Empirical signatures of the evolution of technology from the Price equation

Alec Kosik, Alex Ledger, Jacob Menick, Zackary Dunivin,
Drew Blount, Norman Packard, Mark A. Bedau

Abstract

One of the controversial questions about cultural evolution is whether it is significantly shaped by Darwinian natural selection. We aim to shed some new light on this question with empirical measurements of the evolution of traits in a real cultural system: patented technology. We consider various definitions of patent traits, including *a priori* classifications such as USPTO technology classes, as well as statistically defined classes using a word2vec embedding of documents into a vector space. We define a parent-child network based on patent citations, and empirically quantify evolutionary properties of trait flow within this network using the Price equation, whose terms reveal the extent to which Darwinian selection is operative. We observe how, for a given trait, terms in the Price equation change over time, creating a Price signature for that trait. We compare Price signatures for different trait definitions, and begin the identification of structure in Price signatures. We find that Darwinian selection is sometimes strongly present, and sometimes not, in the roughly 5 million patent records we examine, spanning from 1977 to 2014.

Keywords: patents, patent record, Price equation, selection, evolution of technology

1 Introduction

Many people have wondered whether cultural evolution is significantly shaped by Darwinian natural selection. We provide new empirical measurements of the evolution of traits in one specific cultural context: patented technology. Our results demonstrate one way to quantify the selective and non-selective processes shaping the evolution of real cultural systems.

Many treatments of cultural evolution (**?**, **?**, **?**) focus on the beliefs, norms, institutions, etc. of populations of *humans* and explain the evolution of human culturally transmitted traits by a variety of processes, including the interaction between cultural and biological evolution. Like Basalla (**?**) and Brian Arthur (**?**), we put humans in the background, and instead put in the foreground the cultural *artifacts* themselves. Our specific focus is *patented inventions*, which are one specific part of human culture.

Patented inventions exist only because of humans. Inventions are created through a complex social and cultural process that involves a network of interactions among a great many people, including inventors, designers, producers, consumers, users, suppliers, lawyers, patent examiners, among others. All of these people affect the evolution of patented inventions. At the same time, those humans are themselves affected by many non-human environmental factors, such as economic conditions, supply of components and other resources, technological facility, weather, among many other things. We view humans as part of the complex social and cultural background environment that shapes (and is shaped by) the evolution of technology. In the foreground are the cultural artifacts themselves. We ask what can be learned about the evolution of traits in patents merely from information about the patents themselves.

We study patented inventions by means of a proxy: the first page of the invention's patent record, which contains the patent's title, abstract, issue date, prior art (i.e., the earlier patents it cites), and other important kinds of information. The patent record is an extensive accurate and systematic information about every single patented invention. This extraordinary historical record of new inventions makes it relatively easy to demonstrate and document our methods, but our methods should apply to cultural sources that generate much less uniform and accurate information (e.g., social media feeds like Facebook and Twitter).

A complete and accurate patent citation network can be reconstructed from the citations in the patent record, and we will freely interpret the citation network as a patent genealogy. New patents cite the earlier patents on which they depend and build. We interpret these citations as a reflection of the new patent's "parentage" or immediate ancestry, and call the citing patent a "child" of the cited patent, which we call a "parent" of the citing patent. An invention shares traits with its parents, and we think of these shared traits as "inherited" from the parents even though the mechanism behind a patent sharing traits with its prior art differs from the mechanism behind a biological child sharing traits with its parents. Below we will consider two different ways of defining a patent's traits, one based on classification of a patent (using USPTO categories), and another based on a statistical analysis of the text in the patent's title and abstract, aiming to extract semantic content containing each patent's important technological characteristics.

Figure 1 shows a small part of the genealogy of the patent for bubble-jet printing, to illustrate the intuitive appeal of using the citation network to define a network of parent-child relationships through which traits flow. The nodes are patents, and links are citations (note that only patents receiving at least 30 citations are included in the figure). Nodes and links are colored to reflect the technological traits that characterize each patented invention; we can see that the bubble-jet family tree has sub-families that focus on different kinds of technologies. The distribution of traits (colors) across the genealogy shows the evolution over time of the traits in the population. The present paper presents a quantitative empirical description of the evolution of technology, based on a statistical analysis of how traits flow from parents to children.

After defining a parent-child network based on patent citations, we will quantify evolutionary properties of trait flow within this network using the Price equation, which gives a breakdown of evolutionary changes in trait expression into three components, each of which may be estimated directly from the data. These terms are conventionally interpreted as revealing the extent to which different transformational forces are acting in evolution. In particular, one of the terms is conventionally taken to indicate the degree to which Darwinian selection may be operative. Before making such inferences, however, it is important to realize their limitations: The terms are computed by direct statistical estimation from the data, without reference to the particular mechanisms that produce the statistical results. We know, however, that actual mechanisms for technological evolution result from a complex interactions between people, technologies, corporations, etc., and

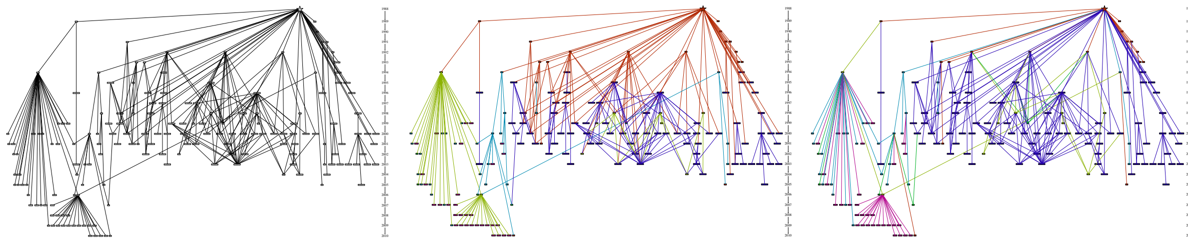


Figure 1: Partial genealogy of US patent number 4723129, entitled "Bubble jet recording method and apparatus in which a heating element generates bubbles in a liquid flow path to project droplets". Nodes are patents, and links are citations between patents. Time flows down the page. The genealogy depicts only the following small subset of the patents in the genealogy: (i) only direct descendants of patent 4723129, (ii) only descendants within four (CHECK) generations of patent 4723129 (great, great grand children or more recent), (iii) only those descendants that themselves receive at least 30 citations. The center and right figures are colored using traits defined by patent category. The center figure shows nodes (and links above them) are colored according to the parent patent's trait. The right figure shows nodes and links colored by the child patent's trait.

that such complexities may have an effect on the statistics we measure. A complete understanding of mechanisms that produce the measurements would require a complete understanding of these complexities. We will, for example, indicate that a certain measurement might indicate Darwinian selection is operative, but we do so only with the recognition that other complexities might affect the measurement as well. In the present work we do not attempt to understand mechanisms, to pin down the causal sources of the measurements. The current work should, however, serve as a starting point for such endeavors, yielding indications for complex interactions between patents that will affect statistical measurements. These difficulties are not unique to our study of the evolution of technology; any discussion of evolutionary dynamics in terms of statistically measured quantities suffers the same limitation, whether for technology, biology, or any other evolutionary context.

1.1 Patent traits

Intuitively, we would like a patents traits to comprise a good characterization of the patented technology. We will consider two ways of defining traits: the first uses patent classifications, and the second uses statistically derived quantities computed from the relative distributions of words in the patent titles and abstracts. Formally, we will consider traits as real valued maps on patents. For the case of traits as classification, the trait value will be an integer labeling one of the classes. For the case of statistical traits, the trait value is a real number that may be computed from the patent title and abstract text as described below.

Classification defined traits: There are several classification schemes for patents; we use the USPTO classification codes. Each patent is assigned one or more codes, and in the case that a patent is assigned more than one code, one of its codes is designated as the *leading code*. For work presented here, we consider only the leading code, but our formalism generalizes straightforwardly to multiple codes. Each code specifies a range of detail, with 454 classes defined, $\sim$16,000 subclasses, and $\sim$150,000 finer grained classes. In this work, we consider only the class level classification. From this, there have been coarser-grained classifications developed for the National Bureau of Economic Research (Hall et al. (2001)), in particular, six categories and 37 subcategories. The six general categories are: Chemical, Communication and Computers, Electrical and Electronic, Mechanical, Drugs and Medical, and Others. The Others category is a grab-bag of subcategories (Agriculture, Husbandry, Food; Amusement Devices; Apparel & Textile; Earth Working & Wells; Furniture, House Fixtures; Heating; Pipes & Joints; Receptacles; and Miscellaneous–Others) and we omit it in our investigation. To summarize: in the present study, we will define traits with respect to three classification levels. In order of decreasing level of detail, they are classes, subcategories, and categories.

Statistically defined traits: Statistically defined traits seek to extract semantic content from a document consisting of a patent's title and abstract, within a corpus consisting of all such documents. If a statistical measure is successful, the semantic content by the statistical measure should do a good job of characterizing the patented technology. One approach for quantifying the intrinsic relevance of particular words (more properly, word stems) w in a document is to compute the relative frequency of a word in the document, weighted by the logarithm of the inverse of the frequency of the word's occurrence in documents throughout the corpus. This statistic is called *term frequency - inverse document frequency*, or tf-idf score of a word w in a given document D:

$$\text{tf-idf}(w, D) = \frac{n_w}{N_D} \times \log(\frac{N_C}{n_d})$$

where n_w is the number of times the word occurs in a document, N_D is the number of words in the document, n_d is the number of documents that contain the word, and N_C is the total number of documents in the corpus. Note that the tf-idf score of a word is document specific, it typically changes across documents. We define a patent's tf-idf traits as the words with the top ten tf-idf scores.

A series of improvements on tf-idf statistics have been made, culminating in the current state of the art, *word2vec* (Mikolov et al. (2013)), an algorithm based on neural networks that are trained to embed words in a high dimensional space, such that clusters in the space correspond to a linguistic context. Each document may then be assigned traits consisting of distances to the different clusters. We will simplify further, and assign to each patent a single trait that is the nearest word2vec cluster.

2 Formalism for hyper-parental evolution

Cultural populations differ from biological populations in many important ways. One of them is the *hyper-parental* quality of cultural populations. While the entities in biological populations typically have only one or two immediate parents, the cultural entities typically have many more immediate parents. If we equate a patent's prior art with its immediate "parents," Figure 2 shows that patented technology is certainly hyper parental. The majority of patents have more than two parents; many have over a dozen parents and the truncated tail of the distribution contains a few patents with thousands of parents. This hyper-parentality of the patent citation network is a dramatic contrast to the uni- or bi-parental lineages typical of biological genealogies. This makes empirical measurement of the hyper-parental evolution of technology traits especially important.

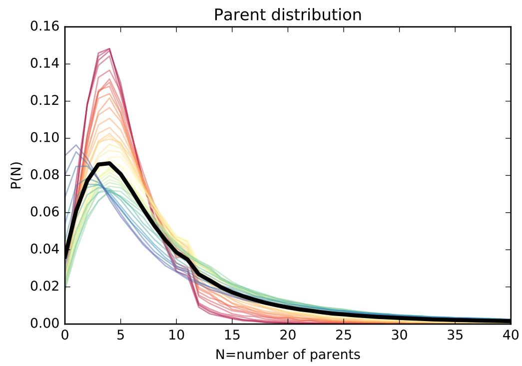


Figure 2: Illustration of hyper-parental nature of patents: probability of having N parents for $1 \leq N \leq 40$. $P(N)$ computed for patents in each year is shown in color, ranging from red to purple, for years 1976-2014. $P(N)$ computed for all patents in that time span is shown in black. Note that hyper-parentality of patented technology is evident by the bulk of patents having many more than two parents.

Our formalism for evolution in hyper-ancestral populations follows Kerr and Godfrey-Smith **?**, adapted to the present context of patent citation networks. We typically follow Kerr and Godfrey-Smith in speaking generally of *ancestors* and *descendants*, but all ancestors are immediate ancestors or parents (cited patents), and all descendants are immediate descendants or children (citing patents).

Mathematical formalisms for evolution typically consider a moment in time, t, with descendants being all offspring immediately after t, and ancestors being the parents that existed before t to produce those offspring. We will chunk the data by years, so t is a year; we use data from 1976 through 2014. We will consider a generation of patents to be all those granted in a particular year, and we will refer to them as the population of descendants, P_d^t. The population of ancestors, P_a^t, is the set of patents cited by all patents in P_d^t. (When convenient, we will drop the explicit t dependence.) We let $n_a = \#(P_a)$ and $n_d = \#(P_d)$. One slight quirk that comes from chunking the data by year is that a given descendant patent in a given year might also be an ancestor for a patent in that same year. In other words, $P_a^t \cap P_d^t \neq \Phi$, typically. The population of potential ancestors grows each year to include the new descendant population, so that $P_a^t \subseteq P_d^t \cup P_d^{t-1} \cup \ldots$

Figure 3 is a schematic showing successive stages in the evolution of a tiny population of patents, highlighting the descendant population for a given year, P_d, in blue and the ancestral population, P_a, in red. A patent never "dies" but remains in the population forever; however, a form of death consists of a patent never having children (never being in any P_a). As noted in the text, it is is possible to have a red ancestor among the blue descendants.

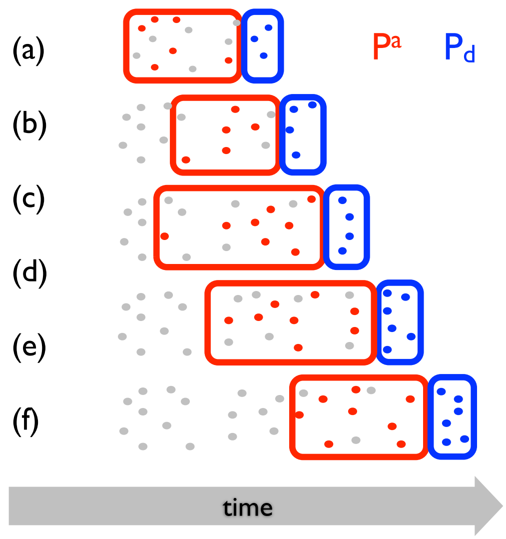


Figure 3: A schematic representation of a small population of patents growing over time (dots are patents). Five successive stages in the evolution of the patents are depicted by (a)-(e), and the ancestral (red) and descendant (blue) populations at each stage are indicated. The Price equation indicates the strength of selective and non-selective components of the total change in a trait X between ancestors and descendants, in these successive pairs of ancestral and descendant populations.

2.1 The ancestor-descendant connection matrix

A number of useful statistics for describing the evolution of hyper-parental population are defined using an ancestor-descendant matrix: an $n_a \times n_d$ boolean matrix, C, that records exactly which ancestral patents i are cited by descendant patents j:

$$C^i_j = \begin{cases} 1 & \text{i is cited by j} \\ 0 & \text{otherwise} \end{cases}$$

The indices i and j range over patents (entities) in populations P_a and P_d. The matrix C is an indicator function filled with 1's and 0's, and the 1's indicate exactly which connections link P_a and P_d. If i is cited by j then i plays some role in producing j.

From C a number of useful statistical quantities can be calculated from an ancestor-descendant matrix, C. $C^*_* = \sum_{i=1}^{n_a} \sum_{j=1}^{n_d} C^i_j$ is the total number of citations (production connections) between ancestors and descendants, i.e., the total number of links in the network connecting P_a and P_d. All of these statistical quantities are implicitly assumed to be indexed to the time between t^a and t_d: here, the year in which a new descendant population of patents is issued.

Focusing on ancestors, $C^i_* = \sum_{j=1}^{n_d} C^i_j$ is the "hit" count (number of citations, or descendants) of ancestor i, i.e., the number of entities in P_d that cite ancestor i (the number of potential information receivers from i). C^a_* is the hit counts (citations received) for all ancestors. This 1-dimensional vector has instances like C^i_*, and it is created by summing counts across all the columns in C (descendants). $\tilde{C}^a_* = C^a_*/(C^*_*/n_a)$ is the 1-dimensional vector of *relative* hit counts, expressed in units of (divided by) the average number of connections (descendants) per ancestor.

Analogously focusing on descendants, $C_j^* = \sum_{i=1}^{n_a} C_j^i$ is the "prior art" (ancestor) count of j, i.e., the number of patents in P_a that are cited by descendant j. C_d^* is the vector of prior art counts (total number of ancestors) for all descendants. This 1-dimensional vector has instances like C_j^*, and it is created by summing counts across the rows (ancestors) in C. $\tilde{C}_d^* = C_d^*/(C_*^*/n_d)$ is the 1-dimensional vector of *relative* hit counts, expressed in units of (divided by) the average number of connections (ancestors) per descendant.

2.2 The Price equation applied to the evolution of technology traits

In this section we will first frame the discussion assuming a particular year, eliminating reference to t in the notation, and then at the end we will add t dependence when we describe the presentation of the data. Every patent i has trait X_i (X_i can be a vector of several traits, but to keep the exposition simple, we will consider a single scalar trait). We will let X_d denote the vector of n_d descendant traits, $X_d = \{X_i | i \in P_d\}$, and X^a denote the vector of n_a ancestor traits, $X^a = \{X_i | i \in P_a\}$. Then $\overline{X_d} = \frac{1}{n_d} \sum_{i \in P_d} X_i$ is the average character value in the descendant population P_d, and $\overline{X^a} = \frac{1}{n_a} \sum_{i \in P_a} X_i$ is the average character value in the ancestor population P_a.

The evolution of a trait X, $\Delta\overline{X}$, is defined as the change in average X value between the ancestral population P_a and the descendant population P_d:

$$\Delta\overline{X} = \overline{X_d} - \overline{X^a}$$

The Price equation describes this difference, ΔX, as a sum of three terms, each of which captures a different aspect of trait flow in evolutionary dynamics. Kerr and Godfrey-Smith (2009) derive a *Generalized Price Equation* (GPE) that handles descendants with variable numbers of ancestors (patents that cite different numbers of prior patents), and is hence appropriate for the hyper-parental ancestry of the patent population. They express ΔX in terms of the connection matrix C_j^i and trait vectors as follows:

$$\Delta\overline{X} = \text{cov}(\tilde{C}_*^a, X^a) + \Delta X_d^a - \text{cov}(\tilde{C}_d^*, X_d), \qquad (1)$$

where ΔX_d^a is the *average change* in X from ancestors to descendants,

$$\Delta X_d^a = \frac{1}{C_*^*} \sum_{i=1}^{n_a} \sum_{j=1}^{n_d} C_j^i \Delta X_j^i,$$

with the average is taken over all descendent-ancestor connections defined by the ancestor-descendant connection metrix C_j^i, and with $\Delta X_j^i = X_j - X^i$, the change in X value between a specific ancestor, i, and one of its descendants, j.

The covariance between an ancestor's X value and its relative descendant count, $\text{cov}(\tilde{C}_*^a, X^a)$, and the covariance between a descendant's X value and the relative ancestor count, $\text{cov}(\tilde{C}_d^*, X_d)$ measure the relation between a patent's traits and the number of its ancestors (hits) or descendants (prior art). The covariances and averages are defined in the standard way for real-valued random variables X and Y: $\text{cov}(X, Y) = \text{ave}[(X - \text{ave}(X))(Y - \text{ave}(Y))] = \text{ave}(XY) - \text{ave}(X)\text{ave}(Y)$.

The GPE describes the amount of evolutionary change in trait X over one year as separated into three terms:

- The ancestor covariance term, $\Delta_{\text{selection}} \equiv \text{cov}(\tilde{C}^a_*, X^a)$, is the total change due to X's differential splitting (fecundity, divergence, descendant number). Classic discussions of the Price equation describe this term as measuring the effect of "selection." If the ancestor covariance term is positive, then X is rising in part because ancestors with higher X values have more descendants. A classic mechanism that produces this statistical signature is positive selection for trait X. If this term is negative, then X is falling because ancestors with higher X values have fewer descendants. This is the classic sign of negative selection against X. An ancestral covariance value that hovered around zero is the classic sign of the absence of selection for or against the trait.

- The average change term, $\Delta_{\text{transformation}} \equiv \Delta X^a_d$, is the total change due to differential production bias (differential "transformation") to trait X, e.g., mutation or inheritance biased toward X. If this term is significantly positive (negative), then X is changing up (down) in part because of a bias that tends to raise (lower) X values in children compared to their parents.

- The descendant covariance term, $\Delta_{\text{convergence}} \equiv \text{cov}(\tilde{C}^*_d, X_d)$, is the total change due to X's differential merging ("convergence", parent number). One form is differential innovation of descendant traits, e.g., parentless innovations ("migrants") biased to certain traits. Another form is differential "dilution" of ancestor traits due to different parent numbers. If the descendant covariance term is significantly positive (negative), then X is rising (falling) in part because descendants with high (low) X values have fewer ancestors.

Ancestor covariance (differential child number, or differential splitting of lineages) is interpreted as the magnitude of Darwinian selection for X, $\Delta_{\text{selection}} \equiv \text{cov}(\tilde{C}^a_*, X^a)$. Accordingly, the remainder of the total change in X between ancestors and descendants, $\Delta_{\text{non-selection}} \equiv \Delta\overline{X} - \text{cov}(\tilde{C}^a_*, X^a) = \Delta X^a_d - \text{cov}(\tilde{C}^*_d, X_d)$, is interpreted as the magnitude of all non-selective processes. The Generalized Price equation divides this total non-selective change between two different processes: differential transformation, ΔX^a_d, and differential parent number (merging), $\text{cov}(\tilde{C}^*_d, X_d)$. Note that the descendant covariance term is *subtracted* in the Price equation; this means that raising the descendant covariance *lowers* the fraction of evolutionary change due to selection.

An essential feature of the Price equation as expressed in Eq. 1 is that *each of the three terms may be estimated directly from the data* for the population of patents. Biological data does not have the same rich specificity, and therefore empirical explorations of the Price equation have not been possible.

3 Results: dynamics of Price statistics – IN PROGRESS

We observed the terms in the Price equation in six NBER technology category traits: Chemical, Computer and Communication, Drugs and Medical, Electric and Electronic, Mechanical, and Other. Each trait was defied operationally in two ways: using UCPTO class assignments and word2vec semantic cluster proximities.

Figure 4 shows what the Price statistics would look like for a neutral dichotomous trait (whether a patent number is odd or even). The size of fluctuation in these statistics the variation that can be expected in Price statistics just due to noise alone. The size of these fluctuations show the rough size of the error bars to be depicted on subsequent Price statistics time series plots.

The next set of Figures compares a given statistic for all six traits. Figure 5 shows average trait values $\overline{X}$ in ancestral and descendant populations for the six NBER technology category traits. Figure 6 shows ΔX (Total Change) for the same traits, and T1 (Selection Change) and T2-T3 (No-Selection Change) for the same traits are shown in Figure 7 shows and Figure 8.

The final set of figures collects all the statistics for each trait. $\Delta\overline{X}$ (Total Change), T1 (Selection Change), and T2-T3 (No Selection Change) are all shown for the Chemical trait in Figure 9, and the same set of Price statistics for the other five traits are shown in Figure 10 (Computers and Communication), Figure 11 (Drugs and Medical), Figure 12 (Electric and Electronic), Figure 13 (Mechanical), and Figure 14 (Other).

There are some striking patterns evident in these data.... TO BE CONTINUED LATER.

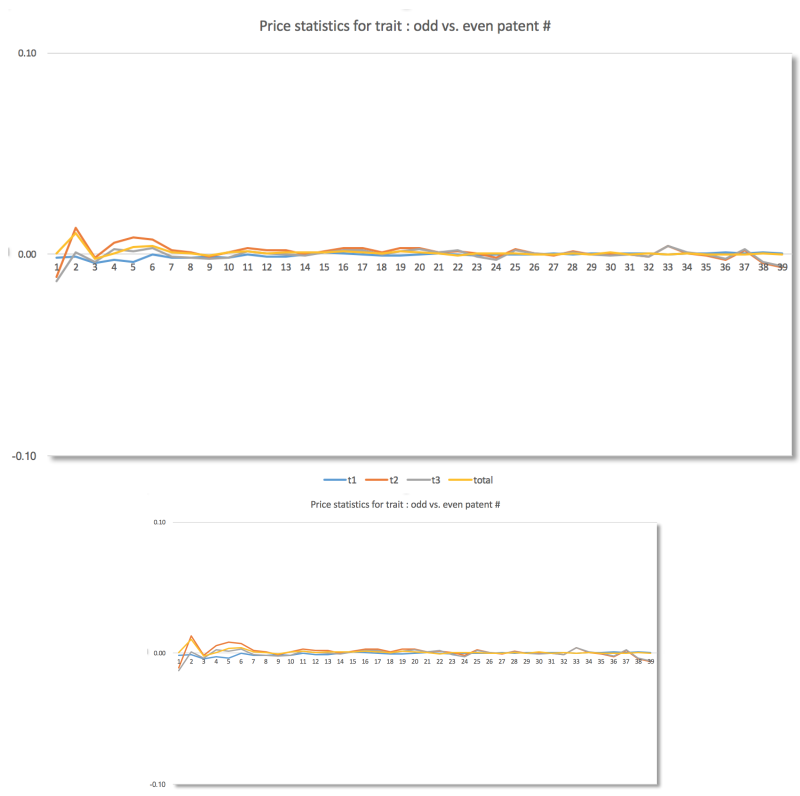


Figure 4: Price statistics for a neutral trait control (odd vs even patent number). These statistics indicate the size of fluctuation that can be expected in Price statistics just due to noise alone. Note that the scale on the y-axis is the same as that used on all subsequent Price statistics time series plots, and the physical size of the two plots matches the size of the subsequent plots of Price statistics.

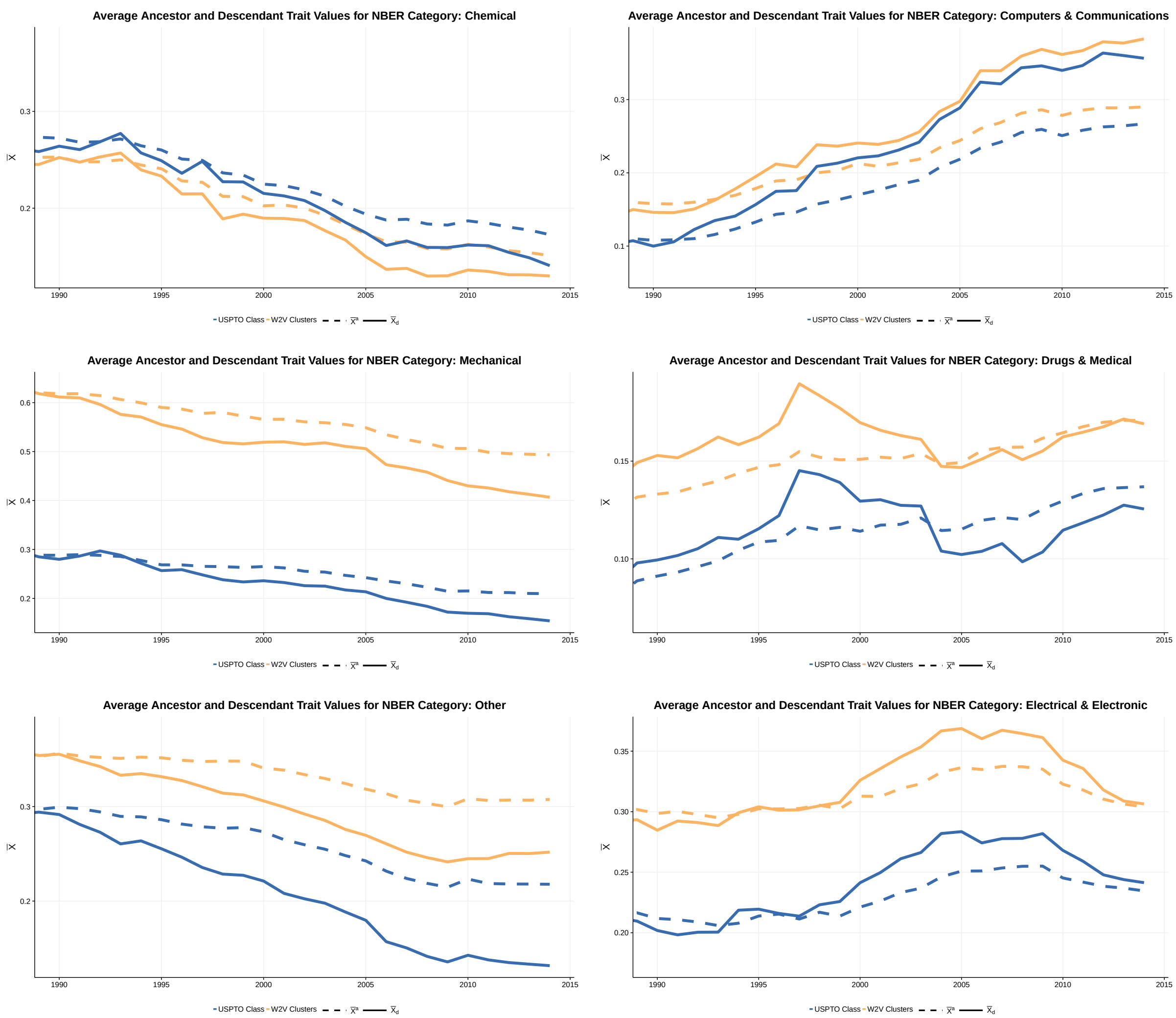


Figure 5: Average trait values $\overline{X}$ (USPTO classes and word2vec clusters) in ancestral and descendant populations for NBER technology category traits: Chemical, Computer and Communication, Mechanical, Drugs and Medical, Other and Electric and Electronic.

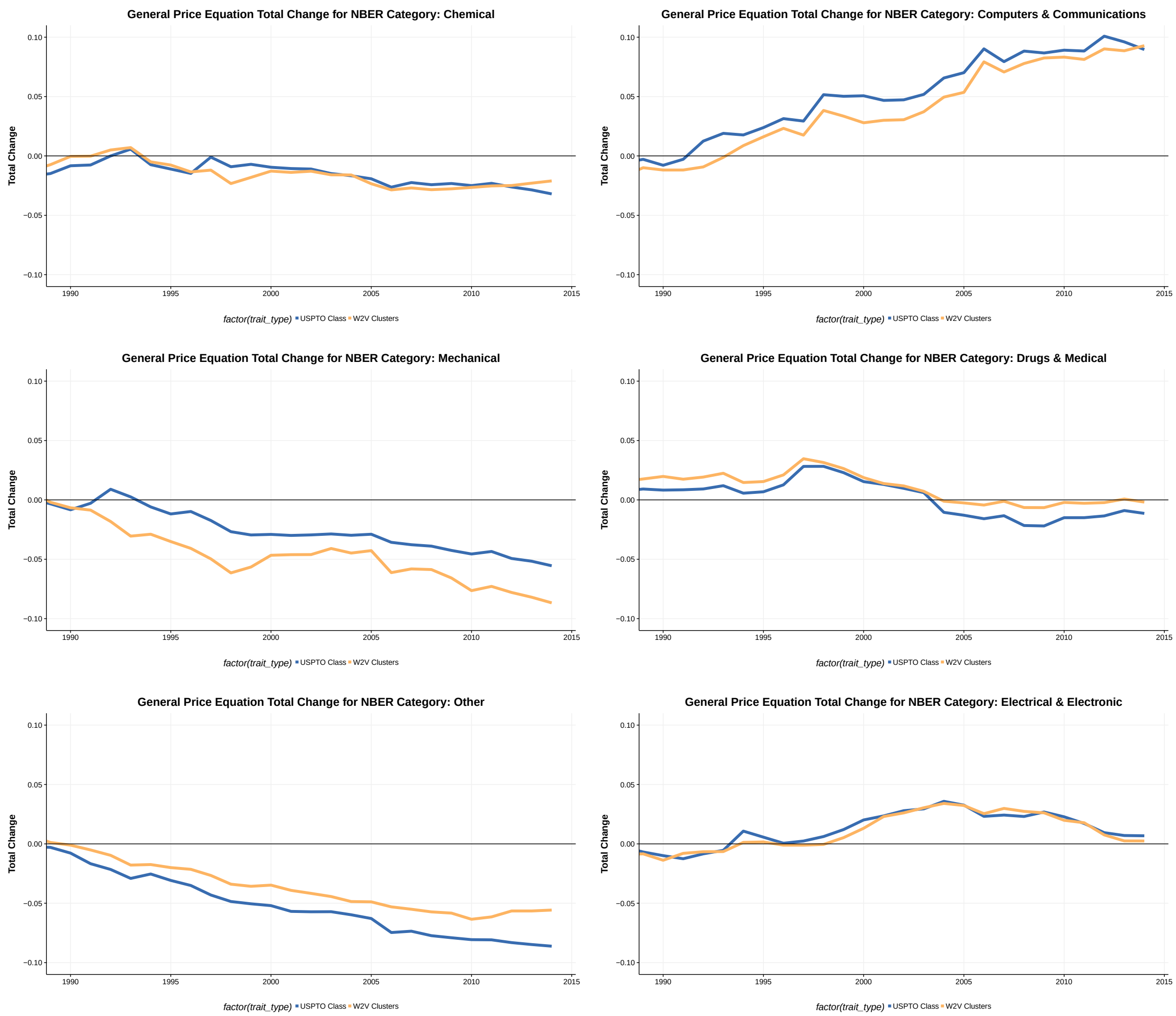


Figure 6: ΔX (Total Change) (USPTO classes and word2vec clusters) for NBER technology category traits: Chemical, Computer and Communication, Mechanical, Drugs and Medical, Other and Electric and Electronic.

Figure 7: T1 (Selection Change) (USPTO classes and word2vec clusters) for NBER technology category traits: Chemical, Computer and Communication, Mechanical, Drugs and Medical, Other and Electric and Electronic.

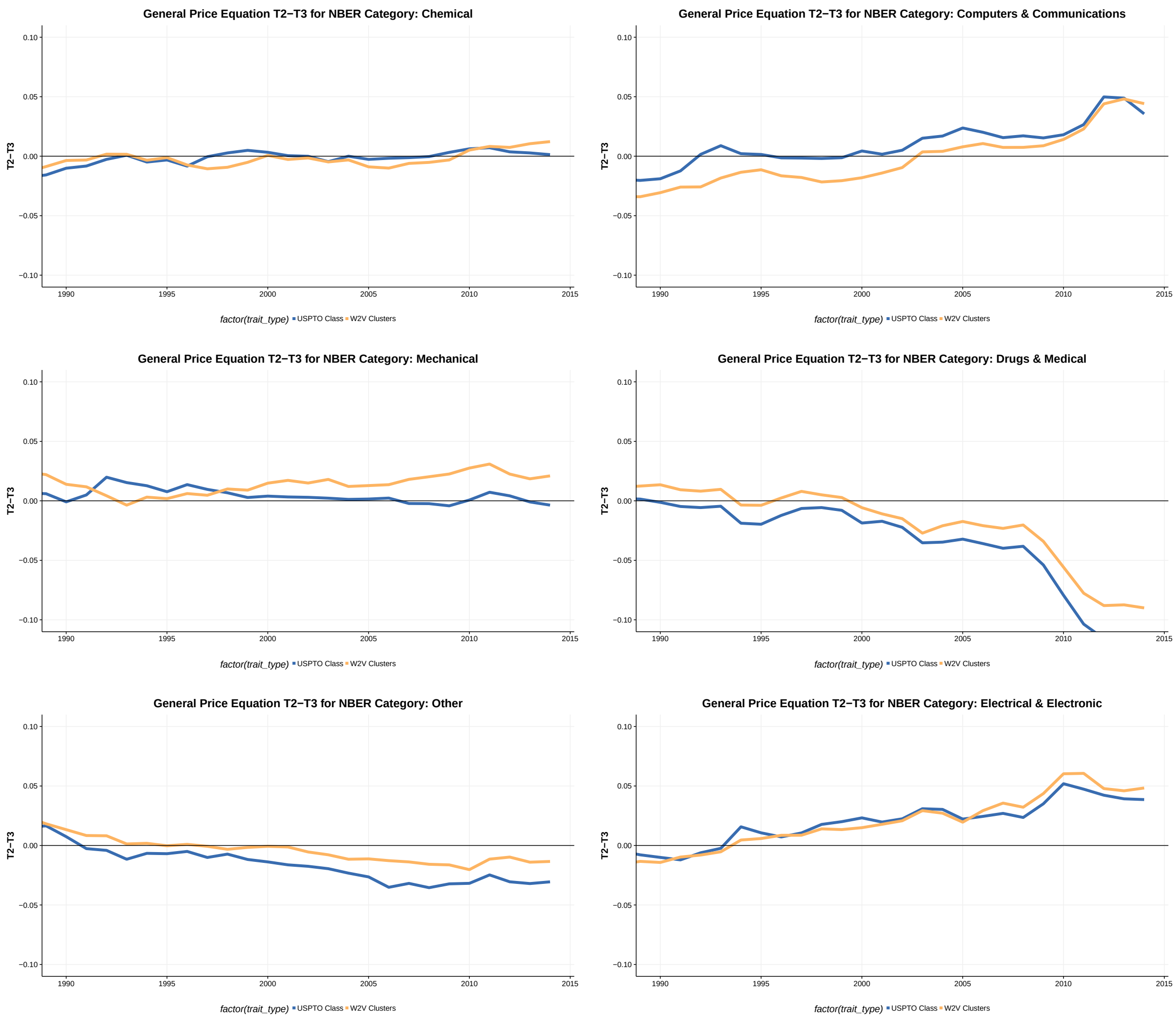


Figure 8: T2-T3 (No Selection Change) (USPTO classes and word2vec clusters) for NBER technology category traits: Chemical, Computer and Communication, Mechanical, Drugs and Medical, Other and Electric and Electronic.

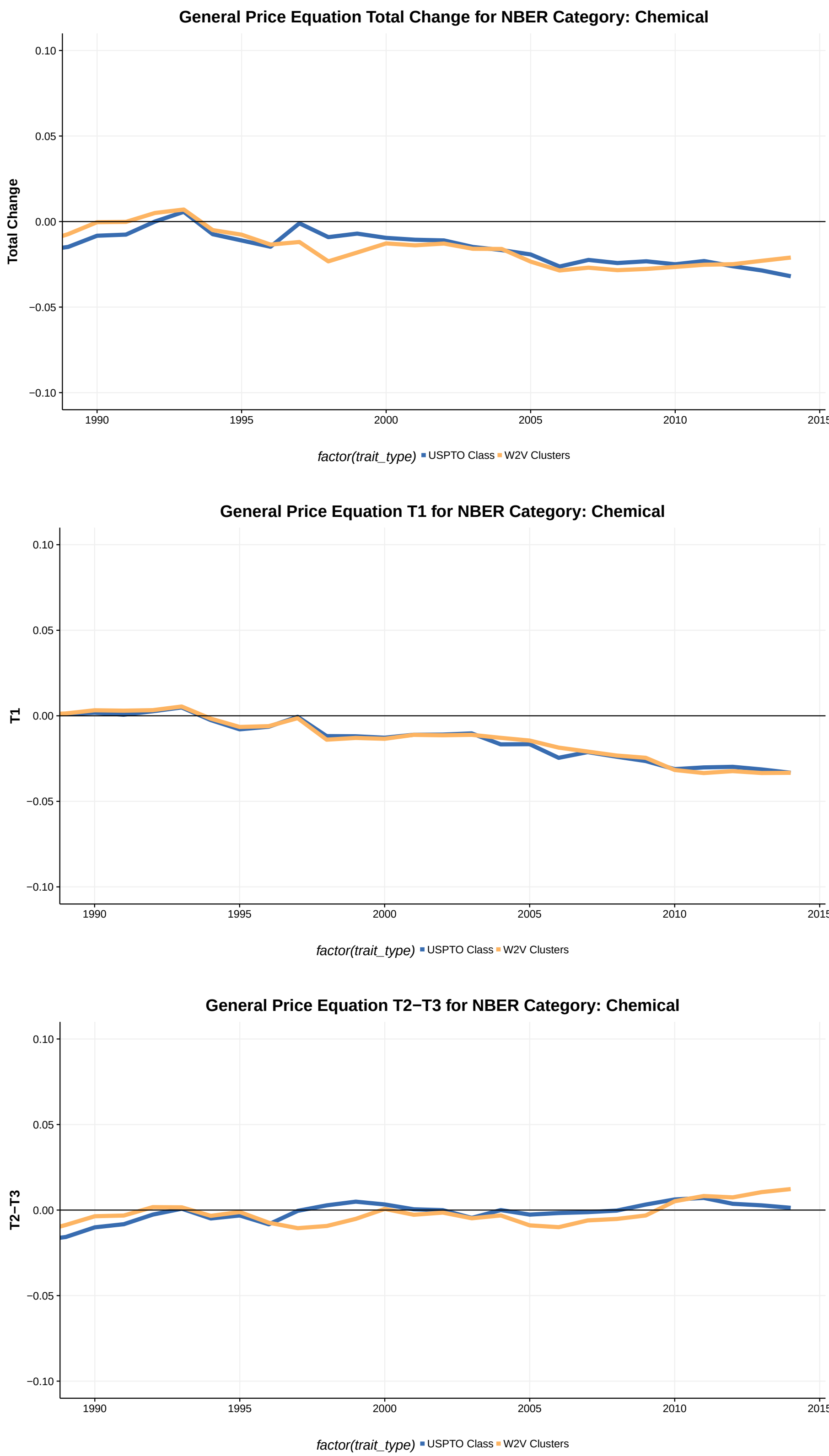


Figure 9: Chemical traits (USPTO classes and word2vec clusters): $\Delta\overline{X}$ (Total Change), T1 (Selection Change), and T2-T3 (No Selection Change).

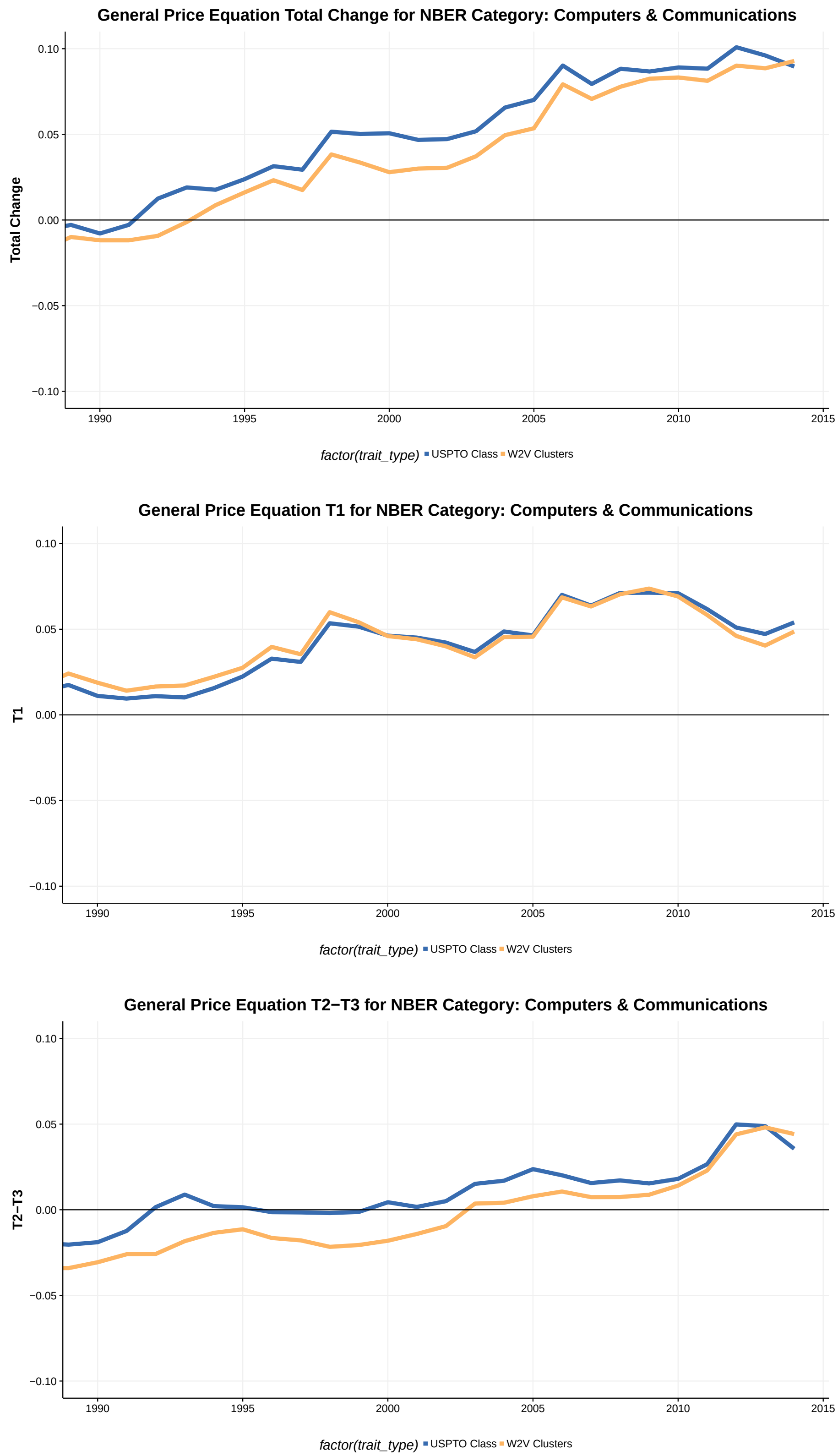
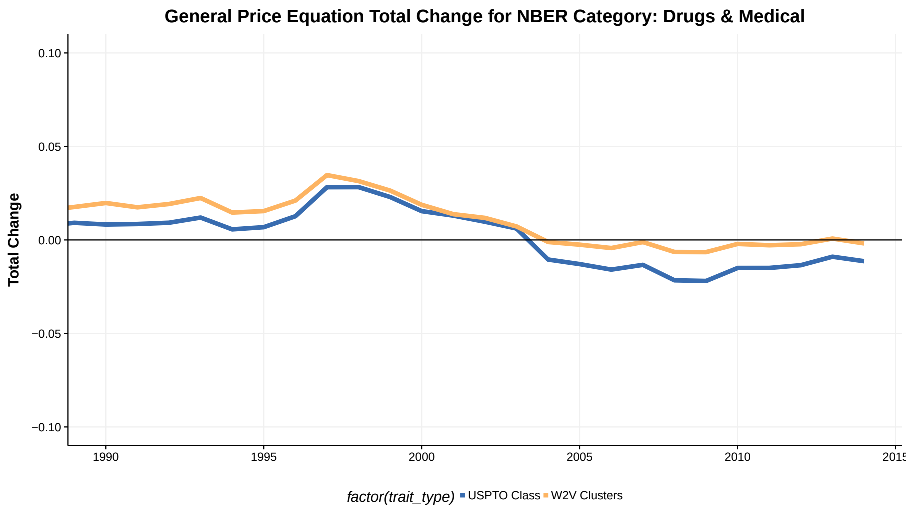
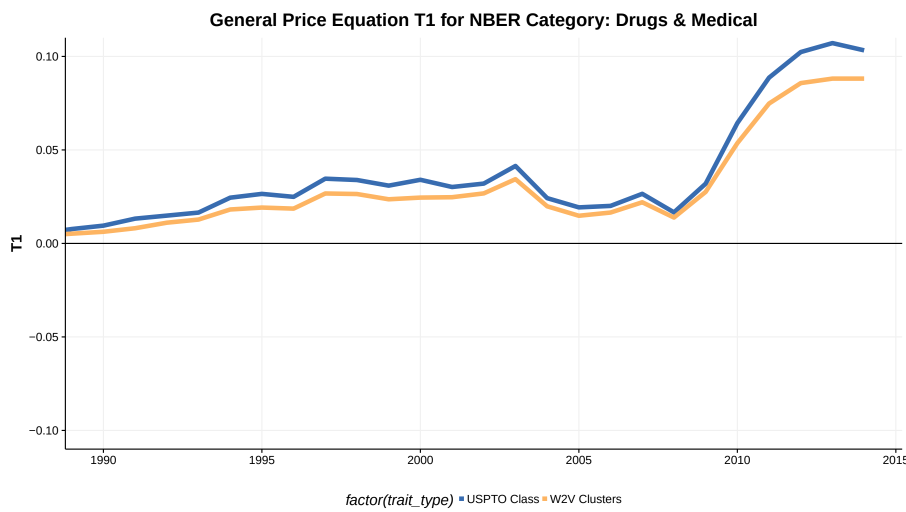


Figure 10: Computer and Communication traits (USPTO classes and word2vec clusters): total change, T1, and T2-T3.





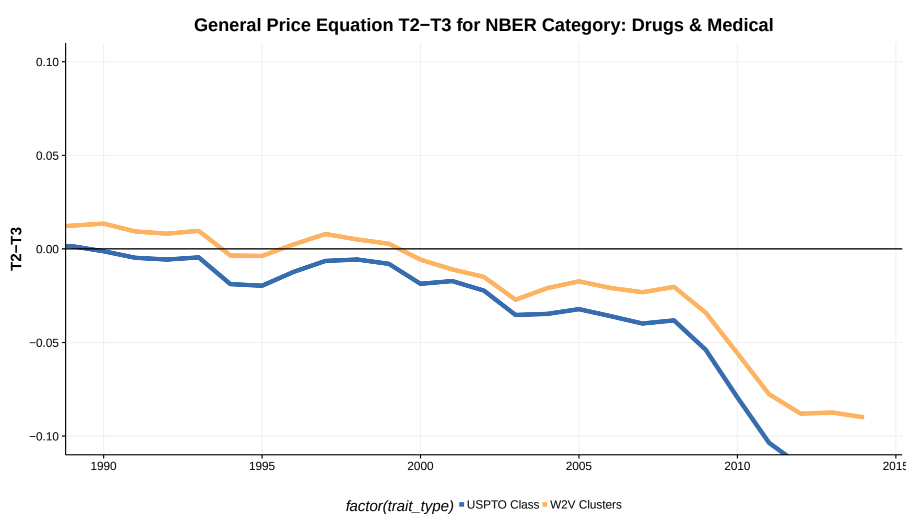
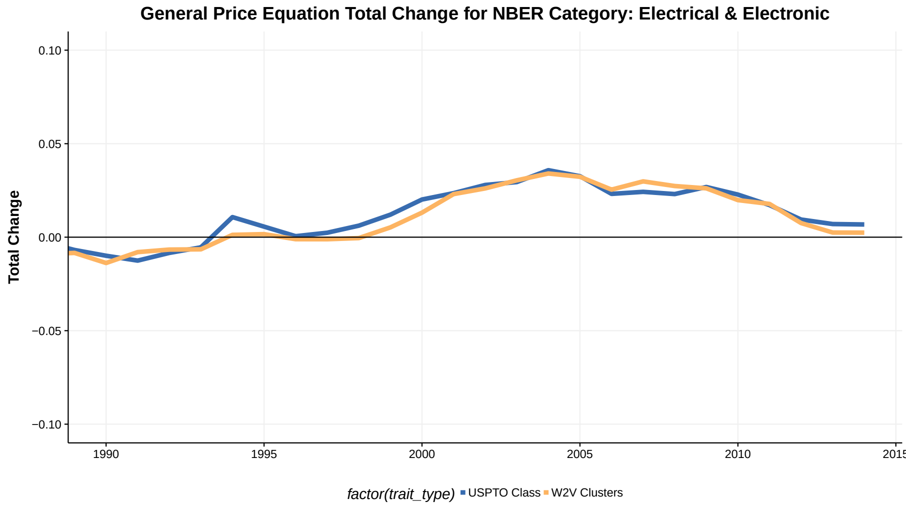
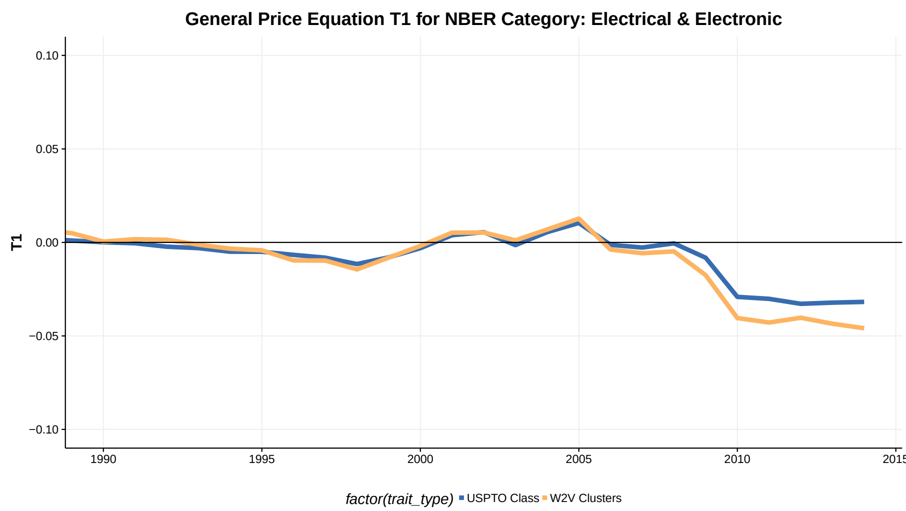


Figure 11: Drugs and Medical traits (USPTO classes and word2vec clusters): total change, T1, and T2-T3.





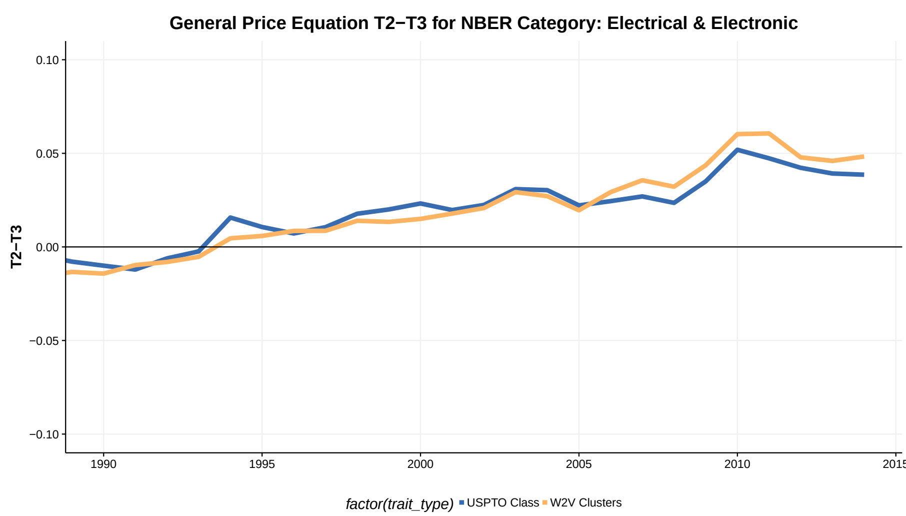


Figure 12: Electric and Electronic traits (USPTO classes and word2vec clusters): total change, T1, and T2-T3.

Figure 13: Mechanical traits (USPTO classes and word2vec clusters): total change, T1, and T2-T3.

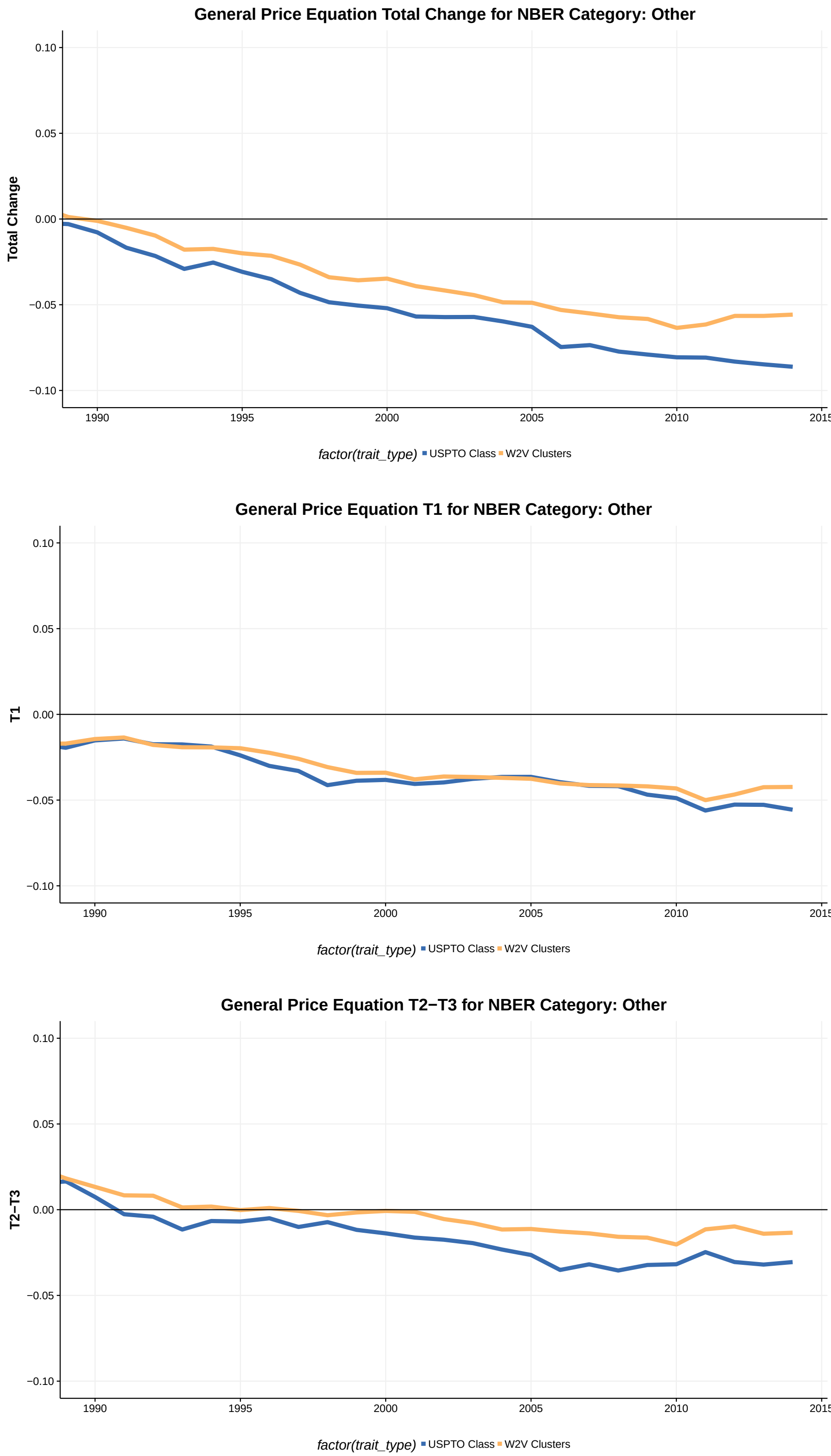


Figure 14: Other traits (USPTO classes and word2vec clusters): total change, T1, and T2-T3.

4 Conclusions

This paper reports a number of new important empirical patterns in the hyper-parental evolution of technology: It demonstrates that parents and children typically share tf-traits (MISSING?). It provides evidence for *positive* selection of Computer, Internet, Methods, and Medical traits, and for *negative* selection of Mechanical and Chemical traits. And it provides evidence for *non-selective* evolution of Electrical traits and Molecular Genetics traits. Some of these patterns have more or less obvious explanations, e.g., the positive selection of Computer and Internet traits, and the negative selection of Mechanical and Chemical traits. Other patterns lack an obvious explanation and remain a subject of current research, e.g., the non-selection-driven evolution of Electrical traits and Molecular Genetics traits. Surprising and hitherto unexplained results are to be expected when making a new kind of empirical observation of a complex evolving system; new and unexpected results are also to be desired.

Many have mined the patent record and reconstructed citation networks, and the Price equation is well recognized and discussed. This paper applies these tools in a new way to achieve a number of important milestones in the study of the evolution of culture and technology: (a) sequential empirical observation of the evolution over time of cultural traits in a real and autonomous natural system; (b) automated "bottom-up" discovery and identification of important traits of each patent described in the patent record; (c) collected a time-series of Price equation measurements. (Note that the Price equation cannot be iterated without additional annual information about the trait distribution in the relevant descendant and ancestral populations and the connection matrix between them. CITE Frank on lack of dynamical sufficiecy)

We here report empirical measurements of shared traits and Price equation terms in a complex evolving system in the natural world. The methods demonstrated here open the door to the quantitative and computational analysis of cultural evolution in other domains (other data sets) using similar methods, involving big data mining, automated data analysis, high experimental-throughput, machine learning, text processing.

This work also has interesting novel epistemological implications in the philosophy of science. The methods and results described here provide new traction on a number of controversial philosophical debates about cultural evolution involving concepts like memetics and cultural Darwinism. Our results provide a new way to compare and contrast cultural and biological evolution, and to investigate conjectures about technological directionality or growth in complexity, etc.

References

Hall, B. H., Jaffe, A. B., and Trajtenberg, M. (2001). The nber patent citation data file: Lessons, insights and methodological tools. Technical report, National Bureau of Economic Research.

Kerr, B. and Godfrey-Smith, P. (2009). Generalization of the Price equation for evolutionary change. *Evolution; international journal of organic evolution*, 63(2):531–536.

Mikolov, T., Yih, W.-t., and Zweig, G. (2013). Linguistic regularities in continuous space word representations. In *HLT-NAACL*, volume 13, pages 746–751.

5 Supplementary figures

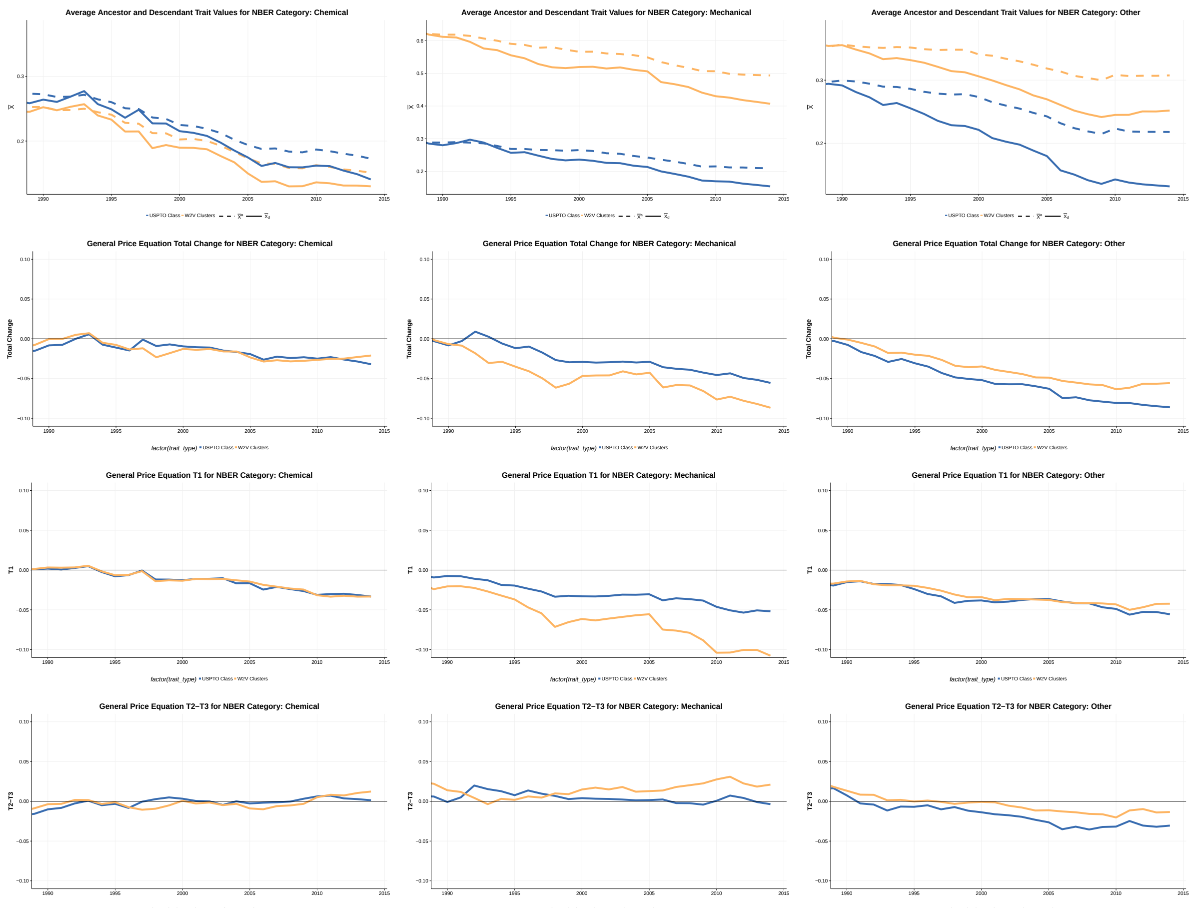


Figure 15: Time series of statistics about the evolution of technology: $\overline{X}$ (Average Trait Value), $\Delta\overline{X}$ (Total Change), T1 (Selection Change), and T2-T3 (No Selection Change). Statistics are shown for the NBER technology categories Chemical, Mechanical, and Other, calculated from a patent's leading USPTO class and its nearest word2vec cluster.

6 Evolution of traits in different technological categories

TO DO: Describe the way data is aggregated in the GPE time series pictures; average GPE values for all keywords in each technology category; smooth the lines using LOESS; gray bands indicate error XXX.

Annual Price equation measurements from 1988 to 2014 for each trait (tf-idf keyword or stem) in each technology category indicated in Table **??** generated data of the form illustrated for the Null, Computer, and Mechanical categories in Figure 20. Note that keywords in the Null category act as expected, exhibiting noisy fluctuations while total change remains essentially near zero. By contrast, Computer and Mechanical traits exhibit dynamics on a scale vastly larger than Null category

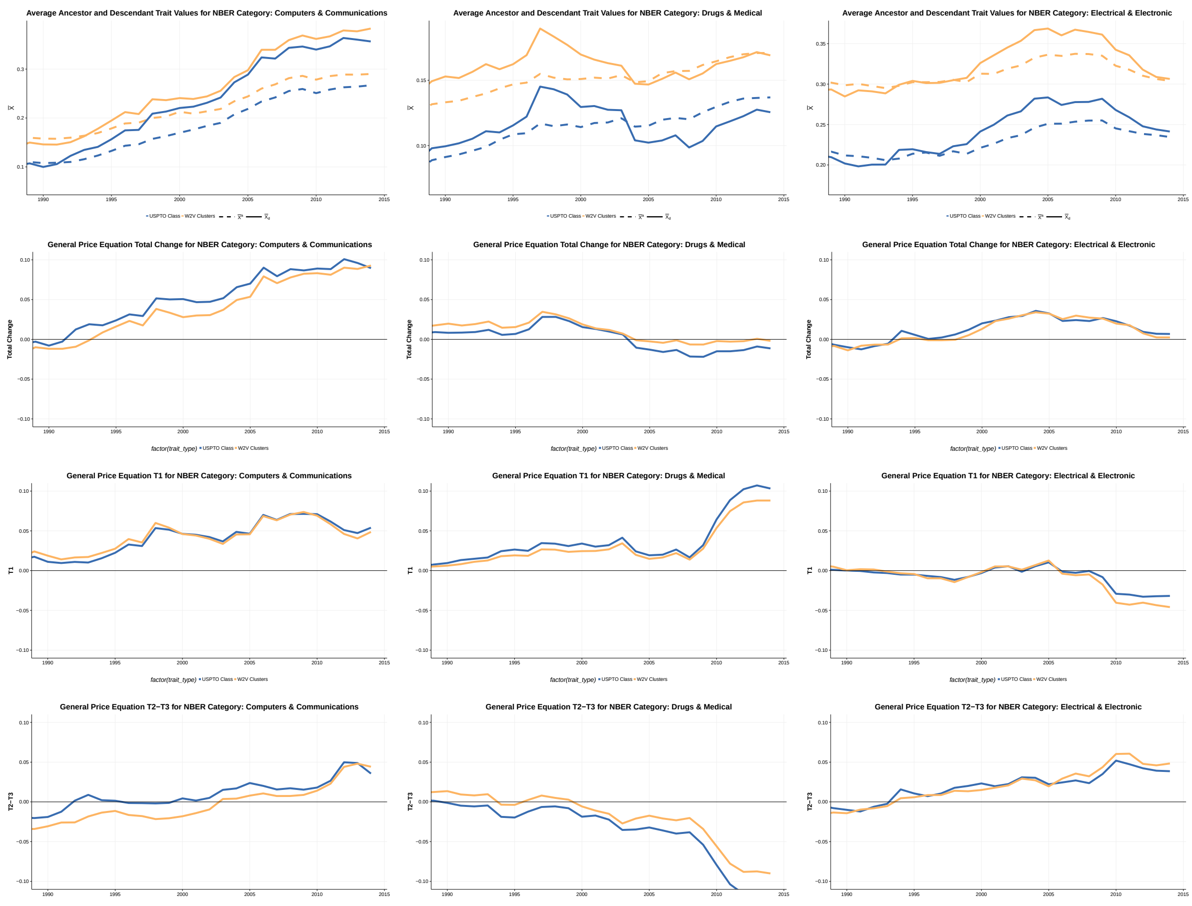


Figure 16: Time series of statistics about the evolution of technology: $\overline{X}$ (Average Trait Value), $\Delta\overline{X}$ (Total Change), T1 (Selection Change), and T2-T3 (No Selection Change). Statistics are shown for the NBER technology categories Computers and Communication (left column), Drugs and Medical (middle column), and Electrical and Electronic (right column), calculated from a patent's leading USPTO class and its nearest word2vec cluster.

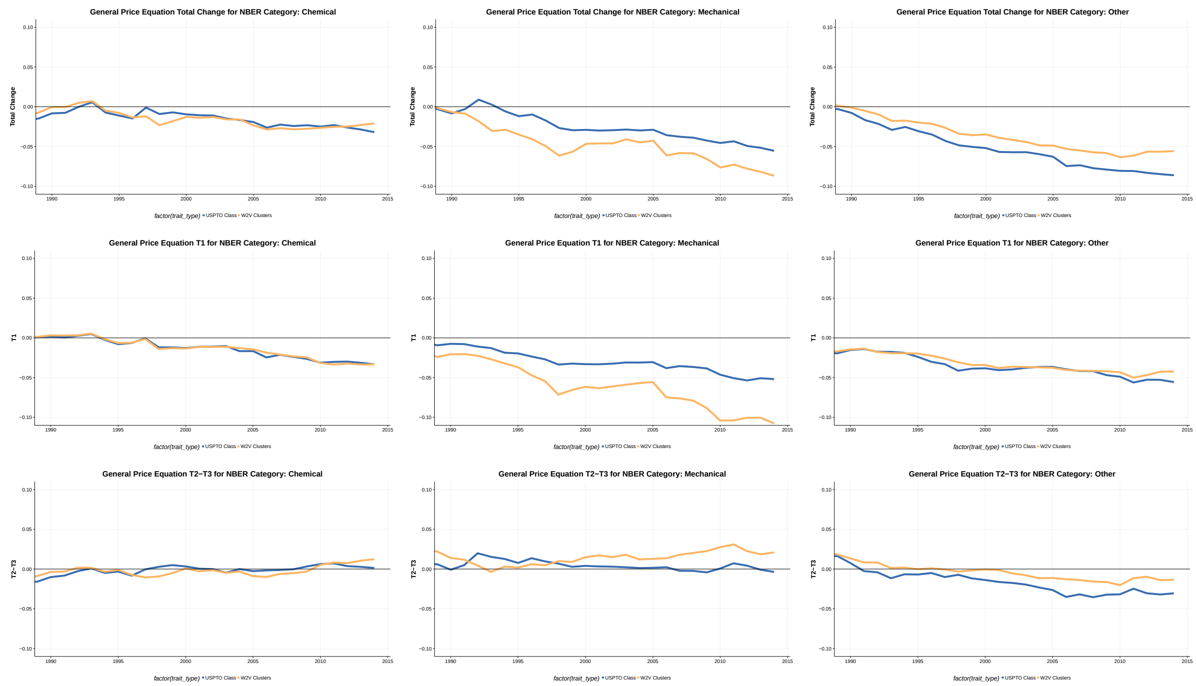


Figure 17: $\Delta\overline{X}$ (Total Change), T1 (Selection Change), and T2-T3 (No Selection Change) for NBER technology traits (USPTO classes and word2vec clusters): Chemical, Mechanical, and Other.

Figure 18: $\Delta\overline{X}$ (Total Change), T1 (Selection Change), and T2-T3 (No Selection Change) for NBER technology traits (USPTO classes and word2vec clusters): Computers and Communication, Drugs and Medical, and Electrical and Electronic.

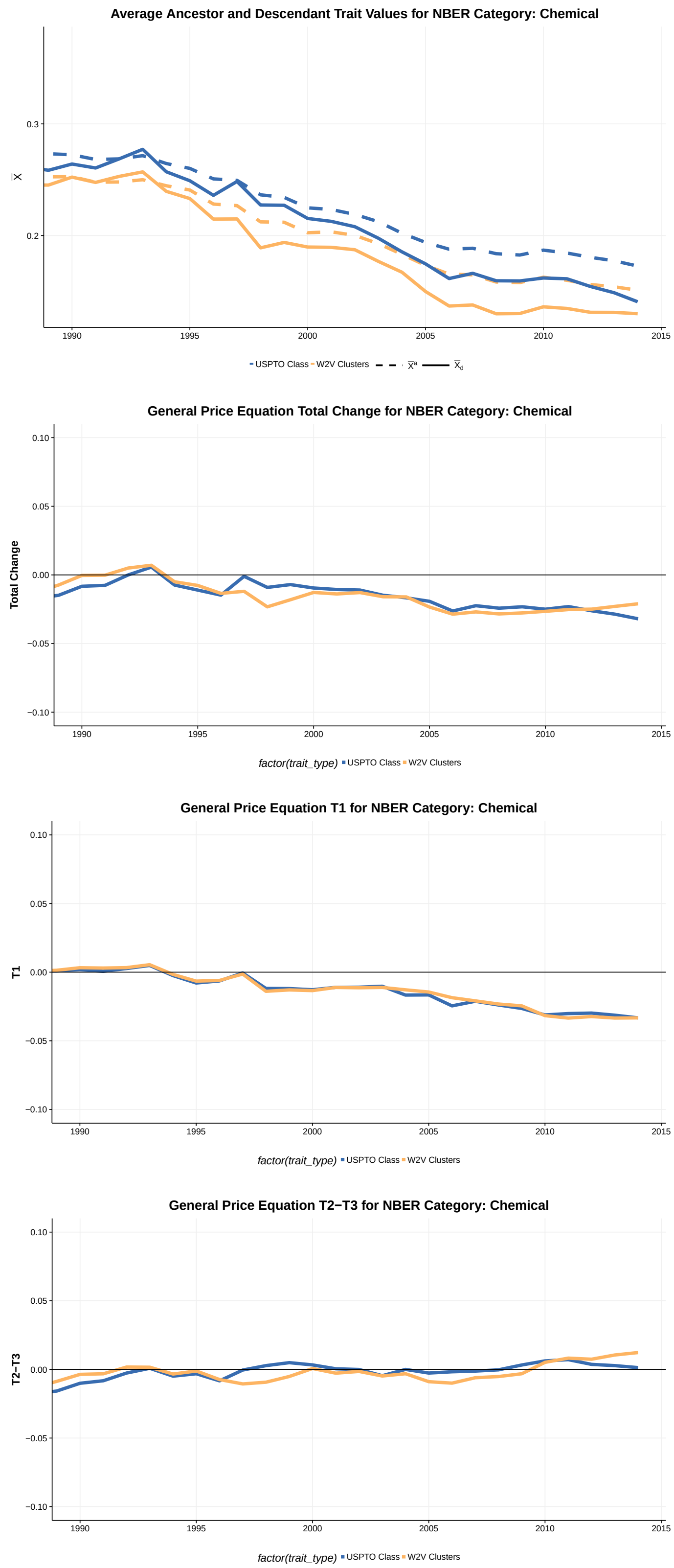


Figure 19: Chemical traits (USPTO classes and word2vec clusters): $\overline{X}$ (Average Value), $\Delta\overline{X}$ (Total Change), T1 (Selection Change), and T2-T3 (No Selection Change).

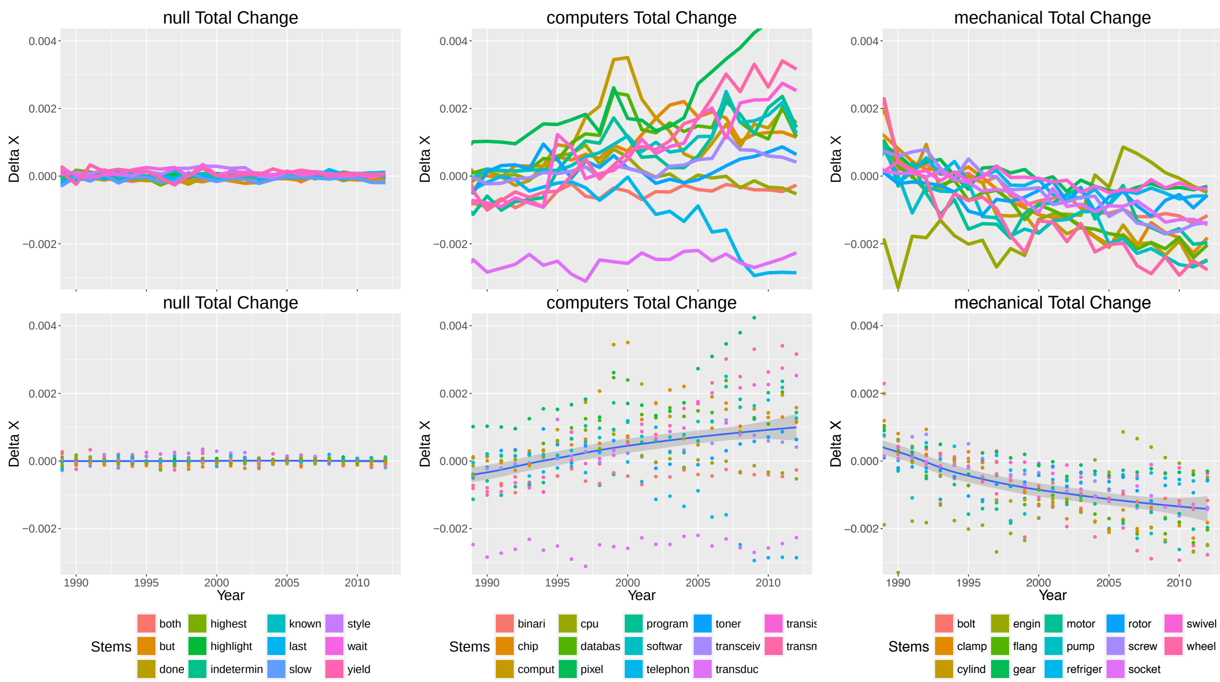


Figure 20: Time series from 1988 to 2014 of total change ($\Delta\overline{X}$) in traits (tf-idf keywords) in three categories: Null, Computer, and Mechanical. Above: line plots for each trait in each category. Below: scatter plots for each trait and category average line with gray error band.

noise. Furthermore, although there is significant variety in the dynamics of different traits within each category, the average behavior of the categories is quite different: Total change in Computer traits on average is positive and significantly increasing, while total change in Mechanical traits on average is negative and significantly falling.

6.1 Parents and children share traits

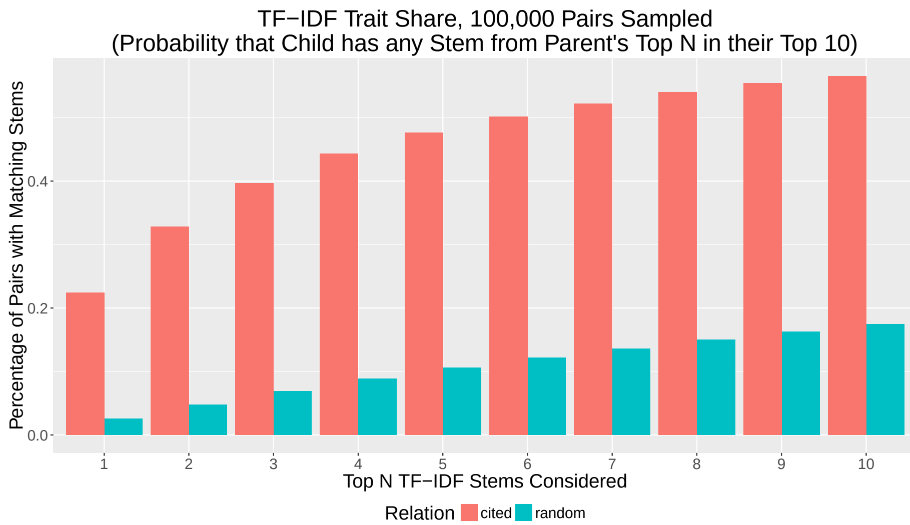


Figure 21: Red histograms show the percentage of children that have the same tf-idf keyword as one of their parents; green histograms show the percentage of shared traits in randomly chosen pairs of patents. Above: Histogram bins indicate the frequency with which children share the parental keyword ranked first (bin 1), ranked first or second (bin 2), ... , ranked among the top 10 (bin 10). Below: Histogram bins indicate the percent of children that share parental tf-idf keyword ranked first (bin 1), second (bin 2), third (bin 3), etc. Results of sampling 100,000 pairs of patents.

Figure 21 shows the fraction of children that share tf-idf words (or stems) with their parents, and compares it with the fraction that share words between randomly selected patents. Two observations stand out in these shared word results. The first observation is that parents are an order of magnitude more likely to share terms with their children than with randomly selected patents. The second observation is that higher ranked parental tf-idf keyword are more likely to be shared with children. Both of these observations make sense. It makes sense that parents and their children are much more likely to share traits than random pairs of patents. And given that the tf-idf metric is designed to measure the importance of a term in a document, it makes sense that parent and child are more likely to share more important terms.

We note that sharing a trait is a necessary condition for the child to “inherit” the trait from its parent, but it is not sufficient. Inheritance is one mechanism that produces shared traits, but so do other mechanisms. When a trait is inherited, the parent’s having the trait plays a crucial causal role in the child having that trait. In biological organisms this causal connection involves the new-born child and all its material embodiment physically being produced by the parent from material in the parent. “Parent” and “child” in cultural populations often have a much more attenuated and indirect “material” connection. One can think of the traits in new patents, for example, as being produced by a very different mechanism than inheritance. For example, one might think of new patents as agents produced by an external independent process, and traits can be assigned to these agents by the same external process; after a patent already exists and has traits, the relevant “prior art” is identified and cited. In the patent records produced by this external process “parents” will share many traits with their “children” without the traits being inherited from parents.

6.2 Positive (negative) selection for Computer (Mechanical) traits.

Figure 24 shows the change in the frequency of traits in technology categories in the 26 years from 1988 to 2014, in both ancestral and descendant populations. Recall that the total change from ancestors to descendants in average X value, $\Delta\overline{X}$, is simply the difference in their average values in the two populations, $\overline{X_d} - \overline{X^a}$. We can see that $\overline{X}$ has roughly the same average value in both ancestral and descendant populations. It's overall trajectory in one population is roughly the same as its trajectory in the other. This means that the difference between them, $\Delta\overline{X}$, in any given year might be relatively small. Nevertheless, over 26 year those small local differences can add up to the large global differences seen in Figure 24.

The evolution of $\overline{X}$ shown in Figure 24 shows a striking pattern: The frequency of the words indicating technology categories change dramatically. Initially Mechanical words are more frequent than Computer words, but Mechanical words steadily fall in frequency, while Computer words steadily rise. By the end, relative frequencies have reversed: Computer words are more frequent than Mechanical words.

In the figure one can also observe a second pattern involving the relative size of $\overline{X}$ in ancestral and descendant populations: $\overline{X}$ generally rises (as in Computers) when and only when $\overline{X}^a > \overline{X}_d$ and $\overline{X}$ generally falls (as in Mechanical) when and only when $\overline{X}^a < \overline{X}_d$. There are some temporary exceptions to this pattern but it often holds.

Figure 25 depicts the annual total change, $\Delta\overline{X}$, in Computer, Mechanical, and Null traits from 1988 to 2014 (above); it also depicts the size of the change in the selection term (below left, ancestor covariance, cov$(\tilde{C}^a_*, X^a)$) and size of the non-selection term (below right, average change minus descendant covariance, ave$(\Delta X^a_d) -$ cov$(\tilde{C}^*_d, X_d)$). This figure provide evidence for a number of conclusions about the evolution of technology from 1988 to 2014.

First, the difference $\Delta\overline{X}$ between descendant and ancestral Null traits is essentially zero, as expected for this control case. The flat zero behavior of the Null control traits contrast dramatically with the changing behavior of Computer and Mechanical traits.

Second, most of the evolution of Mechanical traits is explained by the *selection* term, because overall evolutionary change ($\Delta\overline{X}$) and the selection term both steadily fall, while the no-selection term is largely constant. This downward trend in ancestor covariance of Mechanical traits is the Price equation's classic signature for *negative selection*.

Third, most of the evolution of Computer traits is explained by *positive selection*, because $\Delta\overline{X}$ and ancestor covariance cov$(\tilde{C}^a_*, X^a)$ both rise together, while average change ave(ΔX^a_d) and descendant covariance cov$(\tilde{C}^*_d, X_d)$ are largely constant. In contrast with Mechanical traits, this upward trend in ancestor covariance of Computer traits indicates *positive* selection for Computer traits.

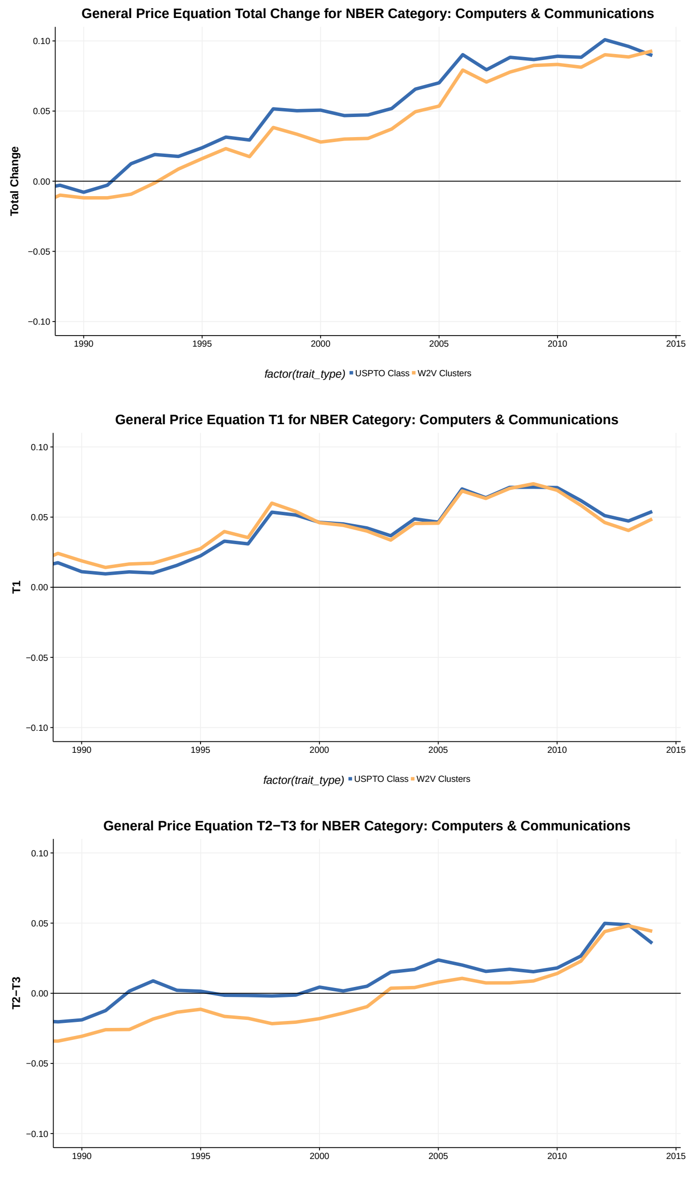


Figure 22: Time series from 1988 to 2014 of $\Delta\overline{X}$ (total change, top), ancestor covariance (selection term, middle) and average change minus descendant covariance (no-selection term, bottom), for Computer traits measured by USPTO classes (green), tf-idf keywords (red), and word2vec clusters (blue).

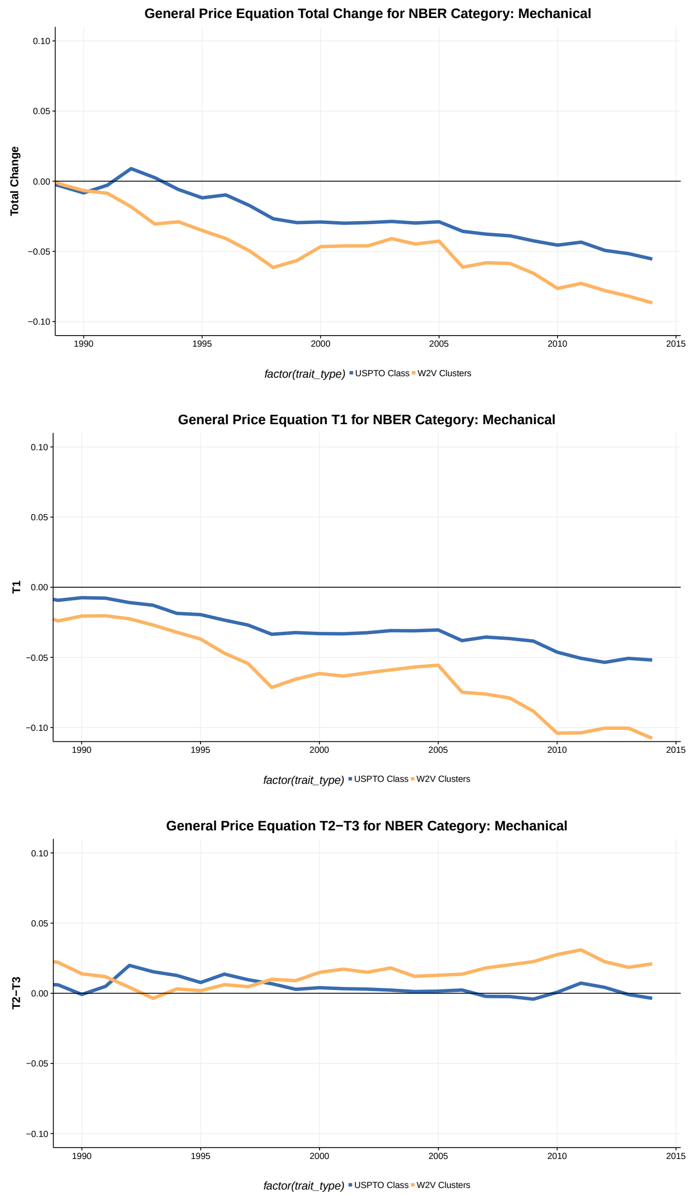


Figure 23: Time series from 1988 to 2014 of $\Delta\overline{X}$ (total change, top), ancestor covariance (selection term, middle) and average change minus descendant covariance (no-selection term, bottom), for Mechanical traits measured by USPTO classes (green), tf-idf keywords (red), and word2vec clusters (blue).

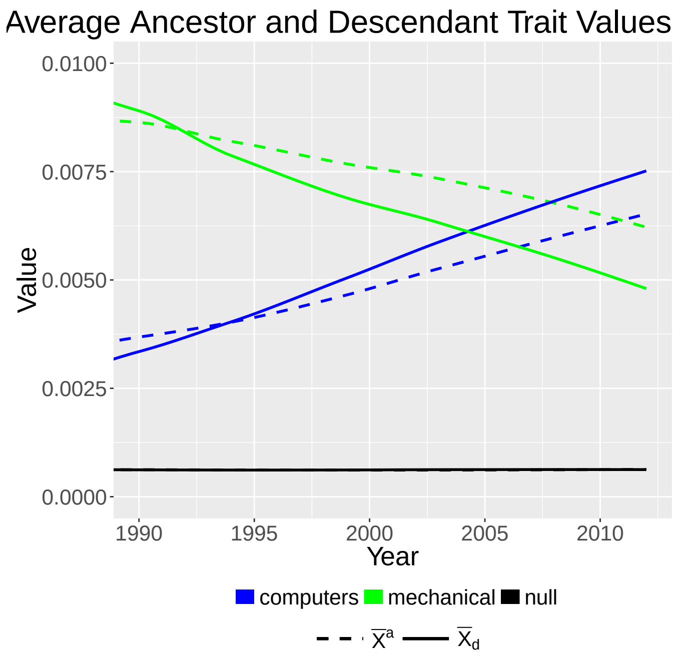


Figure 24: Time series from 1988 to 2014 of $\overline{X^d}$ (solid line) and $\overline{X^a}$ (dashed line), where X consists of tf-idf words or stems in Table **??** that signify the technology categories Computers (blue), Mechanical (green), and Null (black).

To separate the strength of the two non-selective processes, Figure 26 depicts the strength of differential transformation (indicated by the average change ave(ΔX_d^a)) and differential merging (indicated by descendant covariance cov$(\tilde{C}_d^*, X_d)$). If we compare Computer and Mechanical traits, in each case average change and descendant covariance show similar overall dynamics: both terms generally fall for Mechanical traits, and both terms slightly rise and then fall for Computer traits. Thus, when descendant covariance is subtracted from average change to compute the non-selection component of the total evolutionary change, this produces the relatively flat behavior of the non-selection term seen in Figure 25.

Figure 26 also shows that there has been a more or less constant significant bias in average change ave(ΔX_d^a) against Computer traits; children are less likely to have Computer traits than their parents. Similarly, the average change ave(ΔX_d^a) in Mechanical traits starts out in 1988 significantly positive; there is a significant bias in average change in favor of Mechanical traits; children are more likely to have Mechanical traits than their parents. But the average change of Mechanical traits steadily falls all the way to zero by 2014. The explanation for both of these biases is one of many open questions that remain to be investigated.

6.3 Non-selective evolution of Electrical traits

Positive and negative selection are also evident in both Medical and Chemical traits (see Supplementary Figure 31), as the dynamics of total change $\Delta\overline{X}$ (top and bottom right, black) closely mirrors the dynamics of the selection term cov$(\tilde{C}_*^a, X^a)$ (top and bottom right, green). However,

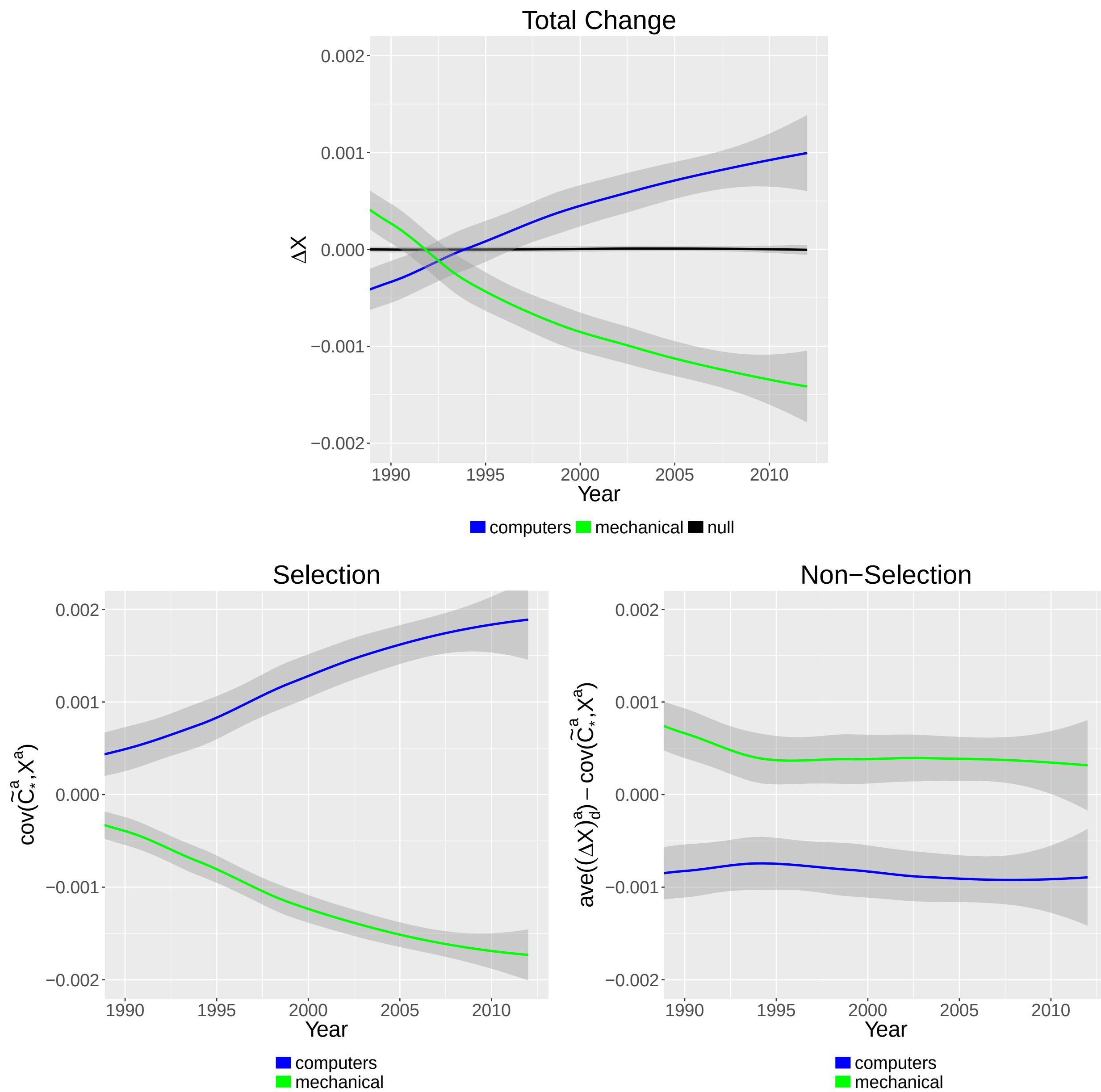


Figure 25: Time series from 1988 to 2014 of $\Delta\overline{X}$ and its division into selection (left, ancestor covariance term) and no-selection (right, average change minus descendant covariance), for Computer and Mechanical tf-idf keywords in Table **??**.

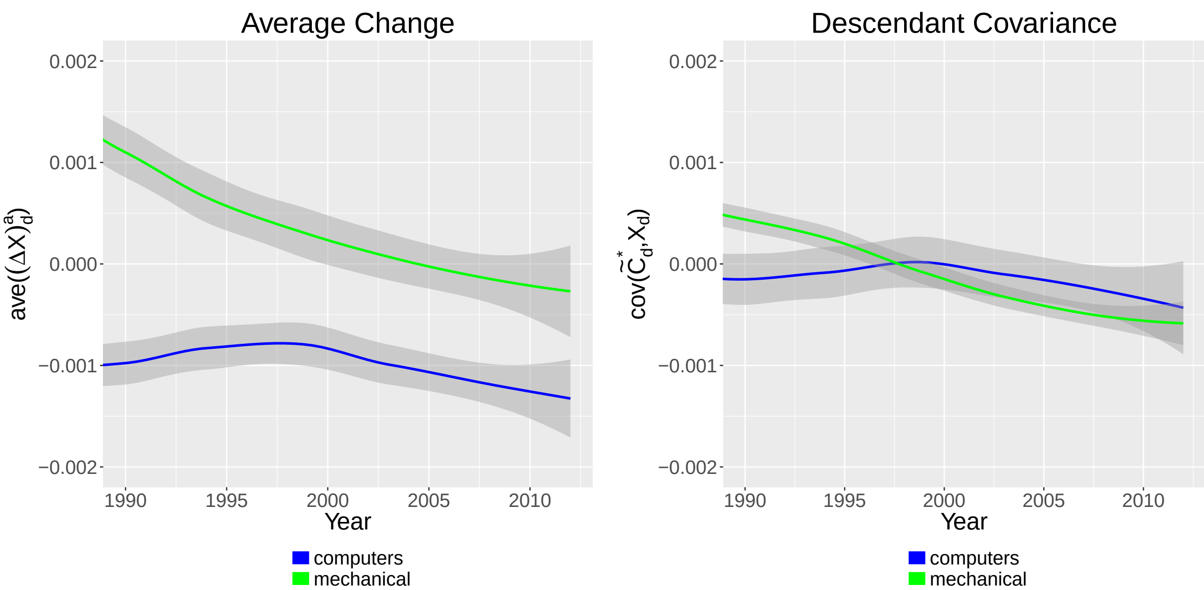


Figure 26: Time series from 1988 to 2014 of the terms in the Price equation the difference between which indicate the strength of all *non-selective* processes, for Computer and Mechanical tf-idf keywords in Table **??**.

things are different with Electrical and Electronic traits. $\Delta\overline{X}$ (black lines) shows a quite positive trend for Electrical traits, similar to its positive trend for Computer traits. But the Price equation decomposition of the total evolutionary change paints a quite different picture for these two similar trends. Figure 28 shows that most of the evolutionary change $\Delta\overline{X}$ (black) of Electrical traits is found in the *non-selection* term (purple) and the behavior of the selection term (green) is relatively flat. Figure 28 shows that the average change (blue) for Electrical traits significantly rises while the descendant covariance term (red) significantly falls, and combining these two effects raises the non-selection term (purple) and the total change (black). This shows that the striking positive trend in total change in Electrical traits is mostly explained by the combination of both non-selective process.

Figure 28 also reveals more of the processes at work in the total evolutionary change, $\Delta\overline{X}$, in Computer traits. The increasing positive trend in total change (black) corresponds to the increasing positive trend in the selection term (ancestral covariance, green), but note that total change is significantly less than selection by a relatively constant amount. This constant deficit in total change corresponds to the significant but generally flat values of the non-selection term (purple) and average change (blue). In other words, the data from 1988 to 2014 show on average a significant bias in average change away from Computer traits. By the end of our window of observation in 2014 we see that the total net positive value of total change, $\Delta\overline{X}$, in Computer traits is mostly explained as positive selection.

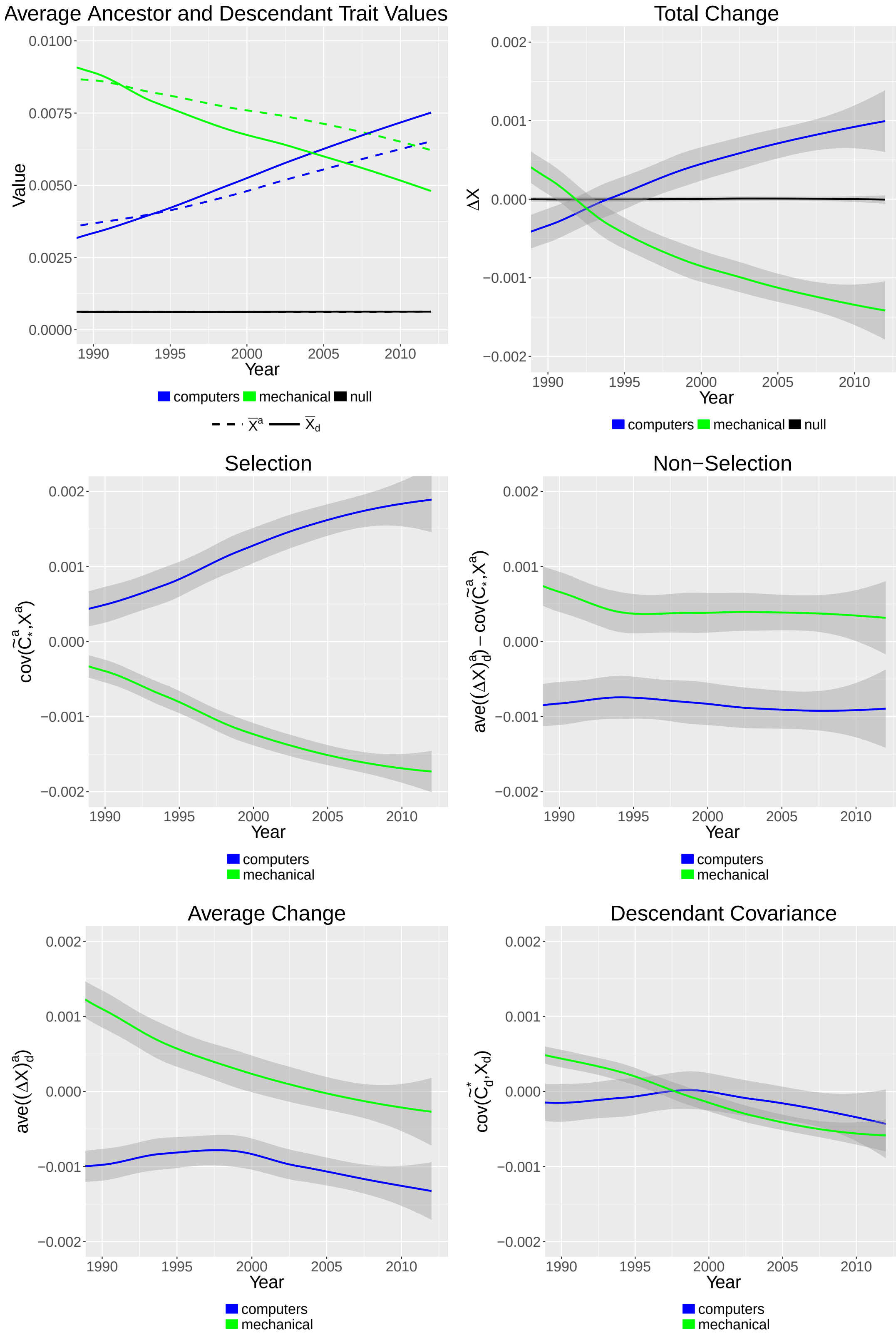


Figure 27: The evolution of trait X from 1988 to 2014, where X consists of tf-idf words (stems) in technology categories in Table **??**. Top: $\overline{X^d}$ (left) and $\overline{X^a}$ (right). Middle: $\Delta\overline{X}$. Bottom: "selection" (cov$(\tilde{C}^a_*, X^a)$, left) and "no-selection" (ave(ΔX^a_d) - cov$(\tilde{C}^*_d, X_d)$. right).

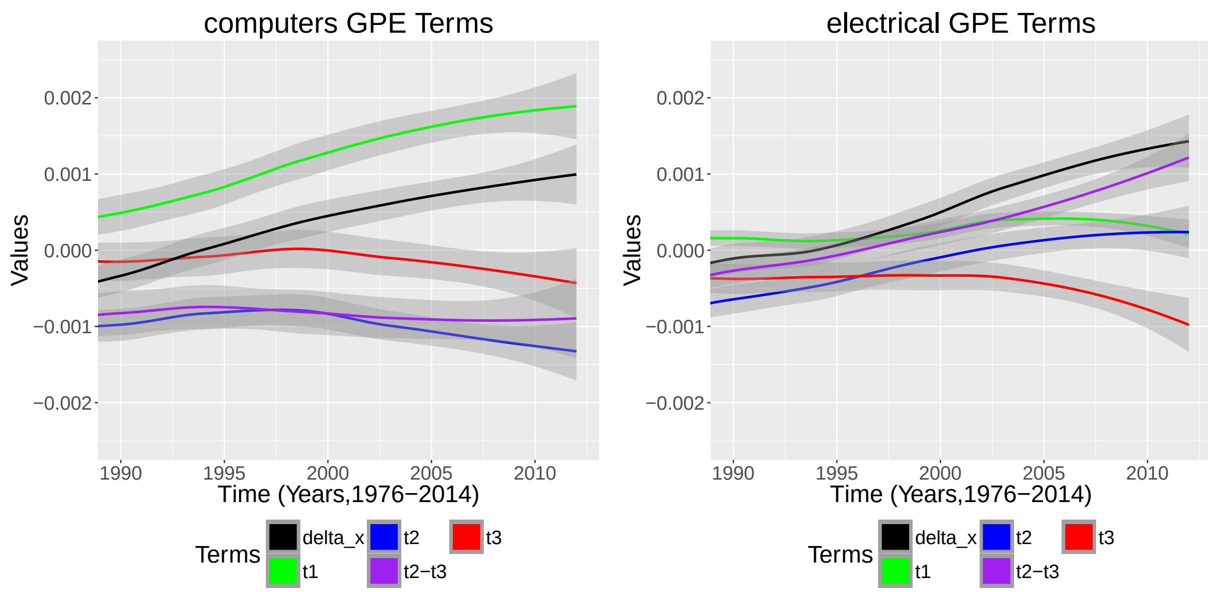


Figure 28: Time series from 1988 to 2014 of the terms in the Price equation Computer and Electrical tf-idf keywords in Table **??**. NOTE NEW COLORING SCHEME

6.4 Evolution of Molecular Genetics, Internet, and Methods traits

The Price equation also illuminates the evolution of three specific *sub-categories* of technologies: Molecular Genetics, Internet, and Methods. The Methods category covers methods of information processing, storage, and representation. Table 1 lists the tf-idf keywords within each specific sub-category.

Table 1: Tf-idf keywords (or stems) chosen as indicative of three technology sub-categories.

Molecular Genetics	Internet	Methods
gene	broadband	global
clone	client	interact
dna	host	interface
polypeptid	layout	metadata
sequence	multimedia	librari
mutate	packet	list
	rout	model
	server	modul
	wireless	notif
	site	select
	host	service
	gps	smart
	hyperlink	

It is clear that the Molecular Genetics sub-category falls under the Drugs and Medical category, and that the Internet sub-category falls under the Communication and Computers category. It is *less* clear how to categorize Methods. Since Methods involve information processing, perhaps it is the category Communication and Computers. But it differs from all of that category's current sub-categories (Communications, Computer Hardware and Software, Computer Peripherals, and Information Storage). Perhaps it should be recognized as a *new* sub-category of Communication and Computers. In any case, it is clear that the Methods sub-category does *not* fall under any other specific *category* in Table **??**. So unless Methods is categorized with Communication and Computers, by default it falls into the *Other* grab-bag, and since Methods does *not* fall under any of Other's specific *sub-categories* (Agriculture, Husbandry, Food; Amusement Devices; Apparel and Textile; Earth Working and Wells; Furniture, House Fixtures; Heating; Pipes and Joints; Receptacles), by default it falls into the grab-bag sub-category, *Miscellaneous*.

Molecular Genetics, Internet, and Methods traits were studied because each sub-category of traits showed a steady increase in frequency, $\overline{X}_d$ (left, blue), in the time period under investigation. A number of conclusions can be drawn from the results shown in Figure 29.

First, note that while $\overline{X}_d$ increases steadily for Molecular Genetics, Internet, and Methods traits, for Molecular Genetics traits $\overline{X}^a$ rises and then falls, and this rise and fall is mirrored by the rise and fall in total evolutionary change $\Delta\overline{X}$ (right, black). In the three sub-categories studied here, the dynamics of $\Delta\overline{X}$ mirror the dynamics of $\overline{X}^a$ but not always the dynamics of $\overline{X}_d$.

Second, note that the rise and fall of $\overline{X}^a$ and $\Delta\overline{X}$ in Molecular Genetics (top left, red) is roughly paralleled by the rise and fall in the non-selection term (top right, purple). Similarly, the rise in $\overline{X}_d$ for Methods traits (bottom left, red) is roughly paralleled by the rise in the non-selection term (bottom right, purple). On the other hand, the rise of $\overline{X}_d$ in Internet traits (middle left, red) *contrasts* with the *fall* in Internet's non-selection term (middle right, purple).

Internet and Methods traits show the classic sign of positive selection, because most of the rise in total evolutionary change corresponds to a rise in the selection term (compare black and green in middle and bottom right) rather than the no-selection term (middle and bottom right, purple). At the same time, the non-selection term is not insignificant; average change and differential transformation both have a significant magnitude but they mostly cancel out each other.

The selection term for Molecular Genetics traits (top right, green) is essentially flat and near zero, so the no-selection term (top right, purple) corresponds to most of the rise and fall in the total evolutionary change (right, black). Furthermore, most of the no-selection term corresponds to the descendant covariance (differential parent number, top right, red). By showing no significant positive or negative selection, The evolution of Molecular Genetics differs from Internet and Methods in the period from 1988 to 2014 in that the *non-selection* term explains most of its total evolutionary change.

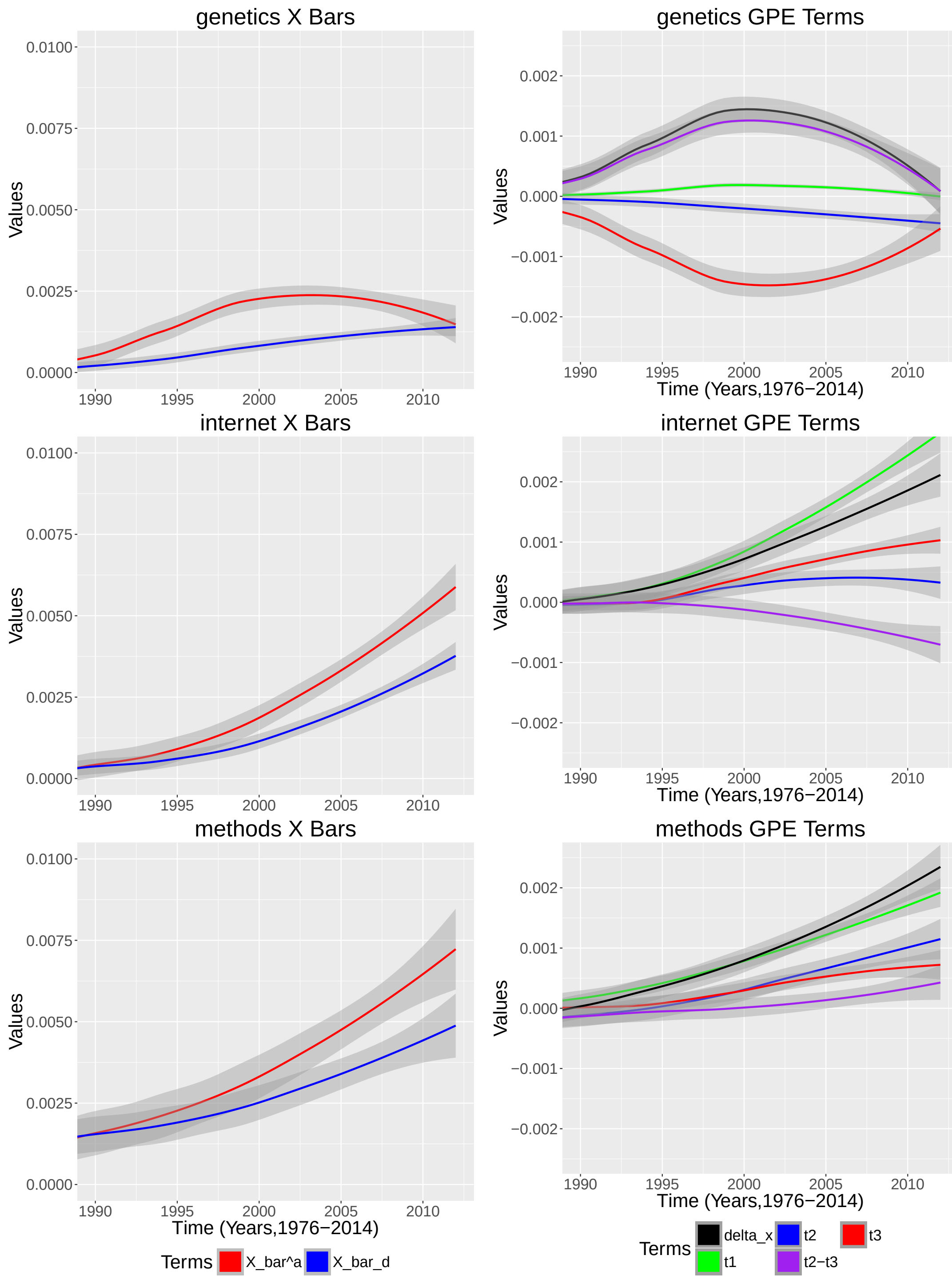


Figure 29: Time series of the terms in the Price equation for the sub-categories Internet (top), Methods (middle), and Molecular Genetics (bottom). Left: Average values of sub-category traits in descendant (blue) and ancestral (red) populations. Right: total change (purple), ancestor covariance or "selection" (black), average change (yellow), descendant covariance (blue), and "non-selection" (green).

7 Supplementary material

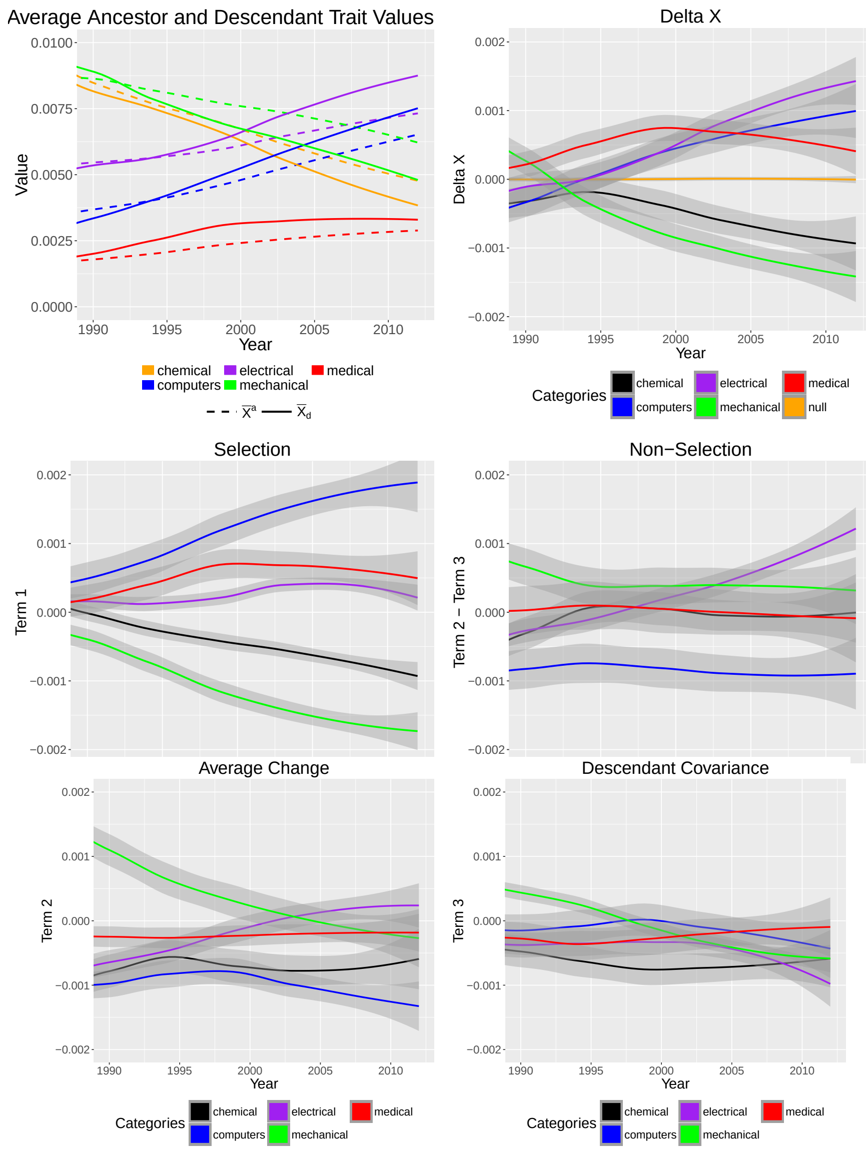


Figure 30: The evolution of trait X from 1988 to 2014, where X consists of tf-idf words (stems) in technology categories in Table **??**. Top: $\overline{X^d}$ (left) and $\overline{X^a}$ (right). Middle: $\Delta\overline{X}$. Bottom: “selection” (cov($\tilde{C}^a_*, X^a$), left) and “no-selection” (ave(ΔX^a_d) - cov($\tilde{C}^*_d, X_d$). right).

7.1 Trait differences for categorical data

One way to address categorical traits (our ’canonical’ computation): for computation of price terms for a given category, consider a trait variable that is binary, equal to one if a patent is in that category, zero if not. Redo the computation for each category, changing the binary trait.

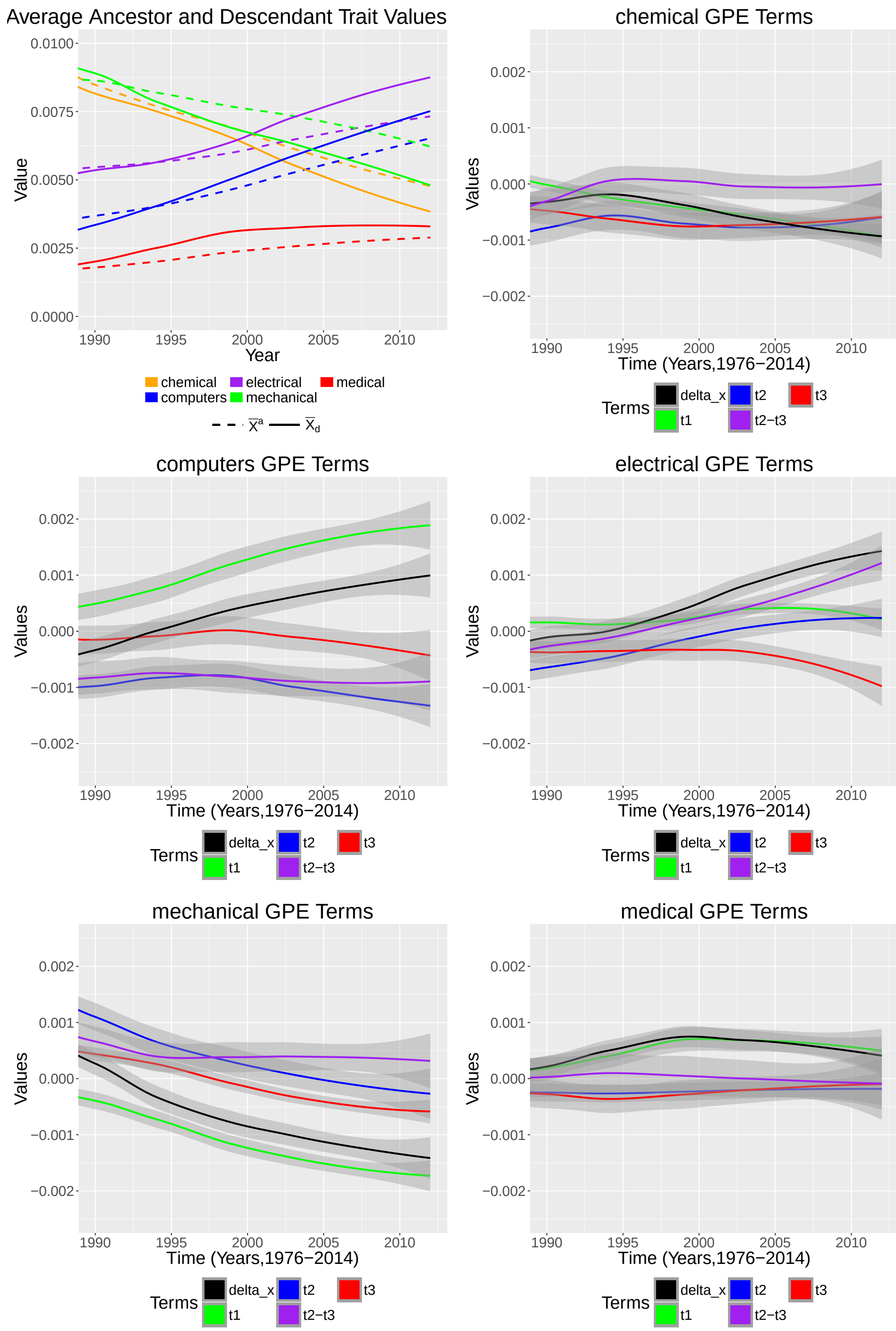


Figure 31: Annual time series from 1988 to 2014 for terms from the Price equation for the five categories of traits in Table **??**: the net total change (black, $\Delta\overline{X}$), the selection term (green, term 1, cov$(\tilde{C}^a_*, X^a)$), the no-selection term (purple, term 2 - term 1, ave(ΔX^a_d) - cov$(\tilde{C}^*_d, X_d)$, the average change (blue, term 2, ave(ΔX^a_d)), and the descendant covariance (red, term 3, cov$(\tilde{C}^*_d, X_d)$).

A different computation: consider category as a single trait having values $\{1, \ldots, N_{categories}\}$ Define the difference between descendant trait and ancestor trait as

$$X_d - X^a = 1 - \delta(X_d, X_a),$$

where $\delta(X_d, X_a) = 1$ if $X_d = X^a$, 0 otherwise. For computation of the covariances, we would need a definition of $ave(X)$ and XY. Could maybe use $ave(X) \equiv \text{mode}(x)$ and $XY \equiv \delta(X, Y)$.

This approach would yield one set of Price terms for all categories.