Patent Laws, Product Lifecycle Lengths, and Multinational Activity
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Online Appendix

A.1 Theory

This section includes detailed derivations of theoretical results appearing in the main body of the paper, as well as several important extensions.

Offshoring incentives, equations (1)-(4): Given ξ_S, a sector-j firm begins offshoring manufacturing activity at product maturity t to maximize expected lifetime profit (1),

$$\begin{aligned} E_m[\Pi_j(t)] &= \int_0^t 2\pi^N ds + E_m\left[\int_t^{T_j} [2\pi^S \cdot 1\{t+m > s\} + (1+\xi_S)\pi^S \cdot 1\{t+m \leq s\}]ds\right] \\ &= 2\pi^N t + 2\pi^S\, E_m[\min\{T_j - t, m\}] + (1+\xi_S)\,\pi^S\, E_m[\max\{0, T_j - t - m\}]. \end{aligned}$$

Notice that the first expectation above is

$$\begin{aligned} E_m[\min\{T_j - t, m\}] &= (T_j - t)\cdot P\{m \geq T_j - t\} + E[m \cdot 1\{m < T_j - t\}] \\ &= (T_j - t)\cdot\left(1 - \frac{T_j - t}{\overline{m}}\right) + \int_0^{T_j - t} m \cdot f(m)dm \\ &= T_j - t - \frac{(T_j - t)^2}{2\overline{m}}, \end{aligned}$$

while the second is

$$\begin{aligned} E_m[\max\{0, T_j - t - m\}] &= E_m[(T_j - t - m)1\{m < T_j - t\}] + E_m[0 \cdot 1\{m \geq T_j - t\}] \\ &= \int_0^{T_j - t} (T_j - t - m) f(m)dm \\ &= \frac{(T_j - t)^2}{\overline{m}} - \int_0^{T_j - t} \frac{m}{\overline{m}}dm \\ &= \frac{(T_j - t)^2}{2\overline{m}}. \end{aligned}$$

The firm's objective is therefore

$$E_m[\Pi_j(t)] = 2\pi^N t + 2\pi^S\left(T_j - t - \frac{(T_j - t)^2}{2\overline{m}}\right) + (1+\xi_S)\pi^S\left(\frac{(T_j - t)^2}{2\overline{m}}\right).$$

Optimizing over the initial offshoring maturity t, it is apparent that

$$\begin{aligned} 0 &= 2\pi^N + 2\pi^S\left(\frac{T_j - t}{\overline{m}} - 1\right) - (1+\xi_S)\pi^S\,\frac{T_j - t}{\overline{m}} \\ \Rightarrow 2(\pi^S - \pi^N) &= \frac{T_j - t}{\overline{m}}(1 - \xi_S)\pi^S \\ \Rightarrow \tau^*(\xi_S) \equiv T_j - t^* &= \frac{\pi^S - \pi^N}{(1-\xi_S)\pi^S}\, 2\overline{m}. \end{aligned}$$

The expression above indicates that firms follow the sector-invariant sourcing rule described by (2), whereby production is offshored at a time-to-obsolescence that is a function of Southern intellectual property protection ξ_S. This result implies a measure of varieties manufactured in the South $S_j(\xi_S)$ as in equation (3) that is weakly decreasing in T_j at any ξ_S: $\frac{\partial S_j(\xi_S)}{\partial T_j} \leq 0$.

The distribution of revenues earned by Southern affiliates across sectors j is also determined by the offshoring cut-off (2),

$$R_j(\xi_S) = \int_{\max\{0, T_j - \tau^*(\xi_S)\}}^{T_j} \left(2r^S(1-\kappa_{im}(t)) + (1+\xi_S)r^S\kappa_{im}(t)\right)\psi_j(t)dt,$$

where $\psi_j(t) = 1/T_j$ is the density of product maturities and $\kappa_{im}(t)$ is the probability that a maturity-t product has been imitated. It is straightforward to see that in each industry, some measure of varieties will be imitated at any point in time: $\kappa_{im}(t) = \frac{t}{\overline{m}}$. This implies that revenues earned by Southern affiliates in sector j are

$$\begin{aligned}
R_j(\xi_S) &= \int_0^{T_j} \left(2r^S(1-\kappa_{im}(t)) + (1+\xi_S)\cdot r^S\kappa_{im}(t)\right)\psi_j(t)dt \\
&= \int_0^{T_j} \left(2r^S(1-\frac{t}{\overline{m}}) + (1+\xi_S)\cdot r^S\frac{t}{\overline{m}}\right)\frac{1}{T_j}dt \\
&= 2r^S\left(1-\frac{T_j}{2\overline{m}}\right) + (1+\xi_S)r^S\frac{T_j}{2\overline{m}}.
\end{aligned}$$

For firms in longer-lifecycle sectors (with $T_j > \tau^*(\xi_S)$), only those with relatively mature products manufacture in the South. Of this fraction, a subset is imitated at any point in time: $\kappa_{im}(t) = \frac{t-[T_j-\tau^*(\xi_S)]}{\overline{m}}$. Total affiliate revenues are therefore

$$\begin{aligned}
R_j(\xi_S) &= \int_{T_j-\tau^*(\xi_S)}^{T_j} \left(2r^S(1-\kappa_{im}(t)) + (1+\xi_S)\cdot r^S\kappa_{im}(t)\right)\psi_j(t)dt \\
&= \int_{T_j-\tau^*(\xi_S)}^{T_j} \left[2r^S\left(1-\frac{t-[T_j-\tau^*(\xi_S)]}{\overline{m}}\right) + (1+\xi_S)\cdot r^S\left(\frac{t-[T_j-\tau^*(\xi_S)]}{\overline{m}}\right)\right]\psi_j(t)dt,
\end{aligned}$$

which, after a change of variables $\widetilde{t} = t - [T_j - \tau^*(\xi_S)]$ can be reduced to

$$\begin{aligned}
R_j(\xi_S) &= \int_0^{\tau^*(\xi_S)} \left[2r^S(1-\frac{\widetilde{t}}{\overline{m}}) + (1+\xi_S)\cdot r^S\frac{\widetilde{t}}{\overline{m}}\right]\frac{1}{T_j}d\widetilde{t} \\
&= \frac{1}{T_j}\left[(2r^S\left(\tau^*(\xi_S) - \frac{\tau^*(\xi_S)^2}{2\overline{m}}\right) + (1+\xi_S)r^S\frac{\tau^*(\xi_S)^2}{2\overline{m}}\right].
\end{aligned}$$

We thus arrive at the distribution of affiliate revenues across sectors, equation (4).

Response to reforms, equations (5)-(6): When the South strengthens intellectual property rights from ξ_S to ξ'_S, the offshoring cut-off rises: $\tau^*(\xi_S) \nearrow \tau^*(\xi'_S)$. As a result, firms offshore to the South manufacturing activity associated with *marginal* varieties. The remaining time to obsolescence τ of a marginal variety is such that it would not yet be offshored under the old patent regime, but is under the strengthened regime: $\tau^*(\xi_S) < \tau < \tau^*(\xi'_S)$. The measure of varieties manufactured in the South is thus higher under the new patent regime, which, building from (3) is described by equation (5) and plotted in the middle panel of Figure 1.

Similarly, revenues earned by Southern affiliates will rise following the patent reform. This reflects the increased measure of varieties manufactured there from (5) as well as the strengthened patent protection provided to existing imitated varieties. These two effects combine to generate an overall increase in observed affiliate revenues as described by equation (6). The pattern of response across sectors is an implication of the distribution of affiliate revenues described by (4). Notice that $\tau^*(\xi_S) < \tau^{*\prime}(\xi_S)$, so that each line of (6) is the difference $R_j(\xi'_S) - R_j(\xi_S)$.

Multiple Southern countries, section I.F: Similar predictions to those above hold in the cross-section of countries with different levels of patent protection. To see this, consider a world that includes two Southern countries, S and S', that are symmetric but for patent institutions summarized by ξ_S and $\xi'_S > \xi_S$, respectively. Suppose that the combined size of S and S' is 1.

Notice that if firms treat each country in isolation, Predictions 1 and 2 apply to S and S' collectively. For example, suppose that imitation is costly, trade costs are infinite, and profit losses due to imitation are high relative to the benefits of offshoring.[1] It can then be shown that firms treat markets in isolation; time-to-obsolescence offshoring cut-offs $\tau^*(\xi_S)$ and $\tau^*(\xi'_S) > \tau^*(\xi_S)$ obtain as above, and all main theoretical results follow.

However, these cross-section predictions also obtain in settings with lower trade costs. Indeed, more interesting cases incorporate the possibility that, with moderate (or negligible) trade costs and two Southern countries, a firm may choose to establish one foreign affiliate that serves both Southern markets. Relatedly, imitators in one Southern country may choose to sell both locally and abroad. To keep things clear, I develop this section by first considering a setting in which imitation products are not traded and trade costs are negligible. I then relax each of these assumptions and investigate the theoretical implications of these considerations.

1— Suppose imitation products are not traded and transport costs are negligible. With two Southern countries, each firm must determine not only when to begin offshoring, but also where to locate offshore manufacturing activity. Notice that because transport costs are zero, the firm optimally consolidates manufacturing in a single, preferred location. This preferred location is the country with higher patent protection, S', for firms in all industries j. However, because we observe multinational activity in countries with both weak and strong patent protection in the data, in this multi-country extension I allow firms' location decisions to depend not only on the maximized value of lifetime profits as a function of patent rights, $\max_t(E_m[\Pi(t)])$ in (1), but also on an unobserved component of the profit function that is independent of offshoring timing t and varies across country-firm pairs; suppose that firms realize this unobserved profit component once at the time manufacturing first begins in the South (e.g. each firm faces an idiosyncratic, country-specific shock to setup costs). This implies a positive probability of offshoring in each Southern country

[1] With a fixed cost of imitation, imitators pursue only varieties with a sufficient remaining economic lifetime. With infinite trade costs, this condition implies that firms delay offshoring until products reach a time-to-obsolescence cut-off, rather than to offshore earlier in the product lifecycle and face imitation risk.

for every product, but only one offshoring location per product.[2] To be more precise, define

$$\begin{aligned}
\pi_{ki} &\equiv \max_t (E_m[\Pi_{ki}(t)]) + \epsilon_{ki} \\
&= \max_t \left[2\pi^N t + 2\pi^S \left(T_{j(k)} - t - \frac{(T_{j(k)} - t)^2}{2\overline{m}} \right) + (1 + \widetilde{\xi}_i)\pi^S \left(\frac{(T_{j(k)} - t)^2}{2\overline{m}} \right) \right] + \epsilon_{ki} \\
&= \left[2\pi^N T_{j(k)} + \frac{(\pi^S - \pi^N)^2}{(1 - \widetilde{\xi}_i)\pi^S} 2\overline{m} \right] + \epsilon_{ki} \\
&\equiv V_{ki} + \epsilon_{ki}, \qquad i = \{S, S'\}
\end{aligned}$$

where $\widetilde{\xi}_i = (1 + \xi_i)/2$, $j(k)$ is the sector associated with variety k, ϵ_{ki} is unobserved and is assumed to be independently and identically distributed across country-variety pairs following a type-1 extreme value distribution. Upon observing ϵ_{kS} and $\epsilon_{kS'}$, firm k determines its offshoring location by comparing π_{kS} and $\pi_{kS'}$: the firm establishes an affiliate in country S if $\pi_{kS} > \pi_{kS'}$, and otherwise offshores in country S'.

Denote the associated logit choice probabilities p_S and $p_{S'}$, respectively, and notice that $p_{S'} > p_S$ because

$$\begin{aligned}
p_{S'} &\equiv \text{Prob}[V_{kS'} + \epsilon_{kS'} > V_{kS} + \epsilon_{kS}] \\
&= \text{Prob}[\epsilon_{kS} < \epsilon_{kS'} + V_{kS'} - V_{kS}] \\
&= \frac{e^{V_{kS'}}}{e^{V_{kS}} + e^{V_{kS'}}} \\
&> \frac{e^{V_{kS}}}{e^{V_{kS}} + e^{V_{kS'}}} = p_S.
\end{aligned}$$

The measure of varieties offshored in S and S' respectively are therefore

$$\begin{aligned}
S_j(\xi_S) &\equiv \int_{\max\{0, T_j - \tau^*(\xi_S)\}}^{T_j} p_S\, \psi_j(t) dt = \min\left\{ p_S,\, p_S \frac{\tau^*(\xi_S)}{T_j} \right\} \\
S_j(\xi'_S) &\equiv \int_{\max\{0, T_j - \tau^*(\xi'_S)\}}^{T_j} p_{S'}\, \psi_j(t) dt = \min\left\{ p_{S'},\, p_{S'} \frac{\tau^*(\xi'_S)}{T_j} \right\}.
\end{aligned}$$

Taking the difference between the two expressions above leads to the following result regarding the measure of varieties offshored in a strong-patent host-country S' versus in a weak-patent host-country S as a function of sectors' product lifecycle lengths T_j:

$$S_j(\xi'_S) - S_j(\xi_S) = \begin{cases} p_{S'} - p_S, & T_j < \tau^*(\xi_S) \\ 1 - p_S \cdot \frac{\tau^*(\xi_S)}{T_j}, & T_j \in [\tau^*(\xi_S), \tau^*(\xi'_S)] \\ p_{S'} \cdot \frac{\tau^*(\xi'_S)}{T_j} - p_S \cdot \frac{\tau^*(\xi_S)}{T_j}, & T_j > \tau^*(\xi'_S). \end{cases}$$

[2] Notice that offshoring in S' and then shifting production to S is never optimal, because the firm exposes its technology in both markets, raising imitation risk, but gains no profit advantage since π^S is identical in S and S'.

This difference is a non-monotonic function of T_j.

2— Consider the additional possibility that imitation goods may be traded across countries. Successfully selling an imitation product requires evading patent authorities, and a key observation in this multi-country setting is that selling imitation goods abroad requires evading such authorities both locally and in the destination country. This necessarily limits the size of the export market for imitators: for example, an imitator in S faces a probability of success selling at home $(1-\xi_S)$, but when selling abroad in S', enjoys only a smaller probability of success $(1-\xi_S)\times(1-\xi'_S)$ (and has no chance of success selling in N). Lifetime profits are therefore similar to equation (1),

$$E_m[\Pi_j(t)] = 2\pi^N t + 2\pi^S\, E_m[\min\{T_j - t, m\}] + (1+\overline{\xi}_S)\,\pi^S\, E_m[\max\{0, T_j - t - m\}],$$

where $\overline{\xi}_S = [\xi_S + \xi'_S + \xi_S(1-\xi'_S)]/2$, but reflect the fact that firms' offshoring decisions now depend on the quality of patent protection in S *and* in S'. However, notice that imitation in S has a stronger effect on firm profits in S than on firm profits in S'. Optimizing over the initial offshoring maturity t, it is apparent that firms offshore to S whenever a product is within $\tau^*(\xi_S, \xi'_S)$ time to obsolescence, where

$$\tau^*(\xi_S, \xi'_S) \equiv T_j - t^* = \frac{\pi^S - \pi^N}{(1-\overline{\xi}_S)\pi^S}\, 2\overline{m},$$

where $\overline{\xi}_S$ is as defined above. An analogous cut-off $\tau^*(\xi'_S, \xi_S)$ may be derived for offshoring to S', but because $\xi'_S > \xi_S$, offshoring there begins earlier in the product lifecycle: $\tau^*(\xi'_S, \xi_S) > \tau^*(\xi_S, \xi'_S)$. As a result, the logit choice probabilities are again such that $p_{S'} > p_S$, and the general expression $S_j(\xi'_S) - S_j(\xi_S)$ above obtains and is a non-monotonic function of T_j.

3— Suppose now that firms face iceberg transport costs $\gamma > 1$ when shipping goods across borders, and for simplicity, return to the setting in 1) above in which imitation goods are not traded. A firm manufacturing in the North now earns flow profits $\pi^N\gamma^{1-\sigma}/2$ in each Southern country by exporting, while a firm manufacturing in S (S') earns flow profits $\pi^S\gamma^{1-\sigma}$ in the North and $\pi^S\gamma^{1-\sigma}/2$ in S' (S) by exporting, where π^i, $i = \{N, S\}$, is as defined above. Because establishing an affiliate is costless, each firm eventually manufactures in both S and S'; however, offshoring timing is country-specific and begins earlier in the lifecycle for countries with relatively strong patent institutions. Specifically, firms with long-lived technologies delay offshoring, exporting from the North to the South early in the product lifecycle, provided that total profits when manufacturing in the North $\pi^N(1+\gamma^{1-\sigma})$ exceed total profits when manufacturing in the South when imitated, which are at most $\pi^S(\gamma^{1-\sigma} + [1+\xi'_S]/2)$ under imitation in S' only. This places an upper bound on γ

$$\pi^N(1+\gamma^{1-\sigma}) > \pi^S(\gamma^{1-\sigma} + \widetilde{\xi}'_S)$$
$$\Rightarrow \gamma < \left(\frac{\pi^S - \pi^N}{\pi^N - \pi^S\widetilde{\xi}'_S}\right)^{\frac{1}{\sigma-1}}$$

where $\widetilde{\xi}'_S = (1+\xi'_S)/2$ as above. Under this condition, sector-j firms delay offshoring to S and S'

based on an equation similar to (1)

$$
\begin{aligned}
E_m[\Pi_j(t_1,t_2)] &= \pi^N t_1 + \pi^S (T_j - t_1)\gamma^{1-\sigma} \\
&+ \left[\pi^N \gamma^{1-\sigma} t_1 + \pi^S E_{m'}[\min\{T_j - t_1, m'\}] + \xi'_S \pi^S E_{m'}[\max\{0, T_j - t_1 - m'\}]\right]/2 \\
&+ \left[\pi^N \gamma^{1-\sigma} t_1 + \pi^S \gamma^{1-\sigma}(t_2 - t_1) + \pi^S E_m[\min\{T_j - t_2, m\}] + \xi_S \pi^S E_m[\max\{0, T_j - t_2 - m\}]\right]/2
\end{aligned}
$$

where t_1 and $t_2 > t_1$ are the product maturities at which manufacturing begins in S' and S, respectively, and m' captures imitation timing in S'. The expression above describes lifetime profits by country, for the North (line 1), S' (line 2), and S (line 3). In the North, the firm earns π^N until offshoring to S' begins at t_1; thereafter, the firm manufactures in the South, earning $\pi^S\gamma^{1-\sigma}$ in the North until the product becomes obsolete at T_j. In S', the firm earns export profits from the North $\pi^N\gamma^{1-\sigma}$ until offshoring begins at t_1; for the product's remaining economic lifetime, the firm then earns either π^S or $\xi'_S\pi^S$ depending on imitation timing m' in S'. In S, the firm initially earns export profits from the North $\pi^N\gamma^{1-\sigma}$ until offshoring to S' begins at t_1; the firm then earns export profits from S', $\pi^S\gamma^{1-\sigma}$, until offshoring to S begins at t_2; for the product's remaining economic lifetime, the firm then earns either π^S or $\xi_S\pi^S$ depending on imitation timing m in S. Optimizing over t_1 and t_2 yields offshoring cut-offs $\tau_1^*(\xi'_S) \equiv T_j - t_{1j}^*$ and $\tau_2^*(\xi_S) \equiv T_j - t_{2j}^* < \tau_1^*(\xi'_S)$. These cut-offs imply that multinational activity follows a non-monotonic pattern across S and S' similar to that in cases 1) and 2) above, and analogous to that derived in the baseline two-country model.

Heterogeneous firms, section I.G: It is simple to show that firms with relatively high productivity levels φ are insensitive to imitation and thus are also insensitive to the quality of offshore patent protection. Specifically, suppose that within-sector productivity differences across innovators can be summarized by a positive firm-specific parameter $\varphi \in [\varphi_L, \varphi_H]$ that affects profits as in Melitz (2003). Firms with higher productivity draws earn higher profits whether manufacturing in the North $\pi^N(\varphi) = \pi^N\varphi^{\sigma-1}$ or in the South $\pi^S(\varphi) = \pi^S\varphi^{\sigma-1}$, where π^N, π^S, and $\sigma > 1$ are as defined in section I. Assume further that imitators share a fixed productivity level below φ_H and compete with innovators on the basis of price in any market where patents are not protected. The link between profits, prices, and marginal production costs implied by monopolistic competition indicate that imitating firms share identical marginal costs, which I denote c_{im}; innovating firms' marginal costs $c^S(\varphi) = c^S/\varphi$ depend on multinationals' baseline marginal costs in the South c^S, as well as φ. Notice that whenever $c^S(\varphi)$ exceeds c_{im}, successful imitators profitably capture unprotected markets. Conversely, when $c^S(\varphi) < c_{im}$, or

$$\varphi > \frac{c^S}{c_{im}} \equiv \overline{\varphi},$$

innovators capture all markets, even those lacking patent protection. As a result, high-productivity firms with $\varphi > \overline{\varphi}$ are unaffected by imitation, and are therefore insensitive to the quality of patent protection in the South.

A.2 Data and Measurement

Measuring product lifecycle lengths, section II.A: The model described in section I indicates that product lifecycle lengths T_j determine the sensitivity of firms' manufacturing location decisions to intellectual property institutions abroad. I now consider an extension of this model in which patents for new innovations cite existing patents upon entry. With this extended model, I will derive an index of T_j that can be constructed using standard datasets (e.g. the NBER U.S. Patent Citations Data File, Hall et al 2001).

Suppose as in section I that new innovations in sector j arrive at a constant Poisson rate and become obsolete after T_j time; let a_j denote the Poisson arrival rate in sector j. Each innovation is associated with a patent that references a set of existing patents ('prior art') relevant to the new technology. Such references impact the value of the new innovation's patent. For example, citing technologically relevant patents is valuable, because failing to include a relevant citation can cause a patent to be invalidated if challenged in court (Caballero and Jaffe 1993). However, by clarifying sensitive legal boundaries, citations limit the scope of the citing patent (Farrell and Shapiro 2008) and may thereby reduce its value. The incentive to cite an existing patent therefore depends both on a) the prior patent's technological proximity to the new innovation, and b) the prior technology's underlying value (which determines the likelihood of litigation, see Allison et al 2004), which I take to be a function of its own remaining lifetime as in section I. Accordingly, I assume that for innovation k, citing a prior sector-j patent i generates the following net value

$$V_{ik}^{j}(t) \equiv v \cdot \max\{T_j - t, 0\} - c_{ik}, \tag{1}$$

where $t > 0$ is the arrival time of innovation k, T_j is the obsolescence date of innovation i introduced at $t = 0$, $v > 0$ is the per-period citation value received by k while technology i is still viable, and c_{ik} is the net fixed cost of a citation by patent k to patent i. The first term in (1) corresponds to item b) above, the prior technology i's value, which depends both on a common per-period value v and i's remaining lifetime $T_j - t$. The second term c_{ik} corresponds to a) and captures technological proximity between k and i: for example, $c_{ik} \equiv c - b_{ik}$, where c is a common fixed citation cost and b_{ik} is an idiosyncratic fixed benefit to k for citing i that is high when technology k is closely-related to i and is low otherwise. I assume that innovation k draws c_{ik} from a distribution f (cdf F) with support $[\underline{c}, \overline{c}]$ (where $\overline{c} > 0$ but $\underline{c}$ may be positive or negative) for each sector-j patent i that exists at t. Upon arrival, patent k cites patent i if and only if $V_{ik}^{j}(t) > 0$.

As above, consider a sector-j technology i with obsolescence date T_j. It follows that for any subsequent innovation k arriving at date $t < T_j$, $F(v(T_j - t))$ is the probability that k cites technology i's patent; that is, $F(v(T_j - t)) = P\{c_{ik} < v(T_j - t)\} = P\{V_{ik}^{j}(t) > 0\}$ is the probability that technology k draws a net fixed cost c_{ik} such that $V_{ik}^{j}(t) > 0$. Therefore, patent i receives citations at the time-varying rate

$$\lambda_j(t) = \begin{cases} a_j \cdot F(v(T_j - t)), & \text{if } 0 \leq t \leq T_j \\ a_j \cdot F(0), & \text{if } t > T_j, \end{cases}$$

as a function of its age t. The expression above implies that the citation rate is initially high; then, either immediately or at some later point begins to gradually decline over time, before eventually reaching a low plateau at T_j; this plateau is positive if $\underline{c} < 0$ and hence $F(0) > 0$, while it is zero if $\underline{c} = 0$. To be exact, the slope of the arrival rate function $\lambda_j(t)$ changes over time as follows

$$\frac{d\lambda_j(t)}{dt} = \begin{cases} 0, & \text{if } t < t_1 \\ -a_j v \cdot f(v(T_j - t)), & \text{if } t_1 \leq t < T_j \\ 0, & \text{if } t \geq T_j, \end{cases}$$

where $t_1 = \max\{0, T_j - \overline{c}/v\}$.

Suppose that the citation history is observable for any patent, within up to $\overline{T}$ time after its introduction, but that the parameters T_j, ν, and a_j are unknown. Based on the observed citation information, it is possible to recover cross-sector variation in T_j. In particular, by specifying a distribution f, explicit moments of the citation process described by $\lambda_j(t)$ above may be derived. For example, assume that c_{ki} follows a uniform distribution on $[-\epsilon, 1-\epsilon]$, with $\nu T_j \leq 1-\epsilon$. Citations to any sector-j patent i then arrive at rate

$$\lambda_j(t) = \begin{cases} a_j \cdot \nu(T_j - t), & \text{if } 0 \leq t \leq T_j \\ a_j \cdot \epsilon, & \text{if } t > T_j. \end{cases}$$

According to this process, each sector-j patent $i = 1, 2, ..., N_j$ receives some random number of citations $X_{ji}(t)$ within t time after it is published. Consider the aggregated citation process $X_j(t) = \sum_{i=1}^{N_j} X_{ji}(t)$ across all N_j sector-j patents. It can be shown that the expected mean citation time within $[0, \overline{T}]$ time is

$$m_j(\overline{T}) \equiv E\left[\frac{1}{X_j(\overline{T})} \sum_{k=1}^{X_j(\overline{T})} t_k\right] = \alpha_j(T_j, \overline{T}) \cdot \frac{T_j}{3} + (1 - \alpha_j(T_j, \overline{T})) \cdot \frac{T_j + \overline{T}}{2}, \tag{2}$$

where $t_1, t_2, ..., t_{X_j(\overline{T})}$ are the respective citation times (or citation lags), and

$$\alpha_j(T_j, \overline{T}) = E\left[X_j(T_j) | X_j(\overline{T}) = n\right] = \frac{vT_j^2}{vT_j^2 + 2\epsilon(\overline{T} - T_j)} \in [0, 1]$$

is the average fraction of citations during $[0, \overline{T}]$ that occur before T_j. Provided that the rate of post-obsolescence citations ϵ is not too large relative to the rate of pre-obsolescence citations v, $m_j(\overline{T})$ monotonically increases in T_j, allowing me to use this as an index of T_j in my empirical analysis. Intuitively, monotonicity obtains because a higher T_j raises the average pre-obsolescence citation time, but also reduces the average fraction of post-obsolescence citations, which tend to have long lags. The first effect dominates provided that the post-obsolescence citation rate ϵ is small relative to v; this seems reasonable given that empirical distributions of class-level patent citation timing show that the citation rate generally declines with patent age. Notice that alternative statistics such as the average maximum citation time or the average sum of citation times are not robust to $\epsilon > 0$ or variation in a_j across sectors. I construct $m_j(\overline{T})$ for each technology class j using patent citation data, as described below. My main empirical results are based on this index of T_j: $\widehat{T}_j = m_j(\overline{T})$.

Lemma 1: *The expected mean patent citation age $m_j(\overline{T})$ within $[0, \overline{T}]$ time is monotonically increasing in the economic lifetime T_j of innovations in sector j.*

Proof of Lemma 1:

$$
\begin{aligned}
m_j(\overline{T}) &= E\left[\frac{1}{X(\overline{T})}\sum_{k=1}^{X(\overline{T})} t_k\right] \\
&= E_n\left[E\left[\frac{1}{X_j(\overline{T})}\sum_{k=1}^{X_j(\overline{T})} t_k \,\middle|\, X_j(\overline{T}) = n\right]\right] \\
&= E_n\left[\frac{1}{n}E_x\Big(x\cdot E[t_k|X_j(T_j)=x] + (n-x)\cdot E[[T_j+t_k]|X_j(\overline{T}-T_j)=n-x]\Big)\right] \\
&= E_n\left[\frac{1}{n}E_x\left(x\cdot\int_0^{T_j} t\,\frac{b_j(t)}{\int_0^{T_j} b_j(s)ds}\,dt + (n-x)\cdot\frac{\overline{T}+T_j}{2}\right)\right], \quad \text{where } b_j(t)\equiv N_j\lambda_j = a_jN_jv(T_j-t) \\
&= E_n\left[\frac{1}{n}E_x\left(x\cdot\frac{T_j}{3} + (n-x)\cdot\frac{\overline{T}+T_j}{2}\right)\right] \\
&= E_n\left[\frac{1}{n}\left(\frac{T_j}{3}\cdot n\,\frac{a_jN_jvT_j^2}{a_jN_jvT_j^2+2\epsilon a_jN_j(\overline{T}-T_j)} + \frac{\overline{T}+T_j}{2}\cdot n\,\frac{2\epsilon a_jN_j(\overline{T}-T_j)}{a_jN_jvT_j^2+2\epsilon a_jN_j(\overline{T}-T_j)}\right)\right] \\
&= \alpha_j(T_j,\overline{T})\cdot\frac{T_j}{3} + (1-\alpha_j(T_j,\overline{T}))\cdot\frac{T_j+\overline{T}}{2},
\end{aligned}
$$

which is increasing in T_j.

Constructing $\widehat{T_j}$: I construct the index proposed above, $\widehat{T_j}$, using information in the NBER Patent Citations Data File (Hall, et al 2001). Each U.S. patent granted between 1976 and 1990 is matched with any patent citing it during 1976–2006. The citation time ("forward citation lag") t is the difference, in years, between the application date of the citing patent and the grant date of the cited patent. For each technology class j, I compute the average citation time ($\overline{T}$) across sector-j patents. I also compute the 75$^{\text{th}}$-percentile and 85$^{\text{th}}$-percentile citation times for each patent class j. I verify that each of these measures is stable across samples restricted to include only patents with a minimum number of citations (20, 50); this helps to ensure that they are not influenced by variation across sectors in the prevalence of "unimportant" patents. Because the truncation limit $\overline{T}$ depends on the cited patent's grant date, I also verify the stability of the measure under a uniform truncation rule, whereby citation lags are limited to 16 years across all patents. As a final step, I translate these product lifecycle length indexes into SIC(3)-level measures using a USPTO concordance (downloaded from ftp://ftp.uspto.gov/pub/taf/sicconc/2005diskette/). SIC(3)-level measures are equal-weighted indexes of the patent class-level measures; the alternative approach of using input-output weights is not appropriate because is unclear how the value-composition of production inputs is related to the value-composition of patented intellectual property within a sector. Stata code is available upon request.

Constructing alternative measures of T_j: I construct alternative class-level proxies based on U.S. patent renewal data. U.S. utility patents issued on or after December 12, 1980 are subject to maintenance fees, which must be paid to keep the patent in force. Maintenance fees are due $3\frac{1}{2}$, $7\frac{1}{2}$, and $11\frac{1}{2}$ years from the date of the original patent grant (see www.uspto.gov/

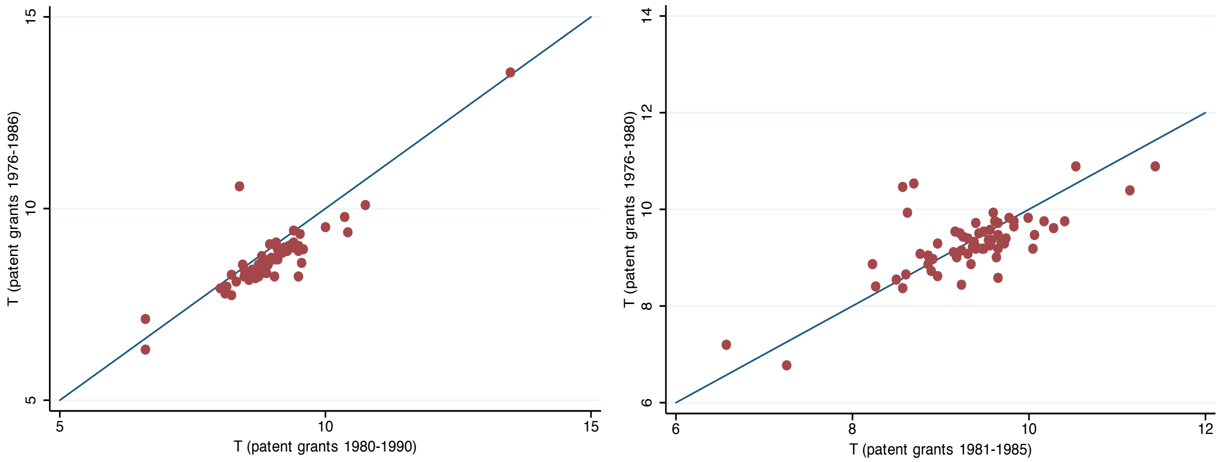
patents/process/maintain.jsp). Using USPTO maintenance fee data (available through Google; see www.google.com/googlebooks/uspto-patents-maintenance-fees.html), which records the dates of all maintenance fee events by patent, I compute each patent's implied duration, and thereby construct a distribution of patent durations by patent class. I then compute moments of this distribution including the mean, 75$^{\text{th}}$ percentile, and 85$^{\text{th}}$ percentile durations. I find that the average renewal-based proxy is minimally correlated with $\widehat{T}_j$, while higher levels of correlation (approximately 30%) obtain for the for the 75$^{\text{th}}$- and 85$^{\text{th}}$-percentile proxies. Robustness checks using this renewal-based alternative also reveal that firms in high-T sectors are significantly more sensitive to patent protection than firms in low-T sectors. Note, however, that there are important differences between my preferred measure and renewal-based measures. As described in Schankerman and Pakes (1986), the renewal decision is based on the private value of continued patent protection to the patentee. By contrast, patent citations underlying $\widehat{T}_j$ represent valuable technological links between the patented innovation and subsequently patented innovations. Whenever the private value of a patented innovation differs from the innovation's value to subsequent innovators—for example due to technology spillovers (Keller and Yeaple 2009, Bloom et al 2013) and imperfect appropriability of knowledge—renewal-based and citation-based indexes of technology durability will tend to diverge. Importantly, because the extent to which firms are able to appropriate the returns to patented innovations differs across industries (Cohen, Nelson, and Walsh 2000), this divergence can affect both the level and the rank-ordering of implied technology durability across industries when durability is inferred from renewals versus from citations. This alternative proxy, much like the turnover rates in Broda and Weinstein (2010), may therefore capture variation beyond that which T is meant to reflect in the model.

Stability of measured product lifecycle lengths T_j over time: The measure of product lifecycle lengths T_j appears to be stable within and across industries over timeI have constructed two comparisons in measured values of T_j: 1) 'Overlapping samples': I compare T_j for a) cited patents granted between 1976–1986 with citations through 2002, and b) cited patents granted between 1980–1990 with citations through 2006; 2) 'Non-overlapping samples': I compare measured T_j for a) cited patents granted between 1976–1980 with citations through 2000, and b) cited patents granted between 1981–1985 with citations through 2005.

For each of these two comparisons, I find small differences on average and a high degree of correlation in T_j values. Specifically, for the 'overlapping samples' comparison (Figure A.1, below left), I find an average change across samples of 0.0366 years (standard deviation 0.0470), and a high degree of correlation across samples (approximately 90%). Similarly for the 'non-overlapping samples' comparison (Figure A.1, below right), I find an average change in measured T_j of 0.0081 years (standard deviation 0.0581). These comparisons indicate certain degree of stability in the product lifecycle length index. Within-sector deviations in measured T_j across comparable samples tend to be small, and most differences are within a range of +/− 0.10 years. Differences are larger for a small number (four) of industries, falling in the range of +/− 0.10 to 0.30 years; this amounts to between a 1% and 5% difference in measured T_j in the shortest-lifecycle industry, and between 0.5% and 3% in the longest-lifecycle industry. Taken together, these comparisons indicate stability in the product lifecycle length measure. Data are available upon request.

Patent rights index: The index of patent protection is published in Ginarte and Park (1997) and Park (2008). The index is available for 122 countries between 1960 and 2005, at five-year inter-

Figure A.1: Changes in Product Lifecycle Lengths over Time



vals, and is the sum of five sub-indexes corresponding to 1) enforcement, 2) coverage, 3) provisions for the loss of protection, 4) duration, and 5) membership in international intellectual property treaties. Further details are described at length in the two aforementioned publications. Based on additional empirical analysis (section V), it is apparent that the most important components of the index for my results are enforcement and membership in international treaties. I thank Walter Park for generously providing me with the complete panel of sub-indexes.

Multinational activity and data sample: Confidential data on the activity abroad of U.S. multinational firms is provided by the Bureau of Economic Analysis through a sworn-status research arrangement. The data include detailed financial and operating information for each foreign affiliate owned (at least a 10% share) by a U.S. entity. The data variables used for this project were extracted from the BEA's comprehensive data files for each benchmark year, and then merged by parent and affiliate identification numbers to form a complete panel. Observations were excluded if a) values were carried over or imputed based on previous survey responses; b) the firm in question was in a sector that did not correspond to any U.S. patent class according to the USPTO concordance described above; or c) the observation was a new entrant in the final year (2004) with a NAICS classification that could not be definitively matched to a SIC code in the industry sample. Of the approximately 55 sectors in the overall benchmark dataset, 37 primarily manufacturing sectors are included in my dataset; this corresponds to approximately 1000 U.S.-based parent companies per year, each with an average of ten foreign affiliate operations.

My empirical analysis relies on affiliate-level sales revenues, assets, and employment reported in benchmark-year surveys in 1982, 1989, 1994, 1999, and 2004. Dependent variables at the country-industry-year level are constructed by aggregating across relevant affiliate operations and then transforming the aggregate quantity as needed. The number of affiliates in Table 4 is determined by counting the number of unique industry-j affiliates operating in country i during period t, and the dependent variable is the log of this quantity. Affiliate sales (assets, employment) in Table 5 is determined by summing the revenues (assets, employment) of industry-j affiliates located in country i during period t. The dependent variable in Table 5 is the log of this quantity. The binary affiliate presence variable in Table 3 is constructed by first taking the set of countries in which multinational activity is observed in at least one sample industry-year pair; for this set of countries, the affiliate presence variable is assigned a zero for any industry-year pair in which there is no multinational activity, and is assigned a one otherwise. Table 8 is based on the same sample of countries, but instead of zeros and ones, includes the ratio of affiliate sales at the country-industry-year level divided by affiliate sales plus U.S. exports at the country-industry-year level. Notice that Tables 3 and 8 necessarily contain more observations than Tables 4–6.

Table 7 considers affiliate-level sales and therefore includes more observations than other tables. Table 7 results also rely on a categorization of affiliates as subsidiaries of Low Productivity and High Productivity firms. This categorization is based on a simple firm-level Solow residual criterion: Low Productivity firms are those with a global mean Solow residual falling in the lower half of the distribution across firms, while all others are High Productivity firms. The global Solow residual for each firm-year is determined by regressing firm-level log value added on firm-level log physical assets, firm-level log employment, industry, and year dummies; firm-year residuals resulting from this regression are averaged over time periods by firm to determine a time-invariant, firm-specific global mean Solow residual. This latter time-invariant measure is used to determine each firm's productivity category (Low Productivity or High Productivity). Firm-level value added for firm k is U.S. parent value added plus the sum of affiliate-level value added across all firm-k foreign affiliates. Firm-level physical assets (the value of plant, property and equipment, net of depreciation) and firm-level employment (number of employees) are constructed similarly. The value of plant, property, and equipment net of depreciation is not available in 1982; this year is therefore excluded from my productivity calculation.

My empirical analysis also relies on two additional variables with only limited coverage, the index of patent protection IPR_{it} and $GDPpc_{it}$. Missing observations impact sample sizes across all tables. Although I also include simple specifications for each table that include minimal controls, I restrict samples across columns so that results within each table are directly comparable. All regression code is available upon request.

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Table A.1: Host-country Patent Laws and Multinational Activity, Industry Level, Industry Characteristics

Dependent variable	1{Positive affiliate sales}		Log affiliate sales		Log affiliate assets		Log affiliate employment		Log number of affiliates	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IPR x T	0.0426	0.2157	0.1638	3.6063	0.1825	3.3736	0.1158	3.0138	0.1201	1.4483
	0.0075***	0.099**	0.0686**	1.1149***	0.0713**	1.0706***	0.0732	1.1553**	0.041***	0.6905**
IPR x T^2		-0.0094		-0.18		-0.1668		-0.1515		-0.0694
		0.0054*		0.0582***		0.0556***		0.0608**		0.0357*
IPR x R&D Intensity	-0.3456	-0.4478	1.8437	2.2348	2.9948	3.3573	4.5416	4.8709	2.9872	3.1381
	0.2428	0.2464*	2.5377	2.5115	2.5126	2.4969	2.1915**	2.1797**	1.135**	2.0976
IPR x R&D Intensity^2	3.3256	3.5998	0.2704	-0.272	0.3029	-0.1999	-12.5519	-13.0085	-7.9395	-8.1488
	0.8923***	0.894***	8.783	8.7219	8.3071	8.252	7.6171	7.6254*	3.6158**	2.0976
Country-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
GDPpc x T Interactions	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
IPR x Plant RTS	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
IPR x HHI	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
IPR x K Intensity	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
IPR x L Intensity	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
IPR x Patent Effectiveness	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
IPR x Secrecy Effectiveness	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	13629	13629	4510	4510	4510	4510	4510	4510	4510	4510
R^2	0.5646	0.5648	0.7073	0.7081	0.713	0.7137	0.6325	0.6332	0.7497	0.7501

Notes: * p<0.10, ** p<0.05, *** p<0.01. This table reports least-squares estimates of equation (7). The dependent variable indicates positive sales by affiliates of U.S.-based multinational firms by country, sector, and year, and is based on firm-level data from the BEA. IPR is the index of patent protection from Ginarte and Park (1997) and Park (2008). T is the product lifecycle length, by industry, and is the average patent citation lag based on data from the USPTO and NBER. R&D Intensity is the average ratio of R&D to sales by industry based on BEA data, Plant RTS and HHI (concentration) come from the 1987 U.S. Census of Manufactures, K Intensity is the ratio of capital assets to sales and L Intentisy is the ratio of employment to sales, both by industry based on BEA data, Patent Effectiveness and Secrecy Effectiveness are from Cohen, Nelson, and Walsh (2000), and GDP per capita (GDPpc) is from the Penn World Table, Heston et al (2009). The sample period is 1982-2004. Standard errors, adjusted for clustering at the country-level, appear below each point estimate.

Table A.2: Host-Country Patent Laws and Affiliate Activity, Industry Level, First Differences

Dependent variable	Indicator for increased sales						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Delta IPR	0.0629						
	0.0218***						
Delta IPR x T		0.0236	1.2058	0.0184	1.0265	0.0526	0.7429
		0.0056***	0.1144***	0.005***	0.1359***	0.0073***	0.1278***
Delta IPR x T^2			-0.0665		-0.0567		-0.0384
			0.0063***		0.0076***		0.0071***
Delta IPR x R&D Intensity						1.9329	4.3895
						0.2193***	0.493***
Delta IPR x R&D Intensity^2							-12.925
							1.6597***
Delta log GDP per Capita	0.2848						
	0.1126**						
Delta log GDPpc x T				0.0556	1.9381	0.0556	1.9381
				0.015***	0.9196**	0.015***	0.9197**
Delta log GDPpc x T^2					-0.1058		-0.1058
					0.0513**		0.0513**
Year FE, Delta Tax Rate	Y	N	N	N	N	N	N
Country-Year FE	N	Y	Y	Y	Y	Y	Y
N	11803	11803	11803	11803	11803	11803	11803
R^2	0.0489	0.2412	0.2526	0.2416	0.2561	0.2556	0.2694

Notes: * p<0.10, ** p<0.05, *** p<0.01. This table reports least-squares estimates of equation (10). The dependent variable indicates an increase in sales by affiliates of U.S.-based multinational firms by country, sector, and year and is based on firm-level data from the BEA. IPR is the index of patent protection from Ginarte and Park (1997) and Park (2008). T is the product lifecycle length, by industry, and is the average patent citation lag based on data from the USPTO and NBER. R&D Intensity is the average ratio of R&D to sales by industry based on BEA data, and GDP per capita (GDPpc) is from the Penn World Table, Heston et al (2009). The sample period is 1982-2004. Standard errors, adjusted for clustering at the country-level, appear below each point estimate. The results are robust to clustering at the sector level, excluding the top five recipients of U.S. outward FDI, China, and India, and the chemical and pharmaceutical industries, as well as including sector-by-year fixed effects. The results shown above were estimated with OLS (Angrist and Pischke 2009), and nearly identical results obtain with probit estimation.

Table A.3: Patent Effectiveness

Dependent variable	Log affiliates sales			Log number of affiliates		
	Patent Effectiveness			Patent Effectiveness		
	Low	High	All Sectors	Low	High	All Sectors
	(1)	(2)	(3)	(4)	(5)	(6)
IPR x T	-3.4134	2.8695	-3.1155	-1.6903	1.8856	-1.5336
	2.5625	0.8476***	2.4241	1.4209	0.4917***	1.3282
IPR x T^2	0.1711	-0.1467	0.1564	0.0871	-0.0955	0.0799
	0.1298	0.0438***	0.1229	0.0726	0.0251***	0.0675
IPR x T x High Patent Effectiveness			6.3283			3.5173
			2.4317**			1.1916***
IPR x T^2 x High Patent Effectiveness			-0.3208			-0.1809
			0.1237**			0.061***
log GDPpc x T	0.4963	-1.4031	-0.5957	-1.9902	1.1492	-2.5532
	3.9097	2.1544	3.7265	2.1761	1.0511	2.0952
log GDPpc x T^2	-0.0361	0.0594	0.0194	0.0955	-0.0747	0.1234
	0.1962	0.1127	0.1877	0.1098	0.0548	0.1054
log GDPpc x T x High Patent Effectiveness			-1.4064			3.6151
			3.4765			1.9191*
log GDPpc x T^2 x High Patent Effectiveness			0.071			-0.1936
			0.1768			0.0982*
Country-Year FE, Industry FE	Y	Y	Y	Y	Y	Y
IPR x High Patent Effectiveness, log GDPpc x High Patent Effectiveness, Tax Rate x High Patent Effectiveness	N	N	Y	N	N	Y
N	2193	2590	4783	2193	2590	4783
R^2	0.6913	0.7208	0.6900	0.7491	0.7614	0.7436

Notes: * p<0.10, ** p<0.05, *** p<0.01. This table reports separate least-squares estimates of equation (7) for sectors with Low and High Patent Effectiveness as well as variants that allow differential effects of IPR based on Patent Effectiveness. The dependent variable is the log of affiliate sales (columns 1-3) or the log number of affiliates (columns 4-6), for U.S.-based multinational firms by country, sector, and year, and based on firm-level data from the BEA. IPR is the index of patent protection from Ginarte and Park (1997) and Park (2008). T is the product lifecycle length, by industry, and is the average patent citation lag based on data from the USPTO and NBER. R&D Intensity is the average ratio of R&D to sales by industry based on BEA data, and GDP per capita (GDPpc) is from the Penn World Table, Heston et al (2009). High Patent effectiveness sectors are those with above-median product patent effectiveness scores (Cohen, Nelson, and Walsh 2000). The sample period is 1982-2004. Standard errors, adjusted for clustering at the country-level, appear below each point estimate. The results are robust to clustering at the sector level, excluding the top five recipients of U.S. outward FDI, China, and India, and the chemical and pharmaceutical industries, as well as including sector-by-year fixed effects.

Table A.4: Product Lifecycle Length Index, by Industry

SIC Code	Industry Name	Product Lifecycle Length Index (Years)
343	Heating Equipment, Except Electric	10.89
341	Metal Cans And Shipping Containers	10.63
345	Screw Machine Products, Bolts, Nuts, Screws	10.42
342	Cutlery, Handtools, And General Hardware	10.41
344	Fabricated Structural Metal Products	10.25
349	Miscellaneous Fabricated Metal Products	10.08
353	Construction, Mining, And Materials Handling	10.05
358	Refrigeration And Service Industry Machinery	9.98
366	Communications Equipment	9.94
351	Engines And Turbines	9.91
369	Miscellaneous Electrical Machinery, Equipment	9.88
335	Rolling, Drawing, Extruding Of Metals	9.87
285	Paints, Varnishes, Lacquers, Enamels	9.81
354	Metalworking Machinery And Equipment	9.81
363	Household Appliances	9.78
352	Farm And Garden Machinery And Equipment	9.78
384	Surgical, Medical, Dental Instruments And Supplies	9.75
289	Miscellaneous Chemical Products	9.73
359	Miscellaneous Industrial And Commercial	9.68
371	Motor Vehicles And Motor Vehicle Equipment	9.64
346	Metal Forgings And Stampings	9.63
386	Photographic Equipment And Supplies	9.61
379	Miscellaneous Transportation Equipment	9.60
355	Special Industry Machinery, Except Metalworking	9.56
220	Textile mill products	9.50
331	Steel Works, Blast Furnaces, Mills	9.46
356	General Industrial Machinery And Equipment	9.44
381	Detection and Navigation Instruments, Equipment	9.42
364	Electric Lighting And Wiring Equipment	9.33
284	Soap, Detergents, Cosmetics	9.22
283	Drugs	9.11
281	Industrial Inorganic Chemicals	9.06
367	Electronic Components And Accessories	8.83
287	Agricultural Chemicals	8.69
357	Computer And Office Equipment	8.38
387	Watches, Clocks, Clockwork Operated Devices	7.37
383	Electronics Machinery	6.73

Notes: The product lifecycle length index is the average patent citation lag (in years) by industry. This measure is constructed at the patent class level using data from the NBER Patent Citations Data File, see Hall, et al (2001), and is then translated into a SIC-3 digit level index using a U.S. Patent and Trademark Office concordance.