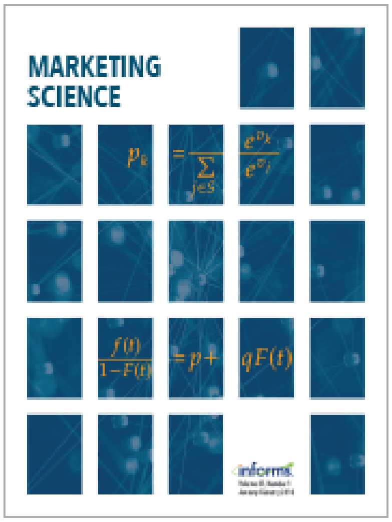

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A Theory for Market Growth or Decline

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Market growth is fundamental to marketing. Frank Bass's seminal diffusion theory explains growth in new product markets. We develop an analogous theory for established markets exhibiting sporadic growth or intermittent declines.

Our theory suggests that market participants repeatedly take successful and unsuccessful actions that cause them to change or to mutate in myriad and often unpredictable ways. The environment sorts these mutations, determining winners and losers. Abundant mutations often cause different market participants to become winners, displacing past winners. Abundant mutations also often cause market growth because the natural selection mechanism leaves more surviving favorable mutations. So one nonobvious falsifiable implication of our theory is that displacement precedes growth and stability precedes decline. Another is that risk taking, diversity of opinions, and experimentation should precede growth.

We develop a metric for measuring displacement. Using multiple publicly available data sets (one including sales for top firms for 55 years and another including sales for all automobile models for 25 years), we find that our metric provides a practical way to measure the rate of mutation and confirm our theory's predictions. Our easily replicated tests show that our displacement metric can predict intermittent market growth or decline in very different contexts without the need for exogenous idiosyncratic explanations. Moreover, other alternative covariates (trends, lagged growth, new product entry, macroeconomic indicators, etc.) are unable to predict growth or decline.

Key words: market growth; growth theory; natural selection; market evolution; forecasting; competitive analysis; market decline; Malthusian competition

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1. Introduction and Objectives

Market growth is fundamental to marketing. Many marketing actions (Lilien and Yoon 1990) promote growth (Cook 1985) including advertising (Balasubramanian and Kumar 1990), new product development (Biyalogorsky et al. 2006), timing (Radas and Shugan 1998), pricing (Ayal and Zif 1979, Kuksov and Xie 2010), and strategy (Urban and Hauser 1980, Dekimpe and Hanssens 1995). Robinson and Min (2002, p. 124) find that "a growing market typically provides more new customers, more new product opportunities, and higher profit margins." Stremersch and Tellis (2004, p. 421) add, "Growth is one of the most persistent and compelling goals of managers today." Hence, understanding growth is critical.

We propose a theory for sporadic market growth or intermittent decline. In brief, our theory of environmental sorting suggests that successful and unsuccessful experimental actions by market participants (strategic, tactical, or accidental), in every period, cause market participants to change or mutate in myriad and often unpredictable ways. Some mutations are good and others bad. Given Malthusian competition (i.e., superiority over competitors) and natural selection (i.e., compatibility with nature), the environment sorts through these myriad mutations, finding winners and losers. Winners often grow, and losers often decline. In some periods, many mutations occur, causing two outcomes: First, the positions of market participants tend to change because more mutations (good or bad) tend to shake up the market. Second, market growth tends to occur because the environment can find more meaningful favorable mutations after the natural selection mechanism eliminates unfavorable mutations. So one nonobvious falsifiable implication of our theory of environmental sorting is that displacement precedes growth and stability precedes decline.

Our theory of environmental sorting does not require measurement, or even knowledge, of every specific mutation. In fact, we allow millions of relevant changes, requiring only an indirect measurement of those changes. For that purpose, we propose an easily computed metric that measures the rate of displacement in the market. Our metric provides a practical way to measure the rate of mutation or change in the market so as to test the theory and to predict market growth or decline.

Using our displacement metric, we empirically test our theory's predictions (hypotheses) using multiple publicly available data sets, making our tests easily replicated. The tests reveal that environmental sorting can explain market growth or decline in different periods and contexts without requiring exogenous idiosyncratic explanations—though such explanations can be valuable.

For example, many studies predict growth using estimated diffusion rates (Sultan et al. 1990, Soberman and Gatignon 2005, Villanueva et al. 2008), labor productivity (Keltner et al. 1999), innovation (Klepper 1996, Pauwels and Hanssens 2007), declining prices (Srinivasan et al. 2000), product features (Golder 2000), social development (Temple and Johnson 1998), research and development (Brandl 2004), quality (Rust et al. 1995), knowledge creation (Cohen and Levinthal 1989), and technological change (Bridges et al. 1991, Nelson and Winter 2002). Although Fornell et al. (2010, p. 28) claim that "consumer spending growth is difficult to predict," remarkably, they find that "customer satisfaction explains a good deal of future growth in discretionary spending" (p. 32). Tellis and Crawford (1981) develop a product evolutionary cycle that extends the traditional product life cycle research using five well-defined patterns. Then Lambkin and Day (1989) model evolution and competition using numerous manifest and latent factors. Dekimpe and Hanssens (1995) identify empirical generalizations about when marketing variables evolve or remain stationary. They find that evolution is empirically tractable and that it links readily observable short-run fluctuations with long-run movements. Anderson and Tushman (1990) discover that technological breakthroughs initiate an era of intense technical variation until a single dominant design emerges; they find a sales pattern similar to that of Bass (1969). Murmann and Tushman (1998) find that capable organizations can advantageously shape dominant designs but that dominant designs can only be known in retrospect. See the online appendix (available at http://dx.doi.org/10.1287/mksc.2013.0813) for a more complete review of the related literature.

2. Our Theory of Established Market Growth (or Decline)

2.1. Our Approach: Using the Natural Selection Mechanism

The most prominent extant growth theory is Frank M. Bass's seminal and pioneering theory for new product market growth (Bass 1969). It develops an analogy between infectious disease diffusion in epidemiology and new product diffusion. We propose a theory of growth (or decline) for established product markets with an analogy between business markets and biological systems. The contagion mechanism found in epidemiology theory inspired Bass. Similarly, the natural selection mechanism (Darwin 1859, Wallace 1905) and Malthusian competition (Sober 1984) inspire our theory of environmental sorting. Epidemics involve the spread of new infectious agents in a population. Both the natural selection mechanism and Malthusian competition involve displacement in established populations facing limited resources.

One important advantage of Bass's (1969) model over other growth models is that "the behavioral assumptions are explicit" (p. 215). Similarly, the natural selection mechanism provides specific behavioral assumptions about the causes for growth or decline. Bass views a new durable as a contagion. His source of growth is the vector of infection (i.e., the carrier that transports the disease), which Bass interprets as word-of-mouth communication. For natural selection, the source of growth is mutations (i.e., often small changes in a genomic sequence) among the members of the biological population. In epidemiological theory, as the number of infections increase, the vector of infection has more opportunities to contact unifected agents. With natural selection, as the number of mutations increase, there are more opportunities for nature to sort and find mutations that help the population grow.

The natural selection mechanism was developed by naturalist Charles Robert Darwin in his 1859 book *The Origin of Species by Means of Natural Selection* and renowned scientist Alfred Russel Wallace (Shermer 2002). Although seemingly biological, the mechanism actually stemmed from the economic ideas of the great political economist Thomas Robert Malthus. Hirshleifer (1977, p. 4) writes, "The co-discoverers of evolution each reported that Malthus' picture of the unremitting pressure of human population upon subsistence provided the key element leading to the idea of evolution by Natural Selection in the struggle for life." Both Darwin (1859, p. 69) and Wallace (1905, p. 239) acknowledge the prominent political economist: "[Malthus] gave Darwin the analogy he needed to move from artificial to Natural Selection, and this was the essential step in his reasoning" (Young 1969, p. 130). Unfortunately, although Malthus's ideas were revolutionary and influential, his views (as well as Wallace's) were extremely controversial and politically unpopular (Kutschera 2003, Morgan 2006, Collard 2009). In fact, Ebenezer Scrooge, the uncompassionate miserly protagonist in Charles Dickens' classic novel *A Christmas Carol*, was supposedly an effigy of Malthus (Henderson 2000, Bowyer 2012).

Decades ago, economist Armen Alchian (1950) developed the similarities between economic and biological competition. However, there are subtle differences between Malthusian competition (challenges imposed by competitors) and natural selection (challenges imposed by nature). Sober (1984) insightfully analogizes Malthusian competition to tennis and natural selection to golf. Renowned British economist Alfred Marshall accepted the natural selection mechanism (Glassburner 1955). His motto, *Natura non facit saltum* ("nature does not make jumps"), implies that "economic evolution was gradual" (Marshall 1898, p. xix) and that economic systems evolve slowly without discontinuities. Of course, not all economists completely accepted the national selection mechanism. As Foster (2000, p. 311) notes, "It is well known that Joseph Schumpeter did not believe that biological analogies were of much use in understanding economic evolution." We focus on a natural selection mechanism for growth and Malthusian competition for decline. See the online appendix for more details.

2.2. Our Theory of Environmental Sorting

Our research objective is to explain and predict intermittent market growth or decline in established markets (i.e., where sales can grow, decline, or stagnate). We are looking for a scalable falsifiable theory of growth that applies to multiple levels of aggregation (e.g., brand, product category, corporate division, firm, submarket, market, economy) and allows any performance measure (e.g., unit sales, dollar sales, assets, profits, price-earnings ratios) for growth favored by the environment. We define the environment as all agents and factors that are not completely controlled by the firm and that help determine the performance of the firm on variables defined later. The environment includes pressures from competitive markets, suppliers, downstream buyers, investors, creditors, and many others. We also seek to empirically test our falsifiable theory of growth using multiple data sets. However, our empirical tests do not require explicit delineation of the environment, which we expect will vary from situation to situation.

Our falsifiable theory employs environmental sorting; we view this as the business market equivalent of natural selection mechanisms in biological systems. Although the natural selection mechanism inspires environmental sorting, we do not claim to capture all the details of biological systems (reproduction, inheritance, phenotypes, common origin, etc.).

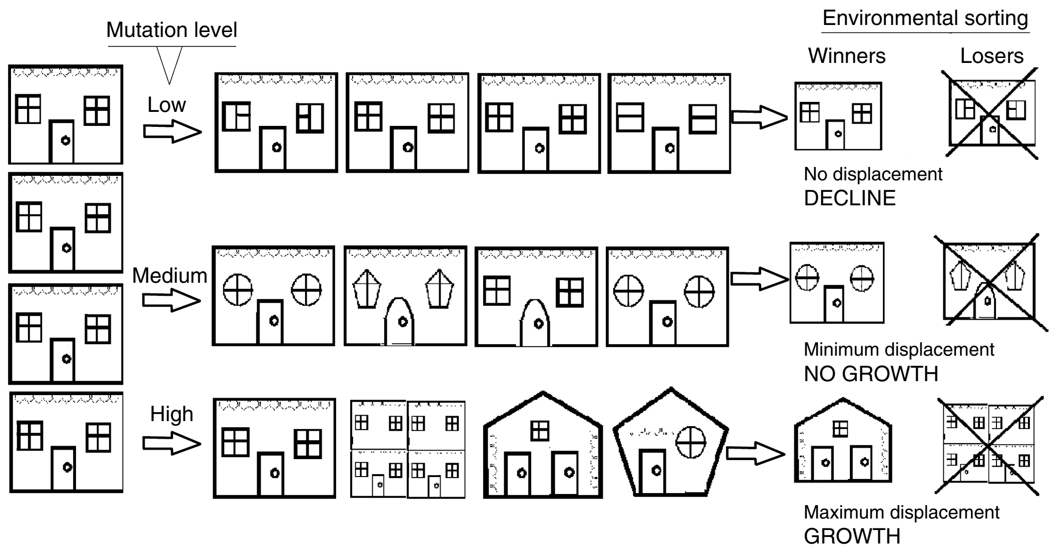
Struggling to survive in competitive environments, astute market participants experiment (Little 1966) and take many seemingly beneficial actions, both minor and major. However, many actions are risky, with uncertain and possibly unintended outcomes (e.g., fortuitous discoveries or damage to brand equity).

Similar to genetic mutation, for business markets, the myriad actions taken by market participants create the needed changes or mutations. These mutations might involve changes in the products, branding, organization, management, corporate mission, supply chain, infrastructure, investments, location, marketing, services, financing, operations, or accounting. Automobile makers might change their dealer relationships, power train, electrical systems, braking systems, luxury features, warranties, collision intervention systems, mobile tools, employee compensation, distributor incentives, advertising positioning, manufacturing, engineering, quality, etc.. The number and magnitude (i.e., level) of these mutations can change each period. Figure 1 depicts our growth theory. It shows three levels of mutation (low, medium, and high) where the number and magnitude differ. The environment selects some but not others.

Emphasizing nature's role, Darwin called his theory natural selection "to contrast it with the artificial selection practiced by plant and animal breeders" (Glick and Kohn 1996, p. xvi). For established markets, the environment does the selection rather than nature (see Figure 1). As defined earlier, the environment includes pressures from competitive markets, suppliers, downstream buyers, investors, creditors, and many others. It determines which mutations prosper. Some market participants change for the better and others for worse. The environment sorts market participants based on whether they have changed favorably or unfavorably, selecting winners and losers. The environment helps participants with favorable changes and hurts others. We call this process *environmental sorting*, where the environment sorts winners from losers. Winners usually grow and losers usually decline. The process continues over time.

Remember, growth occurs at one level, whereas the determination of winners and losers occurs at another. For example, in the auto market, the environment sorts through myriad mutations at the model level while growth occurs at the market level (i.e., for all models). For market growth, winners in the growth period must perform better than winners in past periods. We theorize that this is more likely when there are more mutations because with more mutations, the environment has a better chance of finding new winners (on whatever criteria the environment favors) that are better than past winners. Moreover, the natural selection mechanism eliminates losing mutations regardless of how bad those mutations are, so bad mutations do not necessarily inhibit growth. Hence, we predict that a higher level of mutation should cause market growth. Finally, faced with broader Malthusian competition, a lack of sufficient mutations causes market decline.

Figure 1 A Theory of Market Growth (or Decline)



Moreover, market growth can occur with or without any specific market participant seeking market-level growth. All we require is that market participants take actions for their own perceived benefit and that those actions cause possibly unpredicted and complex mutations at the level of the participant.

The complexity comes from both the myriad ways participants change and how those changes interact with the environment. Fortunately, like natural selection, observing all of these complex changes is unnecessary. Understanding natural selection does not require understanding complex genetics. Darwin (1859) developed his theories without knowledge of molecular biology and advanced genetic research. It is only necessary to observe the outcomes. Similarly, Bass (1969) did not need to make direct observations of infections (i.e., word-of-mouth communication). It was only necessary to observe the outcome of those infections (i.e., sales). In fact, detecting various infections often involves measuring outcomes (e.g., symptoms, antibodies) rather than directly observing infectious agents. Here, we need only to find a metric that captures the rate of environmental sorting by observing one outcome of sorting. We call this metric *displacement* (i.e., a change in the relative rankings of different market participants).

We hypothesize that when firms take actions that create a greater number of mutations with uncertain outcomes, these actions are more likely to upset the status quo. Such actions often cause market participants to change (mutate) in myriad unpredictable ways. It is more likely that with a greater number of mutations, different market participants will become winners, displacing past winners. Hence, the actions (and corresponding mutations) required for more favorable changes are also actions more likely to temporarily or permanently cause displacement. This hypothesis implies a theoretical relationship between market growth and displacement, because both are caused by the same, possibly latent, actions. We define displacement as a change in the relative market positions of market participants on an appropriate (from the environment's viewpoint) measure of performance.

Hence, when market participants exhibit sufficiently large mutations for market-level growth, we should observe a higher level of displacement. Displacement is an indicator of sufficient environmental sorting to initiate future growth because it suggests that there are a greater number of unobserved mutations. A lower level of displacement implies fewer latent mutations and less ability to find superior mutations. The lack of displacement indicates that market participants are not changing at a sufficient rate for growth to occur. So one nonobvious falsifiable implication of our theory is that displacement precedes growth and stability precedes decline. Later (see §3.6), we propose a metric to measure displacement by implicitly measuring the rate of underlying change among the market participants.

In sum, environmental sorting creates growth when latent mutations are large or numerous enough for those mutations to cause displacement (i.e., a change in the relative market positions of different market participants). Mutations that are insufficient to cause growth are often insufficient to change the relative competitive relationships between the market participants.

Consider the automobile category. In different periods, different car models change in myriad ways. See §4.10 for a real-world example. The environment (e.g., consumers, reviewers, car rental companies, policy makers) sorts the changes and then determines the winners and losers. When those changes are insufficient, car models retain their relative market positions. For example, the Ford F-series retains its dominant position. When the mutations are sufficient, new winners can emerge. For instance, the Chevy Silverado might displace the Ford F-series. Hence, more mutations imply both displacement and growth.

Finally, note that environmental change is an insufficient explanation. Although the environment can change over time, there is no natural selection mechanism to eliminate unfavorable environmental changes. Hence, environmental change cannot create a relationship between displacement and either market growth or market decline. A large environmental change is as likely to cause market growth as decline. Moreover, a large change is no more likely to cause growth than a small change. Hence, although environmental changes are inevitable, there is no reason to believe that those changes always favor growth. Instead, environmental changes can create risk and turn previously good actions into bad actions.

2.3. Three Testable Hypotheses

Our falsifiable environmental sorting theory makes at least three testable, nonobvious predictions (or hypotheses) about displacement and growth. Later (see §3.6), we derive a quantitative metric for measuring displacement.

The first testable hypothesis is that the level of displacement is positively correlated with market growth. As the level of displacement increases (reflecting greater mutation), the market grows faster because the new winners perform increasingly better than past winners. This prediction differentiates our theory from plausible alternative theories. One alternative theory is that growth and displacement are negatively correlated because major mistakes by incumbent firms cause both displacement and decline. Another alternative theory is that displacement occurs without growth because firms only take share from other firms. Another alternative is that growth occurs without displacement as past winners gain more resources to grow (Porter 1981) or that growth occurs in proportion to existing shares. All of these alternative theories are plausible and predict the opposite of our theory. Fortunately, empirical analysis can resolve this conflict.

A second testable hypothesis implied by our theory is that current displacement is positively correlated with future market growth. There may be a carryover effect. One reason is that the effect of successful mutations might persist into future periods. For example, some market participants might copy the successful mutations (e.g., new manufacturing techniques) of other participants creating persistent growth. Moreover, some participants might enjoy the advantages of successful mutations (e.g., an organizational restructuring) over several periods. High levels of current mutation might foretell future mutations and reflect a market with aggressive risk-taking participants. Consequently, we hypothesize a positive correlation between current displacement and future growth. Of course, the nature and duration of any carryover likely varies from situation to situation. One alternative hypothesis is that displacement from serious mistakes causes decline over multiple periods (Finkelstein and Sanford 2000).

Our theory of established market growth provides a third testable hypothesis. Consider an environment that is growing more hostile, possibly because of Malthusian competition from competing markets with alternative technologies, alternative sources of labor, or alternative management strategies, for example. Then, a lack of favorable mutations might result in decline. Consequently, we hypothesize that a minimum or critical level of displacement is necessary to maintain the status quo and avoid decline.

All three hypotheses are falsifiable. Our empirical analysis checks the consistency of our three hypotheses with observation after we develop a metric to measure displacement.

2.4. Measuring Growth

To test our hypotheses, we measure growth on some specific performance variable (e.g., unit sales, dollar sales, market share). Choosing that performance variable is not completely arbitrary. Environmental sorting implies growth only on variables favored by the environment. We expect that the environment prefers the usual performance variables. For example, investments and other resources might flow to economic agents that have greater sales, profits, dividends, or cash flows (Rust et al. 2004). In general, there must be environmental factors that reward improvement on the performance variable and allow the environment to sort market participants on that performance variable. Empirical analysis will reveal whether the environment favors any given performance variable resulting in growth on that variable.

Although we have analyzed different performance variables, the sales variable is a widely used one. Market participants with greater sales might obtain greater funding and resources. Resellers might want to sell products and services with greater sales. The sales variable is applicable across many product and service markets at different levels of aggregation and different contexts. Sales are often correlated with other performance variables. U.S. government agencies, the trade press, and academic publications often consider market growth in terms of sales. Bass's (1969) growth theory focuses on sales. In almost every instance, there is some possibility (perhaps remote) of improving sales. Moreover, our subsequent empirical analysis shows that we can explain market growth measured in sales.

3. A Metric for Environmental Sorting

3.1. Measuring Sorting

This section provides a simple illustration of our general approach to measuring the observed outcome (i.e., sorting) of latent mutations in the market. Later (see §3.6), we provide a precise measure.

Let $\mathbb{S}_t[j]$ denote a performance measure for market participant j at time t, where participant j could be a brand, firm, or product category. As noted earlier, the performance variable $\mathbb{S}_t[j]$ could be any relevant measure of performance, including sales, assets, profits, cash flows, or any other variable favored by the environment. However, $\mathbb{S}_t[j]$ is often defined in terms of sales.

Let S_t denote the market size at time t, so that $S_t = \sum_j \mathbb{S}_t[j]$. Our theory suggests that the rate of environmental sorting (current or past) can, in the very least, explain market growth $S_t - S_{t-1}$ from period $t-1$ to period t for any performance variable and might explain growth into future periods as well.

As explained in §2, our theory of growth through environmental sorting provides the testable hypothesis that growth increases as the rate of latent mutation increases. Environmental sorting results in observable displacement. So we expect market growth $S_t - S_{t-1} > 0$ when the relative positions of $\mathbb{S}_t[i]$ and $\mathbb{S}_t[j]$ change. For example, one testable prediction is that $S_t - S_{t-1} > 0$ when $\mathbb{S}_{t-1}[i] > \mathbb{S}_{t-1}[j]$ in period $t-1$ but $\mathbb{S}_t[i] < \mathbb{S}_t[j]$ in period t. Note that this prediction is not tautological. We could (although we do not) hypothesize that change in the relative competitive relationship between any two market participants results from serious mistakes rather than beneficial change. Moreover, that $\mathbb{S}_{t-1}[i] > \mathbb{S}_{t-1}[j]$ and $\mathbb{S}_t[i] < \mathbb{S}_t[j]$ does not necessarily imply $\mathbb{S}_t[i] + \mathbb{S}_t[j] > \mathbb{S}_{t-1}[i] + \mathbb{S}_{t-1}[j]$. As we note in §2, reasonable competing theories could predict the opposite. For example, brand shares could shift without category growth. Thus, other theories might predict displacement without growth. Hence, our theory's hypotheses (predictions) are falsifiable and not obvious.

3.2. Rank as a Unit of Analysis

We now provide a more general method for detecting environmental sorting than that presented in the prior section. As noted in §2, higher rates of environmental sorting imply greater changes in the relative competitive positions of market participants. One way to measure these changes is by ranking market participants and observing changes in those rankings. Hence, to measure the rate of environmental sorting, we define market participants in terms of ranks at each point in time rather than focusing on the identity of particular market participants. The market and time period define the market participants, rather than the other way around. For example, in each period there is a participant of rank r. We compare the performance of the participant of rank r over time (e.g., the automobile with the largest sales at each point in time) rather than comparing the sales of a particular brand (e.g., Camry) over time.

Using ranks, our modified definition of market growth (based on ranks rather than identities) is

$$\Delta_t = \sum_{r=1}^{N} s_t(r) - \sum_{r=1}^{N} s_{t-1}(r) \quad \text{for } t = 2, 3, \ldots, T, \tag{1}$$

where

$r =$ firm rank ($r = 1$ for the largest sales or other performance variable);
$\Delta_t =$ market growth from period $t-1$ to period t;
$s_t(r) =$ performance of the rth-ranked firm (or other population member) in period $t = 1, 2, \ldots, T$;
$T =$ the number of time periods;
$N =$ the number of firms; and
$\sum_{r=1}^{N} s_t(r) =$ market performance (i.e., all ranked firms) in period t.

3.3. Advantages of Using Rank as a Unit of Analysis

The use of rankings is an important departure from much of the prior literature. Using rank as the unit of analysis is compatible with environmental sorting. Identifying market participants by rank (e.g., the sales $s_t(r)$ of the rth-ranked market participant), rather than by their identity (e.g., General Motors, Delta Airlines, Honda Civic), allows an immediate integration of the market definition, the performance variable, and environmental sorting. The market is defined in terms of the performance variable, and the rankings explicitly capture both that performance variable and the process of environmental sorting on the performance variable because market participants can move up or down in the rankings. The change in the rankings or displacement of some firms from their previous rankings provides a valuable metric for detecting the rate of environmental sorting and latent mutation. In addition, using ranks rather than using participant identities has several other advantages, including the following.

1. A rank-based metric clearly distinguishes environmental sorting from many alternative theories.

There is no tautological relationship. Market participants can plausibly move up or down in rank with or without market growth or decline. For example, the sales of all market participants could increase and cause growth without relative changes in ranks.

2. A rank-based metric applies to any market and any performance variable that can be ranked (sales, assets, profits, rate of return, etc.). For example, we can rank product categories by sales, students by test scores, retailers by number of outlets, countries by gross national product (GNP), or race cars by lap times. We can rank 5 or 50 market participants.

3. A rank-based metric allows seamless intertemporal comparisons often inhibited when individual identities are the unit of analysis. Using ranks avoids survivor bias because the market definition always includes the same ranks. The use of ranks allows a consistent market definition when market composition changes over time as new market participants enter, old participants leave, current participants change form, and previous participants reenter. For example, we can explain the growth of the top 100 market participants over time even when individual participants enter, leave, or reenter the market. We can explain the growth of any set of participants. For example, we can use the top 10 brands or the top 100 brands. We can compute rankings without data on specific reasons why particular participants change rank. Moreover, we can easily determine whether the rth-ranked participant is the same participant in any two periods.

4. A rank-based metric is ideal for established markets because growth may or may not involve entry of new market participants. Displacement may be temporary. A market participant might take an action that temporarily displaces a competitor, who later displaces the first participant.

5. A rank-based metric allows mortality and inheritance by definition. The market participant of rank r in period t can differ from the market participant of rank r in the prior period. If a market participant retains its rank, it essentially inherits the same traits. If a different market participant assumes that rank, the rank reflects the new participant's traits.

6. A rank-based metric allows statistical parsimony and a reduction in the number of nuisance parameters. For example, an analysis of the top 100 market participants always requires no more than 100 growth parameters. Using identities as the unit of analysis, in contrast, causes the number of parameters to escalate over time as new participants enter into the analysis.

7. A rank-based metric allows a general concept of environmental sorting. The market is defined by the range in rank of the chosen performance variable (sales, assets, profits, returns on investments, etc.). For example, the market or submarket might be the 10 largest brands, the 10 best baseball teams, the 10 highest income states, or the 10 countries with the largest GNP. Market participants can temporarily or permanently enter or leave without requiring death or bankruptcy.

Consequently, after defining a performance variable (sales, assets, profits, etc.), we rank the market participants on that variable. The rank becomes our new unit of analysis, and the participant corresponding to that rank can change over time regardless of whether or not the participant itself survives.

3.4. Measuring the Rate of Environmental Sorting

Our objective is to determine whether our theory can explain established market growth or decline. The theory suggests that when brands, firms, and other market participants change in some way, the environment (i.e., nature) will determine the favorability of each change. Participants with favorable changes move up in rank while other participants move down. One observed outcome should be a change in the competitive relationships between the market participants. Another observed outcome should be market growth.

When actions causing changes have uncertain outcomes, favorable or unfavorable changes are likely to occur for different participants in different time periods, creating different winners and losers. This prediction of the theory is not obvious, and some alternative theories predict the opposite. For example, consider an auto market consisting of the models Aveo (A), BMW-5 (B), and Cruze (C). Rank the autos in order of increasing sales. Mathematically, let $a(r, t)$ denote the identity of the market participant having rank r at in period t. Suppose the following relationship holds:

$$\text{In period } t-1 \begin{cases} a(1, t-1) = A, \\ a(2, t-1) = B, \\ a(3, t-1) = C, \end{cases}$$
$$\text{where } \mathbb{S}_{t-1}[A] > \mathbb{S}_{t-1}[B] > \mathbb{S}_{t-1}[C]. \tag{2}$$

Now consider two possible cases in period t as follows:

Case I.

$$\text{In period } t \begin{cases} a(1, t) = A, \\ a(2, t) = B, \\ a(3, t) = C, \end{cases}$$
$$\text{where } \mathbb{S}_{t}[A] > \mathbb{S}_{t}[B] > \mathbb{S}_{t}[C]; \tag{3}$$

Case II.

$$\text{In period } t \begin{cases} a(1, t) = B, \\ a(2, t) = C, \\ a(3, t) = A, \end{cases}$$
$$\text{where } \mathbb{S}_{t}[B] > \mathbb{S}_{t}[C] > \mathbb{S}_{t}[A]. \tag{4}$$

In Case I, there is no change in the relative competitive positions of the market participants. In Case II, the market participants change their relative competitive positions. Our theory predicts that market growth is more likely in Case II than in Case I because the former indicates the presence of environmental sorting. Moreover, the theory predicts that future growth is more likely in Case II because the market displays greater displacement, which suggests a higher level of latent mutation.

As noted earlier, the extant literature contains competing predictions about whether growth will be greater in Case I or Case II. For example, a competing theory is that stability encourages expansion, investments, and growth. Another competing theory is that large brands gradually squeeze out small brands. Rich companies get richer and growth occurs without changes in the relative competitive positions of the companies.

3.5. Quantifying Changes in Rank

We predict that actions by market participants having uncertain outcomes, followed by environmental sorting, can result both in changes in the relative competitive positions of the market participants and growth. To test that prediction, we define the following function to detect changes in relative competitive positions:

$$\delta(r,q,t) = \begin{cases} 1 & \text{if } a(r,t-1) = a(q,t), \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

The previous example illustrates the precise computations. Case I had no change in any of the rankings. So $a(1,t-1) = a(1,t) = A$ implies $\delta(1,1,t) = 1$, $a(2,t-1) = a(2,t) = B$ implies $\delta(2,2,t) = 1$, and $a(3,t-1) = a(3,t) = C$ implies $\delta(3,3,t) = 1$. Note that $\delta(r,q,t)$ is 0 for all other rank combinations $(r \neq q)$. In Case II $a(1,t-1) = a(3,t) = A$ implies $\delta(1,3,t) = 1$, $a(2,t-1) = a(1,t) = B$ implies $\delta(2,1,t) = 1$, and $a(3,t-1) = a(2,t) = C$ implies $\delta(3,2,t) = 1$, so every rank changes identity. Note that $\delta(r,q,t)$ is 0 for all other rank combinations.

The following equation represents one simple metric for measuring the change in the relative competitive positions of the market at some period (t):

$$\sum_{r \neq q}^{N} \delta(r,q,t). \tag{6}$$

For Case I, $\sum_{r \neq q}^{M} \delta(r,q,t) = 0$ because $\delta(r,q,t) = 0$ for all $r \neq q$. For Case II, $\sum_{r \neq q}^{M} \delta(r,q,t) = 3$ because $\delta(r,q,t) = 0$ for all $r \neq q$ except for $\delta(1,3,t) = 1$, $\delta(2,1,t) = 1$, and $\delta(3,2,t) = 1$. Although this metric can distinguish between Cases I and II, it has an undesirable property; i.e., minor changes in the relative competitive positions are indistinguishable from major changes. For example, in Case II, Aveo moves from the highest to the lowest rank, but all other cars retain their relative ranks. So $\sum_{r \neq q}^{3} \delta(r,q,t) = 3$, and the metric takes the largest possible value. Now consider the following case, where Dart (D) enters the market in rank 2:

Case III.

$$\text{In period } t \begin{cases} a(1,t) = C, \\ a(2,t) = D, \\ a(3,t) = B, \end{cases}$$
$$\text{or} \quad \mathbb{S}_t[C] > \mathbb{S}_t[D] > \mathbb{S}_t[B]. \tag{7}$$

Case III illustrates a more dramatic shift in the relative competitive positions. In both Cases II and III, Aveo drops in rank. Perhaps Aveo encountered an unexpected transmission problem (maybe reducing entry barriers for a competitor). However, in Case III (unlike Case II), Aveo is no longer ranked, and Dart enters the ranking. Moreover, the BMW-5 no longer has higher sales than the Cruze. Hence, Case III reflects a greater change in relative market positions than does Case II. Unfortunately, the $\sum_{r \neq q}^{N} \delta(r,q,t)$ metric is unable to distinguish between cases such as II and III. The next section proposes a slightly modified metric that overcomes that limitation. That metric is the number of ranked participants that drop in rank or who are no longer ranked.

3.6. Our d_t Displacement Metric

This section overcomes the basic limitation of the $\sum_{r \neq q}^{N} \delta(r,q,t)$ metric with a new metric based on $\sum_{q=1}^{r} \delta(r,q,t)$. The summation $\sum_{r \neq q}^{N} \delta(r,q,t)$ determines how many participants change in rank. The later summation, $\sum_{q=1}^{r} \delta(r,q,t)$, considers only the market participant of rank r and whether that participant drops in rank. To understand how this works, consider the market participant of rank r in period $t-1$. The summation $\sum_{q=1}^{r} \delta(r,q,t)$ is 0 when that market participant drops in rank or leaves the rankings in period t. In contrast, $\sum_{q=1}^{r} \delta(r,q,t)$ is 1 when that market participant retains the same rank or moves up in rank in period t. To consider all N market participants, sum this expression over $r = 1, \ldots, N$. We obtain $\sum_{r=1}^{N} \sum_{q=1}^{r} \delta(r,q,t)$, which considers all the market participants. We subtract $\sum_{r=1}^{N} \sum_{q=1}^{r} \delta(r,q,t)$ from N to obtain a metric that we hypothesize will be positively correlated with future growth. The rate at which Darwinian time is progressing is measured by what we call the d_t metric, or displacement metric:

$$d_t = N - \sum_{r=1}^{N} \sum_{q=1}^{r} \delta(r,q,t) \quad \text{for } t = 2,3,4,\ldots,T. \tag{8}$$

The d_t metric captures the rate of environmental sorting occurring during a particular time period. The d_t metric is the number of ranked participants that are displaced (i.e., drop in rank or who are no longer ranked in that period). Note that the d_t metric is not simply a measure of change among the market participants; it is a measure of whether different market participants are changing at different rates. It is also a measure of whether those relative changes are enough to cause changes in the ranks of the market participants. A change in ranking detects the result of environmental sorting. Our theory predicts that when d_t is large, the environment has found favorable (possibly latent) mutations among the market participants that are sufficient to cause the displacement of some market participants.

3.7. How the d_t Displacement Metric Distinguishes Between Cases I, II, and III

The following computations show how the d_t metric distinguishes between the preceding cases:

$$\textit{Case I: } d_t = 3 - \sum_{q=1}^{1} \delta(1,q,t) - \sum_{q=1}^{2} \delta(2,q,t) - \sum_{q=1}^{3} \delta(3,q,t) = 3 - 1 - 1 - 1 = 0,$$

$$\textit{Case II: } d_t = 3 - \sum_{q=1}^{1} \delta(1,q,t) - \sum_{q=1}^{2} \delta(2,q,t) - \sum_{q=1}^{3} \delta(3,q,t) = 3 - 0 - 1 - 1 = 1,$$

$$\textit{Case III: } d_t = 3 - \sum_{q=1}^{1} \delta(1,q,t) - \sum_{q=1}^{2} \delta(2,q,t) - \sum_{q=1}^{3} \delta(3,q,t) = 3 - 0 - 0 - 1 = 2.$$

There is an increase in the d_t displacement metric from 0 to 1 to 2. Hence, the d_t metric captures the rate of environmental sorting in each of the three cases.

3.8. Advantages of the d_t Displacement Metric

The d_t displacement metric detects latent mutation by measuring the corresponding displacement that it creates. The d_t metric computes the number of ranked market participants that drop in rank in period t (or who are no longer ranked) where market participants are ranked from best to worst on some performance variable (e.g., sales). There are several advantages to measuring environmental sorting in this way:

- The predicted correlation between d_t and growth is not obvious, so it is a fair test of the theory.
- Consistent with Occam's razor, d_t is simple and uses either ordinal or metric data.
- The d_t metric is scalable. It is linear in the number of market participants and does not increase exponentially with the total number of market participants.
- The d_t metric is inherently scaled from 0 to N.
- The d_t metric is general and might apply in many different markets (countries, firms, products, brands, etc.), different performance variables (sales, number of employees, stock price, market capitalization, etc.), and different contexts (sports, markets, contests, sales people, etc.).
- The d_t metric implicitly ignores mutations that are insufficient to produce a change in rankings.
- The d_t metric has the property that does not overweight large drops in rank. A metric measuring upward movement would not have that property.
- Unlike much prior research, the d_t metric might predict periods of sporadic growth, decline, and stagnation. Of course, only empirical analysis can determine whether it can.

4. Empirical Analysis

The objective of this section is to test our scalable theory of established market growth at multiple levels of aggregation using multiple metrics for growth and using multiple databases. Given this objective, our ideal theoretical test should be straightforward, involve publicly available data, be easily replicated, be falsifiable (i.e., capable of showing the theory is wrong), require few statistical adjustments, and avoid obvious econometric issues such as possible endogeneity and aggregation errors.

We have replicated our findings using multiple data sets, but, given space limitations, this section highlights analyses of only two data sets (the Fortune 100 and WardsAuto). These two data sets allow us to test our growth theory using both dollar sales (the Fortune 100 data) and unit sales (the WardsAuto data).

4.1. First Data Set

The Fortune 100 data set is a publicly available database of the top 100 firms (supplemented with Compustat data) during a 55-year period (1955–2009). This database has the following benefits:

- It is easy to replicate our analysis.
- It is easy to check the robustness of our results.
- Endogeneity is absent because a declining Fortune 100 firm does not decide to be a loser.
- This market is established.
- No firm enters the Fortune 100 during their first year of existence.
- Our theory's predictions differ from those of viable alternative or competing hypotheses (e.g., the rich firms grow richer, stability fosters future growth).
- Our data are very accurate (no aggregation issues or missing observations).

Computing growth requires two periods of data; ergo, computing growth loses one degree of freedom (i.e., the first observation), leaving 54 observations. Predicting growth two periods into the future loses two additional degrees of freedom, resulting in 52 observations.

Examination of the Fortune 100 sales reveals that 86.0% of the sales correspond to the top 68 firms. The sales of the top 68 firms have a correlation of 99.9% with the top 100 firms. The growth of the top 68 firms has a correlation of 99.8% with the top 100 firms' growth. Hence, although we do not observe the sales of all firms, these statistics suggest that the top 100 firms are representative of the total market.

4.2. Second Data Set

Our second data set is the monthly U.S. unit automobile sales for 300 months (25 years, from 1980 through 2004). This data set is publicly available for purchase from *Ward's AutoWorld*, the leading industry trade magazine since 1924. It provides accurate data on the automobile industry in two monthly newsletters (*Ward's Automotive Reports* and *Ward's Engine and Vehicle Technology Update*). Computing growth requires two periods of data, so we lose one degree of freedom, leaving 299 observations.

Our data set includes all 1,081 automobile models sold in the United States. Consistent with the Fortune 100 analysis, we analyze each month's top 100 models. These models represent over 86.1% of all 373,000,278 units of auto sales. Sales of the top 100 models have a correlation of 98.3% with the sales for all models. The growth in sales of the top 100 models has a correlation of 99.8% with the growth in sales of all models. So the top 100 models are representative of all 1,081 models and account for most of the sales.

4.3. Summary Statistics

Tables 1(a)–1(c) contain summary statistics for our two data sets. The Fortune 100 data show, on average, very small average annual increases (2.8%) in inflation-adjusted 1983 dollar sales; the WardsAuto data show no average monthly increases in unit sales (0.1%). However, compared with these average increases, there is larger sales variation across periods, with mean absolute percent changes in sales of 5.3% and 10.6%, respectively. The mean d_t metric values for the two data sets are 47.8 and 48.8, respectively, indicating a dynamic market where, on average, 48 participants drop in rank every period. When the d_t metric is above the mean value, sales increase more than half of the time (61.1% and 58.9% for the Fortune 100 and WardsAuto data sets, respectively). When the d_t metric is one standard deviation above the mean value, sales increase most of the time (100.0% and 66.0% for the Fortune 100 and WardsAuto data sets, respectively). When the d_t metric is one standard deviation below the mean value, sales decrease most of the time (62.5% and 100.0% for the Fortune 100 and WardsAuto data sets, respectively). However, as the next section shows, we only predict growth when d_t is well above the mean (a level estimated by the negative intercepts).

Table 1(a) Summary Statistics: Fortune 100 and WardsAuto Data

Market sales information	Fortune 100 ($ millions)	WardsAuto (units)
Mean sales each period	1,429,945	1,070,754
S.D. for sales	731,199	166,553
Mean change in sales	40,291	940
S.D. for change	84,902	130,493
Mean change (in %)	2.8	0.1
S.D. (in %)	210.7	13,878.8
Mean absolute % change	5.3	10.6
Median sales per period	1,396,784	1,071,821
Median change in sales	43,004	−525
Median change (in %)	3.1	0.0

Table 1(b) d_t Statistics: Fortune 100 and WardsAuto Data

d_t statistics	Fortune 100	WardsAuto
Mean	47.8	48.8
Median	48.0	48.0
S.D.	8.6	4.5
Range	43.0	25.0
Sample size	54	299
Mean d_t when sales down	42.1	48.5
Difference when sales are up	+7.7	+2.1
t-statistic for difference	3.1	4.2
p-value	0.0016	0.0000

Table 1(c) Relationship Between d_t and Sales: Fortune 100 and WardsAuto Data

d_t statistics	Fortune 100	WardsAuto
d_t above (below) mean predicts sales up (down) (correct prediction, in %)	61.1	58.9
d_t one sigma above mean predicts sales up (correct prediction, in %)	100.0	66.0
d_t one sigma below mean predicts sales down (correct prediction, in %)	62.5	100.0

4.4. Testing Our Three Hypotheses

As §3 explains, our theory predicts a positive correlation between d_t and market growth. We predict that market participants dropping in rank is not simply a reflection of deteriorating market conditions. In fact, we predict the opposite—that prediction is not obvious and is falsifiable. For example, suppose that growth Δ_t and future growth Δ_{t+} are linear functions of d_t; i.e., $\Delta_t = \alpha + \beta d_t$ and $\Delta_{t+} = \alpha_+ + \beta_+ d_{t+}$. Then, the three hypotheses in §2.3 become, respectively,

(1) $\beta > 0$, (2) $\beta_+ > 0$, and (3) $\alpha, \alpha_+ < 0$ for the estimated parameter values.

Clearly, when the sales of every market participant increase, there is immediate growth without displacement. Hence, environmental sorting theory makes a prediction that is not obvious or tautological. It predicts that future market growth is not necessarily the consequence of common growth. It predicts that future market growth results from the displacement of the competitive positions of some market participants.

4.5. Benchmarks

Our empirical analysis provides a test for our theory of established market growth (or decline) by testing the accuracy of our theory's quantitative predictions. However, benchmarks are useful for determining the difficulty of making accurate predictions. One obvious benchmark is a simple trend variable. Our theory's quantitative predictions should be more accurate than trend-based predictions. Another benchmark is a lagged version of the variable being predicted. For predicting growth, we use last period's growth. This is a very strong—almost unfair—benchmark because lagged or past growth $S_{t-2} - S_{t-1}$ and current growth $S_t - S_{t-1}$ both contain last period's sales (S_{t-1}). Consequently, S_{t-1} appears in both the dependent and the independent variables, possibly creating a spurious correlation for this benchmark.

We also employ the prediction made by Bass (1969) growth theory even though the theory does not necessarily apply to established markets. Nevertheless, the Bass growth model does allow quadratic growth. We estimate the model using all available data to find the fitted values (i.e., predicted sales) for every period. We then regress the fitted values on the actual sales, use the estimated parameters to predict each period's sales and use these predicted sales to compute each period's predicted growth. This procedure gives the Bass growth model every possible predictive advantage.

We test our theory of growth using our d_t displacement metric to predict immediate and future growth. To increase the number of observations and potential predictive ability of our displacement metric, we also use the smoothed versions of our metric ($\bar{d}_t$) computed by averaging the metric over the prior three periods. The basic idea is that predicting growth for several future periods requires averaging our metric over several past periods because displacement can vary across periods. Moreover, smoothing helps eliminate spurious fluctuations caused by using data from only one period.

Note that, unlike some of the benchmark metrics, we calculate d_t from the number of market participants who decline in rank so there is no obvious mathematical relationship between our metric and growth (or any other performance variable). Also note that when prediction alone is the goal (rather than theory testing), then it is often best to average predictions across multiple models and multiple metrics.

4.6. Our Displacement Metric and Entry

One could hypothesize (though we do not) that our metric is related to new entry and that new entry causes growth. The Fortune 100 data lack this information because there is no entry; the top 100 are always established firms. However, we can test the alternative entry hypothesis with our WardsAuto data (which include new models). Table 2 rejects that hypothesis, suggesting that there is no relationship between entry (i.e., the number of new models entering the market) and our metric or market growth.

Hence, there is no relationship between the entry of new car models and contemporaneous market growth. Of course, if new models displace old models, there could be long-term growth.

There is also no relationship between macroeconomic indicators and contemporaneous or future growth in auto sales (see Table 3). Some economic indicators can predict contemporaneous but not future growth of Fortune 100 sales. However, for both data sets, economic indicators have low to very low correlations with our d_t metric. Hence, even if macroeconomic indicators can sometimes predict growth or decline, they do not drive d_t.

Table 2 Correlations with Number of New Automobile Models (i.e., Entry)

Variable	Correlation
Growth top 100 models	−0.0434197
Growth all models	−0.0412693
d_t	0.0197947
Trend	0.0758064

Table 3 Correlations with Economic Variables

Predictor	Correlation with d_t	Correlation with change in auto sales	Correlation with lead change in auto sales
Consumer price index	−0.0802	−0.0263	−0.0223
Industrial production index	−0.0089	0.0953	0.0114
Producer price index	−0.0664	−0.0781	0.0976
Bank prime loan rate	−0.1212	−0.0199	0.0005
Civilian unemployment rate	−0.0122	−0.0289	0.0094
Housing starts	0.0276	−0.0015	−0.0528
Dow Jones stock index	−0.0492	−0.0726	0.0382
Personal savings rate	−0.0089	−0.0008	0.0859

Note. Monthly predictor (January 1980–December 2004).

4.7. Predicting Growth

Even when we can predict absolute sales, market growth remains difficult to predict. For example, suppose sales over time resemble a random walk. Predicting growth is then difficult, if not impossible. The best predictor of sales becomes last-period sales, but the best predictor of growth becomes no growth. No growth is an inadequate theory of growth even though it might be a good null hypothesis.

To test our theory of established market growth, we need to test whether our first hypothesis (see §4.4) is consistent with observation. Tables 4(a) and 4(b) provide the results for the Fortune 100 and WardsAuto data, respectively. The tables show that neither the benchmarks nor the trend variable can predict growth. The trend variable has no ability to predict growth. For both data sets, the F-statistics (0.2 and 0.0, respectively) are not significant. The past (lagged) growth benchmarks have significant F-statistics of 5.8 and 42.6 for the Fortune 100 and WardsAuto data, respectively. However, these F-statistics are less impressive than they appear because both current growth $S_t - S_{t-1}$ and past growth $S_{t-1} - S_{t-2}$ include last-period sales (S_{t-1}). Consequently, there will be a spurious correlation between last period's growth and this period's growth because the variable S_{t-1} appears in the computation of both the dependent and independent variables in the regression. In the next section, we show that removing the common variable by adding additional lags eliminates this spurious correlation and reveals that lagged growth cannot explain future growth.

The Bass (1969) growth model was never intended to predict established market growth. Although it does provide a possible quadratic fit, its predictions produce insignificant F-statistics of 0.1 and 1.7 for the Fortune 100 and WardsAuto data, respectively.

In contrast to these benchmark metrics, our growth theory does very well. The F-statistics for our d_t metric are highly significant. The coefficients have the hypothesized signs (i.e., positive). For the Fortune 100 data, the F-statistic for our d_t displacement metric is significant at the 0.00020 level. For the WardsAuto data, the F-statistic for our d_t displacement metric is significant at the 0.00187 level. Smoothing (averaging d_t over the past three periods) yields significance levels of 0.00107 and 0.01396 for the Fortune 100 and WardsAuto data, respectively. As noted earlier, this analysis is a fair test of our theory because our d_t displacement metric (the number of market participants declining in rank) is conceptually (not mathematically) linked to market growth. In fact, growth and our metric are measured in different units. Our metric is measured in the number of firms or number of automobile models (i.e., dropping in rank), whereas growth is measured in dollars or the number of automobiles sold.

Finally, as predicted, all the estimated intercepts for our d_t metric are negative. The intercepts are $-188{,}620$ and $-225{,}853$ for the Fortune 100 data and $-252{,}406$ and $-371{,}439$ for the WardsAuto data. These negative intercepts confirm our hypothesis that without some positive level of environmental sorting, markets face decline. There must be a minimum level of displacement (changes in the competitive relationships between the market participants) to maintain zero growth and avoid decline. In these cases, the minimum levels are

$$\left(\frac{4{,}793}{188{,}620}\right) = 39.35$$

and

$$\left(\frac{5{,}196.6}{252{,}406}\right) = 48.57,$$

respectively. This finding is consistent with the Red Queen hypothesis (Fisher 1930, p. 44; Van Valen 1973),

Table 4(a) **Predicting Fortune 100 Firms' Sales Growth (1955–2009)**

Predictor	Coefficient	Std. error	t-statistic	F-statistic	R^2	p-value	Intercept
Trend	306.9	747.18	0.41	0.2	0.00	0.68299	31,853
Past growth	0.4	0.15	2.40	5.8	0.10	0.02012	24,954
Bass growth	−0.2	0.68	−0.36	0.1	0.00	0.72369	51,699
d_t	4,793.0	1,197.28	4.00	16.0	0.24	0.00020	−188,620
$\bar{d}_t$	5,564.4	1,606.44	3.46	12.0	0.19	0.00107	−225,853

Table 4(b) **Predicting Top 100 Auto Models' Sales Growth (1980–2004)**

Predictor	Coefficient	Std. error	t-statistic	F-statistic	R^2	p-value	Intercept
Trend	7.3	87.58	0.08	0.0	0.00	0.93399	−149
Past growth	−0.4	0.05	−6.53	42.6	0.13	0.00000	959
Bass growth	−37.0	28.10	−1.32	1.7	0.01	0.18843	36,210
d_t	5,196.6	1,656.11	3.14	9.8	0.03	0.00187	−252,406
$\bar{d}_t$	7,637.8	3,088.43	2.47	6.1	0.02	0.01396	−371,439

which states that biological organisms must constantly evolve to survive when competing organisms are ever-evolving.

In sum, the benchmarks show that predicting growth is not easy. However, our explanatory theory of growth and our displacement metric can predict current and future growth. Moreover, our metric predicts market growth better than every other variable we tried, including new product entry.

4.8. Predicting Future Growth

Recall that our theory predicts that growth or decline is a result of environmental sorting and that d_t measures the amount of environmental sorting occurring in a particular period. We hope that d_t can predict both short- and long-term growth. It is possible that, when displacement levels are high, then growth might occur over several periods because the outcomes of some actions last many periods. Of course, subsequent levels of environmental sorting (low or high) might reverse any past trend.

To test whether our theory can predict future growth, we test whether d_t and the smoothed $\bar{d}_t$ (reflecting displacement over the three past periods) predict future growth. The benchmarks illustrate the difficulty of making accurate predictions. Tables 5(a) and 5(b) show the results for growth predictions, two years into the future, for the Fortune 100 data and the WardsAuto data, respectively. Trend cannot predict future growth. The F-statistics are 0.0 for both data sets. Past growth also cannot predict future growth and has insignificant F-statistics of 0.0 and 1.1 for the Fortune 100 and WardsAuto data, respectively. Neither F-statistic is close to being significant. When predicting multiple years into the future, the past growth benchmark no longer enjoys the advantage of having the quantity (S_{t-1}) in both the independent and dependent variable. The Bass (1969) growth model, which was not designed to predict established market growth, has insignificant F-statistics (0.3 and 2.5, respectively). The inability of these benchmarks to predict future growth illustrates the difficulty of predicting future growth.

Our displacement metric is better; the F-statistics are significant. The d_{t-2} displacement metric is significant at the 0.06184 level for the Fortune 100 data. The smoothed version, averaged over the past three years, is significant at the 0.00783 level. The d_{t-2} displacement metric is significant at the 0.06577 level for the WardsAuto data. Smoothing is significant at the 0.03484 level. As expected, predicting growth to multiple future periods requires averaging our metric over multiple past periods.

Finally, all the coefficients for our displacement metric have the predicted positive signs. All the intercepts have the predicted negative signs. The intercepts are −85,057 and −203,785 for the Fortune 100 data. The intercepts are −150,540 and −322,141 for WardsAuto data. These negative intercepts confirm our theoretical prediction that without some positive level of environmental sorting, markets face decline. There must be a minimum level of displacement to maintain zero growth and avoid decline.

Remember, the d_t displacement metric measures the rate of environmental sorting. It is not just a measure of the myriad mutations in each period; it measures whether those mutations are sufficient (from the environment's viewpoint) to change the relative competitive positions of market participants. Our ability to make long-term predictions suggests that (possibly latent) mutations have some inertia and that their effect persists into future periods. Of course, our theory does not guarantee this; intervening effects often alter long-term trends (Grant and Grant 2002).

Table 5(a) Predicting Fortune 100 Firms' Sales Growth Two Years into the Future (55 Years of Data)

Predictor	Coefficient	Std. error	t-statistic	F-statistic	R^2	p-value	Intercept
Trend	86.8	832.56	0.10	0.0	0.00	0.91744	40,299
Past growth	0.0	0.16	0.11	0.0	0.00	0.91178	41,731
Bass past growth	−0.4	0.74	−0.52	0.3	0.01	0.60721	58,750
d_{t-2}	2,630.0	1,376.77	1.91	3.6	0.07	0.06184	−85,057
$\bar{d}_{t-2}$	5,069.9	1,829.63	2.77	7.7	0.13	0.00783	−203,785

Table 5(b) Predicting Top 100 Auto Models' Sales Growth Two Periods into the Future (25 Years of Data)

Predictor	Coefficient	Std. error	t-statistic	F-statistic	R^2	p-value	Intercept
Trend	1.1	89.01	0.01	0.0	0.00	0.99040	1,098
Past growth	0.1	0.06	1.03	1.1	0.00	0.30465	1,211
Bass past growth	−44.8	28.37	−1.58	2.5	0.01	0.11505	44,635
d_{t-2}	3,100.7	1,678.95	1.85	3.4	0.01	0.06577	−150,540
$\bar{d}_{t-2}$	6,618.0	3,121.65	2.12	4.5	0.02	0.03484	−322,141

This topic requires future research. However, our theory provides some hints as to which variables might explain d_t. These variables are likely related to, among other things, risk taking, diversity of opinions among market participants, and the perceived need to experiment. Any variable that is likely to encourage different changes in different market participants might work.

4.9. Adjusting for Seasonality

Because the WardsAuto data are likely seasonal, it might be appropriate to eliminate seasonality from the data. Given that our objective is to test our theory of growth, it is appropriate to consider and remove any seasonality in the least intrusive and most objective manner (i.e., not favoring our theory). We use 12-month moving averaging to adjust for seasonality. Consequently, we eliminate seasonality from each observation as each contains every seasonal month. For example, our first observation is the average sales from January to December. Our second observation is the average sales from February to January of the following year, and so on. This averaging loses 11 degrees of freedom because the first observation represents the average of the first 12 observations of data. Removing seasonality thus leaves 288 observations for growth predictions.

After eliminating seasonality, Tables 6(a) and 6(b) provide growth predictions for the benchmark metrics and our displacement metric. Each observation reflects a 12-month moving average. So we predict 12 months (Table 6(a)) and 18 months (Table 6(b)) into the future (ensuring no overlapping data).

The tables provide future growth predictions for the benchmark metrics and our displacement metric. Overall, our metric's predictive ability improves further after controlling for seasonality. None of the benchmark metrics can predict future growth at any satisfactory level of significance. By contrast, our displacement metrics exhibit F-statistics significant at the 0.00000 when predicting market growth 12 months into the future and F-statistics significant at 0.00004 and 0.00014 when predicting market growth 18 months into the future. Coefficients are positive as predicted. Finally, all the intercepts for our metric in our empirical analyses are negative. These negative intercepts again confirm our theoretical prediction that, without some positive level of environmental sorting, markets face decline.

4.10. Deep Dive into the Data

This section provides a deep dive into the data to examine and illustrate specific details for one period. Remember, our theory of growth or decline allows for many different sources of change, which can differ by period. In fact, the theory depends on millions of changes with uncertain outcomes. When some of those changes are favorable, the environment will select those changes and growth will occur.

This situation describes many industries, including the automotive industry. For example, there are frequent and numerous changes involving plant productivity, line differentiation, design, promotion, technology, fleet contracts, personnel, and financing. There are also myriad environmental changes involving interest rates, personal income, taxes, inflation, and national economic growth. These changes sometimes cause growth and other times decline. Design changes (which are too numerous to list) involve the frame, interior, exterior, features, build quality, engine, transmission, drive shaft, differential, suspension, paint quality, styling, energy efficiency, sound system, etc.

It therefore can be dangerous to construct specific post hoc explanations for past events without private and exhaustive inside information. However, here, we attempt to analyze one specific case.

Table 6(a) **De-Seasonal Top 100 Auto Models' Sales Growth 12 Months into the Future (25 Years of Data)**

Predictor	Coefficient	Std. error	t-statistic	F-statistic	R^2	p-value	Intercept
Trend	−10.5	6.88	−1.53	2.3	0.01	0.12727	2,605
Past growth	−0.1	0.06	−1.65	2.7	0.01	0.09982	1,284
Bass growth	−2.4	2.48	−0.95	0.9	0.00	0.34460	3,555
d_t	2,155.8	447.33	4.82	23.2	0.08	0.00001	−103,987
$\bar{d}_t$	2,289.5	462.65	4.95	24.5	0.08	0.00000	−110,498

Table 6(b) **De-Seasonal Top 100 Auto Models' Sales Growth 18 Months into the Future (25 Years of Data)**

Predictor	Coefficient	Std. error	t-statistic	F-statistic	R^2	p-value	Intercept
Trend	−15.6	7.04	−2.21	4.9	0.02	0.02774	3,453
Past growth	0.1	0.06	0.86	0.7	0.00	0.39278	1,318
Bass growth	0.0	0.01	−0.84	0.7	0.00	0.39951	1,403
d_{t-2}	2,017.8	451.37	4.47	20.0	0.07	0.00004	−97,048
$\bar{d}_{t-2}$	1,932.3	469.93	4.11	16.9	0.06	0.00014	−92,874

In the last decade of our monthly automobile data, the d_t metric varied from a low of 35 to a high of 59 with a mean of 49. The highest value for the d_t metric (i.e., 59) occurred in December 2002 (i.e., from November 2002 to December 2002). In December 2002, General Motors (GM) launched a promotional "incentive barrage" (Guilford 2003, p. 1). This new strategy involved a combination of incentives, including cash rebates, no down payments, no monthly payment for 90 days, low interest rates, and various dealer incentives including the "Goal Quest" rewards program (Guilford 2002). GM also added some new features across their product line (e.g., HomeLink) and implemented cost cutting (Hakim 2003).

This, of course, was not GM's first or last incentive program. Such programs are very common in the auto industry. However, the program's perfect timing created a strong interaction effect with the environment. GM's best-selling automobiles were pickup trucks and sport utility vehicles (SUVs). The environment was particularly receptive for these. New regulations (emissions, fuel economy) were coming that would likely make future SUV purchases more expensive (Quach 2003). Gasoline prices in 2002 declined by 12% from their 2001 prices (Beresteanu and Li 2011), making SUVs more attractive. There was also an inadvertent end-of-year federal tax break (loophole) for purchasing an SUV (Ball and Lundegaard 2002, Ackman 2003). The tax break was so large that one business person proclaimed, "My accountant told me I better buy something" (Kiley 2003).

These environmental factors were similar in November 2002 and December 2002. There was no obvious environmental change in December 2002. Although some of these factors were favorable for the makers of SUVs, there were also factors that were unfavorable for other automobiles. For example, automobiles featuring fuel economy had less of an advantage. Moreover, even though low gas prices spur auto sales, there was no reason to believe that GM SUVs would benefit more than their competitors' SUVs. However, there was a strong interaction effect between the environment and GM's actions, making those actions particularly effective.

The result was a dramatic improvement in the rankings of many GM automobiles. Table 7 shows the car models with the largest improvement in rank in December 2002. Most of these models are GM's automobiles. Of course, GM models displaced others. Table 7 also shows the car models with the largest decline in rank during that month. Except for Saturn, which was in limited production, none of the declining cars were made by GM. Most of the displaced cars were small economy vehicles rather than SUVs comparable with GM's models. This outcome was caused by the compatibility of GM's actions and the December 2002 environment. The environment was particularly receptive to GM's actions, causing considerable displacement (i.e., a large d_t).

Table 7 Vehicle Models' Change in Rank (November vs. December 2002)

Brand	Model	Origin	Nov 2002	Dec 2002	Change in rank	Examples of new features and comments
Models with largest gain in rank					Gain	
GMC	Yukon XL	United States	100	45	+55	New heavy-duty transmission, new steering gear housing, new starter
GMC	Yukon	United States	81	36	+45	Ultra-low emission certified for California
Buick	LeSabre	United States	56	25	+31	New 16-inch wheels, new radio, trunk release latch, child safety seats
Chevrolet	S10 pickup	United States	55	29	+26	Tachometer, air conditioning, third door, cold-weather package
Chevrolet	Avalanche	United States	82	57	+25	*Motor Trend*'s Truck of the Year, unique convertible cab system
Chevrolet	Express	United States	65	42	+23	Integrated compass, temperature gauge, new starter, steering gear housing
Mazda	Protégé	Japan	94	71	+23	New base engine, carbon fiber décor, larger tires, auto-dimming mirrors
Chevrolet	Suburban	United States	39	17	+22	New base trim, six-way power seats, heated mirrors, exterior side steps
Chevrolet	Tahoe	United States	28	7	+21	Premium ride suspension, power seats, fog lights, side-mounted steps
GMC	Envoy	United States	48	27	+21	Redesigned, all-aluminum in-line engine, new suspension, new look
Lexus	Lexus RX	Japan	73	52	+21	No changes
Models with largest decline in rank					Decline	
Saturn	Saturn S	United States	83	117	−34	Discontinued—soon replaced by larger Saturn Ion
Mitsubishi	Eclipse	United States	86	118	−32	New exterior colors, illuminated mirror, front bumper, door panels
Oldsmobile	Alero	United States	49	81	−32	Oldsmobile soon discontinued—new daytime running lights
Toyota	Matrix	Japan	88	119	−31	Just introduced in prior months
Hyundai	Sonata	Korea	71	101	−30	New suspension, keyless remote, power upgrade, auto-manual transmission
Mitsubishi	Outlander	Japan	78	108	−30	Just introduced in prior months
Kia	Spectra	Korea	85	113	−28	Renamed, exterior styling changes
Dodge	Neon	United States	33	60	−27	Four-speed automatic gearbox, new base model, new crosshair style
Ford	Victoria	United States	69	92	−23	Boosted torque, auto-dimming mirror, new power-adjustable pedals
Buick	Regal	United States	93	110	−17	New variants (hybrid and GS models), smartphone integration, touchscreen
Infiniti	Infiniti G	Japan	72	89	−17	New aluminum alloy wheels, sports package, new exterior colors
Toyota	RAV4	Japan	58	75	−17	Cosmetic changes, new interior/exterior colors

As expected, GM sales increased, but surprisingly, most of those sales did not come from competitors or similar automobiles. Our data show a 21.1% increase in total auto sales in December 2002 versus an average December increase of 4.6% in other years. Hence, the environment in December 2002 was particularly favorable toward GM's actions in that month, causing a dramatic increase in the market for all automobiles. Total automobile sales increased because the environment found changes for some GM models to be particularly favorable, and those changes caused displacement.

However, post hoc explanations can sometimes be misguided and misleading. Note that both the Mazda Protégé and the Lexus RX had significant gains with no apparent changes in strategy. Moreover, GM's Buick Regal showed large declines despite the company's incentive program.

Finally, for the Fortune 100 data, d_t reaches a maximum (69) in 1997, just before the growth of the dot-com bubble (1997–2000). It reaches a minimum (26) in 2006, just before the 2007 global financial crisis.

4.11. Additional Analysis

We have replicated the tests of our theory using other data sets and obtained similar results:

- quarterly growth for shampoo (22 quarters), d_t computed for the top 50 brands ($R^2 = 23\%$);
- quarterly growth for the cereal category (22 quarters), d_t computed for the top 50 brands ($R^2 = 25\%$);
- quarterly growth for beer (22 quarters), d_t computed for the top 50 beer brands ($R^2 = 52\%$);
- per-capita income growth for all countries (1972–2010), d_t for the top 50 countries ($R^2 = 15\%$);
- average per-capita U.S. income growth, d_t for top 10 wealthiest Americans ($R^2 = 44\%$); and
- market capitalization growth for the top 10 worldwide firms (1998–2011), d_t for top 10 public firms ($R^2 = 28\%$).

It is impossible to prove that any theory is correct, but the empirical evidence for our theory is encouraging.

5. Limitations

There are limitations associated with our theory and its implementation. Environmental sorting may no longer explain market growth without competition (sometimes absent in new product markets and regulated monopolies). Growth may require both natural selection (Galor and Moav 2002) that involves optimizing to the environment and Malthusian competition that involves being better than competitors. Our metric for measuring displacement has limitations including not weighting the change in ranking by rank (e.g., moving from rank 1 to rank 2 is weighted the same as a movement from rank 99 to rank 100). Our analysis only considers linear relationships between displacement and growth. Government interventions helping incumbents could create growth without causing displacement. Similar to other theories involving latent constructs, we do not directly measure the construct (mutations) but infer the construct from a metric. We do not explore specific cases when our metric detects changes in rank without growth. Finally, despite significant parameter estimates, the total variance unexplained remains large.

6. Implications

Our theory implies that growth occurs from differential change. One implication might be that growth requires experimentation, where different divisions, departments, or managers adopt different strategies. Our theory also has implications for many decision makers even though it might provide few implications for market participants. The reason is that, similar to equilibrium models, market participants might already be doing their best to survive. Hence, recommending survival or winning may be superfluous. However, our theory is useful for at least two other types of decision makers.

The first type of decision maker is interested in a market beyond his or her own. For example, suppliers to a market could understand when and why downstream markets are likely to grow or decline. Similarly, firms in ancillary markets might benefit from understanding growth in complementary markets. Moreover, firms could understand and possibly predict growth in markets using competitive technologies or markets presenting indirect competition. It is important for firms to understand market growth when structuring their channel (Inman et al. 2004). Retailers might be interested in product category growth when making shelf-space decisions. Automobile manufacturers might be interested in the growth of new power sources, growth of corporate fleets, growth of the rental car market, growth of the taxicab market, growth of the emergency vehicle market, etc. Our theory might allow salespeople to determine which regions are likely to show growth. It might also allow marketing managers to predict which submarkets will grow and which divisions are likely to show growth. Hence, our theory of growth might allow firms to predict which of their markets will grow. As a result, policy makers, regulators, and other entities could better foster growth.

The second type of decision maker who might find our theory useful is interested in understanding growth at a different level of aggregation. Doing that simply requires defining the market participant at a lower level of aggregation as the market of interest. Remember that we can define the market at any level of aggregation (brand, product category, corporate division, firm, submarket, market, economy, etc.). For example, to explain automobile category growth or decline, define the market participants as the individual automobile models (Ford F-series, Toyota Camry, Honda Civic, etc.). To explain U.S. market growth or decline, define the market participants as the U.S. corporations. To explain the growth or decline of Delta Airlines, define the participants at the individual routes—for example, the number of passengers flying each route. An organization can view different divisions or product groups as market participants. Historic reflection reveals that future research usually develops additional implications.

Our theory also makes many nonobvious predictions. For example, it predicts that large differences in opinion among market participants or the propensity to experiment could initiate market growth because both could cause displacement. It also predicts that any variable creating differences might spur growth including risk taking, heterogeneity, different competitive competencies, very different strategies, the use of different technologies, and participants with different histories. Any variable that is likely to encourage different changes among different market participants might work.

In general, theory provides the ability to make testable predictions that are not possible from purely predictive models: "A new theory is therefore only eligible as a part of science if it allows for experimental test of its new predictions. Predictions by theories and their tests by experiments form the basis of the work of scientists" (Pietschmann 1978, p. 905). There are many examples of these predictions, many of which could not be verified until years later. Louis Pasteur's theory correctly predicted that germs on surgeons' hands were killing their patients. Galileo Galilei's theory correctly predicted that all free-falling objects fall at the same rate. Edmond Halley's theory correctly predicted the reappearance of the comet that now bears his name. Dmitri Mendeleev predicted the properties of yet undiscovered chemical elements. Albert Einstein's theory correctly predicted light-bending. Wolfgang Pauli's theory predicted the future discovery of the neutrino. Urbain Le Verrier predicted the future discovery of the planet Neptune.

7. Summary and Findings

Market growth is fundamental to marketing. It influences strategic marketing decisions, their timing, and their effectiveness. The most prominent extant growth theory is the Bass (1969) seminal theory of new product market growth. However, there is no analogous theory for established markets. A few theories attempt to explain market growth as consisting of sporadic growth, intermittent declines, and often stagnation. Our theory of environmental sorting predicts market growth and has many implications (identified in §6).

Our theory for established market growth (and decline) is based on environmental sorting (the business market equivalent of the natural selection mechanism). For biological systems, the natural selection mechanism fuels growth as nature selects winners and losers. In business markets, we hypothesize that market participants take many actions each period that cause them to change or mutate in myriad ways, possibly resulting from experimentation. The environment sorts through those changes, selecting winners and losers.

We theorize that when there are more or greater mutations among the market participants, growth is more likely because the environment will have the opportunity to find and reward more favorable changes. However, actions can create uncertain outcomes. More latent mutations increase the chance that some market participants suffer unfavorable changes. When that occurs, current winners displace past winners temporarily (or permanently), and the market (though not necessarily all market participants) grows. So one nonobvious falsifiable (testable) implication of the theory of environmental sorting is that a high rate of displacement precedes growth, and given Malthusian competition, market stability precedes decline.

We measure the rate of displacement in each period with a simple displacement metric (d_t) that measures the rate at which Darwinian time advances. The d_t metric counts the number of market participants (e.g., firms, brands, divisions, product categories, countries) that decline in rank during the tth period. Changes in rankings measure the effect of environmental sorting, and thus, the d_t metric implicitly measures the rate of latent mutation. Although growth could plausibly occur without changes in rankings (i.e., displacement), our theory of growth (i.e., environmental sorting) suggests that it is less likely. Whether the d_t displacement metric is positively correlated (or correlated at all) with immediate and future growth is an empirical question. Thus, we test our theory of growth by empirically testing, in very different contexts and different levels of aggregation, whether our displacement metric predicts market growth.

As explained earlier, our d_t metric has many practical advantages. For example, computation is straightforward because it only requires the same performance variable (sales, assets, profits, etc.) used to measure growth. Moreover, the d_t metric is somewhat robust to the problems of data availability and measurement error because rankings are often easier to get than precise levels of performance. For example, field sales managers are generally aware of the current rankings of competing firms' sales in a product category even before revenue information is officially available. Another practical advantage is that the d_t metric is implementable in many different contexts and levels of aggregations.

To test our theory of market growth (or decline), we use multiple data sets. We highlight the results from two data sets. First, we use publicly available data for the Fortune 100 firms for 55 years. Second, we use monthly U.S. automobile sales for 300 months (25 years). Our analyses are easily replicated.

The poor predictive ability of multiple benchmarks reveals the difficulty of making accurate quantitative predictions. Even the number of new products cannot explain market growth. In contrast, our theory predicts both immediate growth and future growth. All estimated coefficients have the signs predicted by our theory. It appears that our d_t metric captures one essential prerequisite for future growth.

As predicted, all the intercepts for our displacement metric in our empirical analyses are negative. These negative intercepts confirm our theoretical prediction that without a positive level of environmental sorting, markets face decline. There is a minimum level of displacement (i.e., change in the competitive relationships between the market participants) to maintain zero growth and avoid decline. This preliminary finding has important implications: environmental sorting is not a luxury; it is necessary for growth.

Finally, as noted in the implications section, our theory makes many additional nonobvious predictions. For example, it suggests that growth is related to diversity of opinion among market participants, the propensity to experiment, risk taking, heterogeneity, different competitive competencies, different strategies, different technologies, and participants with different histories. Anything encouraging different changes among different market participants might cause growth.

8. Future Research

Our theory makes several testable predictions that await future research. One concerns whether common improvement across every market participant ever accounts for future growth. It appears that future growth is enhanced by relative change in the competitive positions of the market participants (e.g., firms, divisions, brands, countries). Future growth seems to require more than common improvement. It requires differential change, possibly consistent with dramatic change by perhaps only a small number of market participants. Change requires this small group to exceed the performance (e.g., sales, profits) of other participants. This is not necessarily consistent with an industry adopting a superior technology, launching superior new products or discovering a more effective form of organization. Consequently, internal managerial strategies or public policy involving a focus on common growth or favoring incumbents require scrutiny. Future research might investigate whether an incumbent's fall allows market growth because it reduces barriers to entry for rising competitors. Accomplishing this research may require more deep dives. Finally, future research should consider what variables create growth or decline across multiple periods.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2013.0813.

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References

Ackman D (2003) A fatter deduction for fatter cars. *Forbes* (January 21) http://www.forbes.com/2003/01/21/cx_da_0121topnews.html.

Alchian AA (1950) Uncertainty, evolution, and economic theory. *J. Political Econom.* 58(3):211–221.

Anderson P, Tushman ML (1990) Technological discontinuities and dominant designs: A cyclical model of technological change. *Admin. Sci. Quart.* 35(4):604–633.

Ayal I, Zif J (1979) Market expansion strategies in multinational marketing. *J. Marketing* 43(2):84–94.

Balasubramanian SK, Kumar V (1990) Analyzing variations in advertising and promotional expenditures: Key correlates in consumer, industrial, and service markets. *J. Marketing* 54(2): 57–68.

Ball J, Lundegaard K (2002) Tax breaks for the merely affluent—Quirk in law lets some SUV drivers take big deduction. *Wall Street Journal* (December 19) D1.

Bass FM (1969) A new product growth model for consumer durables. *Management Sci.* 15(5):215–227.

Beresteanu A, Li S (2011) Gasoline prices, government support, and the demand for hybrid vehicles in the U.S. *Internat. Econom. Rev.* 52(1):161–182.

Biyalogorsky E, Boulding W, Staelin R (2006) Stuck in the past: Why managers persist with new product failures. *J. Marketing* 70(2):108–121.

Bowyer J (2012) Malthus and Scrooge. *Forbes* (December 25) http://www.forbes.com/2008/12/24/malthus-dickens-scrooge-oped-cx_jb_1224bowyer.html.

Brandl MW (2004) The misunderstood role of R&D in the global economy: Today and in the future. *IEEE/UT Engrg. Management Conf.* (IEEE, Piscataway, NJ), 41–43.

Bridges E, Coughlan AT, Kalish S (1991) New technology adoption in an innovative marketplace: Micro- and macro-level decision making models. *Internat. J. Forecasting* 7(3):257–270.

Cohen WM, Levinthal DA (1989) Innovation and learning: The two faces of R&D. *Econom. J.* 99(397):569–596.

Collard D (2009) Alfred Russel Wallace and the political economists. *Hist. Political Econom.* 41(4):605–644.

Cook VJ Jr (1985) The net present value of market share. *J. Marketing* 49(3):49–63.

Darwin CR (1859) *On the Origin of Species by Means of Natural Selection, or the Preservation of Favoured Races in the Struggle for Life* (John Murray, London).

Dekimpe MG, Hanssens DM (1995) Empirical generalizations about market evolution and stationarity. *Marketing Sci.* 14(3, Supplement):G109–G121.

Finkelstein S, Sanford SH (2000) Learning from corporate mistakes. *Organ. Dynam.* 29(2):138–148.

Fisher RA (1930) *The Genetical Theory of Natural Selection* (Oxford University Press, New York).

Fornell C, Rust RT, Dekimpe MG (2010) The effect of customer satisfaction on consumer spending growth. *J. Marketing Res.* 47(1):28–35.

Foster J (2000) Competitive selection, self-organisation and Joseph A. Schumpeter. *Bus. Econom. J. Evolution. Econom.* 10(3):311–328.

Galor O, Moav O (2002) Natural selection and the origin of economic growth. *Quart. J. Econom.* 117(4):1133–1191.

Glassburner B (1955) Alfred Marshall on economic history and historical development. *Quart. J. Econom.* 69(4):577–595.

Glick TF, Kohn D (1996) *Introduction to Charles Darwin on Evolution* (Hackett Publishing, Indianapolis).

Golder PN (2000) Historical method in marketing research with new evidence on long-term market share stability. *J. Marketing Res.* 37(2):156–172.

Grant PR, Grant BR (2002) Unpredictable evolution in a 30-year study of Darwin's finches. *Science* 296(5568):707–711.

Guilford D (2002) GM pays for a big sales finish. *Automotive News* 77(6017) 1.

Guilford D (2003) GM incentive barrage will continue. *Automotive News* 77(6019) 1.

Hakim D (2003) GM's profits almost tripled last year. *New York Times* (January 17) C5.

Henderson JP (2000) "Political economy is a mere skeleton unless…": What can social economists learn from Charles Dickens? *Rev. Soc. Econom.* 58(2):141–152.

Hirshleifer J (1977) Economics from a biological viewpoint. *J. Law Econom.* 20(1):1–52.

Inman JJ, Shankar V, Ferraro R (2004) The roles of channel-category associations and geodemographics in channel patronage. *J. Marketing* 68(2):51–71.

Keltner B, Finegold D, Mason G, Wagner K (1999) Market segmentation strategies and service sector productivity. *Calif. Management Rev.* 41(4):84–102.

Kiley D (2003) Bush plan gives huge tax break to buyers of big SUVs. *USA Today* (January 21) http://usatoday.com/money/autos/2003-01-20-suvs_x.htm.

Klepper S (1996) Entry, exit, growth, and innovation over the product life cycle. *Amer. Econom. Rev.* 86(3):562–583.

Kuksov D, Xie Y (2010) Pricing, frills, and customer ratings. *Marketing Sci.* 29(5):925–943.

Kutschera U (2003) A comparative analysis of the Darwin-Wallace papers and the development of the concept of natural selection. *Theory Biosci.* 122(4):343–369.

Lambkin M, Day GS (1989) Evolutionary processes in competitive markets: Beyond the product life cycle. *J. Marketing* 53(3):4–20.

Lilien GL, Yoon E (1990) The timing of competitive market entry: An exploratory study of new industrial products. *Management Sci.* 36(5):568–585.

Little JDC (1966) A model of adaptive control of promotional spending. *Oper. Res.* 14(6):1075–1097.

Marshall A (1898) *Principles of Economics* (Macmillan, London).

Morgan MS (2006) Economic man as model man. *J. Hist. Econom. Thought* 28(1):1–27.

Murmann JP, Tushman ML (1998) Dominant designs, technology cycles, and organizational outcomes. *Res. Organ. Behav.* 20:231–266.

Nelson RR, Winter SG (2002) Evolutionary theorizing in economics. *J. Econom. Perspect.* 16(2):23–46.

Pauwels K, Hanssens DM (2007) Performance regimes and marketing policy shifts. *Marketing Sci.* 26(3):293–311.

Pietschmann H (1978) The rules of scientific discovery demonstrated from examples of the physics of elementary particles. *Foundations Phys.* 8(11–12):905–919.

Porter ME (1981) Strategic interaction: Some lessons from industry histories for theory and antitrust policy. *Antitrust Law Econom. Rev.* 13(3):13–58.

Quach HK (2003) New year brings 1,169 new state laws. *Orange County Register* (January 1). Retrieved from LexisNexis Academic database.

Radas S, Shugan SM (1998) Seasonal marketing and timing new product introductions. *J. Marketing Res.* 35(3):296–315.

Robinson WT, Min S (2002) Is the first to market the first to fail? Empirical evidence for industrial goods businesses. *J. Marketing Res.* 39(1):120–128.

Rust RT, Zahorik AJ, Keiningham TL (1995) Return on quality (ROQ): Making service quality financially accountable. *J. Marketing* 59(2):58–70.

Rust RT, Ambler T, Carpenter G, Kumar V, Srivastava R (2004) Measuring marketing productivity: Current knowledge and future directions. *J. Marketing* 68(4):76–89.

Shermer M (2002) *In Darwin's Shadow: The Life and Science of Alfred Russel Wallace* (Oxford University Press, New York).

Sober E (1984) *The Nature of Selection: Evolutionary Theory in Philosophical Focus* (University of Chicago Press, Chicago).

Soberman D, Gatignon H (2005) Research issues at the boundary of competitive dynamics and market evolution. *Marketing Sci.* 24(1):165–174.

Srinivasan S, Leszczyc PTLP, Bass FM (2000) Market share response and competitive interaction: The impact of temporary, evolving and structural changes in prices. *Internat. J. Res. Marketing* 17(4):281–305.

Stremersch S, Tellis GJ (2004) Understanding and managing international growth of new products. *Internat. J. Res. Marketing* 21(4):421–438.

Sultan F, Farley JU, Lehmann DR (1990) A meta-analysis of applications of diffusion models. *J. Marketing Res.* 27(1):70–77.

Tellis GJ, Crawford CM (1981) An evolutionary approach to product growth theory. *J. Marketing* 45(4):125–132.

Temple J, Johnson PA (1998) Social capability and economic growth. *Quart. J. Econom.* 113(3):965–990.

Urban GL, Hauser JR (1980) *Design and Marketing of New Products* (Prentice-Hall, Englewood Cliffs, NJ).

Van Valen L (1973) A new evolutionary law. *Evolution. Theory* 1(1):1–30.

Villanueva J, Shijin Y, Hanssens DM (2008) The impact of marketing-induced versus word-of-mouth customer acquisition on customer equity growth. *J. Marketing Res.* 45(1):48–59.

Wallace AR (1905) *My Life: A Record of Events and Opinions* (Chapman & Hall, London).

Young RM (1969) Malthus and the evolutionists. *Past Present* 43(1):109–145.