	0.64^b	–	–	–	–	0.36	0.55^a
FRA	–	–	–	0.58^b	0.58^a	–	0.39	–	0.70^a	–	0.57^b	0.45^b	0.81^a	0.53	–	–	–	–	0.64^b	0.63^a
GBR	0.58^c	0.79^a	–	0.49^a	0.55^a	–	0.46^c	0.70^a	–	–	0.69^a	0.59^a	0.67^a	0.07	–	–	0.50^c	–	0.52^b	0.67^a
IDN	–	–	–	–	0.62^b	–	–	–	–	–	0.85^a	0.58^b	0.67^a	0.78^a	–	–	–	–	–	0.64^a
IND	0.24	0.17	–	0.31	0.52^a	0.38	0.61^a	0.57^b	0.69^a	0.85^a	–	0.44^a	0.39^b	0.45^b	–	0.16	0.45	0.44^c	0.31^b	0.41^a
JPN	0.26	−0.13	0.25	0.55^a	0.41^a	0.41	0.57^a	0.45^b	0.59^a	0.58^b	0.44^a	–	0.64^a	0.22	–	0.46	0.63^b	0.26	0.25^c	0.56^a
KOR	0.44	0.47	–	0.59^a	0.41^a	0.70^b	0.27	0.81^a	0.67^a	0.67^a	0.39^b	0.64^a	–	0.20	–	–	–	0.49	0.68^a	0.62^a
MYS	–	–	–	−0.23	0.06	–	0.64^b	0.53	0.07	0.78^a	0.45^b	0.22	0.20	–	–	−0.25	–	0.83^a	0.26	−0.02
PAK	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.88^a
SGP	–	–	–	–	0.79^a	–	–	–	–	–	0.16	0.46	–	−0.25	–	–	–	–	–	0.36
SWE	–	–	–	–	0.31	–	–	–	0.50^c	–	0.45	0.63^b	–	–	–	–	–	–	–	0.70^a
THA	–	–	–	0.50	0.62^b	–	–	–	–	–	0.44^c	0.26	0.49	0.83^a	–	–	–	–	0.49^c	0.31
TWN	0.62^c	–	–	0.54^a	0.59^a	0.38	0.36	0.64^b	0.52^b	–	0.31^b	0.25^c	0.68^a	0.26	–	–	–	0.49^c	–	0.46^a
USA	0.35	0.62^b	0.42	0.65^a	0.58^a	0.29	0.55^a	0.63^a	0.67^a	0.64^a	0.41^a	0.56^a	0.62^a	−0.02	0.88^a	0.36	0.70^a	0.31	0.46^a	–

Notes: Spearman rank correlations are reported. To construct the rankings of industries (defined as six-digit NAICS codes) for each country, we first calculate the cost-weighted average of $\mathcal{APP}$ for each country-industry pair within each year from 1980 to 2018 and then compute the average of these values across those years. We limit the analysis to country-industry pairs with at least 30 observations during this period. Rank correlations are reported only for country pairs with at least 10 overlapping industries. The analysis is based on a panel of publicly traded manufacturing companies. Statistical significance at the 1%, 5%, and 10% levels is denoted by superscripts a, b, and c, respectively. Source: Compustat.

A.7 Robustness to Imputation of NAICS

Step 5 of the data preparation algorithm outlines the process of imputing NAICS values. Below, we replicate three results from the main text for the restricted subset of observations with non-imputed NAICS. Specifically, we restrict the data to cases where the `naicsh` variable was non-empty for the given firm and year in the industry classification files and was unambiguously converted to the 2012 vintage of NAICS (case (a) of Step 5). All other observations are classified as "imputed NAICS."

Table A.8 is based on Table 3, Table A.9 is based on Table 5, and Table A.10 is based on Table 7. We observe that the results remain qualitatively and quantitatively similar, which suggests that our findings are not driven by our procedure for imputing NAICS codes.

Table A.8: Robustness to Imputation of NAICS:
Correlation of $\mathcal{APP}$ with Industry Characteristics in U.S. Manufacturing

Characteristic	Correlation with $\mathcal{APP}$	p-Value
Capital Intensity		
Log (Real Capital Stock / Total Workers)	−0.156	0.015
Log (Capital Expenditures / Payroll)	−0.177	0.006
Skill Intensity		
Log (Non-Production Workers / Total Workers)	0.270	0.000
Non-Production Payroll / Payroll	0.342	0.000
Inventory Intensity		
Inventories / Sales	0.699	0.000
Inventories / (Payroll + Material Costs + Energy Costs)	0.801	0.000
Inventories / (Prod. Worker Wages + Material Costs + Energy Costs)	0.795	0.000
Productivity		
Log (Real Value Added / Total Workers)	0.030	0.640
Total Factor Productivity	−0.010	0.874

Notes: This table replicates Table 3 using only observations with non-imputed NAICS codes. Sources: Compustat, NBER-CES.

Table A.9: Robustness to Imputation of NAICS:
$\mathcal{APP}$ and Cost of Capital in U.S. Manufacturing

Dependent Variable:	Average Period of Production		
	(1)	(2)	(3)
Cost of Capital	-0.093^a	-0.089^a	-0.091^a
	(0.008)	(0.008)	(0.008)
IT Capital Intensity	–	0.012	0.012
	–	(0.021)	(0.019)
Capital Intensity	–	–	−0.019
	–	–	(0.029)
Skill Intensity	–	–	−0.058
	–	–	(0.049)
Labor Productivity	–	–	−0.048
	–	–	(0.049)
R^2	0.810	0.815	0.817
Observations	46,511	42,968	41,458

Notes: This table replicates Table 5 using only observations with non-imputed NAICS codes. Sources: BLS, Compustat, NBER-CES.

Table A.10: Robustness to Imputation of NAICS:
Rank Correlations of Manufacturing Industries by $\mathcal{APP}$ Across Countries

	CAN	CHN	DEU	FRA	GBR	IND	JPN	KOR	MYS	TWN	USA
CAN	–	0.36	–	–	0.59^b	0.68^b	0.66^a	–	–	0.54^c	0.66^a
CHN	0.36	–	–	–	0.52^b	0.30	0.47^a	0.47^c	–	0.47^b	0.59^a
DEU	–	–	–	–	–	–	–	–	–	–	0.68^b
FRA	–	–	–	–	–	–	–	–	–	–	0.84^a
GBR	0.59^b	0.52^b	–	–	–	0.76^a	0.63^a	0.89^a	–	0.71^a	0.83^a
IND	0.68^b	0.30	–	–	0.76^a	–	0.47^a	0.69^a	0.43	0.29	0.46^a
JPN	0.66^a	0.47^a	–	–	0.63^a	0.47^a	–	0.57^a	0.20	0.32^b	0.58^a
KOR	–	0.47^c	–	–	0.89^a	0.69^a	0.57^a	–	–	0.57^b	0.61^a
MYS	–	–	–	–	–	0.43	0.20	–	–	–	0.05
TWN	0.54^c	0.47^b	–	–	0.71^a	0.29	0.32^b	0.57^b	–	–	0.60^a
USA	0.66^a	0.59^a	0.68^b	0.84^a	0.83^a	0.46^a	0.58^a	0.61^a	0.05	0.60^a	–

Notes: This table replicates Table 7 using only observations with non-imputed NAICS codes. Source: Compustat.