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Empirical Confirmation of Creative Destruction from World Trade Data

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Abstract

We show that world trade network datasets contain empirical evidence that the dynamics of innovation in the world economy indeed follows the concept of *creative destruction*, as proposed by J.A. Schumpeter more than half a century ago. National economies can be viewed as complex, evolving systems, driven by a stream of appearance and disappearance of goods and services. Products appear in bursts of creative cascades. We find that products systematically tend to co-appear, and that product appearances lead to massive disappearance events of existing products in the following years. The opposite—disappearances followed by periods of appearances—is not observed. This is an empirical validation of the dominance of cascading competitive replacement events on the scale of national economies, i.e., creative destruction. We find a tendency that more complex products drive out less complex ones, i.e., progress has a direction. Finally we show that the growth trajectory of a country's product output diversity can be understood by a recently proposed evolutionary model of Schumpeterian economic dynamics.

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Introduction

Joseph A. Schumpeter held that the key mechanism of economic development is radical innovation [1,2]. In his view the Walrasian economic equilibrium is continuously disturbed by actions of entrepreneurs, introducing novel goods and services in the market. These innovations may replace existing goods and services and thereby impact related industries. If this happens as a cascading process it is called *creative destruction*. Current colloquial examples of how once market-dominating companies lose their position due to creative destruction include instant photography or printed newspapers in light of the age of digitalization. But is this only the driving force behind major shifts in industrial production and long-term business cycles, or does it also condition economic change on much shorter time-scales?

This question has been addressed using firm entry and exit dates [3], job creation and destruction rates [4], within specific countries [5] or within specific industries [6]. These works capture the complex interplay between factor re-allocation and productivity growth in existing economic sectors. However, little is added to our understanding of the impact of emerging industries on the development of already established parts of the national economy. If a new industrial branch emerges, how does this impact other economic sectors?

Traces of the creation of unprecedented industries can be observed using world trade data. We study the dynamics of the diversity of export products and show that the process through which it changes follows the patterns of creative destruction. The set of products a given country exports reveals the presence of the

nontradable inputs or capabilities that the products require for their production (e.g. specific productive knowledge, infrastructure, legal system, labor skills, regulations, etc.) [7,8]. In this view capabilities are elementary building blocks and each product requires a combination of them to be manufactured. A change in the diversity of a country's product basket indicates a change in its set of capabilities. New capabilities may lead to new products and the abandonment or substitution of already existing products or capabilities. Products requiring one of these abandoned capabilities as input will then disappear, while simple products that require only subsets of capabilities of more complex products may disappear as they are unable to compete for these inputs – creative destruction at work.

In this article we show that typically within a country clusters of products appear simultaneously in bursts. We interpret such a burst as the acquisition of a novel capability which is required as input for each of the newly appearing products. In the years following creative bursts there is an increased chance that already existing products will cease to be exported, that is, emerging industries effectively push out the old ones. The novel products tend to be more sophisticated and complex than the disappearing products, i.e. progress has a direction. Interestingly, we do not observe a higher probability of product appearances following disappearance events of products (see Fig. S2). This means that the canonical mechanism of filling “market niches”, if existing, does not operate in the mode of repopulating previously abandoned market niches. We confirm empirically that creative destruction, cascades of competitive

replacement, plays an important role in the development of national economies. We base our results on the World Trade Flows database compiled by the National Bureau for Economic Research [9].

We apply a recently proposed Schumpeterian diversity dynamics model [2] to account for the evolution of the product diversity of countries. In this model entrepreneurs use and combine available capabilities to create novel goods and services and substitute them for already existing ones. The result is a model economy in a self-organized critical state, characterized by creative and destructive co-evolutionary avalanches. The changes in product diversity and the distribution of product appearances and disappearances observed in world trade data are well explained by this model. The process of creative destruction has previously been modeled within the framework of endogenous growth theory [10–12] in works focusing on endogenous technological change [13–15]. These models are typically build around the same production functions used in neoclassical growth models (e.g. Cobb-Douglas). Instead of modeling technological advance through an exogenous growth rate, often an additional R&D sector is introduced, developing patents and selling them to production firms which become monopolists, leading to an imperfect market. The Schumpeterian diversity dynamics model [2] used here is completely detached from these developments.

Materials and Methods

Diversity Dynamics

The World Trade Flows database [9] contains exports of approximately 200 countries over the years 1984–2000 in about 800 product categories (4-digit SITC rev.2 classification). We include only those countries in the analysis which have a population of at least 1.2 million people and total exports of at least 1 billion USD, for more information see Text S1. We label the countries contained in this database by c , the product category by p and the year by t . The export values $x(p,c,t)$, denominated in USD are then extracted. As a diversification measure of country c in year t the number of products with nonzero export values is used, that is, $D_c(t) = \sum_p \text{sgn}(x(p,c,t))$. The total number of countries is denoted by N_C , the number of products by N_P .

The change of diversity of product exports in world trade data over a timespan of 16 years is shown in Fig.1(a)–(c). For each country index c the diversity $D_c(t)$ is shown for two different years, $D_c(t_1 = 1984)$ in Fig.1(a) and $D_c(t_2 = 2000)$ in Fig.1(b). The net change in diversity for each country between 1984 and 2000, $\Delta D_c = D_c(t_2 = 2000) - D_c(t_1 = 1984)$ is shown in Fig.1(c). Values from trade data are shown in blue and are compared to results of the Schumpeterian diversity dynamics model (in red, to be explained below). There is a general trend towards increased diversity. Countries with a relatively low or high diversity in 1984 show smaller fluctuations in diversity than countries with intermediate initial diversity. That is, countries with a low diversity tend to stay poorly diversified, fully diversified countries stay fully diversified. In between there is a regime of transition countries, some of them showing explosive growth in terms of their economic diversity. We show later that these observations can be described through the onset of a ‘creative phase transition’ [2], a distinguishing property of Schumpeterian diversity dynamics. Let us now empirically investigate the process by which the countries’ product export diversities change.

Let $A(p,c,t)$ be a product indicator function for the appearance of product p in country c between year $t - 1$ and t ,

$$A(p,c,t) = \begin{cases} 1 & \text{if } x(p,c,t-1) \leq \theta \text{ and } x(p,c,t) > \theta, \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

Similarly the indicator function for a product disappearance is

$$D(p,c,t) = \begin{cases} 1 & \text{if } x(p,c,t-1) > \theta \text{ and } x(p,c,t) \leq \theta, \\ 0 & \text{otherwise,} \end{cases} \quad (2)$$

with a threshold value set to $\theta = 100,000$ USD. For more details see Fig. S1. Fig.1(d) and (e) show the distribution of (dis)appearance events A (D) per country c and product p for world trade data and the Schumpeterian diversity dynamics model. They are far from being homogeneously distributed. For example, the number of appearance events per country varies between more than 300 and almost zero across different countries. Further there is a substantial number of products appearing in, say, five countries or less, while others appear in almost one third of all the countries studied. The model captures the functional form of these distributions. The number of appearances clearly exceeds the number of disappearances, consistent with the general trend towards higher diversity.

Co-occurrence Analysis

Creative destruction can be described as a process started by introducing novel goods or services in a national economy. If successful, this stimulates the market introduction of related goods, complimentary to the newly introduced ones. Thereby a novel cluster of inter-related products can form. This cluster may render existing parts of the national economy obsolete. If this process is actually at work within national economies, one would expect two empirical facts to hold. (i) Products enter the market in creative bursts, i.e. not incrementally and (ii) the appearance of goods tends to foster the disappearance of other products. We quantify this with two different product indicators referred to as ‘Schumpeterian Product Indicators’ (SPI). The first is introduced to assess co-occurrences of product (dis)appearances and is denoted $SPI_{XY}^0(p)$. Here X and Y stand for any combination of events A, D for product p . The second SPI measures if an appearance or disappearance event of products at t is correlated to an event of another product within the following τ years and is denoted by $SPI_{XY}^{(\tau)}(p)$.

The empirical marginal appearance (disappearance) frequency $P_A(p)$ ($P_D(p)$) for each product is given by

$$\begin{aligned} P_A(p) &= \sum_{c,t} A(p,c,t), \\ P_D(p) &= \sum_{c,t} D(p,c,t). \end{aligned} \quad (3)$$

The empirical number of co-appearances $P_{AA}(p,q)$ of products p and q across all countries and times is,

$$P_{AA}(p,q) = \sum_{c,t} A(p,c,t)A(q,c,t). \quad (4)$$

The co-occurrence statistics $P_{AD}(p,q)$ and $P_{DD}(p,q)$ are obtained by appropriately substituting disappearance events $D(p,c,t)$ for $A(p,c,t)$ in Eq. 4 (by co-occurrence we will refer to any of the four possible pairs of events for two products p and q , that is (dis)appearance in p together with (dis)appearance in q). Obviously products with a relatively high number of appearances will also be

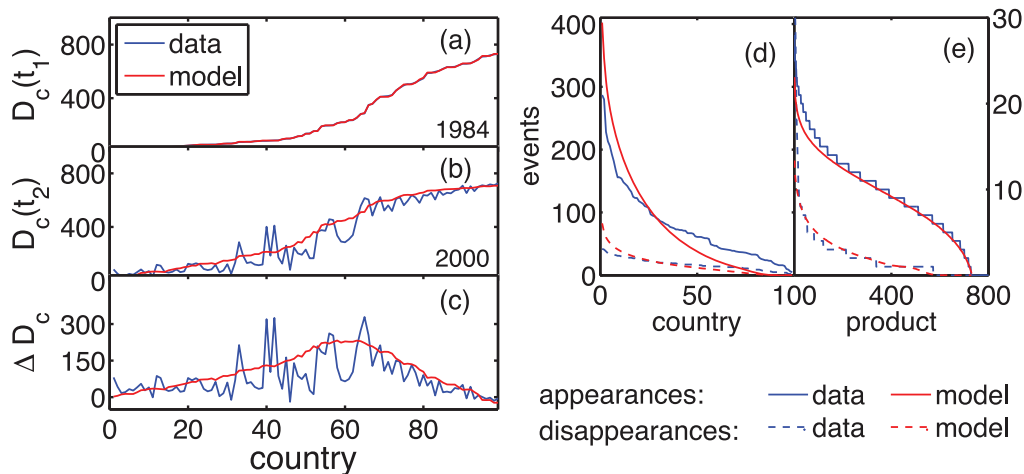


Figure 1. Development of export product diversities. Countries' export product diversities for (a) 1984, (b) 2000 and the net change in diversity between these years (c) are shown for world trade data (blue lines) and the Schumpeterian diversity dynamics model (red). There is a general tendency towards increased diversity which is strongest for countries having initially an intermediate product diversity. The results for diversity change are obtained by using only the subset of countries having non-zero export values in each year. The number of (dis)appearance events for each (d) country and (e) product are shown in the panel to the right for data and model. The model does not only reproduce the general trend of increasing diversity, but also the detailed profile of how many appearance and disappearance events could be observed for different countries and products. Note that in (a)-(c) countries are ranked by their initial diversity, whereas in (d) they are ranked by their number of events. For a goodness-of-fit test between model and data we report the correlation coefficient ρ between data and model results, and the p -value up to which the null hypothesis of no correlation between model and data can be rejected. For the final diversity in (b) we find $\rho_b = 0.97$, $p_b < 10^{-57}$ and for diversity changes in (c) $\rho_c = 0.65$, $p_c < 10^{-12}$. For the appearances (disappearances) per country in (d) we find $\rho_{d_1} = 0.99$, $p_{d_1} < 10^{-87}$ ($\rho_{d_2} = 0.96$, $p_{d_2} < 10^{-56}$), for appearances (disappearances) per product (e) $\rho_{e_1} = 0.99$, $p_{e_1} < 10^{-255}$ ($\rho_{e_2} = 0.85$, $p_{e_2} < 10^{-207}$). doi:10.1371/journal.pone.0038924.g001

more likely to co-appear. Consequently whenever one compares co-occurrence statistics of two different pairs of products one has to correct for this bias. A simple way to do this is to compare the number of measured co-occurrences of two products to their marginal (dis)appearance frequencies given in Eq. 3. For this we define the pairwise conditional co-occurrence measure as $\tilde{P}_{AA}(p,q) \equiv \frac{P_{AA}(p,q)}{\max[P_A(p), P_A(q)]}$. The idea is that given two products p and q we take the product with the higher appearance probability, say p , and measure how often q appears conditional on an appearance event of p in the same country. To quantify in how many co-occurrence events a given product participates, one can define an *SPI* for simultaneous appearances $SPI_{AA}^0(p)$ by

$$SPI_{AA}^0(p) = \frac{1}{\mathcal{N}} \sum_q \tilde{P}_{AA}(p,q). \quad (5)$$

where \mathcal{N} is a normalization factor given by $\mathcal{N} = (N_p - 1)N_C$ guaranteeing that the index lies within the range $(0,1)$ and is thus comparable across datasets of different sizes. It is straight forward to define *SPIs* for other pairs of events $XY \in \{AD, DA, DD\}$.

We proceed to quantify to what extent an appearance event in year t is related to disappearance events at a later time $t' > t$. Assume a maximal lag of τ years between the two events, $t < t' \leq t + \tau$. If not denoted otherwise, we work with a value of $\tau = 3$ years. A simple measure is the number of all appearances of p which are followed by disappearances of q within the next τ years in the same country and summed over all countries, i.e. $P_{AD}^{(\tau)}(p,q) = \sum_{c,t} \sum_{t'=t+1}^{t+\tau} A(p,c,t)D(q,c,t')$. This number can be

compared to the count of appearances of product q followed by disappearances of p , i.e. we exchange the roles of p and q . If there an asymmetry emerges when exchanging p and q in $P_{AD}^{(\tau)}(p,q)$, this indicates that p appearing before q disappears is observed more often than the other way around. In this spirit, for each product p a time-lagged *SPI* is defined as

$$SPI_{AD}^{(\tau)}(p) = \frac{1}{\mathcal{N}} \sum_q [P_{AD}^{(\tau)}(p,q) - P_{AD}^{(\tau)}(q,p)], \quad (6)$$

This index is within the range $(-1, +1)$. Intuitively, if one thinks of the appearance of p followed by disappearance of q within a country as a replacement, a positive value of $SPI_{AD}^{(\tau)}(p)$ means that, on average, p replaces more often any other product q than p itself is replaced by q . The higher the $SPI_{AD}^{(\tau)}(p)$ value for p , the higher the tendency that p can act as a substitute for other products.

For the purpose of statistical analysis we construct a surrogate dataset with the aim to destroy the correlations in the timing of (dis)appearances while the event statistics (as shown in Fig.1 (d) and (e)) are preserved. The surrogate data is prepared as follows. Each event is given by a triplet (p_i, c_i, t_i) where index i runs over all appearance (disappearance) events in the data. For each i we fix p_i and c_i while shuffling the years t_i between the events in the triplets. Formally this defines a random permutation $\mathcal{P} : \{i\} \mapsto \{i\}$ over the set of all event indexes i . One may then calculate the co-occurrence measures from the triplet $(p_i, c_i, \mathcal{P}(t_i))$ and average the result over many realizations of \mathcal{P} . This ensures that the marginal distributions of the events (Fig. 1 (d) and (e)) remain unchanged

while all correlations in the timing of appearances or disappearances are destroyed.

Results

Products Appear in Bursts

In Fig. 2 we show the maximum spanning tree for products obtained from the pairwise conditional co-appearance measure, $\bar{P}_{AA}(p,q)$. This allows to construct similarity matrices for product categories from which the maximum spanning tree, shown in Fig. 2, is constructed (see Text S3). Nodes in the network represent product categories according to the SITC rev.2 4-digit classification. The color of the nodes represents the products' Leamer classes [16]. This is a classification based on relative factor intensities such as amount of capital, labor, land, skills etc. A similar visualization route has been followed to construct the product space [17]. Fig. 2 suggests that the clusters of co-appearing products require one or several common capabilities. Once a country acquires or upgrades these capabilities, it starts to report exports in these product categories. Their appearances are simultaneously observed as a creative burst within the same Leamer class. Some of these clusters are highlighted in Fig. 2 and point at a non-random structure in product co-appearance dynamics.

To make this structure explicit we compare $SPI_{AA}^0(p)$ values for trade and the surrogate data, see histogram in Fig. 3(a). A huge difference between trade and surrogate data is found. This indicates the presence of strong temporal correlations between individual product appearances. Products appear simultaneously in bursts. A way to interpret this is that the co-appearing products require a common capability to be manufactured. When a national economy acquires this capability the corresponding cluster of products can appear. In this sense the observation of a newly emerging cluster of inter-related products serves as a proxy for a country's development of a novel capability. This process is not unique within a given country, it can be observed in a substantial fraction of them (since the indicator values are averages calculated over more than one hundred countries). This may hint at common patterns in the diversification trajectory of individual national economies.

Creative Destruction at Work

There is a tendency for specific products to substitute or replace others. This can be seen as deviations in the distribution of indicator values $SPI_{AD}^{(\tau)}(p)$ between world trade and surrogate data, see Fig. 3(b). A high value of $P_{AD}^{(\tau)}(p,q) - P_{AD}^{(\tau)}(q,p)$ corresponds to the dominance of the pattern: 'product p appears and q disappears later in the same country' in a large number of them independently. This is a direct fingerprint of creative destruction at work, i.e. emerging industries pushing out the old. It is interesting to note that the opposite process – the disappearance of a product is followed by the appearance of another one – is not observed to a significant extent, see Figs. S2 and S9. For the DA case surrogate and data SPI s are practically identical. To measure the statistical significance of deviations from the surrogate data we formulate the null hypothesis that both surrogate and trade data are drawn from a normal distribution with the same mean. The p -value using the alternative hypothesis that the trade data shows a higher mean than the surrogate data is computed for all four possible combinations: AA , AD , DA , and DD . The results are listed in Table 1, together with p -values from various robustness tests as described in Text S2. This series of tests confirms that the results above are not a consequence of trivial effects such as fluctuations in the trade records (case ' $\theta = 200$ k USD'), the

artificial creation of product categories due to changes in reporting schemes ('all products with positive exports') or the transition out of communism of former Soviet countries ('Excl. FSU'), see Text S2. Results are also robust with respect to changes in the time-period ('1989–2000'), the choice of the maximal lag τ (' $\tau = 5$ ', ' $\tau = 7$ ') or the underlying dataset ('UN Comtrade data', [18]).

Progress has a Direction

Is it true that more complex products replace less complex ones? Do products produced by richer countries replace products associated with poorer ones? To elucidate this, we quantify the change in complexity and income levels associated with individual AD processes via a set of product indicators.

Product income indicator PRODY. This indicator for a given product is the weighted average of the per capita GDPs of countries exporting it. It is a weighted average of the income per capita of the countries that have revealed comparative advantage in that product [19]. A more sophisticated product, in principle, should be made by richer countries. Let us define the difference in $PRODY$ for products p and q as $\Delta PRODY(p,q,\tau) = PRODY(p| \text{ appears at } t) - PRODY(q| \text{ disappears at } t')$ with $t < t' \leq t + \tau$.

Product complexity indicator. The Product Complexity Index PCI is an indicator for the economic complexity involved in manufacturing a given product [20]. The PCI is a combination of the ubiquity of a product (i.e. the number of countries that make it) and the economic diversity of its exporting countries, see Fig. S3 for more details. Products with high PCI typically are made by few highly diversified countries which is indicative of high economic complexity [7]. The change in complexity $\Delta PCI(p,q,\tau)$ between two products is given by $\Delta PCI(p,q,\tau) = PCI(p| \text{ appears at } t) - PCI(q| \text{ disappears at } t')$, $t < t' \leq t + \tau$. A comparison between $PRODY$ and PCI values for each country is shown in Fig. S3.

Killer index. We refer to $KI(p) \equiv SPI_{AD}^{(\tau)}(p)$ as the 'Killer Index' for each product p . It measures the likelihood that the appearance of a given product p is observed with the disappearance of any other product in the next τ years.

Extinction index. The likelihood that a product disappears together with the appearance of any other product τ years earlier is expressed by its 'Extinction Index' $XI(q) = \sum_p P_{AD}^{(\tau)}(p,q) - P_{AD}^{(\tau)}(q,p)$. We set $\tau = 3$.

The creative destruction dynamics is dominated by products with a high value of $KI(p)$ or $XI(q)$. $\Delta PCI(p,q,\tau)$ and $\Delta PRODY(p,q,\tau)$ are thus measured for each AD process with $\tau = 3$, where the appearing (disappearing) product has one of the hundred highest values of $KI(p)$ ($XI(q)$). A positive ΔPCI indicates an increase in economic complexity of the country where this AD process was observed. A positive $\Delta PRODY$ indicates that the country is upgrading its exports towards those made by richer countries. Histograms for ΔPCI and $\Delta PRODY$ are shown in Fig. 4. There is a clear skew to the positive side for both quantities. Products with a higher tendency to be pushed from the market have in general lower economic complexity than products from appearing industrial branches.

One could imagine that this effect is stronger in emerging economies than in mature ones. To test this, one can compare ΔPCI and $\Delta PRODY$ distributions for different economies by aggregating the countries into seven regions (Latin America and the Caribbean, East-Asia and the Pacific, Middle-east and North-Africa, Sub-Saharan Africa, South-Asia, Western Europe and Northern America, Eastern Europe), as done in Figs. S4 and S5. A clear development towards higher economic complexity can be seen for Latin America, Eastern Europe and East Asia & Pacific.

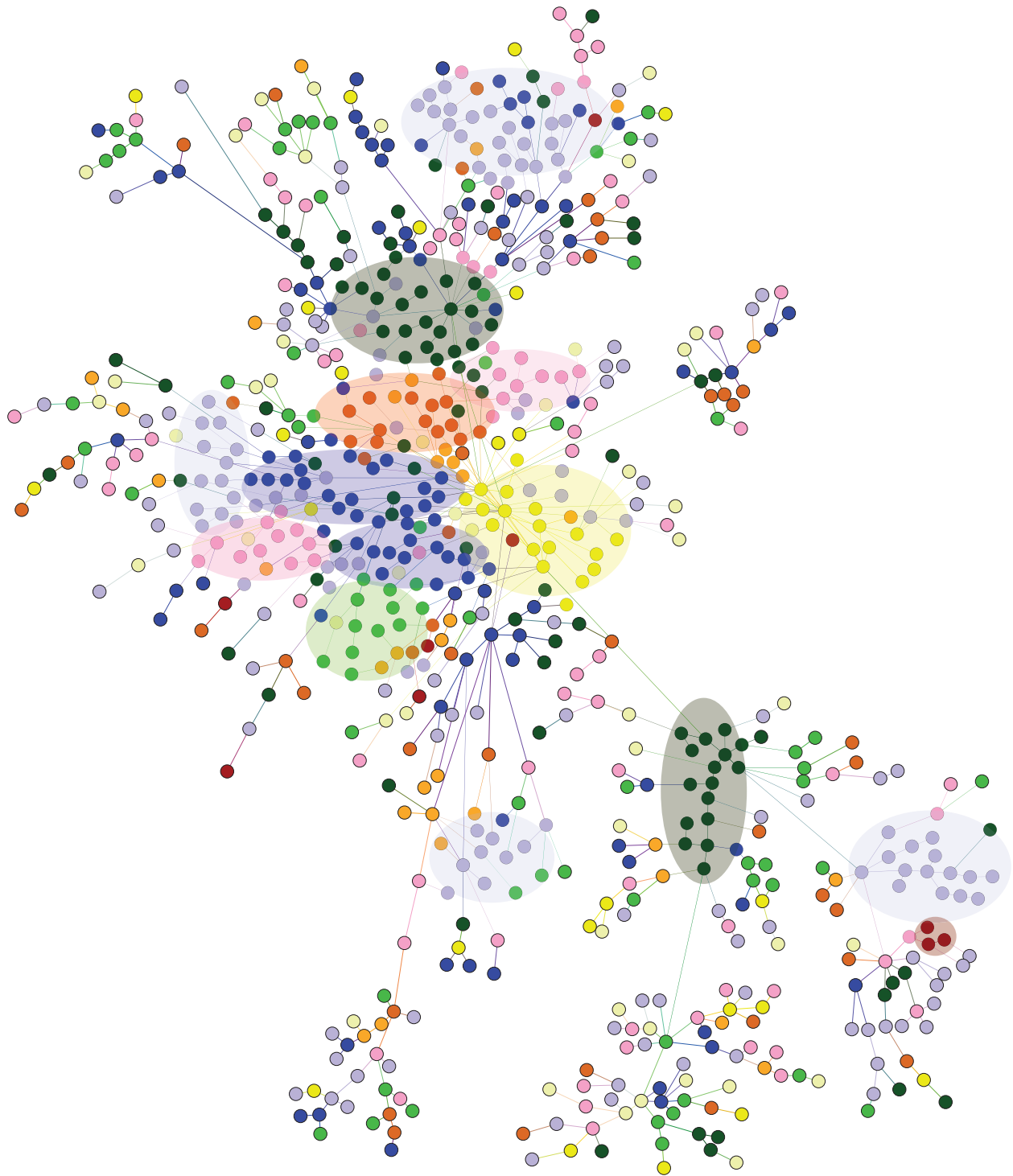


Figure 2. Maximum spanning tree for the network given by the co-occurrence measure $\hat{P}_{AA}(p,q)$. Some of the clusters of co-appearing products are highlighted as guides to the eye. It is suggested that these clusters of products require a common capability before they can be exported. Once a country acquires all of these capabilities, a creative burst of novel products which require them as input may be the consequence. doi:10.1371/journal.pone.0038924.g002

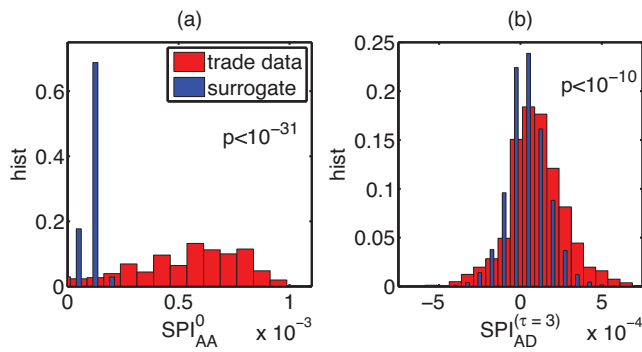


Figure 3. Histograms for Schumpeterian Product Index (a) $SPI_{AA}^0(p)$ for co-appearances AA , and (b) $SPI_{AD}^{(\tau=3)}(p)$ for $\tau=3$ years. SPI s are shown for the surrogate data (blue) and the trade data (red). The distributions for the trade data are significantly shifted to the right when compared to the surrogate data. The distribution in (a) suggests that products appear in bursts, while (b) implies that appearing products tend to drive other products from the market. doi:10.1371/journal.pone.0038924.g003

The other regions do not display such a strong trend. Western Europe and Northern America are already almost fully diversified and stay that way, whereas e.g. Sub-Saharan Africa stays in the low diversity regime. These results are discussed in more detail in Figs. S6, S7 and S8.

Which Products are the Killers?

Let us get a clearer picture about the products driving the creative destruction process. Are there Leamer classes whose products appear more often than others? Which types of products disappear instead? We consider the matrix $P_{AD}^{(3)}(p,q)$. Each product can be assigned to one of ten Leamer classes, labeled by $l_i, i \in \{1, \dots, 10\}$. One can obtain a measure for AD processes where products from class l_i appear and products from l_j disappear by computing the mean value of $P_{AD}^{(3)}(p,q)$ over all products from the respective Leamer classes. To this end $L(l_i, l_j) = \frac{1}{N} \langle P_{AD}^{(3)}(p,q) \rangle_{p \in l_i, q \in l_j}$ is defined. As before, we are only interested in the ‘net flow’ of AD processes, the antisymmetric Leamer transition matrix, $\Pi = L - L^T$. This is basically the same measurement strategy as discussed for $P_{AD}^{(\tau)}(p,q) - P_{AD}^{(\tau)}(q,p)$, however aggregated to the level of Leamer classes. The matrix is shown in Fig. 5.

A positive value of $\Pi(l_i, l_j)$ indicates that an appearance event of a product from class l_i followed by disappearance of a product

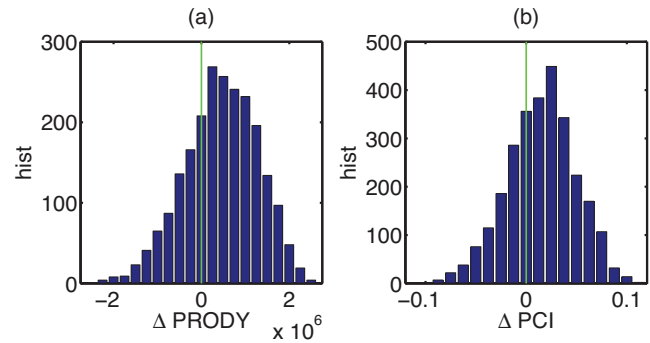


Figure 4. Histograms for change in (a) income level $PRODY$ and (b) product complexity PCI associated with individual creative destruction processes. There is a skew to the positive side in both of them, indicating that national economies are typically restructured into the direction of more complex and higher income products. doi:10.1371/journal.pone.0038924.g004

from l_j , is more often observed than an appearance from l_j followed by disappearance in l_i . Given that AD processes convey information about how national economies are re-structured over time, positive values in Π indicate which parts of the economy are abandoned or disappear because of which other parts. There is a clear trend. Capital and labor intensive products, as well as machinery and chemicals appear much more often than they disappear. Agricultural products and cereals tend to disappear. This intuitively confirms that markets re-structure themselves towards higher economic complexity, as measured by the PCI and observed in Fig. 4. Note that these observations can not be described by diffusion or migration processes of e.g. production facilities or capabilities from one country to another. Each measurement of appearances followed by disappearances takes place within a single country. A product appears within a country and another product disappears later within the same country.

A Simple Model

A recently introduced Schumpeterian diversity dynamics model [2] centers around the assumption that countries have an evolving set of capabilities which firms combine to manufacture products, see Text S5. The economic state of a country is represented by two (high-dimensional) binary vectors, one indicating whether a country has a given capability, the other indicating whether a country exports a given product. These vectors evolve over time in each country. Capabilities can be acquired through entrepreneurs who combine existing capabilities. For example, an existing

Table 1. p -values for $SPI_{XY}^{(\tau)}$ histograms from trade vs. surrogate data.

	$\tau = 3$	$\theta = 200$ k USD	all products with positive exports	cleaned data 1989–2000	Excl. FSU	$\tau = 5$	$\tau = 7$	UN ComTrade data
AA	0.98	1.00	0.93	0.96	1.00	0.94	0.84	1.00
DD	0.95	0.89	0.77	1.00	0.94	0.93	0.99	1.00
AD	$<10^{-10}$	$<10^{-6}$	0.0072	$<10^{-7}$	$<10^{-5}$	$<10^{-7}$	$<10^{-3}$	$<10^{-3}$
DA	0.02	0.11	0.53	0.01	0.40	0.08	0.12	0.081

The column ‘ $\tau = 3$ ’ lists the results as described in the main text. In addition, robustness tests were conducted with results listed in separate columns. ‘ $\theta = 200$ k USD’ uses the same set of countries and a threshold of 200,000 USD below which trade flows are ignored. In ‘all products with positive exports’ all products are included which have positive world exports in each year of the analysis. The column ‘1989–2000’ decreases the number of years included in analysis. Results excluding the FSU and CEE are listed in ‘Excl. FSU’. The maximal lag τ is then increased to $\tau = 5, 7$. The last column reports results using the UN ComTrade dataset, as described in Text S1. doi:10.1371/journal.pone.0038924.t001

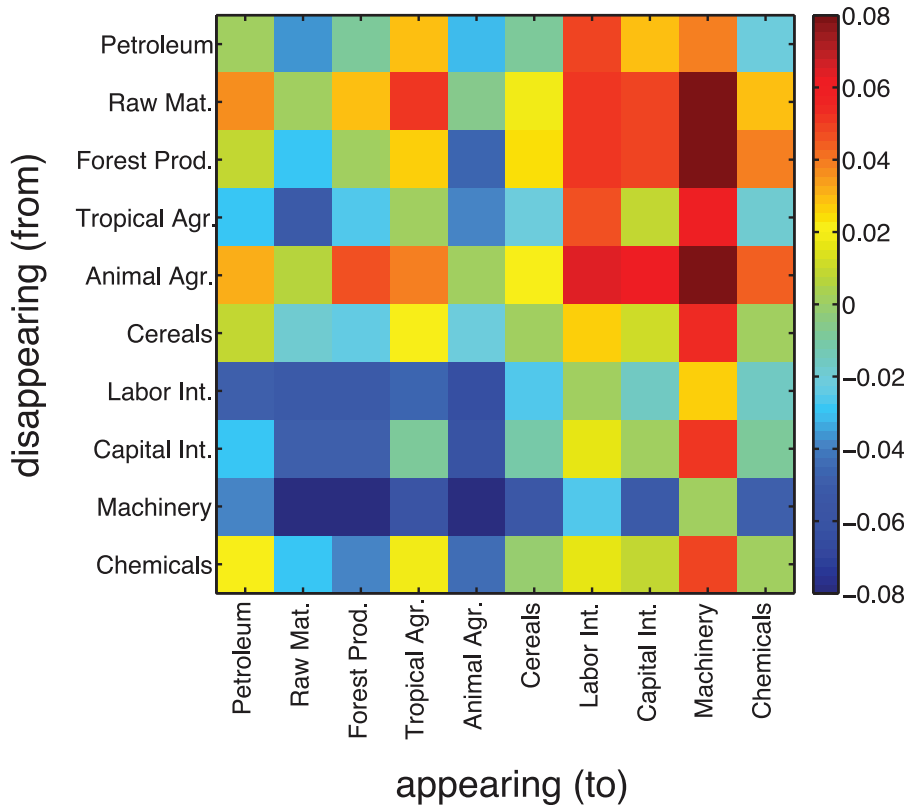


Figure 5. Transition matrix Π between Leamer classes. For each pair of classes (l_i, l_j) it is measured how often an appearance event of a product from class l_i is observed followed by a disappearance of a product from class l_j , compared to the opposite direction. Rows are indexed by the appearing Leamer classes l_i , columns by disappearing ones l_j . A positive value indicates an excess in creative destruction processes between the two classes (from row index to column index). The matrix is by construction anti-symmetric. There is a clear tendency of appearing labor and capital intensive products, as well as machinery and chemicals. Cereals or agricultural products tend to disappear. doi:10.1371/journal.pone.0038924.g005

production infrastructure and a certain type of knowledge stock can be combined to acquire an upgraded production facility. This scheme is shown in Fig. 6, where capabilities are represented by blue squares. In this case capability k is a combination (blue ellipse) of i and j . The model capability assumes that if a country has capability i and j , it will acquire k in the next time-step. Each country can in principle acquire the same number of N_A capabilities, endowed with the same set of combination rules. Each capability has on average r^+ ways by which it may be acquired through combination of two other capabilities (randomly chosen with equal probability).

Each product requires a set of capabilities in order to be produced. In the model a country exports a product if it has *all* necessary capabilities. The simplest possible case (one capability needed for one product) is shown in Fig. 6 where products are represented by red circles. Product p requires capability i , product q requires k . As soon as a country acquires k , it will start to report exports in q . Since one capability may be required for more than one product, all of these products may co-appear with q . In each country each product requires the same set of n_a randomly chosen capabilities.

Capabilities can also be lost or abandoned. There is a chance that q may act as substitute for p . In this case the acquisition of capability k renders i obsolete. With some probability p^- capability i is thus abandoned or destroyed because of k . As a consequence p will then no longer be exported. External events are modeled by assuming that in each time step each capability is lost

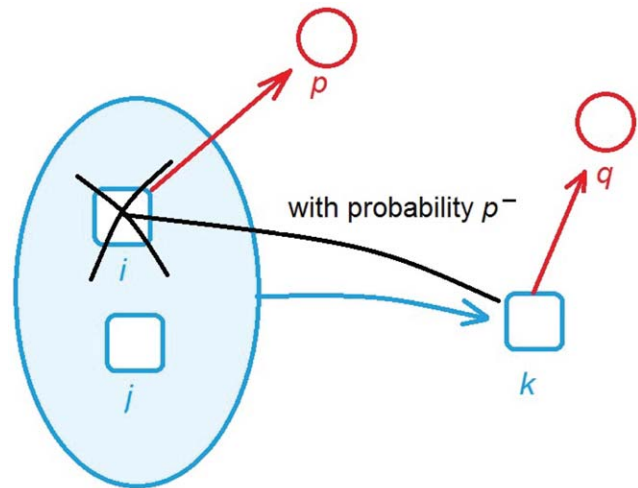


Figure 6. Illustration of the Schumpeterian diversity dynamics model. Capabilities are represented by blue squares, products by red circles. A country can acquire capability k by combining other capabilities i and j . Each product requires a set of capabilities to be produced, e.g. product p requires i and q requires k . There is a chance that a novel product q may act as a substitute for a product p which is made from a subset of capabilities required for k . In this case k may effectively ‘destroy’ its preceding capability i . doi:10.1371/journal.pone.0038924.g006

(acquired) with probability γ if it was previously existing (not existing).

In the model it is further assumed that the rules of how capabilities can be combined, substituted and used as inputs for products are identical in each country. Economies only differ by their initial diversity of products (from which the implied initial diversity of randomly assigned capabilities is calculated). The model is iterated until the number of model (dis)appearances matches the number of events observed in the trade data. The free model parameters are set to $r^+ = 1.65$, $p^- = 0.15$, $\gamma = 0.002$, $N_A = 100$, $n_d = 2$. All other model parameters can be measured in the data. The results reported are independent of N_A [21], and note that γ merely sets the time-scale. Fig. 1 shows a comparison of (a) initial and (b) final product diversity, (c) net diversity change and the number of appearances for each (d) country and (e) product for model and trade data. The complex observed patterns of creative destruction can be explained by the almost embarrassingly simple process of recombining and substituting capabilities. The crucial feature of the model is the existence of a creative phase transition with a position depending on the initial diversity [21,22] and on the parameters r^+ , p^- . If it is below a certain threshold, there are not enough capabilities available to find successful combinations of them. If a country is at, or above this threshold the creative destruction process kicks in, restructuring the market [2]. This way the model may explain why the whole world is not rich, i.e. the increasing differences in economic development between least developed and developed countries. For a complete model specification, including dynamical algorithm, see the Text S5.

Discussion

The main novelty of the approach in this article is to identify, in a large sample of countries, the existence of a systematic relationship between the appearance of new industries and the appearance or disappearance of other industries within the same country. In particular our analysis reveals that (i) products appear cluster-wise in creative bursts which consequently (ii) increases the chance for other, already existing products to be pushed from the market and (iii) the emerging products are typically associated with higher income and a higher level of economic complexity. The effect of shifting production towards higher complexity is strongest in the developing countries of Latin America, Eastern Europe and East Asia and Pacific and barely visible in the least developed countries or Europe and North America (see Text S4 and Fig. S4).

These observations can be explained within an evolutionary model of Schumpeterian economic dynamics [2]. Just as the product portfolio of countries can be explained as a consequence of the presence of productive capabilities in that country [8], changes in a country's product portfolio can be understood through the evolution of its capabilities. Entrepreneurs (firms) upgrade and recombine existing capabilities to create innovations. These may substitute existing industries, restructuring the market. Such a system can exist in three different modes [21,22]. First, if the initial number of capabilities is too low to allow for a sufficient number of novel combinations, the creative destruction process may not set in at all. Second, if the country is already fully diversified progress is also slowed down. In between these regimes there is a third, transition regime, where the creative destruction process is most effective. We calibrate the model with initial product diversities and (dis)appearance rates observed through world trade data, and can reproduce (i) the position of the transition regime from low to high diversity, (ii) the patterns of

(dis)appearance frequencies per country and (iii) the distribution of (dis)appearance frequencies for individual products.

Beyond finding evidence of creative destruction in a large set of national economies, this paper also helps to further reveal the complex topology of industry relatedness. Understanding the drivers of this topology is of the greatest importance for policies to accelerate the economic development of nations.

Supporting Information

Figure S1 Appearance and Disappearance events. Appearance and disappearance events in product p in country c are only included if the underlying diversity timeseries $\text{sgn}(x(p,c,t))$ is of one of the types (a)-(d). The time of the appearance event is then always the first appearance (green dashed line in (a) and (b)), disappearances are the last events (red dashed lines in (c) and (d)). (EPS)

Figure S2 Histograms for Schumpeterian Product Index. Histograms for Schumpeterian Product Index $SPI_{XY}^{(t)}(p)$ for co-appearances AA , co-disappearances DD , and the mixed forms AD and DA (from top to bottom) for maximal time-lag $\tau = 3$. The SPI is shown for the surrogate data (blue) and the trade data (red). A significant fraction of higher SPI values for the trade data are seen for appearance-disappearances. (EPS)

Figure S3 Comparison of PRODY and PCI values for each product category. The PRODY value was computed as in [19] using NBER trade data as an average over each PRODY from the timespan 1993–2000. To compute the PCI we extract the matrix of significant exporters M_{cp} as defined in [7] from the NBER trade data for each year from 1993–2000. Using $k_{c,0} = \sum_p M_{cp}$ and $k_{p,0} = \sum_c M_{cp}$ one computes the matrix $\tilde{M}_{pq} = \sum_c \frac{M_{cp} M_{cq}}{k_{c,0} k_{p,0}}$. The PCI is the average over all years of the eigenvector associated with the second largest eigenvalue of \tilde{M}_{pq} . These two indexes are related to each other. (EPS)

Figure S4 Regional developments in economic complexity. Histograms for change in (top row) income level $PRODY$ and (bottom row) product complexity PCI associated with each AD process for seven different world regions (Latin America and the Caribbean, East-Asia and the Pacific, Middle-east and North-Africa, Sub-saharan Africa, South-Asia, Western Europe and Northern America, Eastern Europe). There is a skew to the positive side most clearly visible for Latin America and the Caribbean, as well as for CEE countries. (EPS)

Figure S5 Development of economic complexity in Eastern Europe. Histograms for change in income level $PRODY$ and (a) product complexity PCI (b) associated with each AD process for Eastern European countries between 1984–1989, that is in a centrally planned economy. The development is more or less symmetric. Compare this to the clear positive skew in (c) and (d), where changes in $PRODY$ and PCI for the same countries between 1990–2000 are shown. This suggests that the increase in economy complexity observed there is due to the shift from planned to market economy. (EPS)

Figure S6 Number of appearances vs SCI for each country. This shows that SCI can not be explained by the number of appearances alone. Observe that e.g. Ecuador and Portugal have the same number of product appearances, but

Ecuador has one of the highest SCIs and Portugal one of the lowest.

(EPS)

Figure S7 GDP vs SCI for each country. Countries cluster into two distinct groups. Western countries are mostly found at the bottom right (low SCI and high GDP), poor countries to the bottom left (low SCI and low GDP), countries with high SCI form a bridge between those two regimes.

(EPS)

Figure S8 GDP vs average PRODY of products not being exported by this country. High GDP countries tend to *not* export products with a low PRODY, i.e. low economic complexity (upper left region of the plot). Low GDP countries miss products with a high PRODY in their export baskets, they are found in the lower right region. Oil exporting countries such as Qatar and the United Arab Emirates deviate from this trend. They achieve high GDP per capita values with significantly less complex products.

(EPS)

Figure S9 Histograms for Schumpeterian Product Index, excluding CEE. Histograms for Schumpeterian Product Index $SPI_{XY}^{(\tau)}(p)$ for co-appearances AA , co-disappearances DD , and the mixed forms AD and DA (from top to bottom) for maximal time-lag $\tau = 3$. Countries from the Former Soviet Union and Eastern Europe are excluded. The SPI is shown for the surrogate data (blue) and the trade data (red). A significant fraction of higher SPI values for the trade data are seen for appearance-disappearances.

(EPS)

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Text S1 A detailed description of the datasets used in this work, as well as the applied filtering and cleaning procedures.

(PDF)

Text S2 Further information on the robustness tests for statistical significance of product co-occurrences.

(PDF)

Text S3 Discussion of the properties of maximum spanning trees.

(PDF)

Text S4 More results and comparisons of different countries and world regions using the indicators discussed in this work.

(PDF)

Text S5 The properties of the Schumpeterian evolutionary model are discussed in greater detail, including the description of a dynamical algorithm for simulation purposes.

(PDF)

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Author Contributions

Conceived and designed the experiments: PK RH ST. Analyzed the data: PK RH ST. Contributed reagents/materials/analysis tools: PK RH ST. Wrote the paper: PK RH ST.