Technological Disruptive Potential and the Evolution of IPOs and Sell-Outs

Donald Bowen, Laurent Frésard, and Gerard Hoberg*

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ABSTRACT

We study the determinants of startups' choice of exit using novel measures of startups' technological characteristics constructed from patent text. We show that startups with more potential to disrupt technological areas are 25% more likely to exit via IPO and 19% less likely to sell-out. These results are consistent with IPOs being favored by startups that can carve out independent market positions, avoiding the need to share gains with an acquirer. We document an economy-wide decline in patents' disruptive potential between 1930 to 2010, and show that this trend explains about 20% of the recent decline in IPOs, and 50% of the surge in sell-outs.

Key words: Initial Public Offerings (IPOs), Acquisitions, Sell-Outs, Technology, Disruption, Venture Capital

JEL classification: G32, G34, G24

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*Virginia Tech, the Universita della Svizzera italiana (Lugano), Swiss Finance Institute, and the University of Southern California respectively. Bowen can be reached at donbowen@vt.edu, Frésard can be reached at laurent.fresard@usi.ch, and Hoberg can be reached at hoberg@marshall.usc.edu. We thank Sunil Muralidhara and Lauren Phillips for excellent research assistance. We also thank Jay Ritter on sales data for IPO firms. For helpful comments, we thank Nick Bloom, Francesco D'Acunto, Francois Degeorge, Francois Derrien, Michael Ewans, Joan Farre-Mensa, Francesco Franzoni, Jack He, Sabrina Howell, Mark Lang, Josh Lerner, Michelle Lowry, Song Ma, Adrien Matray, Dimitris Papanikolaou, Shawn Thomas, Xuan Tian and participants at American University, Arizona State Univesity, Babson, Bocconi University, Boston College, Dauphine University, the CCF conference in Bergen, the CETAFE conference at the University of Southern California, the FinTech Conference at Georgia State University, the FRA conference in Las Vegas, Lehigh University, The Midwest Finance Association meeting in Chicago, the NBER meeting on Productivity, Innovation, and Entrepreneurship, Georgetown University, HEC Paris, Johns Hopkins University, San Diego University, the SFI Research days, Stockholm School of Economics, Universita Cattolica, University of Virginia, Texas Christian University, Toulouse School of Economics, Tsinghua University, CKGSB, The UBC Winter Conference in Whistler, the Universita della Svizzera Italiana (Lugano), the University of Maryland, the University of Zurich, the Western Finance Association meeting in Huntington Beach, and Virginia Tech. All errors are the authors' alone.

I Introduction

Since the late 1990s, the number of private firms exiting via initial public offerings (IPOs) in U.S. markets has sharply declined. At the same time, the number of exits via acquisitions (i.e., sell-outs) has soared. Successful firms are nowadays more likely to sell-out to other (public or private) companies than seek independent public listings, a phenomenon that has recently garnered considerable attention in the media and policy circles.[1] In this paper, we study the determinants and evolution of the exit choices of U.S. startups and show that startups developing technologies with disruptive potential are more likely to go public and are less likely to exit by selling out. We further document that the average disruptive potential of startups has markedly decreased in recent years and estimate that changes in startups' technological traits can explain 20% of the recent decline in IPOs and 50% of the surge in sell-outs.

Our analysis of startups' exits builds on the idea that rational entrepreneurs (and their backers) choose the exit option that maximizes the value of their equity stake. We conjecture that the value offered by outside buyers – dispersed investors in an IPO and strategic buyers in a sell-out – and hence the observed exit types, depends on startups' technological characteristics. We consider that startups' technologies lead to successful exits because they have the potential to either disrupt established technologies, or to complement existing inventions through synergies. The relative attractiveness of IPOs compared to sell-outs thus hinges on the interactions between potential buyers' technologies and those of the startup, as well as the allocation of payoffs between parties. We posit that technologies with disruptive versus synergistic potential differ notably along both dimensions, and therefore trigger distinct exits.

By design, startups developing disruptive technologies offer limited synergistic value to other parties because disruptive inventions tend to be substitutes and primarily aim to replace existing technologies (Acemoglu, Akcigit, and Celik (2014)). In addition, the

[1] Various observers in the media and policy circles worry that the decline in new public listings reflects an erosion in the ability of U.S. financial markets to spur economic growth. See for instance "The endangered public company: The big engine that couldn't," *The Economist* (May 19, 2012) or "US stock markets seek depth in IPO pool," *Financial Times* (January 9, 2018).

economic success of startups with disruptive potential could be achieved while remaining independent entities, without the need for integration or strategic assistance of potential acquirers (Bayar and Chemmanur (2011)). Such independence avoids the need to share future payoffs with another party. Hence startups with technologies with high disruptive potential should favor exiting via a public listing. In contrast, exiting by selling out should be favored by startups with technologies offering significant synergies to potential buyers. Acquisitions of synergistic technologies can improve existing processes or products, and buyers' resources can reduce financial constraints and foster product market success (Bena and Li (2013)). A sell-out is thus optimal when the complementary benefits of synergies overcome the cost of sharing future payoffs.

Testing this hypothesis, and understanding whether the recent IPO and sell-out trends are related to technological changes, requires the ability to systematically measure the technological characteristics of a large sample of startups. We do so by exploiting the voluminous information about technologies contained in the text of all patents filed with the U.S. Patent and Trademark Office (USPTO) between 1930 and 2010 (6.6 million patents). We focus specifically on disruption in the technological space and define the disruptive potential of a given patent as its potential to change the technological path of other firms and eventually disrupt established markets or create new ones (Dahlin and Behrens (2005)).[2] We measure a patent's "technological disruptive potential" (henceforth "disruptive potential" for parsimony) based on the intensity with which its text contains vocabulary that is new or growing fast across all contemporaneous patent applications. For example, the use of genetics words such as "peptide", "clone", or "recombinant" soared in 1995, reflecting concurrent breakthroughs in genome sequencing. Our measure would classify patents extensively using such words in 1995 as having high disruptive potential.[3]

[2]We strictly follow the dictionary definition of "disruption", defined as "*a break or interruption in the normal course or continuation of some activity or process*"(https://www.merriam-webster.com/dictionary/disruption) or equivalently as "*a an interruption in the usual way that a system, process, or event works*" (https://dictionary.cambridge.org/dictionary/english/disruption).

[3]Because our goal is to estimate predictive models of startups' exits, we measure the disruptive potential of patents using only ex ante measurable data from the text contained in all past and contemporaneous patents. See Dahlin and Behrens (2005) for a detailed discussion of the distinction between ex ante and ex post innovation-based measures. The ex ante feature of our measure also eliminates look-ahead bias,

We validate our new measure of patent disruptive potential using many tests. We first show that patents with higher ex ante disruptive potential are associated with significant shifts in the ex post trajectory of related future inventions. Future patents cite these patents more, and we find more ex post "breaks" in citation patterns as defined by Funk and Owen-Smith (2016). Second, more disruptive patents have higher economic value (estimated using stock returns as in Kogan, Papanikolaou, Seru, and Stoffman (2016)), suggesting that the market recognizes their potential to profitably disrupt established markets. Third, we focus on major radical inventions between 1930 and 2010 (i.e., the historically important patents as recognized by the USPTO), which include for instance the television, computer, helicopter, and advances in modern genetics. The vast majority of these breakthrough patents displayed high disruptive potential at the time of their applications.

We further validate our measure of disruptive potential by considering the disclosure of publicly traded firms. To do so, we link startups to publicly traded firms operating in related product markets by computing the textual similarity between their business description and that of public firms from their 10-K reports (see Hoberg and Phillips (2016)). As direct validation of our measure, we find that public firms discuss market disruption significantly more when they operate alongside startups displaying high technological disruptive potential.

Our primary analysis focuses on the exit decisions of 9,167 VC-backed U.S. startups (94,703 patents) over the 1980-2010 period. Our main result is that startups with patents exhibiting more disruptive potential are significantly more likely to go public compared to other startups. At the same time, they are less likely to exit by selling out. This result remains after controlling for startups' age, size, financing rounds, overall financial market conditions, and other patent traits such as technological "breadth" (patents that combine vocabulary from diverse bodies of knowledge), technological similarity to other firms, patent citations, average word age, and originality.[4] The importance of startups'

reduces truncation bias (Lerner and Seru (2017)), and increases the measure's utility to practitioners (to predict outcomes and investor returns) and regulators (to assess the impact of policies in real time).

[4]Our results are also robust to including fixed effects for startup cohorts, geographic locations, technological categories, changes in econometric specifications that vary the horizon over which we measure

disruptive potential is economically large, as a one standard deviation increase in disruptive potential is associated with an increase of 25.2% in the probability that a startup exits via IPO and a decrease of 18.8% in the incidence of a sell-out.

Conceptually, inventions with disruptive potential may lead to the disruption of established technological areas or alternatively to the creation of entirely new areas. We show that startups' disruptive potential matters most in established areas. Specifically, we decompose the text of patents into new versus established vocabularies based on the age of the words used in each patent. We find that the link between startups' disruptive potential and exit choices is mostly driven by their disruptive potential in established technological spaces. This result suggests that the ability to conduct business as a stand-alone entity is particularly compelling when gains potentially come at the expense of existing market participants, and hence the synergies from business combination are low.

Our second major finding is that the economy-wide disruptive potential has declined substantially since the 1950s and that this trend accelerated in the 1990s. Although the overall decline is interrupted by occasional temporary spikes during the 1970s (i.e., computers), the 1980s (i.e., genetics), and the 1990s (i.e., the internet), following each spike, the trend quickly reverts fully back to the long-term sample-wide decline. Notably, our decomposition of disruptive potential shows that the decline is particularly strong in established technology spaces, as we observe the potential to create new technological areas has remained relatively stable. The trends we observe are consistent with recent studies suggesting that new ideas are getting harder to discover and develop (Jones (2009) and Bloom, Jones, Reenen, and Webb (2017)). Our findings indicate that the increased difficulty to discover new ideas appears particularly salient in established markets.

The confluence of our first two main results (startups with disruptive potential exit via IPO, and disruptive potential has been declining), motivates a plausible new technology-based explanation for the aggregate trends away from IPOs and toward sell-outs noted in recent studies. We assess this explanation by estimating cross-sectional exit models (including and excluding our explanatory variables) over an initial period (1980-1995),

exits (ranging from the next quarter to the next five years), and to focusing on the early part of the sample to limit potential truncation bias (Lerner and Seru (2017)).

and use the fitted model to predict exit rates in the subsequent out-of-sample period (1996-2010). A model that excludes our technological characteristics predicts an out-of-sample quarterly IPO rate of 0.84 percentage points. The actual rate was just 0.33 percentage points, confirming that IPOs were abnormally scarce in recent years. Adding our new variables to the fitted model reduces this gap by roughly 20% overall, and 40% for small IPOs, which are the segment displaying the sharpest decline in recent years (see Gao, Ritter, and Zhu (2013)). This improvement is 25% in more stable markets, and just 3% in fluid markets, consistent with disruptive ideas declining most sharply in more established markets. A similar analysis reveals that our new technology measures account for roughly 50% of the recent rise in sell-outs.

Our analysis adds to the recent literature examining explanations for the recent disappearance of IPOs and the contemporaneous rise of sell-outs.[5] Ewens and Farre-Mensa (2018) indicate that part of the IPO decline results from the increased bargaining power of founders, their preference for control, and inexpensive capital in the private market. Gao, Ritter, and Zhu (2013) suggest that the decline in IPOs originates from changes in market structure that favor selling out to realize economies of scope. Doidge, Kahle, Karolyi, and Stulz (2018) argue that an increased focus on intangibles also likely plays an important role. Our paper shows that changes in firms' technological traits (especially disruptive potential) can also account for part of the decline in IPOs and the surge in sell-outs in the recent period. We examine both exit margins jointly and quantify how much of the observed trends are attributable to changes in technological characteristics.

Our findings also add to the literature studying the determinants and performance of startup exits. The vast majority of past studies either examine IPO or sell-out exits in isolation or bundle them into a single proxy for successful exit (Bernstein, Giroud, and Townsend (2016) and Guzman and Stern (2015)). The small number of studies that examine these exit choices jointly indicate that they depend on founders' private benefits of control, product market presence, and firms' growth potential (Cumming and Macintosh (2003), Bayar and Chemmanur (2011), Poulsen and Stegemoller (2008) or, Chemmanur,

[5]See Ritter and Welch (2002) and Lowry, Michaely, and Volkova (2017) for comprehensive surveys.

He, He, and Nandy (2018)). The limited evidence on the role of technology for startups' exit is surprising given the practical importance of exit payoffs in entrepreneurship, and particularly in technology sectors (Wang (2018) or Phillips and Zhdanov (2013)).

Finally, our paper adds to recent studies using patent text to characterize technology. Packalen and Bhattacharya (2018) and Balsmeier, Assaf, Chesebro, Fierro, Johnson, Johnson, Li, Luck, OReagan, Yeh, Zang, and Fleming (2018) identify new ideas based on the first appearance of words (or sequences of words), and analyze their propagation. Kelly, Papanikolaou, Seru, and Taddy (2019) construct a measure of patent quality (or "significance") based on textual similarity with prior and future patents and examine technological change in the long run and its implications for growth. Our study complement theirs as we focus on ex ante technological disruptive potential, its role in explaining startups' exit choices at a micro-level, and the evolution of IPOs and sell-outs in recent years.

II Technological Characteristics and Exit Decisions

Our paper focuses on the decision of successful startups to exit by either listing shares on the stock market or by selling out to other entities. We consider a simple rational framework in which a startup (i.e., the entrepreneurs and their backers) choose the exit method that maximizes the value received by equity holders upon exiting. This payoff is the total value conveyed to the startup by dispersed investors when startups exit through IPO and by strategic buyers when they exit by selling out. As a starting point, the theory of the firm (Grossman and Hart (1986) and Hart and Moore (1990)) suggests that this choice thus depends on whether the startup's value is higher as a stand-alone operating entity or when it is integrated with the assets of another entity. Our central hypothesis is that dichotomy depends on the core characteristics of the startup's technologies.

We hypothesize that a crucial aspect is the extent to which the startup's technology has either "disruptive" or "synergistic" potential relative to existing firms. A technology has disruptive potential if it has the potential to eventually displace (i.e., reduce the value of) existing inventions and significantly influence the path of future innovation in the surrounding technological space (Dahlin and Behrens (2005)). In contrast, a technology has synergistic potential if its features complement (i.e., increase the value of) existing inventions and thus serve to enhance the surrounding technological space. We argue that these core features impact a startups' stand-alone value versus its value as an acquisition target. Hence these features should predict the choice of exit.

By design, technologies with disruptive potential offer limited synergistic value to other parties because they displace rather than improve existing technologies. Startups with such technologies can thus generate high valuations as independent stand-alone entities. In particular, success does not rely on pairing these technologies with those of other firms, and does not require strategic assistance from other firms (Bayar and Chemmanur (2011)).[6] Maintaining independence also avoids the need to share the overall rents with a potential acquirer, further increasing payoffs to initial equity holders who can capture all rents. We thus predict that startups developing technologies with more disruptive potential should favor exits via IPOs.[7]

In contrast, synergistic technologies have low stand-alone values because their economic benefits arise primarily through combinations with existing technologies. In this case, exit via acquisition can achieve higher valuations than stand-alone values (Higgins and Rodriguez (2006)) because it provides a new source for innovation (Holmstrom and Roberts (1998)), facilitates technology coordination (Hart and Holmstrom (2010)) and complements established firms' technology portfolios (Cassiman and Veugelers (2006)). However, this has to be juxtaposed against the fact that selling out requires sharing future rents with the buyer. We thus predict that startups with less disruptive potential and high synergistic potential should prefer exiting via sell-outs. For such firms, the gains to business combination can plausibly outweigh the costs of sharing future rents.[8]

[6] Consistent with this idea, Darby and Zucker (2018) show that biotechnology firms go public when their innovations can be successfully commercialized, Chemmanur, He, He, and Nandy (2018) report that manufacturing firms are more likely to go public than sell-out when they already have a defensible product market presence (i.e., market share), and Poulsen and Stegemoller (2008) and Cumming and Macintosh (2003) show that firms with more growth potential favor exit through IPOs.

[7] Relatedly, Hackbarth, Mathews, and Robinson (2014) show that the value of less developed growth options is higher in a stand-alone entity than in a combined entity. Their theory reinforces our prediction if technologies with disruptive potential are relatively less developed.

[8] In addition, such technologies could also attract higher valuations in sell-out than in IPOs because

Our central hypothesis links exit choices to the fundamental characteristics of their technologies. If the predicted economic tradeoffs are stable over time, and the technological characteristics of startups change over time, our hypothesis has further consequences for the time series. For example, if the disruptive potential of technologies is declining or the synergistic potential is increasing over time, we would predict a corresponding decline in the IPO exit rate and an increase in the sell-out rate. Our hypothesis thus offers a new potential explanation for the aggregate decline in IPOs and the surge in sell-outs documented by recent studies (Gao, Ritter, and Zhu (2013)).

Existing research suggests that such a scenario based on changes in startups' technological characteristics might indeed be valid, at least in part. For instance, Jones (2009) and Bloom, Jones, Reenen, and Webb (2017) provide evidence of a secular decline in the productivity of technological research across different sectors over time, and they argue that such a trend reflects the increased difficulty to find breakthrough ideas. This result is also consistent with product life cycle theories (Abernathy and Utterback (1978) and Klepper (1996)), which posit that innovation slows and becomes more incremental over time as product markets mature. Further supporting this foundation, Wang (2018) finds that entrepreneurs increasingly develop technologies that overlap (i.e., complement) potential acquirers, likely with the intent to trigger profitable sell-outs. This can further crowd-out the incidence of breakthrough innovations. Our second major hypothesis is thus that part of the recent shift in startup exits from IPOs to sell-outs is attributable to a decline in the average disruptive potential of startups' technologies.

III Data and Methods

In this section, we first describe the patent textual data, explain the construction of our new text-based measures of technological characteristics, and then present the characteristics of our startups' sample.

buyers might have better information about synergistic technologies than disruptive ones (Kaplan (2000) or Hirshleifer, Hsu, and Li (2017)).

A Patent Data and Text

We gather information from Google Patents for all 6,595,226 patents that were applied for between 1930 and 2010 and granted by 2013. For each patent, we gather the publication date, application date, names of inventor(s), and initial assignee(s). We also collect the full patent text and information on the technology classification of the patents by converting the U.S. Patent Classification (USPC) into the two-digit NBER technology codes created in Hall, Jaffe, and Trajtenberg (2001). Since we are interested in measuring the technological changes pertaining to the corporate sector, we categorize each patent based on four types of applicants: U.S. public firms, U.S private firms, foreign (private or public) firms, or others (e.g., universities or foundations). For brevity, we describe this classification method in the Internet Appendix (Section IA.A).

[Insert Figure I about here]

The full text of each patent consists of three distinct sections: abstract, claims, and description. The claims section defines the scope of legal protection granted. The description section explicitly describes the characteristics of the invention/innovation. It typically includes a title, technical field, background art, specification example, and industrial applicability. The abstract contains a summary of the disclosure contained in the description and claims sections. Figure I presents an example of a typical patent textual structure (#6285999, “A method for node ranking in a linked database”, assigned to Google in 1998). We append all three sections into a unified body of text because earlier patents do not include all sections, and because the organization of patent text into the three sections may have changed over time (Packalen and Bhattacharya (2018) or Kelly, Papanikolaou, Seru, and Taddy (2019)).

Following earlier studies constructing variables from text (e.g., Hanley and Hoberg (2010) or Hoberg and Phillips (2016)), we represent the text of each patent as a numerical vector with a length equal to the number of distinct words in the union of all patent applications in a given year t. We denote this length N_t.[9] Following the convention in

[9]We organize patents based on their application year rather than the year of the patent grant, as this more accurately reflects the timing of innovation.

the literature, we eliminate commonly-used words (words appearing in more than 25% of all patents in a given year) and rare words (words appearing only in one patent in a given year).[10] Each patent j applied for in year t is then represented by a vector $V_{j,t}$ (of length N_t) in which each element corresponds to the number of times patent j employs one of the unique N_t words used in year t. If patent j does not use a given word, the corresponding element of $V_{j,t}$ is set to zero. This vectorization procedure insures that all patent applications in a given year are represented by a collection of vectors that are in the same space (of dimension N_t).

Due to the large number of words used across all patents in a given year, the vectors $V_{j,t}$ are quite sparse, with most elements being zero. For instance, in 1980, the number of distinct words used in an average patent is 352, and the median is 300, while there are 400,097 distinct words used across all patent applications. In 2000, the average and median are 453 and 338, and the total across all applications is 1,358,694.

B Technological Disruptive Potential

As noted earlier, we define the disruptive potential of a given patent as its potential to change the technological path of other firms operating in related markets and to potentially disrupt established markets or create new ones (Dahlin and Behrens (2005)). Our goal is to construct a variable that is theoretically motivated, measurable ex ante, and highly correlated with (realized) ex post disruption. Indeed, since our research question relies on predictive models of startups' exit, it is important to develop a measure of patents' disruptive potential using only data that is available at the time of their application.[11] To measure technological disruptive potential, we focus on the extent to which a given patent uses vocabulary that is new or experiencing high growth in usage within the set of all contemporaneous patent applications from the same year.

[10] Given the highly technical and rapidly evolving nature of text in the patent corpus, we do not implement additional filters (e.g. nouns only). While this choice might potentially introduce noise into our measurements, it maintains power.

[11] We also believe that an ex ante measure of disruptive potential is also useful to practitioners and regulators who might seek actionable information about the state of innovation in real time and its implications for near-term new product creation, job creation, and the amount of economic value likely to be created from current innovation in coming years.

We start by defining an aggregate vector Z_t in each year t with elements containing the number of times a given word is used across all patent applications in year t. This vector thus represents the aggregate frequency of word usage in the patent corpus in a given year. We then compute the annual rate of change in the usage of each word (from $t-1$ to t) by defining the (annual) vector D_t as:

$$D_t = \frac{Z_t - Z_{t-1}}{Z_t + Z_{t-1}}, \tag{1}$$

where division is element-by-element.[12] The set of annual vectors D_t thus tracks the appearance, disappearance, and growth of specific technological vocabulary across all patents over time. Elements of D_t are positive if the usage of the corresponding words increases from year $t-1$ to t, and negative if it decreases (e.g., words becoming obsolete).

[Insert Table I about here]

As an illustration, Table I displays the ten words experiencing the largest increases and decreases in usage across all patent applications in specific years. For instance, in 1995, we detect an acceleration of terms related to genetics, such as "polypeptides", "clones", "recombinant" and "nucleic", following rapid progress in genome sequencing. In that year, use of terms such as "cassette," "ultrasonic," and "tape" are sharply decreasing. In 2005, the most rapidly growing words are related to the internet and include terms such as "broadband", "click", "configurable", or "telecommunications".

To obtain the disruptive potential of a given patent j, we take the frequency-weighted average of the vector D_t based on the words that patent j uses as follows:

$$\text{Disruptive Potential}_{j,t} = \frac{V_{j,t}}{V_{j,t} \cdot \mathbf{1}} \cdot D_t \times 100, \tag{2}$$

where the operator "$\cdot$" denotes the scalar product between two vectors, and "1" is a unit vector of dimension N_t. Intuitively, patents using words whose usage surges across all patent applications (i.e., have positive entries in the vector D_t) have higher disruptive

[12] To ensure Z_t and Z_{t-1} are in the same space (i.e., the union of N_t and N_{t-1}), we modify Z_{t-1} by adding zero elements for words that newly appeared in year t (as they were not originally in the $t-1$ space). Analogously, we modify Z_t by adding zero elements for words that appeared in year $t-1$ but not year t.

potential. This is the case for patents that either employ words that appear in the patent space for the first time, or that use established words whose usage experiences fast growth across all patents.

Hence, based on the illustrative words presented in Table I, a patent using words such as “polypeptides”, “clones”, “recombinant” and “nucleic” is classified as having disruptive potential if its application year is 1995 (when their growth rates are highest), but not if its application is in 2005. Symmetrically, a patent relying extensively on words whose usage decreases across all patents (i.e., using obsolete vocabulary such as “cassette,” or “tape” in 1995) is classified as having low (and possibly negative) disruptive potential.

Intuitively, not all inventions exhibiting disruptive potential will lead to direct commercial success (Christensen (1997)). As a result, a crucial aspect of our study is to provide evidence that the new proposed measure of disruptive potential performs well in predicting outcomes related to actual disruption. Section IV is fully dedicated to exactly that, and we note here that our measure of disruptive potential indeed strongly predicts influential and disruptive outcomes ex post, as measured by their ex post citation path, their ability to predict which patents appear on influential lists constructed by other scholars, the economic value they create, and the incidence of established firms in the market explicitly complaining about disruption in their public disclosures.

C Technological Breadth and Similarities

We also use the text in patents to measure their technological breadth, as well as their similarities with the patents of economically linked firms. To measure the technological breadth of a patent, we first identify words that are strongly associated with a specific technological field using the six broad technological fields (f) defined by the first digit of the NBER technical classification.[13] Specifically, we count how often a given word is used by patents classified into each field in each year, and keep the two fields with the highest usage of the given word. We define a word as “specialized” (and associated with a field f) in year t if its use in its most popular field is more than 150% that of

[13] “Chemicals”, “Computer and Communication”, “Drugs and Medicine”, Electricity”, “Mechanics”, and “Others”.

its second most popular field in year t. Each word is thus classified into one of the six fields of specialization or it is deemed an "unspecialized" word.[14] Second, we define as $w_{j,t,f}$ the fraction of patent j's specialized words that are classified into each field f. By construction, each $w_{j,t,f}$ lies in the [0,1] interval, and they sum to one for each patent j. We then define technological breadth as:

$$\text{Tech Breadth}_{j,t} = 1 - \sum_{f=1}^{6} w_{j,t,f}^2. \tag{3}$$

This measure is one minus the technological concentration of the patent's vocabulary. Patents have higher technological breadth if they amalgamate vocabularies from different specialized technological fields, and lower breadth when they use vocabulary that primarily concentrates on one specialized technological area.

We measure technological similarity by directly comparing the vocabulary of a given patent to that of patents assigned to three specific groups: lead innovators, private U.S. firms, and foreign firms. We focus on cosine similarity measures (see Sebastiani (2002)), defined as the scalar product between each patent j's normalized word distribution vector $V_{i,t}$ and a normalized word vector aggregating the vocabulary specific to a given group of patents.[15] To capture the similarity of a given patent j with patents of "Lead Innovators" (henceforth LI), we define LIs annually as the ten U.S. public firms with the most patent applications. This set, which includes for instance Microsoft and Intel in 2005 and General Electric and Dow Chemical in 1985, varies over time as the importance of sectors and firms changes. For each set of LIs in year t, we first identify the set of patents applied for by the LIs over the past three years (i.e., from year $t-2$ to t). The aggregate LI word vector in year t ($V_{LI,t}$) contains the aggregate frequency of word usage across this set of patents. We then compute the similarity of any given patent to those of the LIs as:

$$\text{LI Similarity}_{j,t} = \frac{V_{j,t}}{\|V_{j,t}\|} \cdot \frac{V_{LI,t}}{\|V_{LI,t}\|}. \tag{4}$$

Because the word vector $V_{LI,t}$ aggregates word usage across patents of lead innovators in

[14] For instance, words such as "bluetooth" and "wifi" are in the "Computer and Communication" field, and "acid" and "solvent" are in the "Chemicals" field.

[15] The result is bounded in [0,1] and values close to one indicate closer textual similarity.

the last three years, patents exhibiting higher levels of LI similarity contain technologies that are textually close to those of lead innovators.

We use similar methods to compute the similarity between the text in each patent j and the overall text of patents assigned to private U.S. firms or to foreign firms. Specifically, we form the aggregate private firm (foreign firm) word vectors $V_{P,t}$ ($V_{F,t}$) as the aggregate word vector in year t that contains the aggregate frequency of word usage across these sets of patents.[16] We then compute the similarity between each patent j and the contemporaneous patent applications of all private U.S. (foreign) firms based on the cosine similarity between $V_{j,t}$ and $V_{P,t}$ ($V_{F,t}$). These measures are high for patents whose vocabulary is technologically close to that of patents assigned to private U.S. firms or to foreign firms, respectively.

D Linking Patent-Level Traits of VC-backed Startups

Our objective is to link the exit strategy of *all* private firms that are plausible candidates for IPOs or acquisitions to their technological characteristics. Because data limitations preclude this, we focus on a large sample of venture-backed private startups, for which we observe both their technological specificities and their exit choices. We obtain data on VC-backed U.S. firms from Thomson Reuters's VentureXpert (Kaplan, Stromberg, and Sensoy (2002)), which contains detailed information about private startups including the dates of financing rounds and their ultimate exit (e.g., IPO, acquisition, or failure). We focus on the period 1980-2010 and restrict our attention to VC-backed companies (henceforth startups) that are granted at least one patent during the sample period.

To link patents to startups, we follow Bernstein, Giroud, and Townsend (2016) and develop a fuzzy matching algorithm that matches the names of firms in VentureXpert to patent assignees obtained from Google Patents (see Section IA.B of the Internet Appendix for details). The result is an unbalanced panel of startup-quarter observations.[17]

[16] Because these groups contain very large numbers of patents, we aggregate over just the single year t. We also note that when a patent j belongs to a private U.S. firm or a foreign firm, we exclude it from the set of patents used to compute $V_{P,t}$ and $V_{F,t}$, respectively.

[17] Lerner and Seru (2017) note that bias can occur in matching patent assignments to startups because patents can be assigned to subsidiaries with different names than their parent corporations. However, this issue is limited in our sample as startups are small and are unlikely to have complex corporate structures.

A startup enters our sample in the quarter it is founded (based on founding dates in VentureXpert) and exits the sample when its final outcome (IPO, acquisition, or failure) is observed based on the "resolve date" variable in VentureXpert. Startups still active as of November 2017 remain unresolved.[18] We exclude startups if their founding date is missing or if it is later than the resolve date. The sample begins in 1980 to guarantee reliable data on outcomes and ends in 2010. Our final sample contains 347,929 startup-quarter observations, corresponding to 9,167 unique startups and 94,703 patent applications.

We obtain the technological characteristics for each startup-quarter by aggregating each patent-level variable (text-based and others) using their depreciated sums over the past 20 quarters using a quarterly depreciation rate of 5%. For example, the technological disruptive potential of startup i in quarter q corresponds to the depreciated sum of the disruptive potential of all its patent applications in the past five years, normalized by the number of patents startup i applied for over that period.[19] We define the exit variables (IPO or sell-out) as binary variables equal to one if startup i experiences a given exit in quarter q. The construction of all variables is explained in detail in Table A1.

Although our sample does not include all firms that have the potential to go public or get acquired, VC-backed startups nevertheless represent a useful laboratory to study the interplay between technological changes and their exit choices. First, these firms account for a large share of the IPO market (Ritter (2017)) and the production of innovation (Gornall and Strebulaev (2015)). Second, we show later that their IPO and acquisition rates over the last thirty years are comparable to the economy-wide patterns. Third, VC-backed startups generally exit promptly due to the limited lives of most venture capital funds.

[18] Ewens and Farre-Mensa (2018) note that unresolved firms can result from stale data collection. Thus, we code firms as failed if it has been seven years since their last funding round.

[19] Because *Foreign Similarity* and *LI Similarity* are non-trivially correlated (60% and 45%) with *Private Similarity*, in regressions, we orthogonalize *Foreign Similarity* and *LI Similarity* by subtracting *Private Similarity*.

E Descriptive Statistics

Table II presents descriptive statistics for our new text-based technological characteristics as well as existing patent variables from the literature. All variables are defined in Table A1. We present patent-level statistics for the full sample of patents (1930-2010) in Panel A, and startup-quarter-level statistics (1980-2010) in Panel B. Focusing on our central new variable – technological disruptive potential – we note that its empirical empirical distribution is highly skewed. The first row of Panel A indicates that the average disruptive potential of patents is 1.64, the median is 1.27, and the 75^{th} percentile is 2.34. The observed asymmetry indicates that while the vast majority of patents contain incremental inventions, a smaller set of patents appear to be highly disruptive. Despite the aggregation of their patents, we observe a similar asymmetry in the disruptive potential of startups, with a median of zero, and the 75^{th} percentile is 0.98.

[Insert Table II about here]

Table II also provides statistics for our other text-based measures of patent characteristics. Unlike technological disruptive potential, patent breadth is more evenly distributed, indicating less skew in technological specializations. We also observe some variation in similarity across patents, but the overall levels are low, which is not surprising given the large range and diversity in the vocabulary used across all patents. Overall, the patent and startup-quarter statistics are similar, indicating that the technological characteristics of VC-backed startups are roughly representative of those in the economy at large. Relevant for our regression analysis, Panel B further indicates that the quarterly IPO rate (i.e. the number of IPOs in a quarter divided by the number of active startups in that quarter) is 0.38 percentage points, and the quarterly sell-out rate is 0.54 percentage points.[20]

[20]We report additional information about the sample firms in the Internet Appendix in Table IA1. Relative to the founding date, IPOs and acquisitions play out over time. Of these, IPOs occur fastest on average. The average firm applies for its first patent after 4.42 years and receives its first round of VC funding 5.29 years after its founding. All of these numbers are mechanistically reduced when measured relative to the first patent instead of the founding year.

IV Validation of Disruptive Potential

In this section, we consider multiple tests of validity of our measure of technological disruptive potential both at the patent level and at the startup level. First, we examine the link between disruptive potential, ex post citation patterns and economic value at the patent level. Second, we assess the level of disruptive potential of a list of unambiguous breakthrough patents created by outside sources. Third, we explore whether publicly traded firms operating in markets related to startups that score high on disruptive potential actually complain about the possibility of disruption in their 10-K annual reports.

A Citation Patterns and Economic Value

Our initial tests explore directly whether a patent's disruptive potential is realized ex post via three distinct metrics. As we expect disruptive patents to become highly cited if they are shifting the technological direction of other firms, we first consider the (logarithm of one plus the) number of citations the patent receives ex post, gathered from Google Patents.[21] Second and perhaps most direct, we also expect that disruptive patents will actually change not just the intensity of impact (as measured by cites) but also the literal path and direction that technology creation takes going forward. We thus consider an innovative measure of breaks in this path developed by Funk and Owen-Smith (2016), which detects whether patents trigger structural breaks in citation patterns (mCD). This approach is based on whether the patents citing a focal patent also cite the patents cited by the focal patent (see also Wu, Wang, and Evans (2019)). Third, following Kogan, Papanikolaou, Seru, and Stoffman (2016), we examine the economic value of patents as an indicator of each patent's realized potential. This final test is restricted to patents assigned to publicly listed firms, as we measure economic value as the (logarithm of the) estimated market value created by the patent based on the stock market reaction to the patent's issuance.

[Insert Table III about here]

[21] We focus on citations received within five years of the grant date to limit truncation bias, but the results hold when we use all citations as of 2013 or in the first year or two after grant.

Table III presents the results of these three tests, which are based on patent-level regressions. Each ex post metric is regressed on each patent's measured disruptive potential. We include cohort fixed effects (based on grant years) to specifically isolate variation across patents granted in the same year, and we cluster standard errors by cohort. Results in Panel A reveal that our measure of disruptive potential is positively associated with all three ex post metrics. The estimated relationships are also highly statistically significant with t-statistics ranging between 4.35 and 7.48. These results confirm that, on average, patents with more disruptive potential create higher impact in the form of citations, generate more economic value in the stock market, and they trigger a significant shift in the direction of innovation in the technology space.

In Panel B, we additionally control for heterogeneity in the citation patterns and other unobserved variables that might exist across different technology areas as we include interactions between cohort and technology area fixed effects. We define technology areas using two-digit NBER technology codes (Hall, Jaffe, and Trajtenberg (2001)). In Panel C, we additionally include four patent characteristics as control variables to better isolate the unique content of our measure of disruptive potential. These variables are technological breath and similarities between each patent and the set of patents granted to the universe of private, public, and foreign firms. In both panels, we continue to observe strong and positive relationships between outcomes and disruptive potential, consistent with our measure capturing the potential to alter technological paths and displace existing ideas.[22]

B Unambiguous Breakthrough Inventions

Next, we examine whether patents that have been historically recognized for their technological breakthroughs and commercial successes displayed disruptive potential in their application year. We focus on two distinct sets of patents gathered from external sources.

First, we consider a collection of twelve breakthrough patents, as identified by the

[22]We also note that the estimated associations reported in Table III indicate that ex post outcomes are not perfectly predictable, something we expect of any ex ante predictive measure. Hence a patent's disruptive potential often predicts disruptive impact, but not always. This conclusion is consistent with Christensen (1997) and Christensen and Rosenbloom (1995)).

USPTO's "Significant Historical Patents of the United States".[23] Panel A of Table IV displays these patents. We score each patent for their disruptive potential based on their percentile rank in the distribution of (their cohort-adjusted) disruptive potential. For instance, a value of 0.95 indicates that the patent is in the top 5% of the distribution. Reassuringly, these disruptive patents displayed high disruptive potential at the time of their application to the USPTO, as they collectively rank on the 82nd percentile of the disruptive potential distribution. The patents that displayed the highest disruptive potential in this set are the "Complex computer" in 1944 (#2668661) and DNA modifications in 1980 (#4399216), both of which virtually created new industries. Other key inventions, such as the satellite (#2835548), laser (#2929922), and PageRank (#6285999), also use vocabulary that was new and rapidly growing across many patents around the time of their application.[24]

[Insert Table IV about here]

Second, we consider a more comprehensive list of 101 important patents between 1930 and 2010 identified by Kelly, Papanikolaou, Seru, and Taddy (2019) based on several on-line lists of "important" patents. This set encompasses indisputably important and radical inventions that we display in detail in the Appendix for brevity (Table A2). We again score each patent based on its percentile rank in the (cohort-adjusted) distribution of technological disruptive potential, and present summary statistics in Panel B of Table IV. We find that the disruptive potential of these patents is in the 71st percentile on average and the median patent is in the 81st percentile.[25] These average percentiles are measured

[23] Listed patents applied before 1960 come from a list of historical patents at http://www.uspat.com/historical/. More recent patents are noted for the revenue they generated.

[24] Interestingly, some of these breakthrough inventions are barely cited. For instance, the patents related to the invention of the "television" (#1773980) and the "helicopter" (#1848389) are in the lowest percentile of the cohort-adjusted distribution of citations. Yet, our new measure classifies these patents as highly disruptive. Kelly, Papanikolaou, Seru, and Taddy (2019) similarly note that some patents classified as significant based on their measure attract few citations, and provide illustrative examples, such as patent #174465 issued to Graham Bell for the telephone in 1876 having received only 10 citations until March 2018.

[25] For comparison, Kelly, Papanikolaou, Seru, and Taddy (2019) report that the average patent is this same set is in the 84th percentile of the distribution of their patent significance measure, and the average percentile for the KPSS measure for this set of patents is 68. Thus, despite being computed using ex ante information, our measure of disruptive potential appear strongly correlated with that of

rather precisely as the standard error is 0.027. Overall, these findings confirm that the vast majority of breakthrough patents display systematically high levels of measured disruptive potential.

C Perceived Disruption Risk

As a third validity check, we examine whether publicly traded firms actually complain about potential disruption in their 10-K disclosures to the Securities and Exchange Commission when the startups operating in their product markets have patents with high disruptive potential. For each startup in our sample, we identify the set of public firms offering similar products and services using an approach based on Hoberg and Phillips (2016). We obtain product descriptions of startups from VentureXpert as reported in the year of their first round of funding and we use the product descriptions from 10-K reports for the public firms. We then compute the cosine similarity between the product description text of each startup and each public firm in year t. We focus on startups that received their first funding round between 1997 and 2010 as 1997 is the first year we have available 10-K data. This sample includes 5,417 distinct startups (60% of our original startup sample). We identify a startup's public "peers" as the 25 public firms with the highest textual similarity to the startup's product vocabulary.

We then compute the intensity with which the 25 public peers of each startup directly discuss risk of disruption. We do so by computing the fraction of paragraphs in each public firm's 10-K that mention words related to technology-based disruption using three measures. First, we search for paragraphs that contain words having the roots "technol" and "change" to measure whether public peers are discussing exposure to technological changes, a form of technology-specific disruption. Second, we identify paragraphs having words with the roots "technol" and "compet" to identify firms that are explicitly discussing competition in the technology space. Third, we consider the more strict set of paragraphs containing the roots of "technol" and "compet" together with either "disrupt", "change", or "obsoles"

Kelly, Papanikolaou, Seru, and Taddy (2019) which utilize ex post information (i.e., textual similarity with future patents).

[Insert Table V about here]

To assess whether public firms recognize the disruptive potential of related startups, we average these three measures over the 25 public peers for each startup and regress the resulting public-firm measures on the focal startup's technological disruptive potential (measured as of the startup's first funding round, contemporaneous to the assignment of its public peers). Table V displays the results and shows positive associations between the startup's technological disruptive potential and all three disruption mentions measures. The positive relationships hold across specifications that include either year fixed effects or a more complete set of fixed effects including year, technology, startup location, startup age, and startup cohort. These results further support the validity of our measure of disruptive potential and also its economic relevance as established public firms actually discuss disruption in their disclosures.

V Disruptive Potential and Startups' Exits

We now turn to testing whether startups with higher disruptive potential are more likely to exit through a public listing and less likely to sell-out.

A Main Results

Our baseline specification relies on the competing risks regression approach of Fine and Gray (1999) that explicitly models the "risk" of choosing a particular exit in quarter q given that the firm is still unresolved at that time.[26] Startups enter the sample (i.e., become at risk of exiting) when they are founded. Their exit is modeled using competing hazards to reflect multiple potential exit strategies that are mutually exclusive. This approach allows us to estimate the relationships between startups' disruptive potential and the full set of potential exits.

To ensure that we are not capturing the effects of other technological characteristics that may correlate with disruptive potential, we include in the specification the log of one

[26]The use of a competing risk model is relatively rare in finance. One recent exception is Avdjiev, Bogdanova, Bolton, Jiang, and Kartasheva (2017), who examine the determinants of convertible capital choice by banks.

plus the number of patent applications in the past five years, a dummy variable indicating startups with no applications in the past five years, startups' technological breadth, and technological similarities to lead innovators, private firms and foreign firms. We also control for the originality of startups' patents and their patents' citations (both aggregated as stock levels for each startup-quarter as is the case for our text-based variables). Following the literature on IPOs and acquisitions, we also control for overall market activity using market relative valuation and stock returns as well as an identifier for the last quarter of the year (Lowry (2003) and Pastor and Veronesi (2005)). Overall, with the exception of patent citations, all variables included in our model are ex ante measurable. We include citations only to be consistent with the existing literature. We cluster the standard errors by startup to account for any potential within-startup dependencies over time.

[Insert Table VI about here]

The first two columns of Table VI provide support for our central hypothesis. In the first column, we observe a strong positive link between startups' disruptive potential and their likelihood of exiting through an IPO in the next quarter. The point estimate is 0.252 with a t-statistic of 13.09. As predicted, startups with disruptive potential favor remaining independent as stand-alone entities and exit through public listings. On the other hand, column (2) reveals that the odds of exiting via a sell-out are negatively related to startups' disruptive potential. Indeed, the estimated coefficient is negative (-0.188) and statistically significant with a t-statistic of -7.55.[27] In addition to being statistically significant, these baseline estimates reveal economically large relationships: a one standard deviation increase in startups' disruptive potential is associated with a 25.2% increase in the quarterly rate of IPOs, and a 18.8% decrease in the sell-out rate.[28]

[27]These results continue to hold if we only use exits in the form of acquisitions that are are clearly successful to avoid the potential misclassification highlighted by Maats, Metrick, Yasuda, Hinkes, and Vershovski (2011). To do so, we restrict to sell-outs that we can match to acquisitions in the SDC transaction database and that are larger than $25 million (in 2009 dollars). Results are displayed in the Internet Appendix (Table IA2). We thank Josh Lerner for suggesting this test.

[28]As explained in Fine and Gray (1999), regression coefficients from a sub-distribution hazard model denote the magnitude of the relative change in the sub-distribution hazard function associated with a one-unit change in the given covariate. Therefore, estimated coefficients reflect the relative change in the instantaneous rate of the occurrence of the event in those subjects who are event-free.

Table VI shows that the startups' other technological characteristics are also important determinants of startups' exits. We observe for instance that firms' technological breadth is positively related to IPO incidence and is negatively related to sell-out incidence. This follows from the intuition that high breadth technologies are difficult for other firms to integrate and less redeployable toward other uses, thus tend to offer lower synergies to potential buyers (e.g., Bena and Li (2013)). Table VI also indicates that firms whose patents are more similar to those of other private firms are significantly less likely to exit through sell-outs (t-statistic of -8.62) and are marginally more likely to go public (t-statistic of 1.70). These results are in line with the negative link between product market similarity and the likelihood of being an acquisition target documented in Hoberg and Phillips (2010) for public firms. In contrast, firms holding patents that are more similar to that of lead innovators are significantly more likely to go public (t-statistic of 4.58). We also find that future citations (originality) are positively (negatively) associated with exit via both IPO and sell-out. Also, startups are more likely to exit via IPO after periods of strong overall stock market performance, consistent with earlier research. The inclusion of these additional variables further illustrates the robustness of our results.

B Robustness and Dynamics

In the last two columns of Table VI, we report estimates from linear probability models where the dependent variables are indicators for whether a given exit occurs in a given quarter. Although this approach ignores the potential dependence across exits (i.e., competing risks), linear models allow us to include a wider array of fixed effects. We include year, state, technology, age, and cohort fixed effects to estimate the link between exits and technological disruptiveness among startups of the same age, those receiving first funding at the same time, those operating in the same year and state, and those innovating in the same technological fields.[29] We find that our conclusions are largely unaffected, indicating that the association between the disruptive potential of startups and their exits is highly robust. We also estimate (but do not report for brevity) separate logistic and multinomial logistic models for each exit type that include year, state, and technology fixed effects.

[29]Technology fixed effects are based on the most common NBER technology category used in a firm's patents (see Lerner and Seru (2017)).

These tests produce similar results.

In Table VII, we use the same specifications as reported in Table VI, but we further control for startups' financing, as previous research reports that the amount of VC funding (a proxy for startups' implied valuation) predicts startups' exits (Cumming and Macintosh (2003)). These tests are important because our interpretation of the link between disruptive potential and startup exits could be due to VCs providing more funding to startups developing more disruptive technology.[30] Table VII indicates that this is not the case. To account for the possible role of funding, we include startups' cumulative VC funding (from founding to quarter $q-1$) and a binary variable identifying whether startups received funding in the last five years. Across all specifications, we confirm that the financing variables are strong determinants of startups' exit, especially sell-outs. However, our main result for technological disruptive potential is fully robust, indicating that our findings cannot be explained by financing.

[Insert Table VII about here]

Table VIII explores the dynamic links between startups' technological disruptive potential and exits by increasing the measurement window for identifying startup exits from one quarter to five years using increments of one year. We focus on linear specifications that include the full set of fixed effects as described above, and only report coefficients for the technology variables for brevity. Panel A indicates that the positive associations between startups' disruptive potential and IPO incidence remains strong at all horizons. In contrast, Panel B reveals that the negative relation between disruptive potential and the propensity to sell-out is only present at short horizons and then fades after two years.

[Insert Table VIII about here]

Finally, we also consider whether technological traits are related to the propensity of a startup to remain private for longer periods. This analysis is motivated by the evidence in Gao, Ritter, and Zhu (2013) and Ewens and Farre-Mensa (2018) that, in recent

[30] We confirm this intuition in Table IA3 of the Internet Appendix.

years, many startups remain private longer. Panel C of Table VIII presents results from regressions of startups' odds of remaining private at different horizons on their current technological characteristics. The results show that startups with higher disruptive potential exit more quickly on average.

We report the results of additional robustness tests in the Internet Appendix. Table IA2 shows that our results hold when standard errors are clustered by year, startup technology, or startup cohort. The results also hold when we exclude citations as a control, when we only control for the size of a startup's patent portfolio, and in a sub-sample comprised only of startup-quarters that resulted in exits. This latter result confirms that our results are not mechanically driven by startups staying private longer. Table IA4 shows that our results are stable across sub-periods. This ensure that our results are not driven by either (A) startups that have an "unresolved" status or (B) truncation bias associated with patents not yet granted (Lerner and Seru (2017)).

C Established and New Technology Spaces

Conceptually, technologies with disruptive potential may significantly alter the nature of innovation in either *established* technological areas (Tushman and Anderson (1986)), or entirely *new* areas (Acemoglu, Akcigit, and Celik (2014)). To assess which dimension matters, we now consider refined measures of disruptive potential based on either established vocabulary or vocabulary newly appearing in the patent corpus.

Our measure for established technological markets focuses on words that have been used in the patent corpus for at least ten years. We interpret these older words as pertaining to established technology spaces. We thus modify our baseline definition as follows:

$$\text{Disruptive Potential (Established)}_{j,t} = \frac{V_{j,t}^{10+}}{V_{j,t}^{10+} \cdot 1} \cdot D_t^{10+} \times 100, \tag{5}$$

where V^{10+} and D^{10+} are the vectors V and D defined in Section III.B, except we remove elements relating to words less than ten years old within the patent corpus at time t. By construction, this measure is not influenced by young or new words. For example, patents containing the word "internet" in 1993 will not necessarily score highly on this measure because the new term "internet" is not part of the established vocabulary. Instead, patents will score higher when they use older words whose usage suddenly surges in volume across all patent applications in a given year. Such patents thus belong to "second (or later) waves" of innovation within a specific established technology space.[31]

Analogously, to measure the potential of a patent to create entirely new technology areas, we consider only words first observed in the patent corpus during the most recent ten years. We thus modify our baseline definition as follows:

$$\text{Disruptive Potential (New)}_{j,t} = \frac{V_{j,t}^{<10}}{V_{j,t}^{<10} \cdot \mathbf{1}} \cdot D_t^{<10} \times 100, \tag{6}$$

where $V^{<10}$ and $D^{<10}$ are the vectors V and D as before, but we only keep the elements relating to words less than ten years old at time t. Intuitively, the above two measures form a complete decomposition of our main variable of disruptive potential into two components: potential to disrupt existing and new technology areas.[32]

[Insert Table IX about here]

To examine the relationship between exits and these two distinct components, we aggregate the above patent-level measures to firm-quarter variables (analogously to our original variable) and we include both components in our baseline regressions. Table IX presents the results for the competing risk and OLS models. We find that IPO exits are strongly related to startups' potential to disrupt established areas (with t-statistics of 10.20 and 5.54), but not to their potential to create new areas (with t-statistics of 0.99 and -0.90). Similarly, the incidence of sell-outs is more strongly negative for established markets although both components are significant. We conclude that disruption in existing technological areas is more important in determining startup exits. This result further

[31] An example is patent #7,663,607 for multipoint touchscreens, which was granted to Apple in 2010. This patent introduced new ways to combine existing technologies at a point in time when cell phones, display technology, and user-interfaces were the focus of a wave of rapidly expanding patenting activity.

[32] Apple's aforementioned touchscreen patent resembles the former; it scores in the 84th percentile of the former, but in the 2nd percentile of the latter. Conversely, the earliest patents in a sequence of breakthrough patents governing co-transformation (a method of altering multiple genes) have high levels of *Disruptive Potential (New)*. Key patents on co-transformation in later years subsequently shifted towards higher levels of *Disruptive Potential (Established)*. This trend emerges clearly in other technology spaces we examined including semiconductors.

suggests that the ability to conduct business as a stand-alone entity (and exit via IPO) is particularly valuable when gains potentially come at the expense of existing market participants.

D The Product Markets of Exiting Startups

To further validate the mechanisms linking startups' disruptive potential to their choice of exit, we examine the product market characteristics of the 848 startups present in our sample that go public after 1997. Because these startups become publicly traded, we are able to link their technological disruptive potential to the product market attributes that are only measurable for public firms. We consider three such characteristics (measured in the year of their initial public listing): product market concentration (HHI), the total similarity of the firm's products to publicly traded peers (TSimm), and product market fluidity. These variables are available since 1997 and obtained from Hoberg and Phillips (2016) and Hoberg, Phillips, and Prabhala (2014).

[Insert Table X about here]

Following the life cycle theory predictions of Abernathy and Utterback (1978) we anticipate that disruption-prone markets are those for which competing early-stage startups are highly active and thus likely to discover superior technologies. We thus assess whether going-public startups displaying higher disruptive potential exit into more competitive, less differentiated, and more fluid product markets. Table X confirms these specific predictions. Newly-public firms with more technological disruptive potential indeed exit into markets that are more fluid, contested, and thus subject to disruption. In contrast, IPO firms with less disruptive potential exit into more stable markets, with less competition, and higher levels of product differentiation.

VI The Evolution of Disruptive Potential

Our results thus far illustrate a strong cross-sectional relationship between startups' exit decisions and their technological disruptive potential. This section studies the aggregate evolution of patents' and startups' disruptive potential.

A Patents' Disruptive Potential in the Last Century

We compute aggregate disruptive potential using an average based on a 20-quarter rolling window.[33] Panel A of Figure II plots the result from 1930 to 2010 annualized using a four-quarters moving average. The figure shows transitory periods of sharply increasing disruptive potential with an initial peak around 1950 at a level that is roughly double that in 1930. The period around 1950 is often viewed as time of radical innovation in manufacturing technologies, featuring the invention of the television, transistor, jet engine, nylon, and xerography. A second peak occurs in the mid-seventies, corresponding to innovation related to the computer. The last two peaks of technological disruption appear in the late eighties and mid-nineties, reflecting waves of inventions related to genetics (e.g., methods of recombination) and the mass adoption of the Internet.

[Insert Figure II about here]

Despite these periodic surges in disruption, the 1930-2010 period is characterized by a protracted and steady long-term decline in the disruptive potential of U.S. patents. Between 1950 and 2010, the average disruptive potential of patents has significantly decreased, with levels in 2010 being roughly one quarter that of 1950. Importantly, this decline is not due to changes in the composition of patents (e.g., shifts across technology classes) as we continue to observe a similar trend after we account for broad technology and location fixed effects (unreported for brevity). Rather, the decline indicates a widespread deceleration in vocabulary usage growth rates among U.S. patents.[34]

Panel B of Figure II plots separately the evolution of the two components of patents' disruptive potential, defined in Section V.C. We note that most of the variation in patents' disruptive potential comes from the potential to disrupt established technological areas. Indeed, the aggregate potential of patents to create new areas has remained stable until the eighties, increasing slightly in the 1990s, and declining after 2000. Taken together,

[33] We first sum disruptive potential over the patents applied for in a given quarter. We then apply a 5% quarterly rate of depreciation over the 20 rolling quarters and then divide by the number of patents applied for in these 20 quarters to arrive at the average disruptive potential over time.

[34] To conserve space, we display and discuss our other text-based variables (the aggregate evolution of patents' technological breath and similarity to groups of patents) in the Internet Appendix.

the secular decline in patents' disruptive potential echoes recent research highlighting the increasing difficulty to generate new ideas (e.g., Jones (2009) and Bloom, Jones, Reenen, and Webb (2017)). Our findings suggest that the increased challenge to discover new ideas appears particularly salient concerning ideas with the potential to transform established markets.

B Disruptive Potential, IPO, and Acquisitions

We next contrast the decline in patents' disruptive potential to the aggregate evolution of IPOs and acquisitions. We obtain data on IPOs from Jay Ritter's website and exclude non-operating companies, as well as IPOs with an offer price lower than $5 per share, unit offers, small best effort offers, bank and savings and loans IPOs, natural resource limited partnerships, companies not listed in CRSP within 6 month of their IPO, and foreign firms' IPOs. Data on acquisitions are from the Thomson Reuters SDC Platinum Database, and include all domestic completed acquisitions (of private or public firms) coded as a merger, acquisition of majority interest, or acquisition of assets giving the acquirer a majority stake.

[Insert Figure III about here]

The left panel of Figure III plots the number of IPOs for each quarter between 1980 and 2010. The patterns are similar to those reported by Gao, Ritter, and Zhu (2013), Doidge, Karolyi, and Stulz (2017), and Ewens and Farre-Mensa (2018). To facilitate comparison, the right panel displays the evolution of aggregate patents' disruptive potential during the same period. The evolution of IPO activity rather closely maps the aggregate dynamics of disruptive potential during this thirty-year period. The number of IPOs drops around 1990, coinciding with a decline in disruptive potential that follows the earlier surge in genetic science in the mid-1980s. There were more IPOs as the nineties progressed, when disruptive potential experienced a very large increase. The decline in IPO intensity then began in the early 2000s, when the average disruptive potential of U.S. patents also started to plummet. Although much of the variation appears linked to disruptive potential, the rise in exits around 2005 appears unrelated, and might be linked to increased private equity activity during this time.

The middle panel of Figure III plots the evolution of the number of acquisitions, both in total and separately for private firms. The number of acquisitions has increased since 1980, with a strong acceleration in the mid-nineties. We note subsequent declines in acquisitions in the aftermath of the technology bubble and the financial crisis. Yet, the number of acquisitions remains significantly higher since the mid-nineties when compared to the 1980-1995 period, suggesting a relationship between the surge in aggregate acquisitions and the decline in disruptive potential of U.S. patents. Although the aggregate pattern for sell-outs is less striking than that for IPOs, it suggests that acquisitions tend to be high when overall disruptive potential is lower.

[Insert Figure IV about here]

In Figure IV, we display the evolution of disruptive potential along with IPO and sell-out rates for the startups in our sample. For the sake of comparison, we compute the aggregate stock of each variable for the set of patents granted to startups as in Figure II. In addition, we scale the aggregate quarterly number of IPOs and acquisitions by lagged real GDP to obtain aggregate exit rates. Reassuringly, the trends in our startup sample closely map those of the aggregate dynamics, indicating that the technological changes and exit patterns occurring among startups is mirroring economy-wide changes. We again observe that periods with elevated disruptive potential exhibit more intense IPO rates, and lower sell-out rates.

VII Disappearing IPOs and Surging Sell-Outs

We now estimate whether (and how much of) the recent shift in exits away from IPOs toward sell-outs could be attributed to changes in disruptive potential and other technological characteristics.

A Prediction Errors for Startups' Exit

To examine the impact of changing technological characteristics on startups' exit choice, we use methods from the disappearing dividends literature (see Fama and French (2001) and Hoberg and Prabhala (2009)) and proceed in two steps. First, we estimate two linear probability models (a "Base" model and a "Text" model) using quarter-by-quarter Fama and MacBeth (1973) regressions where the dependent variable is the incidence of IPO exits in each quarter during the initial period 1980-1995 (the "pre-period"). The base model's independent variables are from the existing literature and include the (log) of the startups' age and the startup's patent stock. The Text model adds to this startups' disruptive potential and the additional text-based technology traits considered in this study. Second, we compute predicted values of IPO incidence for each startup-quarter in the 1996-2010 period (the "post-period") by using the average coefficients estimated in the pre-period as a predictive model, and applying this predictive model using the actual values of the independent variables in the post-period. We then average the predicted IPO rates across all startups in each quarter and compare them to the actual observed quarterly IPO rates in the post-period. Since the coefficients are locked in at their pre-period fitted values, we are able to isolate variation in these predicted IPO rates in the post-period that is due to changing startups' characteristics. We repeat these steps for sell-outs to compare actual and predicted sell-out rates.

[Insert Table XI about here]

Test 1 in Panel A of Table XI indicates that the base model yields an average predicted quarterly IPO rate of 0.84 percentage points in the post-period. This predicted incidence is substantially higher than the actual IPO rate, which is 0.33 percentage points per quarter in the post-period, implying a prediction error of 0.51. The predicted IPO rate is thus 2.5 times higher than the actual rate, confirming that observed IPO rates in the post-period are "abnormally" low. Using the Text model, the average predicted IPO quarterly rate in the post-period declines to 0.75 percentage points, which is still higher than the actual incidence rate as the prediction error is 0.42. In the rest of Table Table XI we modify the definition of the pre- and post-periods or to the forecasting horizon considered (i.e., the lags between the dependent and independent variables). Although a significant portion remains unexplained, our overall finding across the array of specifications shown in the Panel A is that changes in technological characteristics account for roughly 19% of the recent decline in IPO rates.

Panel B reports parallel analysis for sell-out rates. A benchmark linear model that excludes our technology variables estimated in the pre-period yields an average predicted sell-out incidence of 0.60 percentage points per quarter in the post-period. Compared to the actual rate of 0.86 per quarter, the base model's prediction is 42% lower than the actual rate, suggesting that the prevalence of sell-outs in recent years is "abnormally" high. Using the Text model, the prediction gap narrows significantly, as we obtain a predicted sell-out rate of 0.75 percentage points per quarter. When we alter specifications in the remainder of Panel B, we observe that changes in startups' technological characteristics explain between 26% and 71% of the surge in sell-outs. We conclude that roughly 50% (the average across specifications) of the surge in trade sales is accounted for by changes in startups' technological characteristics.

B Small and Large IPOs

The recent dearth of IPOs is particularly pronounced for smaller-company IPOs (see Gao, Ritter, and Zhu (2013) and Doidge, Kahle, Karolyi, and Stulz (2018)). To further validate the role of technological changes in explaining the recent decline in IPOs, we rerun the analysis in Table XI separately for small and large IPO exits. We measure IPO size using pre-IPO sales data from Gao, Ritter, and Zhu (2013) and inflation adjusted to 2009 dollars. We define an IPO as "small" if its pre-IPO sales are below the median in our sample ($25 million), and as "large" if its pre-IPO sales exceeds that amount. We then examine each subsample and estimate the probability that a given startup exits through a small (large) IPO in a given quarter in the pre-period quarter-by-quarter. As before, we estimate the model with and without our text-based technological variables, and compare the predicted IPO rate in the out-of-sample period to the actual rate.

[Insert Table XII about here]

Table XII displays the results. Panel A indicates that, across six specifications which vary the definition of the pre- and post-periods or the forecasting horizon, changes in startups' technological traits account for roughly 37% of the disappearing small IPO anomaly in the recent period. In sharp contrast, Panel B reveals that adding startups' technological characteristics to the regression models (estimated in the pre-period) does not bring the average predicted rate of large IPOs closer to its actual value in the post-period. We conclude that changes in startups' technological characteristics are particularity important to explaining the decline in small IPOs.

C The Role of Product Market Stability

We also explore the role of product market maturity in explaining the recent shift from IPOs to sell-outs. We posit that markets reaching maturity (e.g., markets that effectively reached a dominant product design) are likely to experience the most extreme decline in IPO rates. In these markets, breakthrough inventions obtain only with very high search costs (Jones (2009) and Bloom, Jones, Reenen, and Webb (2017)) as the best ideas are already "picked over", so that the decline of startups' disruptive potential should be a stronger predictor of lower IPO activity. To test this idea, we follow Hoberg, Phillips, and Prabhala (2014) and compute the degree of product market fluidity in each startup's product market from 1980 to 2010 using the business description text that is available at the time of the first funding round in Thomson Reuters's VentureXpert. We first compute the aggregate change in product description vocabulary used by startups as the year-over-year change in the frequency of word usage across all business descriptions. This quantity is computed separately for each word and the result is stored in an aggregate vector containing the set of word frequency changes for all words (this procedure is similar to that in Equation (1)). Second, for a given startup, we compute the frequency-weighted average of this aggregate change vector where the weights are the frequency of words used by the startup in its own business description (this calculation is similar to that in Equation (2)). The resulting variable is a product fluidity measure similar to the one used in Hoberg, Phillips, and Prabhala (2014), but defined over all startups receiving their first money between 1980 and 2010.

[Insert Table XIII about here]

To assess whether changes in startups' technological traits account for the recent decline in IPOs differently in stable and unstable markets, we divide our startup-quarter observations into above and below median fluidity sub-samples, based on median break-points chosen separately for each cohort of startups (based on the year of the first funding round) and repeat the prediction procedure discussed above across each sub-sample. Panel A confirms that startups operating in stable markets are less likely to exit via IPO relative to startups in fluid markets, with IPO rates of 0.30% and 0.37% per quarter in the post-period (1996-2010). Moreover, changes in startups' technological characteristics explain roughly 25% of the dearth of IPOs in stable markets. This figure is tightly estimated across different specifications. In contrast, changes in startups' technological attributes account for just 3% of the dearth of IPOs in fluid markets. This figure ranges between -7% and 15% across different specifications. Although market stability is relevant for understanding the evolution of IPOs, Panel B indicates that such stability has little effect in moderating our ability to explain the surging sell-outs anomaly, as the average improvement is 50% and 49% in stable and fluid markets, respectively.

VIII Conclusions

We develop new measures of technological disruptive potential and other technology characteristics using textual analysis of 6,595,226 U.S. patents from 1930 and 2010. We document that these characteristics are highly influential in predicting which startups will exit via IPO or sell-out. We find that startups with more disruptive potential are more likely to exit via IPO, and are less likely to exit via sell outs, especially in established markets. Understanding the economics of startups' with disruptive potential is most intuitive when juxtaposed against the concept of synergistic potential (patents that complement and refine existing technologies). Startups with disruptive potential likely favor IPOs because disruptive technologies tend to be economic substitutes for existing technologies and lack synergies for buyers. Additionally, these technologies likely enable startups to establish independent markets, allowing their owners to extract all rents without having to share with a potential acquirer.

In contrast, patents with low disruptive potential and high synergistic potential tend to have high complementary value when combined with existing technologies. Startups owning these patents likely favor sell-outs because the existence of synergies facilitates increased value creation through business combinations, and higher value exit prices to shareholders despite the need to share the gains with an acquirer.

Our second major finding is that technological traits have changed dramatically over time. Most notable, we document an economy-wide decline in technological disruptive potential that began after World War II. Because our central thesis is that startups with disruptive potential are more likely to exit via IPO, it follows that the aggregate decline in disruptive potential we document might also explain the recent aggregate decline in IPOs and the surge in sell-outs. We estimate that roughly 20% of the decline in IPOs can be attributable to changes in technological traits. Analogously, roughly 50% of the surge in sell-outs can be explained by these same variables.

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Figure I: Example of a Google Patent page

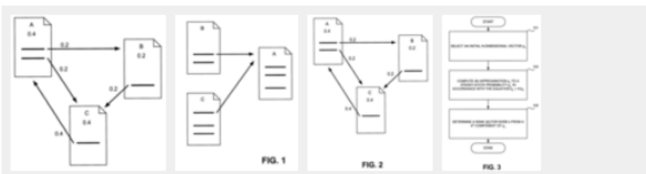
This figure shows the structure of a Google Patent page. The depicted patent is 6,285,999, commonly known as PageRank. Available at https://patents.google.com/patent/US6285999.

Method for node ranking in a linked database

Abstract

A method assigns importance ranks to nodes in a linked database, such as any database of documents containing citations, the world wide web or any other hypermedia database. The rank assigned to a document is calculated from the ranks of documents citing it. In addition, the rank of a document is calculated from a constant representing the probability that a browser through the database will randomly jump to the document. The method is particularly useful in enhancing the performance of search engine results for hypermedia databases, such as the world wide web, whose documents have a large variation in quality.

Images (4)



Classifications

G06F17/30864 Retrieval from the Internet, e.g. browsers by querying, e.g. search engines or meta-search engines, crawling techniques, push systems

G06F17/30728 Information retrieval; Database structures therefor ; File system structures therefor of unstructured textual data based on associated metadata or manual classification, e.g. bibliographic data using citations

Y10S707/99935 Query augmenting and refining, e.g. inexact access

Y10S707/99937 Sorting

Hide more classifications

US6285999B1
US Grant

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Inventor: Lawrence Page

Current Assignee: Leland Stanford Junior University , Google LLC

Original Assignee: Leland Stanford Junior University

Priority date: 1997-01-10

Family: US (10)

Date	App/Pub Number	Status
1998-01-09	US09004827	Expired - Lifetime
2001-09-04	US6285999B1	Grant
Show 8 more applications		
2012	US13616965	Expired - Lifetime

Info: Patent citations (28), Non-patent citations (20), Cited by (812), Legal events, Similar documents, Priority and Related Applications

External links: USPTO, USPTO Assignment, Espacenet, Global Dossier, Discuss

Description

CROSS-REFERENCES TO RELATED APPLICATIONS

This application claims priority from U.S. provisional patent application Ser. No. 60/035,205 filed Jan. 10, 1997, which is incorporated herein by reference.

STATEMENT REGARDING GOVERNMENT SUPPORT

This invention was supported in part by the National Science Foundation grant number IRI-9411306-4. The Government has certain rights in the invention.

FIELD OF THE INVENTION

This invention relates generally to techniques for analyzing linked databases. More particularly, it relates to methods for assigning ranks to nodes in a linked database, such as any database of documents containing citations, the world wide web or any other hypermedia database.

BACKGROUND OF THE INVENTION

Due to the developments in computer technology and its increase in

Claims (29)

What is claimed is:

1. A computer implemented method of scoring a plurality of linked documents, comprising:

obtaining a plurality of documents, at least some of the documents being linked documents, at least some of the documents being linking documents, and at least some of the documents being both linked documents and linking documents, each of the linked documents being pointed to by a link in one or more of the linking documents;

assigning a score to each of the linked documents based on scores of the one or more linking documents and

processing the linked documents according to their scores.

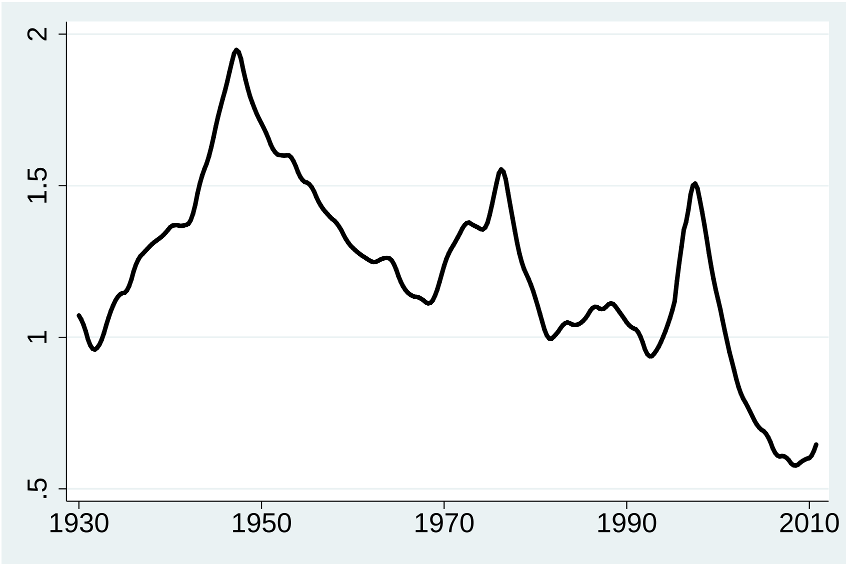
2. The method of claim **1**, wherein the assigning includes:

identifying a weighting factor for each of the linking documents, the weighting factor being dependent on the number of links to the one or more linking documents, and

Figure II: Time Series of Aggregate Disruptive Potential

This figure reports the evolution of *Disruptive Potential* for the aggregate patent corpus from 1930 to 2010. *Disruptive Potential* is defined at the patent level in Section III.B and Equation 2. *Disruptive Potential (Established)* and *Disruptive Potential (New)* are defined at the patent level in Equations 5 and 6, respectively. To compute the aggregate stocks, we first compute the sum of each of the patent-level characteristics for patents applied for in a given quarter. We then compute a rolling depreciated sum of the prior 20 quarters, using a 5% quarterly rate of depreciation. Finally, we normalize the rolling stock by the number of patents applied for in the 20 prior quarters. The underlying patent-level measures are winsorized at 1/99% level annually. All series are reported as four quarter moving averages.

Panel A: Disruptive Potential



Panel B: Decomposition of Disruptive Potential

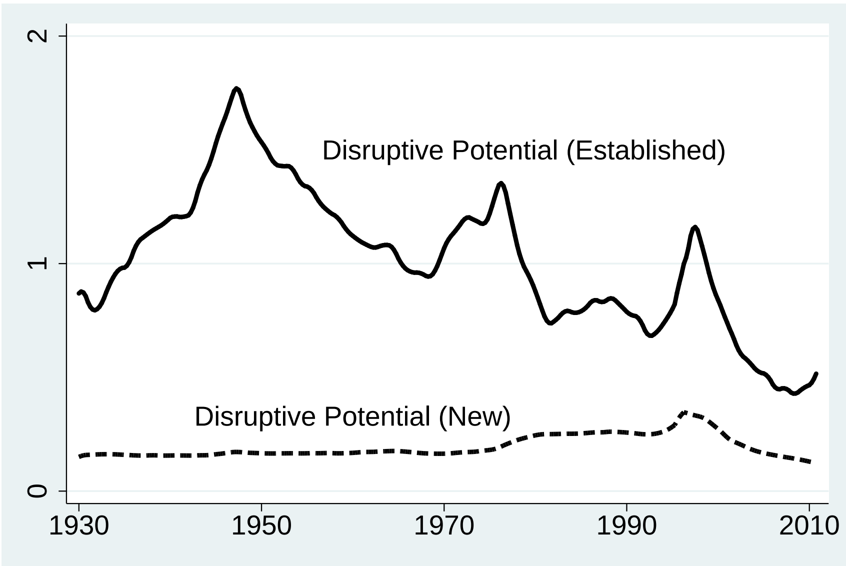


Figure III: Trends in Aggregate IPOs and Acquisitions

This figure reports the evolution between 1980 and 2010 the quarterly number of IPOs in the left panel and acquisitions in the middle panel. We obtain data on IPOs from Jay Ritter's website, and exclude non-operating companies, as well as IPOs with an offer price lower than \$5 per share, unit offers, small best effort offers, bank and savings and loans IPOs, natural resource limited partnerships, companies not listed in CRSP within 6 month of their IPO, and foreign firms' IPOs. Data on acquisitions are from the Thomson Reuters SDC Platinum Database, and include all domestic completed acquisitions (of private or public firms) coded as a merger, acquisition of majority interest, or acquisition of assets giving the acquirer a majority stake. For comparison, we include *Disruptive Potential* (from Figure II) over the same period in the right panel. All series are reported as four quarter moving averages.

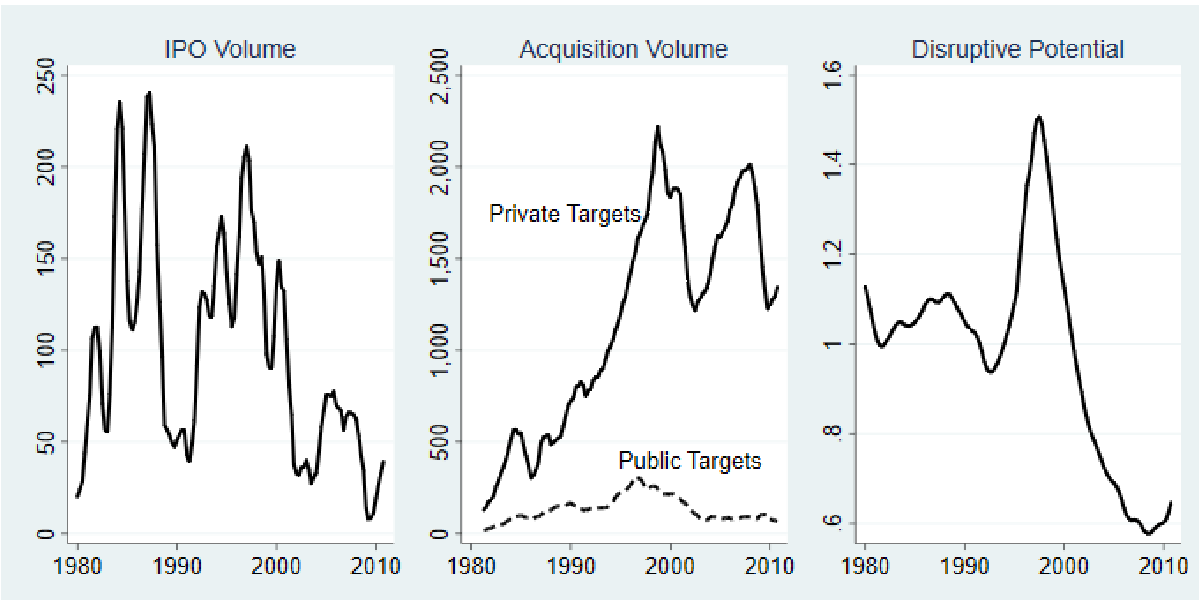
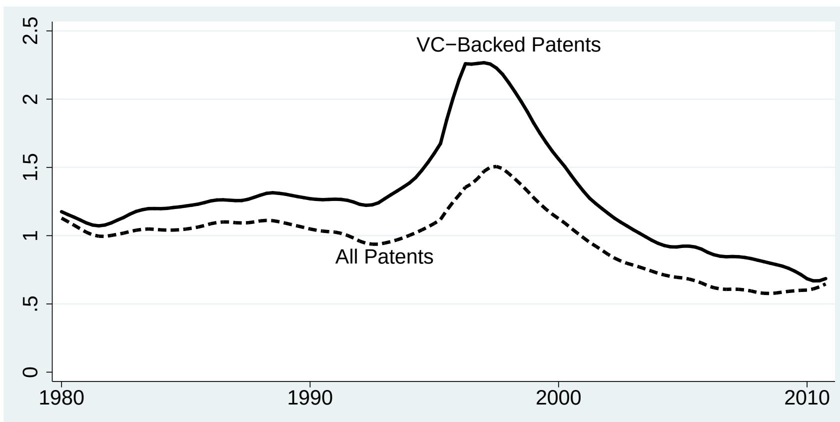


Figure IV: VC-Backed Startups: Disruptive Potential and Exit Trends

This figure compares trends among the startup sample to aggregate data. Panel A reports *Disruptive Potential* of patents held by VC-backed startups from 1980 to 2010 (solid line) and of all patents (dashed line). *Disruptive Potential* is defined at the patent level in Section III. The time series are constructed from the patent-level data as in Figure II. Panel B reports in the solid lines the percentage of startups that exit in the sample during the year via IPO or sell-out (left axis). The dashed lines report aggregate trends on IPOs and sell-outs of private targets and are reported in dashed lines as a fraction of lagged real GDP (right axis). Real GDP is in units of $100m. Aggregate data on IPOs and sell-outs are described in Figure III, except that in Panel B below, only private targets are included for sell-outs. All series are reported as four quarter moving averages.

Panel A: Disruptive Potential – Startup Sample vs. Aggregate Data



Panel B: Exits – Startup Sample vs. Aggregate Data

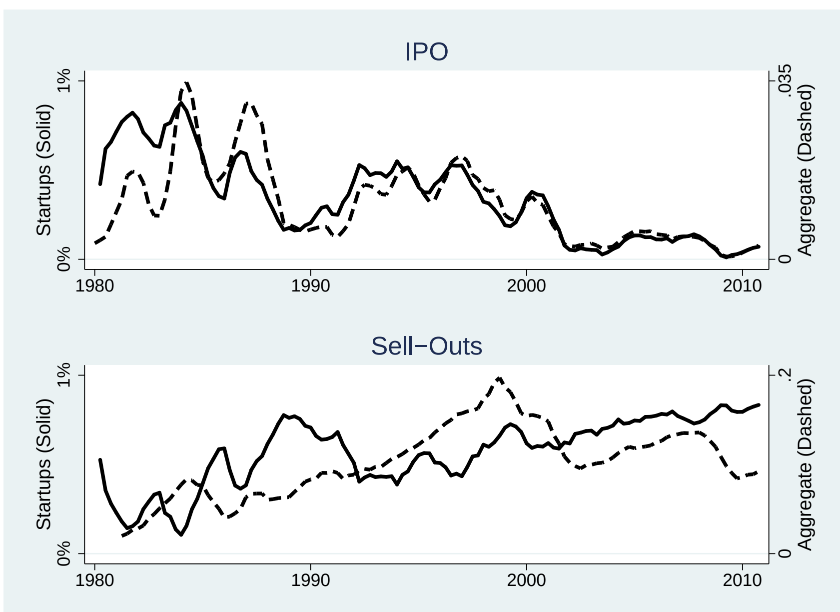


Table I: Changes in Patent Word Usage: Examples

This table reports, for five illustrative years between 1930 and 2010, how innovation has changed based on the text within patents. Panel A lists the ten words that have the largest year-over-year increase in use across all patents. Panel B lists the ten words that have the largest year-over-year decrease in use across all patents.

Panel A: Words with largest increase in use

1935	**1975**	**1985**	**1995**	**2005**
cent	bolts	laser	polypeptides	broadband
leaves	effort	japanese	deletion	intervening
axes	lithium	wavelength	clones	candidates
packing	user	publication	polypeptide	click
column	describes	blood	peptides	configurable
lead	exemplary	infrared	recombinant	luminance
coupled	entitled	polymer	cdna	abstract
notch	typically	mount	nucleic	acquiring
copper	phantom	optical	transcription	telecommunications
chain	exploded	comparative	plasmid	gamma

Panel B: Words with largest decline in use

1935	**1975**	**1985**	**1995**	**2005**
chambers	assistant	sulfuric	cassette	vegetable
crank	inventor	collection	ultrasonic	acyl
boiling	inventors	crude	machining	spiral
agent	firm	stock	abutment	gram
seats	priority	dioxide	tape	wedge
yield	john	evident	sand	gelatin
reducing	foreign	hydrocarbon	packing	crude
engine	sept	shut	bottle	oven
bell	june	circuitry	slidable	maybe
film	corporation	oxides	insofar	drilling

Table II: Summary Statistics: Patent-level Sample

This table presents summary statistics for patent applications between 1930 and 2010 in Panel A and for the quarterly sample of venture-backed startups between 1980 and 2010 in Panel B. Startups are in the sample from their founding date until the quarter of their final outcome. Note that some startups remain private at the end of the sample period. The startup sample is further detailed in Section V.D. *Disruptive Potential* is defined at the patent level in Section III.B and at the startup-quarter level in Section III.D. Remaining variables are defined in Table A1. P25 and P75 denote the 25th and 75th percentiles. The underlying patent level measures are winsorized at the 1/99% level annually.

Panel A: Patent sample

	N	Mean	SD	P25	Median	P75
Disruptive Potential	6,594,248	1.64	1.81	0.51	1.27	2.34
Tech Breadth	6,594,143	0.42	0.22	0.24	0.47	0.60
Private Similarity	6,594,248	0.15	0.05	0.12	0.15	0.18
LI Similarity	6,594,248	0.11	0.05	0.06	0.09	0.13
Foreign Similarity	6,594,248	0.15	0.06	0.11	0.14	0.19
Originality	5,335,987	0.40	0.33	0.00	0.46	0.67
# of Cites	6,595,226	1.58	2.91	0.00	1.00	2.00
KPSS Value	1,781,386	9.75	23.69	0.73	3.25	9.16
mCD	4,245,716	0.56	1.83	0.00	0.00	0.38

Panel B: Startup-quarter sample

	N	Mean	SD	P25	Median	P75
Disruptive Potential	347,929	0.66	1.14	0.00	0.00	0.98
Tech Breadth	347,929	0.13	0.18	0.00	0.01	0.27
Private Similarity	347,929	0.06	0.06	0.00	0.06	0.11
LI Similarity	347,929	0.04	0.05	0.00	0.03	0.07
Foreign Similarity	347,929	0.05	0.06	0.00	0.04	0.09
Log(1+Firm Age)	347,929	3.07	1.15	2.40	3.18	3.76
No PatApps[q-1,q-20]	347,929	0.47	0.50	0.00	0.00	1.00
Log(1+PatApps[q-1,q-20])	347,929	0.79	0.97	0.00	0.69	1.39
Log(MTB) (q-2)	347,929	0.15	0.08	0.11	0.15	0.19
MKT Return [q-2,q-1]	347,929	0.01	0.13	-0.08	0.02	0.09
Q4	347,929	0.25	0.43	0.00	0.00	0.00
Originality	347,929	0.16	0.20	0.00	0.00	0.31
Log(1+Cites)	347,929	0.54	0.70	0.00	0.00	1.02
IPO rate (x100)	347,929	0.42	6.43	0.00	0.00	0.00
Sell-Out rate (x100)	347,929	0.73	8.50	0.00	0.00	0.00

Table III: Technological Disruptive Potential: Citation Patterns and Economic Value

This table presents regressions on a sample of patents granted between 1930 and 2010. Independent variables are defined in Table A1, while dependent variables are defined in Section III. To facilitate interpretation, all controls are standardized. All measures are winsorized at the 1/99% level annually. *LI Similarity* and *Foreign Similarity* are orthogonalized relative to *Private Similarity*. Fixed effects are included based on a patent's grant year (cohort) and technology category. Adjusted R^2 is reported as a percentage. Standard errors are clustered by the patent's grant year and are reported in parentheses. The symbols ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log(1+Cites) (1)	mCD (2)	Log(1+KPSS Value) (3)
Panel A: Cohort fixed effects, no controls			
Disruptive Potential	0.035***	0.104***	0.080***
	(6.92)	(4.35)	(7.48)
Observations	6,033,343	4,245,630	1,697,481
R2 (%)	10.0	27.4	6.4
Panel B: Cohort-by-technology fixed effects, no controls			
Disruptive Potential	0.033***	0.078***	0.054***
	(8.93)	(4.62)	(5.99)
Observations	6,033,292	4,245,585	1,697,455
R2 (%)	15.9	30.0	12.1
Panel C: Cohort-by-technology fixed effects, with controls			
Disruptive Potential	0.030***	0.070***	0.033***
	(8.88)	(4.40)	(4.08)
Tech Breadth	-0.021***	-0.031***	-0.028**
	(-6.30)	(-4.17)	(-2.38)
Private Similarity	0.106***	0.064**	0.087***
	(15.87)	(2.29)	(6.53)
LI Similarity	0.128***	0.061*	0.363***
	(16.85)	(1.79)	(12.00)
Foreign Similarity	-0.064***	0.022	-0.534***
	(-10.64)	(0.85)	(-11.33)
Observations	6,033,230	4,245,584	1,697,435
R2 (%)	17.2	30.1	18.9

Table IV: Technological Disruptive Potential: Examples of Important Patents
This table reports the percentiles of various patent-level characteristics for important patents. Percentiles are cohort-adjusted, i.e., we remove year fixed effects before computing percentiles. In Panel A, we consider twelve unambiguous breakthrough patents. Patents before 1960 are from the USPTO's "Significant Historical Patents of the United States" and more recent patents are noted for the revenue they generated. In Panel B, we report summary statistics for the percentiles of a more comprehensive list of 101 patents between 1930 and 2010 identified by Kelly, Papanikolaou, Seru, and Taddy (2019) (henceforth, KPST) based on several on-line lists of "important" patents. These patents are listed in detail in Table A2. The percentiles for the KPST measure are taken directly from their Table A.6. All other variables are defined in Table A1. "Brdth" and "Orig" are short for *Tech Breadth* and *Originality*, respectively. The underlying patent-level measures are winsorized at 1/99% level annually.

Patent	Year	DP	Cites	KPSS	mCD	KPST	Brth	Orig	Note
Panel A: Examples of Important Patents									
1,773,980	1930	0.88	0.7			0.98	0.64		TV
1,848,389	1932	0.73	0.68			0.94	0.3		Helicopter
2,404,334	1946	0.59	0.97			0.23	0.8		Jet Engine
2,524,035	1950	0.68	0.96	0.85		0.75	0.45	0.89	Transistor
2,569,347	1951	0.72	0.96	0.79		0.63	0.48	0.72	Junction Transistor
2,668,661	1954	1	0.87	0.8		0.98	0.85	0.83	Modern digital computer
2,835,548	1958	0.75	0.79			0.85	1	0.97	Satellite
2,929,922	1960	0.91	0.97	0.9		0.89	0.61		Laser
4,237,224	1980	0.96	0.98		0.99	1	0.62		Cohen/Boyer patent
4,399,216	1983	1	0.99		0.99	1	0.68	0.26	"Axel" patent
4,681,893	1987	0.7	1	0.58	0.99	N/A	0.3	0.4	Lipitor patent
6,285,999	2001	0.92	1		0.98	0.99	0.13	0.74	PageRank (Google)
Panel B: Summary of All Important Patents									
Average:		0.71	0.75	0.68	0.61	0.84	0.53	0.55	
Median:		0.81	0.80	0.75	0.81	0.90	0.54	0.62	
Std error:		(0.03)	(0.02)	(0.04)	(0.06)	(0.02)	(0.03)	(0.04)	

Table V: Startup-Level Validity Tests: Perceived Disruption Risk

This table presents validity tests based on textual analysis of the 10-Ks of public peers of VC-backed startups. The sample is a cross-section of startups measured during the year in which they receive their first round of funding. As discussed in Section IV.C, we link each startup to the 25 public firms whose product descriptions—reported by VenturXpert as of the first VC round—are most similar. In columns (1)-(3), the dependent variable is the average fraction of paragraphs in public peers 10-Ks that mention words with roots "technol" and "change". In columns (4)-(6), the dependent variable is based on paragraphs with a root of "technol" and "compet". In columns (7)-(9), the dependent variable is based on paragraphs with a root of "technol" and "compet", together with either "disrupt", "change", or "obsoles". Thus, these variables measure the intensity with which the public peers of a given startup discuss technology-based market disruption, as discussed in Section IV.C. All variables are defined in Table A1 and the underlying patent-level measures are winsorized at the 1/99% level annually. Adjusted R^2 is reported as a percentage. Standard errors are heteroskedastic robust and are reported in parentheses. The symbols ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Discussion of:	Technology and change			Technology and competition			Technology, competition, and disruption		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Disruptive Potential	0.016***	0.012***	0.007**	0.039***	0.031***	0.025***	0.010***	0.007***	0.005**
	(4.75)	(3.89)	(2.24)	(4.49)	(3.64)	(2.82)	(4.48)	(3.42)	(2.15)
Constant	0.370***			1.401***			0.251***		
	(112.53)			(151.99)			(110.54)		
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Technology FE	No	No	Yes	No	No	Yes	No	No	Yes
Location FE	No	No	Yes	No	No	Yes	No	No	Yes
Firm Age FE	No	No	Yes	No	No	Yes	No	No	Yes
Firm Cohort FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	5,417	5,417	5,313	5,417	5,417	5,313	5,417	5,417	5,313
R2 (%)	0.4	6.6	30.2	0.3	4.9	21.0	0.4	8.1	25.3

Table VI: The Determinants of Startups' Exits - Baseline

This table presents cross-sectional tests relating startups' ex ante technological traits to their exit. The outcomes we consider are IPO and sell-out (acquisition). The sample is a quarterly panel of VC-backed startups from 1980-2010 and is described in Section III.D. Columns (1)-(2) use a competing risk hazard model and columns (3)-(4) use an OLS linear probability model. To facilitate interpretation, coefficients for OLS estimates report the incremental % change in a given outcome. Independent variables are lagged one quarter unless explicitly noted and all controls are standardized for convenience, except for the *Q4* and *No PatApps[q-1,q-20]* dummy variables. All variables are defined in Table A1. *LI Similarity* and *Foreign Similarity* are orthogonalized relative to *Private Similarity*. The underlying patent-level measures are winsorized at the 1/99% level annually. Technology fixed effects are based on the most common NBER-technology category across a firm's patents. Location fixed effects are based on the state reported in VentureXpert. Adjusted R^2 is reported as a percentage. Standard errors are clustered by startup and are reported in parentheses. The symbols ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Competing Risk Hazard		OLS	
	IPO	Sell-Out	IPO	Sell-Out
	(1)	(2)	(3)	(4)
Disruptive Potential	0.252***	-0.188***	0.082***	-0.067***
	(13.09)	(-7.55)	(4.04)	(-3.42)
Tech Breadth	0.510***	-0.210***	0.091***	-0.140***
	(10.02)	(-5.50)	(3.28)	(-4.39)
Private Similarity	0.127*	-0.479***	0.037	-0.433***
	(1.70)	(-8.62)	(1.06)	(-9.47)
LI Similarity	0.248***	-0.005	0.056*	-0.059
	(4.58)	(-0.12)	(1.80)	(-1.64)
Foreign Similarity	-0.056	-0.003	-0.017	0.059**
	(-1.42)	(-0.11)	(-0.93)	(2.39)
No PatApps[q-1,q-20]	1.648***	-2.172***	0.350***	-1.657***
	(10.75)	(-22.17)	(5.11)	(-15.09)
Log(1+PatApps[q-1,q-20])	0.327***	-0.056**	0.175***	-0.087***
	(9.65)	(-2.11)	(7.25)	(-2.97)
Log(MTB) (q-2)	0.133***	0.162***	0.151***	0.044
	(5.15)	(8.94)	(4.20)	(0.82)
MKT Return [q-2,q-1]	0.341***	0.004	0.046***	0.036*
	(11.92)	(0.16)	(3.55)	(1.79)
Q4	-0.059	0.114**	0.137***	0.370***
	(-0.77)	(2.05)	(2.86)	(5.75)
Originality	-0.125***	-0.175***	-0.028	-0.178***
	(-3.11)	(-6.01)	(-1.44)	(-7.34)
Log(1+Cites)	0.171***	0.118***	0.075***	0.152***
	(3.95)	(3.96)	(3.64)	(5.38)
Year FE	No	No	Yes	Yes
Technology FE	No	No	Yes	Yes
Location FE	No	No	Yes	Yes
Firm Age FE	No	No	Yes	Yes
Firm Cohort FE	No	No	Yes	Yes
Observations	346,490	345,403	342,146	342,146
R2 (%)	N/A	N/A	0.5	0.6

Table VII: Determinants of Startups' Exits - Financing

This table presents cross-sectional tests relating startups' ex ante technological traits to their exit. Each of the models repeats the corresponding model from Table VI, but adds endogenous financing controls. *log(CumVCFunding)* is the log of cumulative VC funding the firm receives between its founding and $q-1$. *No Funding[q-1,q-20]* is a control equal to one if the firm has not received funding in the prior 20 quarters. For brevity, we only report the new financing controls and *Disruptive Potential*. To facilitate interpretation, coefficients for OLS estimates report the incremental % change in a given outcome, and *Disruptive Potential* is standardized. Independent variables are lagged one quarter unless explicitly noted. The underlying patent-level measures are winsorized at the 1/99% level annually. Adjusted R^2 is reported as a percentage. Standard errors are clustered by startup and are reported in parentheses. The symbols ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Competing Risk Hazard		OLS	
	IPO (1)	Sell-Out (2)	IPO (3)	Sell-Out (4)
Disruptive Potential	0.263***	-0.170***	0.075***	-0.077***
	(13.66)	(-6.82)	(3.70)	(-4.00)
log(CumVCFunding)	0.074***	0.138***	0.059***	0.119***
	(4.56)	(10.18)	(8.83)	(15.01)
No Funding[q-1,q-20]	-0.927***	-2.508***	-0.126**	0.130**
	(-5.35)	(-9.79)	(-2.22)	(1.99)
Controls	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Technology FE	No	No	Yes	Yes
Location FE	No	No	Yes	Yes
Firm Age FE	No	No	Yes	Yes
Firm Cohort FE	No	No	Yes	Yes
Observations	346,490	345,403	342,146	342,146
R2 (%)	N/A	N/A	0.7	0.8

Table VIII: The Determinants of Startups' Exits - Dynamic Responses

This table presents dynamic cross-sectional tests relating startups' ex ante technological traits to their exit over several horizons. In Panel A, column 1 repeats the OLS model examining IPO exits from column 3 in Table VI. Columns 2-6 subsequently replace the one-period ahead IPO exit indicator with longer horizons. We repeat this analysis for sell-outs in Panel B. Panel C examines whether a firm is still private (i.e. no IPO, or sell-out). In all models, the sample, independent variables, and coefficient interpretation are the same as the OLS models in Table VI. Independent variables are standardized for convenience. *LI Similarity* and *Foreign Similarity* are orthogonalized relative to *Private Similarity*. For brevity, the control variables and fixed effects are omitted. Standard errors are clustered by startup and are reported in parentheses. The symbols ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Exit within next:	Qtr (1)	Year (2)	2 Years (3)	3 Years (4)	4 Years (5)	5 Years (6)
Panel A: Exit by IPO						
Disruptive Potential	0.082***	0.299***	0.420***	0.424**	0.472**	0.466**
	(4.04)	(3.88)	(3.14)	(2.49)	(2.34)	(2.07)
Tech Breadth	0.091***	0.362***	0.714***	0.973***	1.167***	1.229***
	(3.28)	(3.54)	(3.85)	(3.90)	(3.81)	(3.52)
Private Similarity	0.037	0.120	0.215	0.261	0.492	0.623
	(1.06)	(0.94)	(0.95)	(0.87)	(1.34)	(1.52)
LI Similarity	0.056*	0.182	0.287	0.265	0.313	0.270
	(1.80)	(1.57)	(1.40)	(0.95)	(0.91)	(0.69)
Foreign Similarity	-0.017	-0.045	-0.029	0.007	-0.045	-0.089
	(-0.93)	(-0.64)	(-0.22)	(0.04)	(-0.21)	(-0.36)
Panel B: Exit by Sell-Out						
Disruptive Potential	-0.067***	-0.191**	-0.145	-0.055	0.011	0.089
	(-3.42)	(-2.46)	(-0.92)	(-0.25)	(0.04)	(0.28)
Tech Breadth	-0.140***	-0.600***	-1.086***	-1.501***	-1.899***	-2.056***
	(-4.39)	(-4.85)	(-4.60)	(-4.43)	(-4.43)	(-4.10)
Private Similarity	-0.433***	-1.468***	-2.123***	-2.052***	-1.485**	-0.628
	(-9.47)	(-8.23)	(-6.24)	(-4.28)	(-2.53)	(-0.93)
LI Similarity	-0.059	-0.164	-0.012	0.303	0.652	1.297**
	(-1.64)	(-1.14)	(-0.04)	(0.75)	(1.29)	(2.20)
Foreign Similarity	0.059**	0.158	0.059	-0.219	-0.460	-0.924**
	(2.39)	(1.60)	(0.31)	(-0.79)	(-1.30)	(-2.24)
Panel C: Still Private						
Disruptive Potential	-0.056*	-0.267**	-0.564***	-0.745***	-0.859***	-0.880**
	(-1.94)	(-2.41)	(-2.77)	(-2.76)	(-2.70)	(-2.54)
Tech Breadth	0.044	0.147	0.175	0.223	0.402	0.516
	(0.99)	(0.88)	(0.57)	(0.53)	(0.79)	(0.89)
Private Similarity	0.359***	1.301***	2.049***	2.235***	1.778***	1.305*
	(5.98)	(5.82)	(5.01)	(4.04)	(2.69)	(1.77)
LI Similarity	0.045	0.137	0.092	-0.038	-0.311	-0.842
	(0.90)	(0.73)	(0.26)	(-0.08)	(-0.54)	(-1.30)
Foreign Similarity	-0.088***	-0.279**	-0.409*	-0.390	-0.392	-0.161
	(-2.65)	(-2.20)	(-1.73)	(-1.19)	(-0.98)	(-0.36)

Table IX: The Determinants of Startups' Exits - Decomposition

This table presents cross-sectional tests relating startups' ex ante technological traits to their exit. Each of the models repeats the corresponding model from Table VI, but replaces the main variable *Disruptive Potential* with a decomposition by focusing on a subset of words in the patent corpus for each year. *Disruptive Potential (Established)* is defined in Equation 5 based on words that are at least ten years old in a given year. *Disruptive Potential (New)* is defined in Equation 6 based on words that less than ten years old in a given year. For brevity, we only report the coefficients on the decomposed variables. To facilitate interpretation, coefficients for OLS estimates report the incremental % change in a given outcome, and *Disruptive Potential (Established)* and *Disruptive Potential (New)* are standardized. Independent variables are lagged one quarter unless explicitly noted. The underlying patent-level measures are winsorized at the 1/99% level annually. Adjusted R^2 is reported as a percentage. Standard errors are clustered by startup and are reported in parentheses. The symbols ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Competing Risk Hazard		OLS	
	IPO	Sell-Out	IPO	Sell-Out
	(1)	(2)	(3)	(4)
Disruptive Potential (Established)	0.306***	-0.146***	0.116***	-0.038*
	(10.20)	(-6.47)	(5.54)	(-1.78)
Disruptive Potential (New)	0.022	-0.066***	-0.014	-0.036**
	(0.99)	(-2.90)	(-0.90)	(-1.97)
Controls	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Technology FE	No	No	Yes	Yes
Location FE	No	No	Yes	Yes
Firm Age FE	No	No	Yes	Yes
Firm Cohort FE	No	No	Yes	Yes
Observations	346,490	345,403	342,146	342,146
R2 (%)	N/A	N/A	0.5	0.6

Table X: Startup-Level Validity Tests: Post-IPO competition

This table presents validity tests based on a sub-sample of VC-backed startups that go public after 1997 where we are able to merge in both public firm identifiers (GVKEY) and obtain data on the product space of the firm (on startups' IPO year). The dependent variables *HHI* and *TSimm*, from Hoberg and Phillips (2016), are text-based measures of industry concentration and total similarity among a firm's public peers, respectively. *Product Mkt Fluidity* is from Hoberg, Phillips, and Prabhala (2014). All variables are defined in Table A1 and the underlying patent-level measures are winsorized at the 1/99% level annually. We include year fixed effects for the year of IPO. Adjusted R^2 is reported as a percentage. Standard errors are heteroskedastic robust and are reported in parentheses. The symbols ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	HHI (1)	Log(TSimm) (2)	Product Mkt Fluidity (3)
Disruptive Potential	-0.012**	0.073**	0.245**
	(-2.18)	(2.10)	(2.16)
Year FE	Yes	Yes	Yes
Observations	523	523	524
R2 (%)	1.7	1.7	2.5

Table XI: Explaining Aggregate IPO and Sell-Out Rates

This table presents the out-of-sample performance of predictive models of startups' exit using variables standard in the IPO and acquisition literature (the "Base" model) and a model which augments the "Base" model with the new text-based technological variables (the "Text" model). Panel A examines IPO exits and Panel B examines sell-outs. In a given test (column 1), we estimate a Fama and MacBeth (1973) regression quarter-by-quarter where the dependent variable is a dummy indicating an IPO exit (Panel A) or indicating a sell-out exit (Panel B) based on the horizon listed in column 2 (ranging from one quarter to three years) and using the ex ante measurable independent variables in Table VI. This model is fitted using the early part of our sample, which begins in 1980 and ends before the out-of-sample period (noted in column 3). These fitted Fama-MacBeth coefficients from the early period are then used in the out-of-sample post period (listed in column 3) to predict the average IPO rate and sell-out rate. These predicted exit rates are then compared to the actual rates to compute the fraction of the disappearing IPOs or surging sell-outs anomaly that is explained by either the "Base" model or the "Text" model as noted in columns (5) to (8). Column 9 reports the percentage of each anomaly that cannot be explained by the base model that is explained by the Text model. All probabilities in columns (4)-(8) are reported as percentage points.

Test	Pred-iction Horizon	Post Period	True Exit Rate	Predicted Exit Rate		Error		Text Impr
				Base	Text	Base	Text	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Panel A: IPO Exits				
1	1Q	[1996,2010]	0.33	0.84	0.75	0.50	0.42	**16%**
2	1Q	[1998,2010]	0.27	0.85	0.76	0.58	0.49	**16%**
3	1Q	[2000,2010]	0.22	0.85	0.75	0.63	0.53	**16%**
4	1Y	[1996,2010]	1.27	3.34	2.89	2.07	1.63	**21%**
5	2Y	[1996,2010]	2.45	6.50	5.59	4.05	3.15	**22%**
6	3Y	[1996,2010]	3.56	9.46	8.17	5.90	4.60	**22%**
				Panel B: Sell-Out Exits				
7	1Q	[1996,2010]	0.86	0.60	0.75	-0.25	-0.11	**57%**
8	1Q	[1998,2010]	0.91	0.63	0.80	-0.27	-0.10	**62%**
9	1Q	[2000,2010]	0.95	0.68	0.87	-0.27	-0.08	**71%**
10	1Y	[1996,2010]	3.49	2.52	2.96	-0.98	-0.54	**45%**
11	2Y	[1996,2010]	7.19	5.30	5.94	-1.88	-1.25	**34%**
12	3Y	[1996,2010]	10.96	8.21	8.93	-2.75	-2.03	**26%**

Table XII: Explaining Aggregate IPO Rates (Small vs Big IPOs)

This table presents the out-of-sample performance of predictive models of startups' exit using variables standard in the IPO and acquisition literature (the "Base" model) and a model which augments the "Base" model with the new text-based technological variables (the "Text" model). Panel A examines small IPO exits and Panel B big IPO exits. We define an IPO as "small" if its pre-IPO sales are below the median in our sample ($25 million), and as "large" if its pre-IPO sales exceeds that amount. In a given test (column 1), we estimate a Fama and MacBeth (1973) regression quarter-by-quarter where the dependent variable is a dummy indicating an IPO exit (Panel A) or indicating a sell-out exit (Panel B) based on the horizon listed in column 2 (ranging from one quarter to three years) and using the ex ante measurable independent variables in Table VI. This model is fitted using the early part of our sample, which begins in 1980 and ends before the out-of-sample period (noted in column 3). These fitted Fama-MacBeth coefficients from the early period are then used in the out-of-sample post period (listed in column 3) to predict the average IPO rate and sell-out rate. These predicted exit rates are then compared to the actual rates to compute the fraction of the disappearing IPOs or surging sell-outs anomaly that is explained by either the "Base" model or the "Text" model as noted in columns (5) to (8). Column 9 reports the percentage of each anomaly that cannot be explained by the base model that is explained by the Text model. All probabilities in columns (4)-(8) are reported as percentage points.

	Pred-iction		True Exit	Predicted Exit Rate		Error		Text
Test	Horizon	Post Period	Rate	Base	Text	Base	Text	Impr
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Small IPO Exits								
7	1Q	[1996,2010]	0.15	0.35	0.28	0.21	0.13	**36%**
8	1Q	[1998,2010]	0.12	0.38	0.29	0.26	0.18	**32%**
9	1Q	[2000,2010]	0.08	0.38	0.30	0.30	0.21	**28%**
10	1Y	[1996,2010]	0.55	1.45	1.02	0.90	0.47	**48%**
11	2Y	[1996,2010]	1.06	2.86	2.10	1.80	1.04	**42%**
12	3Y	[1996,2010]	1.53	4.17	3.22	2.65	1.69	**36%**
Panel B: Big IPO Exits								
1	1Q	[1996,2010]	0.13	0.35	0.38	0.22	0.25	**-13%**
2	1Q	[1998,2010]	0.11	0.35	0.38	0.24	0.27	**-11%**
3	1Q	[2000,2010]	0.10	0.34	0.36	0.24	0.27	**-9%**
4	1Y	[1996,2010]	0.51	1.36	1.41	0.86	0.91	**-6%**
5	2Y	[1996,2010]	0.99	2.64	2.54	1.65	1.55	**6%**
6	3Y	[1996,2010]	1.46	3.86	3.59	2.39	2.12	**11%**

Table XIII: Explaining Aggregate IPO and Sell-Out Rates (Stable vs Fluid Markets)

This table presents the out-of-sample performance of predictive models of startups' exit with variables standard in the IPO and acquisition literature (the "Base" model) and a model which augments the "Base" model with the new text-based technological variables (the "Text" model). Panel A examines IPO exits and Panel B examines sell-outs. The procedure is analogous to that described in Table XI, except each test is repeated for two sub-samples: *Stable Markets* and *Fluid Markets*, which are defined in Section VII.C. We omit the model-implied out-of-sample probabilities to conserve space.

			Stable Market Subsample				**Fluid Market Subsample**			
Test (1)	Pred. Horizon (2)	Post Period (3)	True Rate (4)	Base Error (5)	Text Error (6)	Text Impr (7)	True Rate (8)	Base Error (9)	Text Error (10)	Text Impr (11)
			Panel A: IPO Exits							
1	1Q	[1996,2010]	0.30	0.41	0.31	**26%**	0.37	0.62	0.67	**-7%**
2	1Q	[1998,2010]	0.26	0.45	0.33	**27%**	0.29	0.75	0.79	**-5%**
3	1Q	[2000,2010]	0.24	0.44	0.32	**29%**	0.20	0.86	0.89	**-4%**
4	1Y	[1996,2010]	1.14	1.69	1.29	**24%**	1.42	2.57	2.29	**11%**
5	2Y	[1996,2010]	2.20	3.32	2.60	**22%**	2.74	5.02	4.27	**15%**
6	3Y	[1996,2010]	3.23	4.75	3.68	**22%**	3.96	7.38	6.51	**12%**
			Panel B: Sell-Out Exits							
7	1Q	[1996,2010]	0.85	-0.16	-0.04	**73%**	0.86	-0.37	-0.21	**44%**
8	1Q	[1998,2010]	0.89	-0.17	-0.04	**75%**	0.93	-0.40	-0.19	**52%**
9	1Q	[2000,2010]	0.91	-0.16	-0.01	**93%**	0.98	-0.40	-0.17	**57%**
10	1Y	[1996,2010]	3.43	-0.59	-0.34	**43%**	3.55	-1.46	-0.79	**46%**
11	2Y	[1996,2010]	6.97	-1.05	-0.89	**15%**	7.39	-2.90	-1.56	**46%**
12	3Y	[1996,2010]	10.52	-1.44	-1.43	**1%**	11.38	-4.32	-2.32	**46%**

Table A1: Variable Definitions

Patent-Level Variables	
Disruptive Potential	See Equation 2 and Section III.B.
Tech Breadth	See Equation 3 and Section III.C.
LI Similarity	See Equation 4 and Section III.C.
Private Similarity	Similar to *LI Similarity*. See Section III.C.
Foreign Similarity	Similar to *LI Similarity*. See Section III.C.
KPSS Value	From Kogan, Papanikolaou, Seru, and Stoffman (2016).
# of Cites	Number of citations received in the first five years after publication by the USPTO. Citations up to December 31, 2013.
mCD	From Funk and Owen-Smith (2016).
Originality	The originality of a focal patent is defined as 1 minus the HHI of the technology fields of the patents cited by the focal patent (Trajtenberg, Henderson, and Jaffe (1997)). We use the adjustment given in Hall, Jaffe, and Trajtenberg (2001) to reduce bias for patents that contain few backward citations. We convert U.S. Patent Classifications to the NBER technology codes so that *Tech Breadth* and *Originality* are based on the same granularity of technology classifications.
Disruptive Potential (Established)	See Equation 5 and Section III.C.
Disruptive Potential (New)	See Equation 6 and Section III.C.
Startup-Quarter Variables	
Disruptive Potential	The depreciated sum of patent-level *Disruptive Potential* for patents the firm applied for over the prior 20 quarters. Quarterly depreciation is 5%. We normalize the depreciated sum by the number of patents the startup applied for. See Section III.D for more.
Tech Breadth	Converted to startup-quarter like *Disruptive Potential*.
Private Similarity	Converted to startup-quarter like *Disruptive Potential*.
LI Similarity	Converted to startup-quarter like *Disruptive Potential*.
Foreign Similarity	Converted to startup-quarter like *Disruptive Potential*.
Log(1+Cites)	Log of the stock of citations. Citations for a startup-quarter is the sum of the *# of Cites* (patent-level variable defined above) for patents the startup applies for in the quarter. Note that this is forward-looking. The stock is computed using a quarterly depreciation of 5%.
Originality	Converted to startup-quarter like *Disruptive Potential*.
No PatApps[q-1,q-20]	Dummy variable equal to one if the startup has not applied for a patent (which was eventually granted) during the last 20 quarters.
Log(1+PatApps[q-1,q-20])	The # of (granted) patent applications in the last 20 quarters.
IPO	One if the startup goes public in the quarter, zero before.
Sell-out	One if the startup is acquired in the quarter, zero before.
Disruptive Potential (Established)	Converted to startup-quarter like *Disruptive Potential*.
Disruptive Potential (New)	Converted to startup-quarter like *Disruptive Potential*.
Quarterly variables	
Log(MTB) (q-2)	Aggregate market-to-book is computed quarterly using all firms in the CRSP-Compustat database. We sum each subcomponent of MTB across all firms, then compute $MTB = (at - ceq + mve - txdb)/at$ as defined in Kaplan and Zingales (1997).
MKT Return [q-2,q-1]	From Ken French's daily factor file using geometric compounding.
Q4	One if $t-1$ is the fourth quarter (and t is the first quarter), else zero.

Table A2: Percentiles of various statistics for a sample of important patents
The patents below are the 1930-2010 subset of key important patents listed in Kelly, Papanikolaou, Seru, and Taddy (2019) (henceforth, KPST) over which the textual measures in this paper are defined. The percentiles for the KPST measure are taken directly from their Table A.6. Remaining variables are defined in Table A1. "Brdth" and "Orig" are short for *Tech Breadth* and *Originality*, respectively. The underlying patent-level measures are winsorized at 1/99% level annually. Percentiles are cohort-adjusted, i.e., we remove year fixed effects before computing percentiles.

Patent	Grant Year	Dsrpt Potent	Cites	KPSS	mCD	KPST	Brdth	Orig	Priv Simm	LI Simm	Frgn Simm
Panel A: Summary statistics of percentiles in Panel B											
Average:		0.71	0.75	0.68	0.61	0.84	0.53	0.55	0.52	0.63	0.57
Median:		0.81	0.80	0.75	0.81	0.90	0.54	0.62	0.51	0.69	0.59
Std error:		(0.03)	(0.02)	(0.04)	(0.06)	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Panel B: Percentiles of various measures for breakthrough patents											
1,773,079	1930	0.10	0.70			0.95	0.69		0.91	0.68	0.85
1,773,080	1930	0.50	0.70			0.95	0.31		0.18	0.28	0.37
1,773,980	1930	0.88	0.70			0.98	0.64		0.49	0.97	0.91
1,800,156	1931	0.86	0.70			0.97	0.47		0.83	0.59	0.86
1,821,525	1931	0.48	0.68			0.55	0.98		0.96	0.96	0.92
1,835,031	1931	0.83	0.68	0.75		0.90	0.96		0.60	0.96	0.80
1,848,389	1932	0.73	0.68			0.94	0.30		0.94	0.79	0.89
1,867,377	1932	0.12	0.69			0.75	0.36		0.52	0.54	0.35
1,925,554	1933	0.88	0.68			0.92	0.83		0.20	0.72	0.59
1,929,453	1933	0.95	0.66			0.98	0.26		0.82	0.70	0.90
1,941,066	1933	0.78	0.68			0.93	0.74		0.19	0.97	0.86
1,948,384	1934	0.78	0.66			0.87	0.79		0.21	0.76	0.66
1,949,446	1934	0.50	0.66			0.55	0.31		0.83	0.57	0.48
1,980,972	1934	1.00	0.65			0.98	0.18		0.84	0.79	1.00
2,021,907	1935	0.60	0.67			0.89	0.99		0.28	0.82	0.65
2,059,884	1936	0.94	0.66	0.63		0.59	0.46		0.41	0.72	0.89
2,071,250	1937	0.98	0.67	0.84		0.89	0.30		0.97	0.91	1.00
2,087,683	1937	0.86	0.66			0.92	0.68		0.37	0.84	0.91
2,153,729	1939	1.00	0.65			0.96	0.16		0.67	0.73	1.00
2,188,396	1940	0.78	0.63	0.60		1.00	0.17		0.83	0.62	0.80
2,206,634	1940	0.93	0.65			0.98	0.57		0.68	0.71	0.97
2,230,654	1941	0.93	0.62			0.93	0.25		0.88	0.75	0.51
2,258,841	1941	0.38	0.56			0.23	0.88		0.72	0.52	0.83
2,292,387	1942	0.52	0.56			0.95	0.94		0.58	0.81	0.63
2,297,691	1942	0.14	0.62			0.62	0.87		0.67	0.69	0.76
2,329,074	1943	0.91	0.89			0.56	0.20		0.99	0.95	0.98
2,390,636	1945	0.18	0.95			0.79	0.57		0.08	0.14	0.33
2,404,334	1946	0.59	0.97			0.23	0.80		0.83	0.79	0.96
2,436,265	1948	0.37	0.95			0.74	0.39	0.26	0.76	0.75	0.66
2,451,804	1948	0.92	0.93			0.74	0.20	0.06	0.94	0.80	0.50
2,495,429	1950	0.85	0.96			0.21	0.86	0.92	0.39	0.71	0.32
2,524,035	1950	0.68	0.96	0.85		0.75	0.45	0.89	0.66	0.93	0.90
2,543,181	1951	0.74	0.96			0.63	0.32	0.61	0.93	0.85	0.71

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Patent	Grant Year	Dsrpt Potent	Cites	KPSS	mCD	KPST	Brdth	Orig	Priv Simm	LI Simm	Frgn Simm
2,569,347	1951	0.72	0.96	0.79		0.63	0.48	0.72	0.79	0.99	0.95
2,642,679	1953	0.10	0.81			0.55	0.67	0.40	0.97	0.68	0.92
2,668,661	1954	1.00	0.87	0.80		0.98	0.85	0.83	0.01	0.01	0.01
2,682,050	1954	0.84	0.42			0.77	0.99	0.18	0.29	0.66	0.46
2,682,235	1954	0.88	0.63			0.60	0.99		0.10	0.23	0.15
2,691,028	1954	0.90	0.40			0.96	0.05		0.97	0.92	0.94
2,699,054	1955	0.21	0.97			0.97	0.23	0.77	0.98	0.97	0.98
2,708,656	1955	1.00	0.97			0.99	0.93		0.01	0.01	0.01
2,708,722	1955	0.91	0.97			0.78	0.44	0.99	0.08	0.75	0.43
2,717,437	1955	0.52	0.80			0.43	0.45	0.17	0.03	0.06	0.11
2,724,711	1955	0.99	0.39			0.82	0.06		0.46	0.75	0.78
2,752,339	1956	0.79	0.91			0.88	0.04	0.20	0.95	0.95	0.96
2,756,226	1956	0.89	0.60			0.71	0.18	0.98	0.34	0.63	0.86
2,797,183	1957	1.00	0.80			0.90	0.24	0.98	0.84	0.70	0.87
2,816,721	1957	0.59	0.95			0.72	0.46		0.42	0.52	0.72
2,817,025	1957	0.24	0.97			0.71	0.48		0.90	1.00	0.77
2,835,548	1958	0.75	0.79			0.85	1.00	0.97	0.65	0.42	0.55
2,866,012	1958	0.25	0.98			0.81	0.54	0.15	0.97	0.97	0.87
2,879,439	1959	0.72	0.97			0.77	0.80	0.55	0.44	0.82	0.55
2,929,922	1960	0.91	0.97	0.90		0.89	0.61		0.39	0.66	0.58
2,937,186	1960	0.99	0.58			0.89	0.12	0.13	0.99	0.97	1.00
2,947,611	1960	0.47	0.34	0.58		0.77	0.57		0.94	0.95	0.94
2,956,114	1960	0.45	0.90	0.71		0.74	0.55	0.39	0.98	0.98	0.90
2,981,877	1961	0.82	0.98			0.98	0.42	0.10	0.60	0.81	0.47
3,057,356	1962	0.89	0.97			0.93	0.54	0.09	0.55	0.94	0.58
3,093,346	1963	0.92	0.98			0.93	0.82	0.82	0.40	0.53	0.51
3,097,366	1963	0.28	0.55			0.41	0.99	0.73	0.86	0.62	0.77
3,118,022	1964	0.33	0.29	0.89		0.70	0.71		0.70	0.77	0.60
3,156,523	1964	0.05	0.46			0.85	0.25	1.00	0.86	0.83	0.98
3,174,267	1965	0.42	0.89	0.48		0.55	0.94	0.73	0.45	0.09	0.16
3,220,816	1965	0.06	0.54			0.85	0.42	0.09	0.03	0.14	0.09
3,287,323	1966	0.29	0.32	0.56		0.70	0.13	0.39	0.56	0.98	0.99
3,478,216	1969	0.42	0.80			0.84	0.37	0.62	0.35	0.64	0.46
3,574,791	1971	0.21	0.96	0.93		0.82	0.19		0.79	1.00	0.99
3,663,762	1972	0.38	0.97	0.84		0.78	0.68	0.26	0.13	0.40	0.09
3,789,832	1974	0.76	0.89			0.74	0.91	0.79	0.54	0.85	0.65
3,858,232	1974	0.32	0.98	0.97		0.71	0.78	0.95	0.58	0.94	0.77
3,906,166	1975	0.86	0.92	0.55		0.71	0.93	0.29	0.45	0.73	0.42
4,136,359	1979	0.71	0.76		0.89	0.97	0.69		0.63	0.98	0.83
4,229,761	1980	0.64	0.30			0.92	0.80	1.00	0.02	0.17	0.09
4,237,224	1980	0.96	0.98		0.99	1.00	0.62		0.05	0.22	0.14
4,363,877	1998		1.00		0.98	1.00					
4,371,752	1983	0.96	0.99		0.95	0.94	0.30	0.28	0.72	0.99	0.82
4,399,216	1983	1.00	0.99		0.99	1.00	0.68	0.26	0.04	0.18	0.07
4,437,122	1993		1.00	0.61	0.99	1.00					
4,464,652	1984	0.39	0.99	0.90	0.95	0.89	0.86	0.78	0.95	0.82	0.80
4,468,464	1984	1.00	0.92		0.16	1.00	0.58		0.04	0.16	0.12
4,590,598	1986	0.67	0.28	0.93	0.19	0.58	0.78	0.91	0.82	0.93	0.84
4,634,665	1987	0.96	0.78		0.97	0.99	0.53		0.05	0.18	0.07
4,683,195	1987	0.93	0.11	0.42	0.99	0.97	0.72		0.34	0.63	0.55

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Patent	Grant Year	Dsrpt Potent	Cites	KPSS	mCD	KPST	Brdth	Orig	Priv Simm	LI Simm	Frgn Simm
4,683,202	1990		0.14	0.38	0.99	0.94					
4,736,866	1988	1.00	0.92		0.96	1.00	0.47	0.24	0.02	0.07	0.02
4,744,360	1988	0.80	0.83		0.21	0.91	0.68	0.18	0.55	0.64	0.57
4,799,258	1989	0.80	1.00		0.82	0.95	0.32	0.95	0.20	0.55	0.14
4,816,397	1989	1.00	0.94		0.48	0.98	0.60	0.99	0.20	0.41	0.23
4,816,567	1989	0.94	0.15	0.82	0.95	0.99	0.66	0.58	0.27	0.54	0.34
4,838,644	1989	0.78	0.88		0.85	0.92	0.95	0.20	0.82	0.93	0.87
4,889,818	1989	0.92	0.99	0.53	0.05	0.98	0.71	0.20	0.50	0.75	0.65
4,965,188	1990	0.93	0.99	0.49	0.02	0.98	0.75	0.20	0.40	0.72	0.61
5,061,620	1991	0.93	0.99		0.98	1.00	0.36		0.11	0.16	0.10
5,071,161	1991	0.48	1.00		0.94	0.67	0.94	0.20	0.68	0.47	0.39
5,108,388	1992	0.91	0.88	0.42	0.15	0.97	0.85	0.45	0.42	0.54	0.36
5,149,636	1992	0.66	0.48		0.24	0.99	0.52	0.19	0.05	0.18	0.07
5,179,017	1993	0.95	0.41		0.32	1.00	0.31		0.16	0.33	0.24
5,184,830	1993	0.62	0.94		0.31	0.98	0.34	0.43	0.84	0.88	0.89
5,194,299	1993	0.51	0.94	0.81	0.11	0.73	0.31	0.81	0.62	0.48	0.56
5,225,539	1993	0.98	0.99		0.99	1.00	0.52		0.10	0.26	0.17
5,272,628	1993	1.00	0.99	0.99	0.40	0.99	0.23	0.78	0.14	0.44	0.13
5,747,282	1998	1.00	0.45	0.08	0.95	0.97	0.15		0.39	0.30	0.32
5,770,429	1998	0.99	0.01		0.79	0.61	0.13	0.86	0.36	0.27	0.31
5,837,492	1998	1.00	0.01	0.04		0.83	0.28		0.39	0.39	0.40
5,939,598	1999	1.00	0.57	0.53	0.21	1.00	0.31	0.68	0.21	0.28	0.27
5,960,411	1999	0.87	1.00	1.00	0.22	1.00	0.03	0.85	0.18	0.50	0.09
6,230,409	2001	0.53	0.07		0.32	0.75	0.96	0.74	0.80	0.24	0.38
6,285,999	2001	0.92	1.00		0.98	0.99	0.13	0.74	0.13	0.47	0.12
6,331,415	2001	0.65	0.97	0.95	0.18	0.99	0.60	0.47	0.39	0.64	0.49
6,455,275	2002	0.99	0.45		0.04	0.98	0.13	0.12	0.45	0.40	0.46
6,574,628	2003	0.87	0.98		0.13	1.00	0.04	0.74	0.29	0.65	0.22
6,955,484	2005	0.07	0.75		0.79	0.78	0.68	0.63	0.63	0.24	0.35
6,985,922	2006	0.83	0.98		0.92	0.93	0.10	0.90	0.21	0.62	0.11

Internet Appendix for

"Technological Disruptive Potential and the Evolution of IPOs and Sell-Outs"

August 2019

This appendix contains additional material not reported in the paper to preserve space.

IA.A Defining the Entity Type of Patents' Assignees

To classify if a patent is granted to (A) a private, domestic U.S. firm, (B) an international firm, or (C) a U.S. public firm, we use the following procedure. First, we find all patents assigned to public firms. We obtain the GVKEY for assignees from the NBER patent dataset, and augment this with Kogan, Papanikolaou, Seru, and Stoffman (2016). We use all assignee links for the entire 1900-2013 period. Also note that Kogan, Papanikolaou, Seru, and Stoffman (2016) contains PERMNO identifiers, which we convert to GVKEY using a link table from WRDS. When the headquarters country from CRSP-Compustat is available, we mark these firms as either international firms or U.S. public firms. Next, we output the top 3,000 remaining assignees and manually classify the entity type. After these steps, 3,126,605 patents are classified as either U.S. public firms or foreign firms.

Second, we use information from the NBER classification of assignees and manual categorization to remove patents assigned to governmental entities, research think tanks, or universities.

Third, we directly identify patents assigned to foreign firms when the last word in the assignee name is an unambiguous foreign legal identifier, such as "GMBH", "PLC", and "Aktiengesellschaft". We also identify patents granted to foreign firms when the assignee is a firm (e.g. "CORP") and USPTO data indicates that the assignee is not domestic. This step identifies 898,797 patents granted to foreign firms.

Fourth, we classify entities as U.S. private domestic firms when the assignee is a firm (e.g. "CORP") and USPTO data indicates the assignee is domestic. Previous steps affirmatively prevent us from calling a corporation a private domestic firm if the corporate is a public firm, a think tank, or international corporation.

In total, we classify the entity type of 78% of all patents granted from 1900-2013. Moreover, during our main analysis period (1980-2010), we are able to classify the assignee entity type for 92% of patent applications. Of the 4,161,306 applied for in the main analysis period, 12% are private U.S. firms, 27% are public U.S. firms, 41% are foreign firms, 8% are unclassified, and 11% are "other".

IA.B Matching patents to VentureXpert

We download all data on firms receiving venture capital funding starting in 1970 and ending in 2013 from VentureXpert using SDC Platinum. In addition to the dates of venture financing, we also download data indicating each portfolio company's founding date, its final resolution (as IPO, acquisition, or unresolved) and date of resolution, the company's name and the number of financing rounds it received.

Merging VentureXpert with the patent-level data requires a link between firms in the patent database (the initial assignees) and firms in the VentureXpert database. We develop a fuzzy matching algorithm—outlined below—to match firms in both databases using their names. The algorithm matches 532,660 patents granted between 1966 and 2013 to 19,324 VC-backed firms.[35] 96.6% of the patent matches and 90.7% of the VC-backed firms are matched via exact matches on the raw firm name in both datasets or on a cleaned version of the firm name.

The matching procedure begins by standardizing assignee names in the patent dataset and in Venture VentureXpert, using a name standarization routine from Nada Wasi.[36] This standardizes common company suffixes and prefixes and produces stem names. We also modify this program to exclude all information after a company suffix, as this is typically address information erroneously stored in the name field by the USPTO. After standardizing the names, we use the following steps to match firms in the two datasets:

1. We compare all *original string* names in each dataset, adjusted only to replace all uppercase characters. If a single VC-backed firm is an exact match where the patent application is after the firm's founding date, we accept the match. This step matches 59,026 patents to VC-backed firms, or 11% of the accepted matches.
2. For the remaining patents, we compare all *cleaned string* names in each dataset. If a single VC-backed firm is an exact match where the patent application is after the firm's founding date, we accept the match. This step matches 455,456 patents to VC-backed firms, or 86% of accepted matches.
3. For the remaining patents, we select matches using a fuzzy matching technique, with rules based on random sampling and validation checks in a hold out sample. This step matches 18,178 patents to VC-backed firms, or 3% of accepted matches. The steps are as follows:
   (a) We compute string comparison scores by comparing all *cleaned string* names in each dataset using several different string comparison functions. We do this three separate times, requiring that (1) the first three characters are exact matches, (2) the first five characters are exact matches, and (3) the first seven characters are exact matches. We then output a random sample of patents for an RA to examine.
   (b) The highest performing rule was a bi-gram match function with the restriction that the first seven characters were equivalent in both the patent assignee and company name. For each remaining patent, we keep as candidate matches any pair with equivalent name stems and the highest bi-gram match above 75%.
   (c) A random subset of suggested matches, in addition all borderline suggested matches, were reviewed by hand.

As a result of this matching process, our patent-level database contains U.S. private firms that both (A) have patents and (B) have received VC funding. Aside from imperfections in the matching process, which could be material, this database is the universe of such firms.[37] For each such firm, we have data indicating its final outcome and text-based data indicating the details of the firm's patents, and when they were applied for and granted. This data allows us to examine both (A) potential drivers of VC funding among firms that have patents but have not yet received funding, and (B) final resolutions of private status as IPOs or acquisitions. Cross-sectional and time series examination of both form the basis of our hypothesis testing.

[35] Firms can receive patents before VC funding.

[36] http://www-personal.umich.edu/~nwasi/programs.html

[37] Lerner and Seru (2017) note that using string matching to identify firms suffers from a limitation when private firms have patents issued to legal entities with different names, such as subsidiaries or shell companies meant to obfuscate the owner. This limitation can not be avoided, but is reduced for our sample of interest. VC-backed private firms are typically small and thus are unlikely to have distinctly named subsidiaries for research). Moreover, obfuscation is most often used by *non-practicing entities*, often called patent trolls, which are unlikely to be a material number of firms in our 19,324 firm sample.

IA.C Additional Results

1. Figure IA1 presents the evolution of text-based characteristics of the aggregate patent corpus from 1930 to 2010. The overall level of breadth steadily increases between 1930 to 1970. Beginning in the mid-seventies, there is a twenty-year period of growth in overall patent breadth which reaches a peak in the mid-nineties that was 20% above the 1970 level. In the most recent years, however, there is a large decline in the breadth of U.S. patents, dropping by about 25% between the mid-nineties and 2010. We also find an inverse U-shaped pattern in patent similarities over the last century. All three measures steadily increase until the eighties, as the text in the average U.S. patent during this period became increasingly similar to patents assigned to private U.S. firms, foreign firms, and lead innovators. Beginning in the eighties, however, these trends reversed, leading to marked declines in the similarity measures. The recent period is thus characterized by patents becoming both more specialized (i.e., lower technological breadth) and more distinct across firms.

2. Table IA1 presents information on the timing of key life events for startups in the main analysis sample.

3. Table IA2 presents robustness tests of the main results on the determinants of startups' exit from Table VI.

4. Table IA3 presents regressions of startups' financing on their technological characteristics.

5. Table IA4 presents subsample tests of the main OLS models on the determinants of startups' exit from Table VI. The subsamples are based on the date of the observation.

Figure IA1: Trends in Aggregate Technology Variables

This figure reports characteristics of the aggregate patent corpus from 1930 to 2010. The variables are defined at the patent level in Section III. To compute the aggregate stocks, we first compute the sum of each of the patent-level characteristics for patents applied for in a given quarter. We then compute a rolling depreciated sum of the prior 20 quarters, using a 5% quarterly rate of depreciation. Finally, we normalize the rolling stock by the number of patents applied for in the 20 prior quarters. The underlying patent-level measures are winsorized at 1/99% level annually. The series presented are four quarter moving averages to smooth out seasonality.

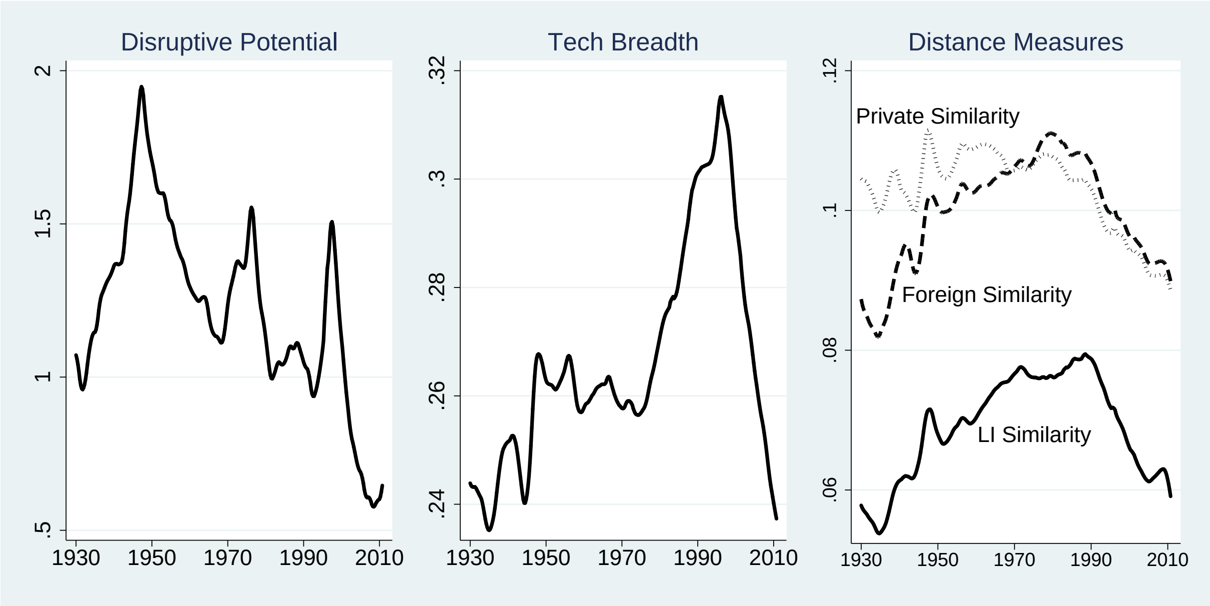

Table IA1: Years between keys events for ventured-backed Startups

This table presents information of key events for startups in the main analysis sample described in Panel B of Table II and Section III.D. A startup's first patent is based on the earliest application date for (eventually) granted patents. Information on VC funding, timing, and exits are from VentureXpert, and patenting information is from Google Patents.

Panel A: Events after the startup's founding

		Years between the startup's founding and event				
Event	N (startups)	Mean	SD	P25	Median	P75
First patent	9,167	4.42	10.76	0.75	2.25	5.75
VC funding	9,167	5.29	10.63	0.50	1.75	5.50
IPO	1,677	9.41	9.89	4.50	7.00	11.25
Acquisition	3,377	11.23	10.50	6.00	8.50	12.75

Panel B: Events after the startup's first patent

		Years between the startup's first patent and event				
Event	N (startup)	Mean	SD	P25	Median	P75
VC funding	9,167	0.87	7.78	-2.00	-0.25	2.50
IPO	1,677	3.10	8.45	-0.50	3.00	6.75
Acquisition	3,377	7.46	7.00	3.75	6.25	10.00

Table IA2: Robustness of baseline results

This table presents robustness tests of the main results in Table VI. For brevity, we only report the main coefficient on *Disruptive Potential* for each test. Each row corresponds to an alteration of the main test. Aside from the listed alteration, each of the models within a row repeats the corresponding model in the same column of Table VI. To facilitate interpretation, coefficients for OLS estimates report the incremental % change in a given outcome, and *Disruptive Potential* is standardized and lagged one quarter. The underlying patent-level measures are winsorized at the 1/99% level annually. Standard errors are clustered by startup unless otherwise noted and are reported in parentheses. The symbols ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

		Competing Risk Hazard		OLS	
		IPO	Sell-Out	IPO	Sell-Out
Test #	Test alteration	(1)	(2)	(3)	(4)
(1)	Cluster standard errors by technology	0.252***	-0.188***	0.081***	-0.067***
		(13.56)	(-8.90)	(8.25)	(-3.98)
(2)	Cluster standard errors by year	0.252***	-0.188***	0.081***	-0.067**
		(7.84)	(-5.78)	(3.13)	(-2.47)
(3)	Cluster standard errors by firm cohort	0.252***	-0.188***	0.081***	-0.067***
		(8.54)	(-5.97)	(3.40)	(-2.94)
(4)	Only controls: *No PatApps[q-1,q-20]*	0.267***	-0.098***	0.091***	-0.035*
	and *Log(1+PatApps[q-1,q-20])*	(15.03)	(-4.70)	(4.73)	(-1.94)
(5)	Exclude *Log(1+Cites)* as control	0.267***	-0.167***	0.093***	-0.045**
		(14.26)	(-6.98)	(4.59)	(-2.35)
(6)	Recode sell-outs as "liquidations" if		-0.183***		-0.053***
	exit value below $25m (2009 dollars)		(-6.76)		(-2.88)
(7)	Cross-section as of exit date	0.360***	-0.449***	2.041**	-2.041**
	for IPO and Sell-Out firms	(10.22)	(-7.69)	(2.41)	(-2.41)
		N=4,019	N=4,019	N=3,913	N=3,913

Table IA3: The Determinants of Startups' VC Funding

This table presents OLS cross-sectional tests relating a firm's ex ante technological traits and its VC financing. The outcomes we consider are the log of cumulative VC funding (*Cum.Funds*) the firm receives between its founding and quarter q, and *New Round*, a binary variable that equals one if a firm receives a new round of VC financing in quarter q. In all models, the sample, independent variables, and coefficient interpretation are the same as the OLS models in Table VI. Independent variables are standardized for convenience and lagged one quarter. *LI Similarity* and *Foreign Similarity* are orthogonalized relative to *Private Similarity*. For brevity, control variables are omitted. Adjusted R^2 is reported as a percentage. Standard errors are clustered by firm and are reported in parentheses. The symbols ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Ind. Variable:	Cum.Funds	New round	Cum.Funds		New Round	
Sample:	Whole	Whole	pre-95	post-95	pre-95	post-95
	(1)	(2)	(3)	(4)	(5)	(6)
Disruptive Potential	0.162***	0.670***	0.919***	0.466***	0.139***	0.162***
	(5.02)	(6.82)	(5.33)	(4.08)	(2.59)	(4.44)
Tech Breadth	-0.323***	0.017	0.309	-0.299	-0.164	-0.441***
	(-5.91)	(0.11)	(0.87)	(-1.59)	(-1.50)	(-6.65)
Private Similarity	0.060	1.247***	0.866**	1.265***	0.037	0.018
	(0.92)	(6.21)	(2.00)	(5.39)	(0.28)	(0.24)
LI Similarity	0.207***	0.477***	0.415	0.267	0.128	0.124*
	(3.52)	(2.76)	(1.15)	(1.27)	(1.12)	(1.70)
Foreign Similarity	-0.054	-0.025	0.380	-0.198	0.128	-0.088*
	(-1.30)	(-0.21)	(1.34)	(-1.42)	(1.38)	(-1.85)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	342,146	347,918	114,364	233,550	112,643	229,499
Firms	9,145	9,167	3,972	7,543	3,951	7,483
R2 (%)	32.4	2.2	2.6	1.6	24.7	27.6

Table IA4: Subsample analysis of startups' exit: Time

This table repeats the OLS cross-sectional tests in columns (3)-(4) from Table VI on two subsamples. The tests relate a startup's ex ante technological traits and its ultimate outcome. We split the sample based on the observation date. Even numbered columns include observations before January 1, 1996 and odd numbered columns include observations on or after January 1, 1996. In all models, the definition of independent variables and interpretation of coefficients are the same as the OLS models in Table VI. Independent variables are lagged one quarter and standardized for convenience. Note that we standardize variables *within* the subsample of the test. *LI Similarity* and *Foreign Similarity* are orthogonalized relative to *Private Similarity*. For brevity, the control variables are omitted. All variables are winsorized at the 1/99% level annually. Technology fixed effects are based on the most common NBER-technology category across a startup's patents. Location fixed effects are based on the state reported in VentureXpert. Adjusted R^2 is reported as a percentage. Standard errors are clustered by startup and are reported in parentheses. The symbols ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Exit Type:	IPO		Acquisition	
Observation before/after 1995:	Before (1)	After (2)	Before (3)	After (4)
Disruptive Potential	0.127***	0.089***	-0.186***	-0.025
	(2.73)	(4.41)	(-6.32)	(-0.98)
Tech Breadth	0.109	0.012	-0.286***	-0.179***
	(1.31)	(0.47)	(-3.91)	(-4.68)
Private Similarity	-0.017	-0.017	-0.164*	-0.466***
	(-0.16)	(-0.56)	(-1.76)	(-9.18)
LI Similarity	-0.001	-0.019	0.017	-0.062
	(-0.01)	(-0.64)	(0.24)	(-1.34)
Foreign Similarity	0.062	-0.008	-0.036	0.077***
	(0.87)	(-0.45)	(-0.66)	(2.69)
Year FE	Yes	Yes	Yes	Yes
Technology FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
Firm Age FE	Yes	Yes	Yes	Yes
Firm Cohort FE	Yes	Yes	Yes	Yes
Observations	112,643	229,499	112,643	229,499
Firms	3,951	7,483	3,951	7,483
R2 (%)	0.3	0.5	0.4	0.6