The Creativity Decline: Evidence from US Patents *

Aakash Kalyani†

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Abstract

I argue that the exponential increase in patents and slowdown in productivity growth over the last few decades is explained by a declining share of creative patents, partly driven by a lack of younger inventors. To separate creative from derivative patents, I develop a novel, text-based, measure of patent creativity: the share of two-word combinations that did not appear in previous patents. I show that only creative and not derivative patents are associated with significant improvements in firm level productivity and stock market valuations. Using the measure, I show that younger inventors on average file more creative patents. To estimate the effect of changing US demographics on aggregate creativity and productivity growth, I build a growth model with endogenous creation and adoption of technologies. In this model, falling population growth explains 42% of the observed decline in patent creativity, 32% of the slowdown in productivity growth, and 15% of the increase in derivative patenting.

Keywords: Creativity, innovation, productivity, patents, text-as-data, demographics, government.

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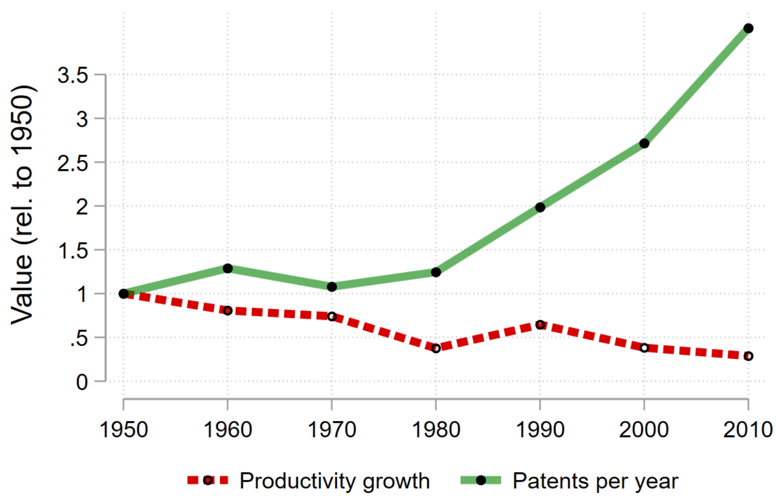
Email: aakashk@bu.edu Mailing Address: Boston University, Dept. of Economics, 270 Bay State Rd., Room 514, Boston, MA 02215

†**Boston University**

1. Introduction

Patents are a commonly-used and granularly available measure of intensity of innovation in an economy. However, over the past few decades, as R&D investments and US patents produced have increased exponentially year-over-year, productivity growth has either stagnated or slowed down (Bloom et al., 2020; Gordon, 2012)(figure 1). Why are inventors and firms increasingly investing in patents when there are limited productivity benefits from them? If there are benefits, then why don't they materialize in aggregate total factor productivity (TFP)? These questions remain a contentious topic of academic and policy debates.

Figure 1: Productivity growth and patents



In this paper, I reconcile the rise in patents with the slowdown in aggregate productivity growth by documenting a decline in creativity of patents, and show that this declining creativity is partly driven by a shift in composition of inventors towards less creative ones. I develop a new text-based measure of patent creativity to distinguish creative from derivative patents, and document a decline in the share of creative patents. The decline in creativity is sharp enough such that the increase in overall number of patents is entirely driven by rise in derivative patents. By contrast, creative patents follow the pattern of aggregate productivity growth. Using this measure, I make two empirical observations to show that benefits of creative patents outweigh those of derivative patents. First, I show that patents which are more creative spur more follow-on innovations. Second, to show the importance of declining creativity for productivity growth, I document that only creative and not derivative patents are associated with improvements in productivity and market valuations at the firm level. Despite these benefits, inventors and firms continue to file more creative than derivative patents. I show that this is because creativity is not evenly dispersed across inventors, and that composition of inventors is a key determinant of their creativity. In particular, I show that patents filed by new-entrants, and women and minority ethnicity authors are significantly more creative than others. On the theoretical side, I build a model which brings all the empirical insights together by mapping the composition of innovators into the aggregate share of creative innovations, and then estimating aggregate productivity growth as a function of aggregate creativity. In this model, I perform counterfactuals with changing population growth, and increasing inclusion of women and other minorities into patenting. Through the lens of the model, I also investigate the role of government subsidies in boosting creativity and productivity growth.

I begin by developing a novel text-based measure of patent creativity to distinguish creative from derivative patenting. A patent describes in detail the working or features of an invention, and to do so uses a range of technical terminology. The measure uses the share of previously unused technical terminology in a patent to quantify the extent to which an invention comprises of novel features, products or processes. To construct the measure, I decompose the text of each patent into two-word combinations or bigrams (e.g. 'machine learning'), and subsequently remove those which are commonly-used in everyday English language to obtain a list of technical bigrams. I then classify these technical bigrams into ones which were previously unused in the five years before the patent was filed. This process yields the share of new technical bigrams in a patent which is my baseline measure of patent creativity.

My approach has two differences from Kelly et al. (2021), the closest paper to mine. First, Kelly et al. (2021) evaluate intellectual impact of a patent on follow-on innovation, and use data 5 years before and after patent filing, while I use only data prior to the patent to evaluate creativity. So, for example, I can evaluate the creativity of patent published in 2022 while they would need to wait until 2027 to observe all subsequently filed patents.

Second, I use technical bigrams to define creativity of patents while they use word similarity where a patent is mapped into groups of around four thousand words[1].

Next, I validate that my measure indeed captures the degree to which an invention comprises of novel components. Through examination of top scoring 'creative patents', I observe that almost all of them discuss the introduction of new products, processes or features. On the other hand, the lowest scoring or 'derivative' patents either propose minor changes to already filed patents or combine existing inventions. I undertake a series of validation exercises to further bolster these observations. First, I show that when firms file creative patents, firm management talks significantly more about new product introductions in quarterly earnings conference calls. Second, in weeks when firms are granted a creative patent, they experience a higher stock market return of about 3%[2]. Derivative patents on the other hand do not predict any significant increase in stock returns. This finding remains largely unchanged even after accounting for ex-post quality of derivative patenting, using measures such as citations. Third, even though patent creativity contains no ex-post information, more creative patents receive more citations. In fact, creative patents receive significantly more citations than derivative patents up to 20 years after being filed. Fourth, I show that creative patents are costlier investments for a firm, and that a creative patent is associated with about 7% higher R&D expenditure than a derivative patent. Finally, I show that creative patents cite more academic papers, and tend to cite more recent academic papers. These findings together suggest that creative patents are costly investments which tend to originate from recent academic research and generate higher ex-post value than derivative patents.

Having validated my measure, I next document a secular decline in US patent creativity. I find that the average patent in 2018 is less than half as creative than the average patent in 1981. This decline is strong enough such that the increase in patenting is entirely driven by the rise of derivative patents, patents which score low on patent creativity. That is aggregate number of new technical bigrams in all US patents is declining even though the number of

[1] Kelly et al. (2021) drop words which are used in fewer than 20 patents because these words are not relevant for generating similarities; a majority of creative (new) bigrams are mentioned in fewer than 20 patents.

[2] According to Schumpeterian models of creative destruction, novel products signal higher future profitability(Aghion and Howitt, 1992a).

patents (and the amount of patent text) is increasing. On the contrary, creative patents follow the pattern of aggregate productivity growth. Creative patents per year grow by 0.75% per year during the 80s and 90s, and then fall sharply by 4.38% per year post 2000s. I show that the rise in creative patenting in the 1990s is primarily driven by computer manufacturing, IT and related sectors. In order to ensure that the decline in creativity is not a bi-product of text based construction of my measure, I conduct a wide variety of robustness exercises. I leverage different sections of a patent and show that even when I use just the patent title to calculate creativity, the decline in creativity is unchanged. To show that the decline in creativity is not driven by converging use of language, I use Google books, a near universe database of digital books, and recalculate patent creativity after removing two word combinations in books published around patent filings, and find no significant change in the trend. I also find that patents use about 8% of the two word combinations in Google books, which suggests that there is not a lack of two-word combinations to write about.

To show that creativity decline is relevant for lackluster productivity growth, I turn to the firm level relationship between productivity growth, and creative and derivative patenting. I find that firms which file more patents experience higher productivity growth, however this association is entirely driven by creative patenting. In particular, when I separate patenting into creative and derivative, I find that only creative and not derivative patenting is significantly associated with firm-level productivity growth. This finding holds even for the most restrictive specification with firm fixed effects. I also find that only creative patenting is associated with improvements in firm-level labor productivity and capital investment. These findings suggest a significant private benefit from creative patenting. I also show that creative patents have larger productivity benefits than those internalized within the firm. The association between creative patenting and industry level productivity growth is about 10 times higher than at the firm level. Including the effect of these apparent spillovers, creative patenting explains about 14% of the variation in industry level productivity growth.

Using the rich micro-data on patent creativity, I show that creativity is not evenly dispersed across inventors. First, I show that first-time inventors file patents which are about 50% more creative than the average patent in my sample and this number falls to 15% for second-time patentors, 12% for third time, and so on. In other words, an inventor's first patent on average is their most creative one. Second, I also show that women and ethnic minorities tend to file significantly more creative patents. According to my measure, these results suggest a strong link between composition of inventors and creative innovations. I do find that the demographic composition of innovators has changed drastically over the past three decades: share of patents by first-timers have halved, while those by women and minorities have doubled.

To evaluate how changing composition of inventors affects aggregate creativity and productivity growth, I build a general equilibrium growth model. Contribution of the model is to map aggregate demographic changes into composition of creative vs derivative innovations, and then estimate the changes in aggregate productivity growth while accounting for larger social benefits of creative innovations. In my model, innovators act as entrepreneurs and earn profits from producing their differentiated variety with a specific productivity/technology. Along with earning profits, they also exist in either a derivative or creative state. In the derivative state at every instant, innovators make a choice to either stick to their current technology or abandon it and search for a different one. If they choose stick to their technology, they continue to enjoy profits from production using that technology. When they abandon and search for a different technology, they either adopt another existing technology at random while continuing to be in the derivative state (as in Perla and Tonetti (2014)) or they move to the creative state. This choice structure implies that innovators will choose to abandon less productive technologies. In the creative state, innovators productivity goes through an exogenous explosive stochastic process (Geometric Brownian Motion), which results in a heavy tail of technologies in the long-run. At any instant, some innovators in the creative state lose their creativity and move from creative to derivative state while retaining their technology. In the derivative state, they enjoy profits with that technology till they choose to abandon it, and then repeat the cycle. On top of this, I add free entry and labor supply grows at a constant rate. Entrants upon entry search for a technology to produce with. Similar to existing innovators who have abandoned their ideas, their search leads them to either an existing technology in the derivative state or the creative state. Relying on empirical evidence, entrants in the model are more likely to land in creative state than existing innovators who abandon their technologies. In the steady state, innovators per capita are constant which implies that the rate of entry is equal to the growth rate of labor supply.

This structure of the model generates an endogenous share of creative innovators which depends on rate of entry, and how creative how creative entrants are. A higher share of creative innovators leads to a thicker tail of technologies, which incentivizes derivative innovators to abandon their technologies, and search for a new technology via immitation or creation. This is the second amplifying effect on creativity, where creative innovators can push their peers to be creative. Productivity growth in this model is a result of derivative innovators abandoning their less productivity technologies and creative innovators expanding the frontier. Productivity growth in this economy depends on the share of creative innovators.

I calibrate the model using micro-data on patent creativity, where creative or derivative patents are assumed to be a paper trails left by innovators while operating in creative or derivative state. The model is calibrated to match three key moments: (i) only creative innovators experience productivity growth, (ii) excess valuation of creative vs derivative patents, (iii) the creativity vs tenure profile of innovators. I perform counterfactuals for three well-known long trends in the US between 1950 and 2010: 1) Falling population growth, 2) Rise in women's labor force participation, and 3) Rise in rate of immigration. I find that falling population growth in the model explains 43% of the decrease creativity in the economy, 31% of the decrease in productivity growth, and 15% of the increase in patenting or innovators per capita. The model also predicts that increasing women's participation in labor-force and increasing immigration increases creativity and productivity growth by 5-6%, not enough to mitigate the effects of decreasing population growth.

Related Literature. My efforts contribute to several different strands of literature. My first contribution is a measure of patent creativity, which is a new approach to measuring technological change and correlates at firm, industry and aggregate levels with productivity growth. Kelly et al. (2021) is closest in terms of methodology to this paper. They develop a text-similarity based measure to identify patents which have the most influence on follow-on innovation. Lerner and Seru (2022) summarize the method to use year-normalized citations as a measure of patent quality. A large set of studies use a patent's effect on follow-on innovation as their measure of its quality and degree of technological change (e.g. Akcigit and Kerr (2018), Acemoglu et al. (2018)). My measure is closer in spirit to measures of originality. For example, Hall et al. (2001) use citations and Watzinger and Schnitzer (2019) use references to academic papers to develop measures of patent novelty/originality. Lanjouw and Schankerman (2004) use number of claims in a patent as a measure of quality. Prior literature has also used accounting data on outputs and inputs to directly measure technological change using methodologies in Olley and Pakes (1996) and Levinsohn and Petrin (2003).

A major contribution out of this paper is to show that while an increase in R&D investment has resulted in an increase in patents, it has not resulted in an increase in creative patents. This finding contributes to a growing literature within economic growth led by Gordon (2012) and Bloom et al. (2020), which documents that over the last fifty years the rise in patents and research spending has not been accompanied by an increase in aggregate productivity growth. Syverson (2017) and Byrne et al. (2016) argue that more recently productivity growth has in fact declined. A parallel literature in finance documents a rise in intangible investment, driven by increase in R&D investment, and a fall in the rate of capital investment (e.g. Corrado et al. (2009), Peters and Taylor (2017)).

This paper also establishes that these patterns are partly driven by changing composition of inventors towards less creative ones. These findings complement several other proposed other explanations for these patterns: ICT and intagible investments (Aghion et al. (2019), De Ridder (2019) and Corhay et al. (2020)), a slowdown in diffusion (Akcigit and Kerr (2018) and Akcigit and Ates (2021)), or demographic trends (Jones (2020), Peters and Walsh (2021), Hopenhayn et al. (2018) and Karahan et al. (2019)). Ever since Jensen (1993), financial economists have recognized that expenditures in innovation may be heterogeneous in terms of their impact on firm value.

This paper also contributes by documenting the role of demographics in generating creative innovations. My story builds on an extensive literature in corporate finance which studies the role of gender, age, diversity and other characteristics in making executive and investment decisions, and often attributes reasons to behavioral and psychological differences (e.g. Adams and Ferreira (2009), Faccio et al. (2016), Weber and Zulehner (2010), Hirshleifer et al. (2012), Acemoglu et al. (2014)). A large literature in science and innovation (e.g. Galenson and Weinberg (2000), Jones and Weinberg (2011), Koffi (2021) and Jones (2010)) also documents a significant role for age and gender in innovation.

Finally, I add to the theoretical literature in innovation and growth by modeling endogenous creation and diffusion in a single framework. This literature is pioneered by Romer (1986), Romer (1990) , Segerstrom et al. (1990), Rivera-Batiz and Romer (1991), Grossman and Helpman (1991), Grossman and Helpman (1994), Aghion and Howitt (1992b), Kortum (1997). I particularly build on recent models of ideas and knowledge diffusion, e.g. Lucas Jr and Moll (2014), Perla and Tonetti (2014), Perla et al. (2021), Benhabib et al. (2021), Luttmer (2012).

2. Measuring Creativity in US Patents

A. Data

My primary text-to-data source is patents granted by the US patent office (USPTO) to US inventors[3] and filed between 1976 and 2018[4,5]. For these 2,749,329 patents, I collect and parse title, abstract, brief and detailed description of the invention, and claim of invention. I then decompose each patent into two-word combinations or bigrams (e.g. 'cloud computing'), which is the unit of my analysis. In all these patents contain more than 50 million two-word combinations. In section 2, I describe in detail how I construct the measure of patent creativity.

I use three other text-data sources to complement patent text data. To extract technical two-word combinations from text of patents and remove phrases used in general usage, I use the Corpus of Historical American English (COHA) which is a decade by decade representative sample of English text sourced from magazines, articles, books and newspapers. For

[3] All inventors who report filing from locations within the US are classified as US inventors.

[4] To avoid selection issues due to publication lags while maximizing coverage, I only keep patents filed during or before 2018. There are frequently large gaps between filing and granting dates of patents (Lerner and Seru (2022)) which leads to a tail off in patents towards the end of the sample period.

[5] Patents granted before 1976 are published as images with text translated from them using Optical Character Recognition Technology. As highlighted in Kelly et al. (2021), this text contains contains a lot of spelling mistakes for the purpose of my analysis. Therefore, I exclude patents granted before 1976.

robustness exercises, I use Google books n-gram database, which provides a year-by-year count of two-word combinations in 7 million (near universe) of digitized books. For the purpose of validation, I use full text of transcripts of quarterly earnings conference calls. These are discussions of quarterly earnings by executives and analysts, and contain some of the most important issues facing firms (Hassan et al., 2019; Bushee et al., 2003).

To collect data on patent inventors, I use the disambiguated inventor data with unique inventor identifier provided by Monath, Madhavan, DiPietro, McCallum, and Jones (Monath et al.)[6]. Gender attribution of inventors is from Breschi et al. (2017), and is based on name and gender countrywise database from the WIPO worldwide gender-name dictionary (WGND)[7]. In addition, I use name-based algorithm developed by Sood and Laohaprapanon (2018) to classify inventors into ethnicities by continent. The algorithm uses the full name of inventors along with Florida voter registration data and Wikipedia to make ethnicity from names. More details are in Appendix A.

In addition, I collect data on filing and grant years from PatentsView. I perform firm level analysis by matching patents to publicly listed firms using the match provided by Dorn et al. (2020) and Kogan et al. (2017). I complement this with accounting data for publicly listed firms from Standard and Poor's Compustat North America and Global data products, and daily firm stock prices from Centre for Research in Security Prices (CRSP). Appendix Table 1 provides summary statistics and Appendix A provides details of data construction.

B. *Defining Patent Creativity*

My goal is to measure the share of previously unused or newly introduced technical terminology in a patent: patent creativity. Terminology in a patent is clearly relevant to the functioning or features of the invention, and thus, with this classification exercise I aim to capture the degree to which an invention comprises of novel features, products or processes.

To create this measure of creativity for each patent, I use two-word combinations or bigrams[8] (e.g. 'machine learning') as my unit of analysis. In other words, I decompose the

[6] Downloaded from PatentsView.

[7] Downloaded from PatentsView.

[8] Recent studies using text-to-data approaches in economics have used bigrams as their unit of analysis (e.g. Hassan et al. (2019), Bloom et al. (2021)) guided by computation linguistics (e.g. Bekkerman and

full text of a patent (p) into a list of bigrams contained in the patent ($b = 1, ...B_p$). Then, to focus on bigrams which describe technical terminology rather than ones which are commonly used in English language, I remove bigrams which either contain filler words[9] ('a', 'the', 'of', etc.) or are contained in Corpus of Historical American English (COHA).[10]. Finally, to measure creativity in a patent p filed in year t, I count the share of technical bigrams which have not been mentioned in patents filed in the five years before the patent($\bigcup_{p' \in P_{t-5 \to t-1}} B_{p'}$). Formally,

$$\text{Patent Creativity}_p = \frac{1}{|B_p|} \sum_{b=1}^{B_p} 1\{b \notin \mathbb{P}_{p'}\}$$

where b = 1,2...B_p are bigrams in patent p, and $\mathbb{P}_{p'}$ is the collection of all bigrams used in patents filed 5 years before the patent p. To aid interpretation and account for level differences in use of new terminology across domains, I standardize patent creativity by the average in a technology class throughout the sample. Therefore, the average patent creativity score is 1 by definition. Appendix table 1 Panel A shows patent-level summary stats. On an average, a patent contains 4,003 bigrams out of which roughly 10% (or 423) are technical bigrams. Out of these, roughly 10% (or 44) are classified as creative bigrams and the rest as derivative bigrams.

When aggregating patent creativity up to the firm level, I define a dummy variable which denotes a patent as creative if it has a patent creativity greater than two[11] or twice the technology class average. Other patents are classified as derivative. Through this definition, I classify 14.79% of total patents as creative patents. Therefore, creative and derivative

Allan (2004), Tan et al. (2002)) research which suggests that accuracy of text classification usually improves when bigrams ('machine learning') are used instead of words ('machine').

[9]These filler words are also called stop words and are the most frequent words in most collections of English language text.

[10]COHA is a decade by decade collection of fiction and non-fiction books, magazine and newspaper articles. For my baseline measure, I will remove bigrams which are used in COHA till 1959, and later perform robustness exercises by removing all available decades.

[11]In the following sections, Conclusions remain unchanged when I perform robustness exercises with a cut-off of one and three instead of two. See Appendix Table 1.

patenting at the firm level is defined as:

$$\text{(1)} \qquad \text{Creative Patenting}_{i,t} = \sum_{p \in P_{i,t}} 1\{\text{Patent Creativity}_p \geq 2\}$$
$$\text{Derivative Patenting}_{i,t} = \sum_{p \in P_{i,t}} 1\{\text{Patent Creativity}_p < 2\}$$

where $P_{i,t}$ is the set of patents applied in year t by firm i. Table 1 Panel B and Panel C shows summary statistics for firm-week and firm-year level observations. On an average in my sample, firms in my sample file 12.47 patents per year out of which 1.37 or 10.99% are creative and rest are derivative.

C. Validation

In this section, I describe the output of my measure and provide evidence to validate that patent creativity captures the degree to which an invention comprises of new features, products or processes. I also show that this is a unique new dimension of innovations, particularly different from citations and other measures of influence on follow-on innovations.

Appendix table 2 shows a list of most creative patents with at least one creative bigram in their title. The top most creative patent is assigned to NGK Insulators, Ltd. and has a patent creativity score of 11.23, which means that this patent is 11.23 times creative than the average patent in its technology class. This patent describes a method for producing a new product, polymer line-post insulator, and contains two creative technical bigrams in its title: 'polymer lp' and 'lp insulator'. Authors of the patent argue that their invention differs from other standard insulators in the sense that it is attached in an inclined fashion to a line post[12]. In this case, and similarly in almost all of the top 20 patents, I find that the creative bigrams capture introduction of a new product, feature, or process. On the other hand, Table 3 gives examples of 20 randomly sampled patents with zero creativity. These patents either are minor improvements over existing patents or use combinations of previously formulated inventions instead of new introductions. For example, one of the

[12]While describing background of the invention, the authors state that: "The construction of the polymer LP insulator 51 mentioned above is not so different from that of insulators. However, the polymer LP insulator is secured to a pole in an inclined manner by means of a securing holder, when it is actually used for supporting a transmission line."

derivative patents is assigned to Teladoc Health Inc and it describes a 'Telepresence robot with a camera boom'. The authors argue and acknowledge that their invention is inspired by previous medical robotic systems and mobile tele-presence inventions[13].

I next validate the interpretation of patent creativity in five different ways. First, I show that management is likely to talk about new product introductions when the firm files creative patents. Second, I find evidence of strong stock market reactions to creative but not derivative patents. Third, I show that more creative patents receive on an average receive more citations, and the variance in citations received increases as patents become more creative. Fourth, firms spend more on R&D per patent when they file creative patents. Fifth, creative patents cite more recent academic papers.

Management discussions of new product introductions. In table 1, I regress the number of quarterly earnings calls (between 0 and 4) which mention words related to 'new product introductions'[14] on the inverse hyperbolic sine of creative patents while controlling for firm and year fixed effects. In column 1, I find that a 1 percent increase in creative patenting is associated with 5.8 percent more earnings calls with mentions of new product introductions. In column 2, I add inverse hyperbolic sine of derivative patenting, and find that the coefficient of creative patenting is largely unchanged. These estimates show that firms are twice as likely to discuss new product introductions in their earnings discussions when they file creative patents than when they file derivative patents. In columns 3 and 4, I repeat the analysis with mention of 'new design' keywords instead of 'new product introduction' keywords. I find that, in this case, 'new design' mentions are associated with derivative instead of creative patenting.

Stock Returns. Appendix Table 1 Panel B, presents the variables in the analysis. Primary variables of interest are creative and derivative patents granted to the firm i in week t for the years between 1991 and 2014. Only about 2% of observations record non-zero patent filings. The average firm in the sample files about 0.17 patents out of which 0.03

[13] The authors of this patent are Yulun Wang, Charles S. Jordan, Kevin Hanrahan, Daniel Steven Sanchez, and Marco Pinter. Yulun Wang and Charles S. Jordan have previously produced patents in medicinal robotics, while Daniel Steven Sanchez and Marco Pinter have previously produced patents in remote tele-presence robotics.

[14] New product introduction word list: new product, begin producing, begin making, new equipment, new introduction, unveil, new feature, start offering.

are creative and 0.14 are derivative. Stock returns at the weekly level are calculated by adding up daily stock returns. I exclude periods of stock market volatility (1999-2001 and 2007-2009) to avoid large movements in stock returns. I complement the analysis by adding ex-post quality weighted derivative patenting and adding firm level controls for past R&D expenditures, and market betas. Market betas for a firm are calculated by regressing the firm's weekly stock returns on weekly S&P 500 returns.

In Table 2 Panel A, I present the results from estimates of the following specification:

$$r_{i,t} = \alpha + \beta \ IHS(\text{Creative Patents}_{i,t}) + X_{i,t} + \delta_t + \epsilon_{i,t} \tag{2}$$

$r_{i,t}$ denotes stock returns and $IHS(\text{Creative Patents}_{i,t})$ denotes inverse hyperbolic sine of creative patents for firm i in week t. The inverse hyperbolic sine function, IHS, approximates the logarithm function while retaining zeros, so the coefficient β approximates the elasticity of stock returns to creative patents. $X_{i,t}$ are controls for derivative patents, past five years' R&D expenditures and market betas, and δ_t are time fixed effects. In column 1, with only time fixed effects, I find a positive and statistically significant relationship between creative patents and stock returns. A 1% increase in creative patents is associated with 0.16% increase in stock market return. In column 2, I add controls for R&D spending and market betas, which reduces the magnitude to 0.09%. Given that the average firm files 0.03 creative patents per week, this implies that one additional creative patent is associated with an increase of 3.1% in market return for the average firm. In column 3, I add derivative patents to the specification and find that the coefficient of Ihs(derivative patents) is a precisely estimated zero and the coefficient of creative patents is unaffected. In other words, only creative patents and not derivative patents significantly predicts stock returns. In columns 4 and 5, I replace derivative patents with ex-post quality, citations or influence, weighted derivative patents. So, those derivative patents which higher citations or those which have larger influence on follow-on innovations receve more weight while counting derivative patents [15]. I find that the conclusions remain unchanged - only creative and not derivative patents are associated

[15] Influence is calculated by dividing forward similarity, similarity with all patents in 5 years after a patent is filed, by backward similarity, similarity with all patents in 5 years before a patent is filed. The similarity data is provided by Kelly et al. (2021).

with stock returns[16].

As a placebo test, I probe time variation in the association between creative patenting and stock returns, and estimate the following:

$$r_{i,t} = \alpha + \sum_{\tau=-4}^{4} \beta_\tau IHS(\text{Creative Patents}_{i,t-\tau}) + \chi_{i,t} + \delta_t + \epsilon_{i,t} \tag{3}$$

where the specification is same as before except that I estimate β_τ for leads and lags of *creative patenting*. Appendix Figure 2 presents the β_τ coefficients along with ninety-five percent confidence intervals. Although there could be patent related information released into the public domain in weeks preceding and following patent publication, it is reassuring to note that only contemporaneously published creative patents is strongly associated with stock returns, and not past or future creative patents. In figure 1, as an additional placebo test, I repeat the analysis but with stock returns from the same week of previous year and find that any lead or lag of current year creative patents does not predict previous year's stock returns.

Appendix figure 1 and appendix table 4 show results from various robustness checks. Appendix figure 1 shows that creative patents are strongly associated with stock returns regardless of the cut-off chosen to aggregate patent creativity into creative patenting (as in equation 1). Appendix table 4 columns 1-3 shows that results are largely unchanged with I consider different variations in how patents are aggregated to calculate *creative patenting*. In Appendix table 4 columns 4-7, I show that when I calculate *creative patenting* using different sections of the patent (title, abstract, description or claims) the results are unchanged in terms of sign and statistical significance, however, the magnitudes are slightly attenuated relative to magnitudes when I consider the full patent.

Comparison against other measures of originality. In Table 2 Panel B, I compare the stock

[16] These results and magnitudes are consistent with findings in earlier studies of positive stock market returns around new-to-market product introductions. Srinivasan et al. (2009) find that new-to-market product announcements in the automobile industry are associated with about 3 percent higher stock return, which they note is higher than new-to-firm product introductions and other product introductions. Chen (2008) finds that news chatter related to new product announcements is associated with about 1.5 percent higher stock return. Finally, Krieger et al. (2022) find that novel drugs patents are 7-8 percent more valuable than other patents.

return predictions of creative patents against other previously proposed measures of patent originality. I consider four such measures: backward looking text similarity (Kelly et al. (2021)), distribution of citations across technology classes (Hall et al. (2001)), number of academic citations (Watzinger and Schnitzer (2019)), and number of claims of invention in a patent (Lanjouw and Schankerman (2004)). All these measures are based on a common theme to measure the degree to which invention in a patent separates itself from other inventions. As with creative patents, I define an original patent using a dummy for original patents if a patent has an originality score more than twice the technology class sample average. Roughly 10-20% of patents for each of these measures are classified as original. In Table 2 Panel B Columns 2-5 show that none of these measures significantly impact the coefficient estimates of creative patents, and do not elicit a stock market reaction in my chosen specification.

Patent creativity and ex-post measures of patent quality. I examine the relationship between patent creativity and ex-post measures of patent quality, e.g. citations. For each patent p, I tabulate citations received by the patent 10 years after filing and normalize these by technology-class and year. In figure 2 panel A, I present a binned scatter plot of normalized citations on patent creativity, along with a fitted polynomial fitted line and 95% confidence intervals. I find that while more creative patents do on average receive more citations. However, this relationship is not strictly monotonic and linear. The figure shows that till patent creativity reaches 1 (roughly bottom 50 percentiles of patent creativity distribution), increasing creativity is associated with a monotonic increase in citations. However, increasing patent creativity beyond 1 is associated with more extreme realizations of citations and does not guarantee a corresponding increase in average realized citations. In figure 2 panel B, I find a similar relationship between patent creativity and extreme realizations of patent *influence* on follow-on innovation. Patent *influence* measure was proposed by Kelly et al. (2021) and is calculated by dividing similarity of the patent with future patents and past patents.

In appendix figure 3, I investigate the dynamic response of citation to creative patents in the form of a binned scatter plot of citations by year for creative and derivative patents. I show that there are no significant differences in received citations between the two sets of patents in the first two years after filing. However, creative patents receive higher and most persistent citations after that. I find that twenty years after filing, creative patents receive about 8% more citations than derivative patents. [17]

R&D Expenditure per patent. I now analyze the relationship between R&D spending, and creative and derivative patenting. For this analysis, to accurately calculate R&D expenditures per patent, I restrict my sample to panel of manufacturing firms which file patents for at least 10 years in the sample. In appendix table 1, I present summary statistics of creative and derivative patenting, and R&D expenditure per patent for a firm i in year t. An average firm spends \$34,663 per patent, produces 12.47 patents; out of which 1.37 patents are creative patents (10.9%) and 11.10 patents are derivative (89.1%).

In Figure 3 presents the results from a binned scatter plot of creative patenting as a percentage of overall patenting and R&D expenditure per patent. I find a strong-positive linear relationship between R&D expenditure per patent and the average patent creativity of patents filed by firm i in time t. The plot suggests that firms spend much more creative than derivative patents[18]. These estimates suggests that a firm with one additional creative patent spends about \$5,298 or 15.26% more on R&D per patent.

Academia. I show that patents which cite recent academic papers tend to be more creative. To show this, in table 3, I regress patent creativity on dummies indicating whether a patent cites academic papers, and then separating academic papers into recently published or older academic papers. Recent academic papers are ones which are published within 5 year before a patent filing year. In column 1, I find that patents which cite academic papers are 36.91% (.34/0.91) more creative than other patents, and explain about 4.3% of the variation in patent creativity. In column 2, I verify that this is not driven by differences in academic citations across technology classes by including technology class fixed effect. In column 3, I separate citations into recent and older academic citation and find that the correlation between academic citations and patent creativity is entirely driven by citation to

[17] This finding is in line with theoretical insights in Jovanovic and Rob (1989), where the authors highlight that diffusion is a function of differences in knowledge, the more creative the invention the larger time it takes to diffuse.

[18] In appendix table 5, I present OLS estimates for the same binned-scatter plot with increasingly restrictive set of fixed effects (column 1 to column 4), and confirm the strong positive relationship even in the most restrictive specification with firm fixed effects in column 4

recent academic papers.

The conclusion from these validation exercises is that cross-sectional variation of patent creativity lines up intuitively with costs and benefits of innovations containing new products, features and processes. I have shown evidence to suggest that creative patents translate into products or processes which feature in management discussions, elicit stock market reactions and spur follow-on innovation. Furthermore, creative patents are associated with higher costs and tend to rely on recent academic developments.

3. The Creativity Slowdown

Having shown that patent creativity varies in a way which is highly indicative of new products, features or processes, I document that US patents have become less creative and more derivative over the last three decades. Figure 4 shows that as the overall number of patents per capita have almost tripled over the last three decades, average patent creativity of these patents has halved. In 1981, the average patent creativity ($Avg(\text{patent creativity}_p)_t$) is 1.39, which means that the average patent filed in 1981 is 39% more creative than the average patent filed between 1981-2018. By the end of my sample in 2018, the average patent creativity falls by 61% to 0.52. This drop in average patent creativity is strong enough such that creative patents per capita have decreased over time. In Figure 5, I decompose overall patents per capita into creative patents per capita, with patent creativity more than 2, and derivative patents per capita, using the rule in equation 1. I find that the number of creative patents per capita decreased by 32.83% from 49 creative patents per million people to 33 creative patents per million people between 1981 and 2018. This decrease is not monotonic over the years. There is a slight increase in creative patents per capita of about 10.20% between 1980 and 1990, and a sharp decrease between 1990 and 2018. Productivity growth mimics these patterns in creative patenting. Productivity growth increases by 0.49 percentage points between 1980s and 1990s, and then falls by 0.66 percentage points between 1990s and 2010s.

Industry Patterns. To understand the variation in patterns of creative and derivative patenting across industries, in figure 6 panel A, I plot creative patents by year for major patenting industries. These pictures show that the rise in creative patenting during the early 1990s is driven by computer and related manufacturing. During the late 1990s, rise in creative patenting is driven by patenting by online stores and information technology (IT) service industries, which is consistent with prior evidence on improvements in IT leading to above average growth during the 1990s (De Ridder, 2019; Fernald, 2015). Throughout my sample, creative patenting for all other manufacturing except computers has been declining since the early 1990s. In figure 6 panel B, I show that, in contrast to creative patents, overall patents have been on the rise for all industries.

Robustness. There are two potential concerns with interpreting a decline in average patent creativity, measured using patent text, as an economically meaningful decline in share of creative innovations: increasing patent lengths and evolving language trends. To show that increasing patent lengths do not drive the decline in patent creativity, I leverage different section of a patent. Appendix figure 5 Panel A, shows that the increase in patent lengths is entirely driven by the detailed description section. In Panel B, I plot patent creativity for different sections of the patent and show that the decline in patent creativity is independent of the section of the patent. Patent titles and abstracts are particularly convenient for this robustness because they summarize the content of the patent in limited words, and it is reassuring that the creativity decline persists even when restricting the text to these two sections.

Next, I show that converging use of language across patents also does not drive patent creativity [19]. To address this, I remove any (creative or derivative) technical bigrams in a patent that are used in Google books published in the five years before a patent is filed[20]. Appendix Figure 6 plots the resulting time series and it is comforting to note that the pattern of creativity remains largely unchanged. I also count the total number of technical two-word combinations in Google books between 1981 and 2012[21], and compare that against patents. Patents on the whole use only about 7% of overall two word combinations used in Google books, which suggests that there is not a lack of two-word combinations to represent inventions.

[19]The potential concern is that new two word combinations appearing in general language are more likely to be used in more recent patents than in past ones.

[20]For two word combinations in books by year, I use the dataset made available by Google which uses near universe of digitized books. https://books.google.com/advanced_book_search

[21]Last year of availability of Google books.

Having documented the decline in patent creativity, I next show that this decline has implications for productivity growth by studying the relationship between firm-level productivity growth, and creative and derivative patenting.

4. Patent Creativity and TFP Growth for firms and industries

In this section, I present evidence to show that only creative (and not derivative) patents represent technological change within the firm by examining firm and industry level correlations between creative and derivative patenting and, productivity growth.

Firm level. I construct two measures of productivity for firm i in year t: first, as my baseline, using Olley and Pakes (1996) to calculate total factor productivity (TFP), and second, as a robustness, using sales per employee to calculate labor productivity. I calculate creative patenting using the total count of patents filed filed by firm i in year t with patent creativity greater than 2, using the rule as in equation 1. Having calculated TFP and creative patenting, I examine the relationship between TFP growth and creative patenting using estimates of the following specification:

$$\Delta^5 log(TFP)_{i,t} = \alpha + \beta_1 IHS(\text{Creative Patents})_{i,t} + \beta_2 IHS(R\&D)_{i,t-1} + \chi_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}$$

where $\Delta^5 log(TFP)_{i,t}$ is 5-year differences in $log(TFP)$ and $IHS(\text{Creative Patents})_{i,t}$ is the inverse hyperbolic sine of creative patents filed by firm i in year t. I add controls for past R&D expenditures ($IHS(R\&D)_{i,t-1}$), lags of overall industry sales, and polynomials of firm age[22]. All specifications include time fixed effects δ_t and build up to firm fixed effects (δ_i). I restrict my analysis to manufacturing firms which file at least 10 patents between 1991 and 2014.

The findings are presented in table 4. In column 1, I start with patents, and find that within industries, firms which file more patents do experience higher productivity growth. In other words, firms which file more patents also experience higher productivity growth. However, in column 2 and 3, when decomposing patents into creative and derivative patents, I find that this relationship between patents and productivity growth is driven by creative

[22] Firm age is calculated as year since initial public offering.

rather than derivative patents. In column 4, I repeat the analysis but replace industry fixed effects with firm fixed effects. I find that only creative patents are significantly associated with productivity improvements, while derivative patents are not. The coefficient of creative patents is positive and statistically significant while that of derivative patents is negative and statistically insignificant. In my most preferred specification in column 4, the OLS coefficient of $Ihs(creativepatents)$ implies that doubling creative patents while keeping R&D expenditures constant is associated with an increase in TFP growth of 0.22 percentage points. In other words, an additional creative patent is associated with an increase in TFP growth of 0.0017 percentage points. In columns 5 and 6, I show that the coefficients are unchanged when weighting derivative patents by citations or influence.

In table 5, with the same specification as before, I corroborate these findings with data on labor productivity and capital investment. It is comforting to note that the conclusions remain unchanged: only creative (and not derivative) patents are associated with improvements in labor productivity and capital investments. In my preferred specification with firm fixed effects in column 6, I find that one more creative patent is associated with a 0.063% increase in labor productivity, and a 0.065% increase in investment rate. Appendix table 7 provides detailed results for investment in parallel with productivity growth regressions. In addition to this, appendix table 6 shows that none of the other measures of ex-ante originality are useful in predicting productivity growth.

Industry level. I find similar patterns at the industry level. To analyze the relationship between creative patenting and productivity growth at the industry level, I collect multi-factor productivity data from the Bureau of Economic Analysis and aggregate patenting counts for 4-digit NAICS industries. Mapping of patents into industries is only readily available for patents assigned to public firms. To aggregate counts of all creative and derivative patents separately for NAICS industries, I use the distribution of patents across technology classes and then use mapping of technology classes into industries calculated by using patents assigned to public firms. To examine the correlation between productivity growth and creative and derivative patenting, I use the following specification:

$$\Delta^5 log(TFP_{i,t}) = \alpha + \beta_C Ihs(\text{creative patents}_{i,t}) + \beta_D Ihs(\text{derivative patents}_{i,t}) + \delta_i + \delta_t$$

where $\Delta^5 log(TFP_{i,t})$ denotes 5-year changes in log of TFP for industry i in year t, $Ihs(\text{creative patents}_{i,t})$ is the inverse hyperbolic sine of creative patents and $Ihs(\text{derivative patents}_{i,t})$ is the inverse hyperbolic sine of derivative patents. In the tightest specification, I add controls for industry and year fixed effects.

Table 6 shows the results. In line with firm-level findings, Columns 1 shows that overall patents do not predict within industry differences in productivity growth. Furthermore, columns 2-4 show that only creative and not derivative patents predict productivity growth with industry fixed effects. In the most conservative specification in Column 4, the magnitudes suggest that industries with a 1% increase in creative patents experience a 2.20 percentage point higher productivity growth. The average industry in my sample files 205 creative patents per year, which implies that an additional creative patent is associated with 0.011 (2.20/205) percentage points increase in productivity growth. Together, creative and derivative patenting explain about 9.7% of the variation in productivity growth within industries. These magnitudes are about 10 times higher than the magnitudes for firm-level analysis, understandably, because the benefits of creative patents are not limited to the firm which files them. These benefits are more widely realized through subsequent spillovers. I quantify these larger productivity benefits of creative innovations further with the structure of my model in section 6.

5. Drivers of creativity

Having documented that the decline in creativity has implications for productivity growth, I exploit inventor data and government funding acknowledgement in a patent to examine drivers of patent creativity, and propose possible explanations for the decline. I show that new-entrants, women and minority authors file more creative patents than others; however, that new-entry is by-far the biggest driver of patent creativity. I compliment this with time series evidence which shows that new-entry into patenting has been falling. I also find evidence which suggests that government funding plays a particularly important role in promoting creative innovations.

In Figure 7, I plot coefficients from a regression of patent creativity on an inventor's patent order for first five patents. The sample is of all US inventors who file at least 5 patents between 1981 and 2018, and I add controls for technology class and year fixed effects. I find that an inventor's first patent is on average their most creative one. In particular, coefficient of the first patent is about 1.26 (s.e.=0.02), which implies that the first patent by inventors is on average 26% more creative than the average patent in my sample. Coefficient of the second patent is 1.05 (s.e.=0.01), the third patent is 0.99 (s.e.=0.01), the fourth patent is 0.94 (s.e.=0.01) and the fifth patent is 0.93 (s.e.=0.01). Patents filed after the first five patents are about 0.84 (s.e.=0.001) times as creative as the average patent in my sample. These estimates imply that inventor's first patent is on an average 52% more creative than patents filed after the first 5 patents, and that creativity falls monotonically as inventors patent more.

For comparison, figure 8 shows that patents authored by women and minorities are 10.8% more creative and patents filed by ethnic minorities are about 2.2% more creative than the average patent in my sample[23]. I use name-based classifiers to classify inventors into men and women, and majority and minority ethnicities. All names which are classified as non-European are classified as minorities into patenting. However, in comparison to patent creativity of first-time inventors, these magnitudes are significantly smaller.

Figure 8 also shows that government funded patents are 35% more creative than the average patent in my sample. I use the data on government funding of patents provided by Fleming et al. (2019), who tabulate acknowledgments to US government agencies in patent text. In appendix table 9, I show explore this relationship in further detail and find that patents owned by government agencies 48.7% (s.e. = 0.027) more creative than the average patent in my sample, while the corresponding estimate for patents owned by corporations and funded by US government agencies is 33.5% (s.e. = 0.027) . Higher patent creativity of government funded patents could admit various interpretations. For instance, there are certainly larger benefits of creative patents than those internalized by a private firm and a government might take into account these benefits while investing into innovations.

I perform various robustness exercises to show that these differences in creativity of first-time inventors and government funded patents are not driven by time trends in creativity, and

[23] This is consistent with studies emphasizing the role of immigration on innovation, for example Burchardi et al. (2020).

that they result in meaningful variation in stock returns. First, Appendix Table 12 collects all the drivers together and compares them in a single regression framework. In particular, column 5 regresses patent creativity on all the drivers, and shows that coefficients remain largely unchanged. Appendix Table 10 Columns 2-4 show, by repeating the regression for patents published decade by decade, that the level difference in creativity between patents filed by new-entrants versus existing ones is persistent through the years. Second, Appendix Table 11 regresses stock returns on inverse hyperbolic since of first-time patents, and shows that a 1% increase in first-time patents granted to firm i in week t is associated with a 7.2% increase in stock return. However, column 2 regresses stock returns on both creative patenting and first-time patents, and shows that this association is entirely driven by an increase in creative patenting.

Next, I highlight that composition of these innovators is changing over time and these cross-sectional differences in creativity are playing a role in determining aggregate share of creative patents. In figure 9, I plot the percentage of patents by the above three groups: new entrants, women, and ethnic minorities. I find that the share of patents by first-timers has declined from about 30% in 1981 to 12% in 2015. I also find that the share of patents by women (7% to 19%) and ethnic minorities (4% to 10%) has been steadily increasing over time.

So far, I have shown three facts about creative patenting. First, at the firm level, an additional creative patent is associated with an additional 3.1% return and about 0.0017 percentage point increase in TFP growth for the firm. Second, patents filed by new entrants are 48.7% more creative than patents filed later on. I have also shown that patents by women authors, minority authors or government agencies are significantly more creative. Fourth, I showed that there have been significant long run changes in composition of innovations. Especially, new-entry into patenting has declined. To quantify changing composition of inventors on aggregate creativity and productivity growth, I use structure of the growth model in the next section (section 6). I will rationalize the decline in entry through falling US population growth. The model will use the documented cross-sectional differences in patent creativity across innovators, and the relationship between creative patenting, and productivity growth and stock returns to estimate the effect of declining entry on aggregate creativity and productivity growth.

6. Creativity in a Model

In this section, I develop an endogenous growth model with creativity and subsequent spillovers of creative innovations. The model builds on the structure of spillovers in Perla and Tonetti (2014). I add a formal model of creativity, where different groups of inventors differ in their ability to perform creative innovations. I begin description of the model environment by detailing the household and production sector, which are standard in the literature (see Perla et al. (2021)). The novel addition is creative innovations, described as a part of the innovation sector.

A. *Preferences and production*

Preferences. A representative household is endowed with labor L, which exogenously grows at g_L. g_L represents growth in total labor supply and could be driven by higher population growth, immigration or higher labor force participation. Time is continuous and infinite horizon. Utility of the representative consumer is:

$$\bar{U}(t) = \int_t^{\infty} U(C(t)) \exp^{-\rho(\tilde{t}-t)}\, d\tilde{t}$$

$$s.t. \qquad C(t) \leq \frac{W(t)}{P(t)} \left(L_p(t) + L_E(t) + L_\chi(t)\right) + \Pi_t$$

Utility function is a time-discounted value of infinite stream of instantaneous utilities (U) over a consumption good (C), aggregated over micro varieties by a competitive final goods producer. ρ is the discount factor, and instantaneous utility is CRRA power utility with risk aversion factor γ.

$\frac{W(t)}{P(t)}$ is the real wage, and labor supply is distributed over production $L_p(t)$, entry costs $L_E(t)$, and cost of adoption $L_\chi(t)$.

Production. The final good is produced by a competitive producer by aggregating a set of varieties $N(t)$, which is each produced by an innovator acting as an entrepreneur. Innovators produce using labor $l(z)$ as the only input in production and differ in their productivities Z. These productivities are distributed according to a distribution $\Phi(Z)$.

While producing innovators earn the following profits as a result of optimally chosen quantities under a CES structure:

$$\Pi(Z) = \frac{1}{\sigma}\left(\frac{P(Z)}{P}\right)^{1-\sigma}\frac{Y}{P}$$

B. Innovation

At each instant, innovators hold a technology of productivity Z, and exist in either in derivative state D or in creative state C with respect to their innovation. In both states, they make profits from producing their variety with technology Z.

In the derivative state, along with earning profits, innovators choose whether to maintain their current technology or abandon it and search for another one. Their flow value of holding technology Z at time t in state D is:

$$rV_D(t,Z) = \underbrace{\Pi(t,Z)}_{\text{flow profits}} + \underbrace{\max\left(V_N - V_D(t,Z) - \eta\frac{W(t)}{P(t)}, 0\right)}_{\text{abandon and search}} + \underbrace{\partial_t V_D(t,Z)}_{\text{continuation value}} \tag{4}$$

where r is the interest rate, V_N is the expected value of searching for another technology and η is the search cost in terms of labor units. When innovators abandon their technology, they are either assigned another technology at random with probability (p_C) and continue to be in the derivative state, or they move on to the creative state with probability $(1 - p_C)$.

$$V_N(t) = p_C \int_{M(t)}^{\infty} V_C(t,Z)d\Phi_C(Z) + (1 - p_C)\int_{M(t)}^{\infty} V_D(t,Z)d\Phi_D(Z)$$

where Φ_C denotes the distribution of technologies of creative innovators and Φ_D denotes the distribution of technologies of derivative innovators. Both of these distributions are endogenous and are determined under equilibrium, described in detail in following discussion.

This choice structure implies that at every instant a derivative entrepreneur is evaluating their current valuation $V_D(t,Z)$ against the net value of choosing a new technology $V_N(t) - \eta\frac{W(t)}{P(t)}$. Because $V_D(t,Z)$ is increasing in Z, the structure of this decision implies that there exists a cut-off productivity $M(t)$ below which all entrepreneurs choose to abandon their technology and search another one. This choice structure is also the same as in Perla and Tonetti (2014) except that they do not have formulation of the creative state ($p_C = 0$). For convenience, I define the rate of growth of this threshold $M(t)$ as $g_m(t) = \frac{M^{'}(t)}{M(t)}$.

In the creative state, innovators make improvements on their productivity, and I assume that entrepreneur's productivity evolves according to a reflective-Geometric Brownian Motion (GBM):

$$\begin{aligned} \frac{dZ_t}{Z_t} &= \left(\mu + \frac{\nu^2}{2}\right) dt + \nu dW_t && \text{if } Z > M(t) \\ \frac{dZ_t}{Z_t} &= \max\left\{\left(\mu + \frac{\nu^2}{2}\right) dt + \nu dW_t, 0\right\} && \text{if } Z = M(t) \end{aligned}$$

where μ_t is the drift, ν_t is the volatility, W_t is Brownian motion, and $M(t)$ is the continuously evolving lower bound of the distribution of productivities. Reflective Brownian motion prevents productivity to be pushed below $M(t)$. Along the BGP, this GBM will result in a power-tail distribution of productivities.

With some exogenous probability, a creative inventor moves on to the derivative state while holding on to their technology Z. The resulting law of motion of firm's valuation in the creative state evolves according to the following HJB equation:

$$\begin{aligned} rV_C(t,Z) = \underbrace{\Pi(t,Z)}_{\text{flow profits}} + \underbrace{\mu Z \partial_Z V_C(t,Z) + \frac{\nu^2}{2} Z^2 \partial_Z^2 V_C(t,Z)}_{\text{GBM}} + \\ \underbrace{\alpha(V_D(Z,t) - V_C(t,Z))}_{\text{Derivative shock}} + \underbrace{\partial_t V_C(t,Z)}_{\text{Continuation value}} \end{aligned} \tag{5}$$

For derivations, please refer to the model appendix.

Entry. At each instant, an infinite mass of entrepreneurs is waiting to enter. These entrants make a decision similar to derivative entrepreneurs. They pay a fixed cost $\eta_E \frac{W(t)}{P(t)}$ to enter, and then $\eta \frac{W(t)}{P(t)}$ to search for a technology to produce with. The only difference for entrants versus derivative entrepreneurs is that they realize the creative state with probability p_C^E, which is larger than the probability with which derivative entrepreneurs join the creative state p_C.

$$\text{Enter if} \qquad V_N^E - (\eta_E + \eta)\frac{W}{P} \geq 0$$
$$\text{where } V_N^E = p_C^E \int_{M(t)}^{\infty} V_C(Z) d\Phi_C(Z) + (1 - p_C^E) \int_{M(t)}^{\infty} V_D(Z) d\Phi_D(Z)$$

C. *Productivity Distributions*

The final part of the environment is law of motion of the productivity distributions. The following Kolmogorov forward equations describe the evolution of the creative (Φ_C) and derivative productivity distributions (Φ_D) by summarizing the inflow and outflow of entrepreneurs at each point in the productivity distribution:

(6)
$$\partial_t \Phi_D(t,Z) = \underbrace{(1-p_C^E)E(t)\frac{\Phi_D(t,Z)}{N(t)} + (1-p_C^I)S(t)\frac{\Phi_D(t,Z)}{N(t)}}_{\text{Entry and abandoning existing}} + \underbrace{\alpha\Phi_C(t,Z)}_{\text{From creative state}} - \underbrace{\frac{S(t)}{N(t)}}_{\text{Abandoning}}$$

(7)
$$\partial_t \Phi_C(t,Z) = \underbrace{\frac{\Phi_C(t,Z)}{C(t)}(p_C^E E(t) + p_C^I S(t))}_{\text{Entry and abandoning existing}} - \underbrace{\alpha\Phi_C(t,Z)}_{\text{Switch to derivative}} \underbrace{- \mu Z \partial_Z \Phi_C(t,Z) + \frac{\nu^2}{2} Z^2 \partial_Z^2 \Phi_C(t,Z)}_{\text{GBM}}$$

Left hand side of each equation is the time evolution of derivative and creative distributions at productivity Z and time t. Evolution of derivative entrepreneurs is a combination of four terms. First term denotes two sources of additions to the innovators in the derivative state: $1 - p_C^E$ share of incoming innovators who enter and $1 - p_C$ share of existing innovators who abandon their technologies. Second term reflects the third source, which is incoming inventors who get the derivative shock in the creative state. Third and last term reflects subtractions which is the set of abandoning existing inventors at the threshold ($M(t)$). Evolution of the creative distribution is given by three terms. First denotes two sources of additions to the innovators in the creative state: p_C^E share of incoming innovators who enter and p_C share of existing innovators who abandon their technologies. The second denotes subtractions in the form of innovators receiving a shock and moving to derivative state. The final term denotes the set of changes in the set of innovators at Z following GBM.

D. *Computing a balanced growth path equilibrium (BGP)*

Having described the environment, I now define and summarize the computation of the balanced growth path (BGP) equilibrium.

Assumption 1 *To compute the BGP, I assume that the initial derivative distribution at $t = 0$ is a Pareto Distribution.*

$$\Phi_D(t = 0) = M(0)Z^{-\alpha_{D,0}}$$

where $\alpha_{D,0}$ is a free parameter.

Definition of BGP. *A balanced growth path equilibrium consists of initial distributions for creative and derivative entrepreneurs: $\Phi_D(0), \Phi_C(0)$ with support $[M(0), \infty)$. A sequence of distributions $\{\Phi(t, Z)\}_{t>0}$, entrepreneur adoption policies $M(t)$, entrepreneur set prices $p_D(t, Z)$ and labor prices $l(t, Z)$, wages $\{W(t)\}_{t\geq 0}$, endogenous measure of varieties $\{\Omega_N(t), \Omega_C(t)\}_{t\geq 0}$, and a growth rate $g > 0$.*

- *Given aggregate prices, and distributions:*
  - *Entrepreneurs valuations and adoption choices are given by equations 5 and 4.*
  - *$M(t)$ evolves at a constant rate $g_m = \frac{M'(t)}{M(t)}$*
  - *$p(t, Z)$ and $l(t, Z)$ are optimal static choices.*
  - *The mass of entrepreneurs in derivative $N(t)$ and creative modes are consistent with free entry.*
- *Product and labor market clears at each instant.*
- *The distribution of productivities for creative and derivative entrepreneurs are stationary when scaled.*

E. Theoretical Results

Before I solve the complete equilibrium through computation, I partially solve the model to provide intuition for what determines growth, and how population growth affect growth.

Lemma 1 *Given that productivity for creative entrepreneur evolves according to an exogenous reflective GBM, following Gabaix (1999) and Luttmer (2007), the tail parameter of resulting Pareto distribution for creative entrepreneurs is a function of relative drift and volatility:*

$$\alpha_C = 1 - 2\frac{\mu - g_m}{\nu^2}$$

Proof. I prove this by guessing a Pareto distribution with parameter α_C and verifying that it solves equation **??**. Intuitively, if the economy is growing at a faster rate, then the tail of technologies as a result of technological improvements in the creative state is thinner. ·

Lemma 2 *Along the balanced growth path, the ratio of entry to total number of entrepreneurs is given by the population growth rate:*

$$\frac{E}{N} = g_L$$

where N is the mass of innovators.

Proof. Along the BGP, innovators per capita (N/L) is constant, which implies that the rate of population growth $(\frac{\dot{L}}{L} = g_L)$ is equal to the rate of entry $(\frac{\dot{N}}{N})$. Refer to the online appendix for more details. ·

Lemma 3 *Share of creative innovators in the economy is a function of rate of entry (population growth) and rate of existing innovators abandoning their technologies:*

$$\Omega_C = \frac{p_C^E g_L + p_C S_N}{g_L + \alpha}$$

Proof. I prove this following the finding that percentage of creative innovators is constant along the BGP. Technical derivation is in the online appendix. Intuitively, share of creative innovators in the economy is given by two sources of creative innovators: entry through population growth and existing innovators abandoning their technologies. Increasing α naturally increases the rate at which innovators lose their creativity, and resulting in a decrease in the share of creative innovators. ·

Proposition 1 *Along the balanced growth path, the density of productivities for derivative distribution is a weighted mixture of two Pareto distributions: 1) the derivative Pareto distribution that the economy was initialized with in Assumption 1, and 2) the creative pareto derived in Lemma 1,*

$$\Phi_D(\infty, z) = \zeta(\Omega_C)\ \Phi_C(\infty, z) + (1 - \zeta(\Omega_C))\ \Phi_D(0, z) \tag{8}$$

where

$$\zeta(\Omega_C) = \frac{\alpha_D \alpha p_C \Omega_C}{(\alpha_D - \alpha_C)(g_L(1 - p_C^E) + (1 - p_C)\Omega_C \alpha)}$$

Given that $p_C < 1$, $\zeta(\Omega_C)$ is an increasing function in Ω_C.

Proof. I prove this by guessing a weighted Pareto with weight ζ for the derivative distribution along BGP and verifying that it solves equation **??**. Refer to the online appendix for more details. ·

Lemma 4 *The growth rate of aggregate productivity ($Y(t)/L_p(t)$) along the balanced growth path is given by the growth rate of the abandoning barrier ($M(t)$):*

$$g_{Y(t)/L_p(t)} = g_m = \frac{M'(t)}{M(t)}$$

Proof. Distribution of productivities in this economy is a mixture of Pareto distribution with different tail parameters but a common minimum support at the abandoning threshold ($M(t)$). Along the stationary BGP, the tail parameter is constant with the only $M(t)$ evolving. As a result of this and CES revenue structure, the aggregate productivity is same at any point but scaled by $M(t)$, which results in the proposition. For a more technical proof, refer to the online appendix. ·

Proposition 2 *Along the balanced growth path, there is direct relationship between percentage of creative innovators and productivity growth.*

$$g_m = \frac{g_L(1-p_C^E)+\alpha(1-p_C)\Omega_C}{\alpha_D p_C(1-\Omega_C)} \tag{9}$$

Assuming that $g_L << \Omega_C$ *and* $p_C^E >> p_C$*:*

$$g_m \approx \frac{\alpha(1-p_C)\Omega_C}{\alpha_D p_C(1-\Omega_C)} \tag{10}$$

Proof. I solve the system of equations given by normalized Kolmogorov Forward Equations (equation **??**). Refer to the online appendix for more details.·

These results provide insight into how population growth affects creativity and growth in this economy. Lemma 1 shows that creative process for the inventors result in a Pareto tailed distribution of productivities, where thickness of the tail is depends on GBM parameters. Lemma 2 shows that population growth feeds into the innovation sector along the BGP by affecting the rate of entry. Lemma 3 shows that share of creative inventors is driven by rate of entry (population growth) and the rate of existing innovators abandoning their technologies. Proposition 1 shows that a higher share of creative innovators improves the set of technologies available for adoption, thereby increasing incentives for existing innovators to abandon technologies. This in turn has a feedback effect on share of creative innovators and serves as an amplification for the effect of higher population growth on creativity. Finally, proposition 2 shows that share of creative innovators in the economy is a sufficient statistic for productivity growth. This is because higher share of creative inventors pushes the frontier at a faster rate with the GBM, and it also forces existing inventors to abandon their less productive technologies.

Algorithm to compute equilibrium. To compute the equilibrium through computation, I use a search algorithm to look for a value of labor in production (L_p) and a productivity growth rate (g_m) which solves together the Kolmogorov forward equations (6 and 7) and HJB equations (4 and 5), along with balancing total labor supply in the economy. More details about the solution process are in the theoretical appendix.

F. *Calibration*

In this section, I describe calibration of the model to fit a combination of moments from US macroeconomic data, and moments highlighted in the empirical results in sections 4 and 5. I fit the model to data points of the US economy in the early 1980s, and calculate counterfactual equlibrium decade by decade between 1950-2010. The following table highlights calibrated moments:

Key parameters

Parameter	Value
Discount factor (ρ)	0.01
Elasticity of substitution (σ)	3.15
Initial derivative tail parameter (α_D)	4.99
Drift of creative GBM (μ)	0.0017
Volatility of creative GBM (ν_C)	0.038

Parameter	Value
Updating cost (η_S)	6.55
Entry cost (η_E)	4.32
Updating creativity probability (p_c^E)	0.18
Entry creativity probability (p_c^E)	0.37
Creative-derivative transition probability (α)	0.14

This calibration is a combination of substituting values from the literature and moments from creativity and macroeconomic data. I calibrate discount factor(ρ), elasticity of substitution(σ), and tail parameter of starting derivative distribution (α_D) exactly as specified in Perla et al. (2021). The remaining seven parameters are calibrated to exactly match the following seven moments.

Aggregate Productivity Growth. To calculate aggregate US productivity, I use growth in multi-factor productivity provided by the Bureau of Economic Analysis (BEA) and take averages by decade. The average multi-factor productivity growth between 1971-80 was 1.48%.

Percentage of Entrepreneurs in the Economy. I calibrate this moment using the percentage of business owners/managers out of total employed workforce in the US, which is 12.5%.

Creative entrepreneur's/firm's productivity growth. To calculate this, I use the estimated relationship between a creative patent and productivity growth in table 4. I set the value of μ to exactly match this value. Derivative entrepreneurs by assumption do not experience any productivity improvements.

Inventor's creativity life-cycle dynamics. This moment is calculated using lifecyle dynamics of creativity in figure 7. I use two moments from this figure. First, the entry creativity premium or the probability that an entrant files a creative patent (23%). Second, with each additional patent, the probability of filing a creative patent decreases by 14%. These two moments pin down the value of the value of p_C^E and α.

Percentage of Creative Patents. The percentage of creative patents in 1981 plotted in figure 4. In the model, I assume that creative and derivative entrepreneurs each file one patent in each period. Therefore, the share of creative patents in the model is $\frac{C}{C+D}$. This moment is used to pin down p_C^U

Creative versus derivative patent valuation. To calculate this moment, I use coefficients from the relationship between creative and derivative patenting and stock returns in section 2. The coefficients in the OLS estimates imply that on an average creative patents are worth 14.81% more than derivative patents. This moment helps pin down the tail parameter of the creative state. Given the drift parameter of the creative entpreneurs and Lemma 1, this moment, therefore, pins down the volatility of GBM of the creative entpreneurs.

Having calibrated the ten parameters, I set population growth to 1.44%, as in the 1980s. At the end of this calibration exercise, I obtain a creative tail parameter of 3.30 ($\leq \alpha_{D,0} =$ 4.99), and a derivative distribution of productivities with weight of 78% on the creative distribution. Along with these, the elasticity of substitution across varieties (σ) calibrated to 3.17 results in a Pareto tail parameter of 1.75 for the innovator incomes. Note that earlier studies has found income distributions with tail parameters slightly above 1 (e.g. Luttmer (2007)).

G. Counterfactuals

I now discuss how the economy, presented and calibrated as above, is affected by declining population growth, increasing participation of women in the labor force and rise in immigration. To answer this, I compute the stationary BGP equilibrium of this economy for changing values of US population growth decade by decade. For these different equilibria corresponding to decade by decade values of population growth, I calculate share of creative innovators, productivity growth and innovators per capita. Share of creative innovators and innovators per capita are model analogs for average creativity and total number of innovators in the economy.

Table 7 presents the results from a declining population growth in the model while keeping all other parameters constant. US labor force growth declined from 2.5% in 1950s to 2.3% in 1980s to 0.6% in 2010s. This decline in the model results in a 18.39% decline in share of creative entrepreneurs, which explains about 42.90% of the creativity decline in my sample of patents. The model estimates that in 1950, the derivative distribution had a weight w of 86% on the creative pareto, and this falls to about 26% in 2010, which leads to a 29.06% decrease in drawing a new derivative idea. Given this, the percentage of innovators who adopt declines by 0.44%. As a result, growth slows down by 18.96%, which explains about 31.16% of the overall productivity growth slowdown in the data. The model also explains about 15.33% of the rise in entrepreneurs or innovators in the data driven by the 42.96% increase in the valuation of drawing a creative idea and that new entrants are more likely to draw a creative idea than updating derivative entpreneurs.

Table 8 presents results from rise in labor force participation of women. To run this counterfactual, I re-interpret g_L, growth rate of labor supply, as effective increase in labor supply as a resut of the increase in population growth due to a higher rate of labor force participation by women. The counterfactual, thus is keeping the population growth the same as in 1980 but changing the rate of female labor force participation, which changes the rate effective entry to innovation. To account for higher creativity of women, I also recalculate p_C^E according to table **??**. With this analysis, I find that an increase in labor force participation by women has resulted in an increase in creativity by 3.75% and productivity growth of 4.38%.

Flow of immigrants per capita in the US in 1950s was close to 0.3 immigrants per 100 people, which has increased to 0.6 immigrants per 100 people. As compared to the decline in population growth, during the past 5 decades, my analysis shows that increase in rate of immigration predicts less than 1% of the increase creativity and productivity. However, during 2010s when rate of population growth is at 0.6%, doubling the rate of immigration boosts creativity by 8.81% and productivity growth by 8.86%.

H. Government subsidy to promote creativity and growth

In this section, I make a case for government to subsidize research and improve composition of innovations towards more creative ones with the lens of the model and some empirical validation. In particular, how increasing subsidies search cost for new technologies when abandoning current technology (η) affect aggregate creativity and growth. The government has an incentive to undertake such a subsidy where as private entities do not have incentives to do the same because they only internalize private benefits of creative innovations. I also test whether the government funds more creative innovations in reality using data on patent creativity. I find that in fact patents owned and funded by US government are significantly more creative than other patents. I also document that even thought the government has incentives to subsidize research, the share of research in the US funded by the government has reduced over time (appendix figure 8).

In figure 10, I use the model to plot the share of creative innovators (in Panel A), productivity growth (in Panel B), inventors per capita capita (in Panel C) for different values (on the x-axis) of subsidies to η or the cost to searching for a new technology. In the model, a 10 percentage point increase in government subsidies, which is doubling the current rate of subsidy in the data, results in 0.3 percentage point (or 3%) increase in creativity (share of innovators in the creative state). This results in a an improvement of 0.06 percentage point (or 5%) in productivity growth. Increasing subsidies for searching new technologies also lead to an increase in the level of entry and therefore a 17.54% increase in innovators per capita.

As a validation in the data, I provide empirical evidence to show that the US government funds more creative research than private entities. In appendix table 9, I correlate patent creativity on different degrees of government involvement in a patent. I find that patents which acknowledge public funding are about 52.9% more creative than the average patent in the sample. I show that these patents on an average are more creative than government funded and privately owned patents. Furthermore, patents which cite government owned or cite government funded patents tend to be less creative than the average patent in my sample.

7. Conclusion

In this paper, I argue that the recent increase in patenting, accompanied by a decrease in productivity growth, is largely driven by an increase in derivative and not creative patenting. To do this, I develop a novel measure of patent creativity, which captures the extent to which an innovation described in a patent breaks new ground versus builds on existing innovations. More importantly, it does not condition on ex-post success or influence of a patent. I show a range of results which corroborate that creative patents hold private and social value in an economically meaningful way. I show that creative patents predict higher stock market returns, are more expensive, and generate more follow-on innovations than derivative patents.

Using this measure, I document that only creative patents are associated with productivity growth within the firm, and that average patent creativity has halved over the past few decades. Using the data, I show that composition of inventors, in particular new-entrants, women and minorities are key drivers of creativity at the micro level.

Finally, with the help of a model, I show that the decline in creativity and productivity growth is partly driven by falling new entry into patenting driven by population growth, and the increase in labor force participation by women and minorities have not been near enough to mitigate the effects of that.

My results enforce confidence that patent creativity captures an important new dimension in innovations, and opens up a number of avenues for future research.

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Tables and Figures

Table 1: Validation: Creative patenting, and 'new product' and 'new design' mentions in earnings calls

	# earnings w/ 'new product' bigrams$_{i,t}$		# earnings w/ 'new design' bigrams$_{i,t}$	
	(1)	(2)	(3)	(4)
ihs(creative patenting$_{i,t}$)	0.058***	0.049***	0.012	0.007
	(0.018)	(0.018)	(0.009)	(0.010)
ihs(derivative patenting$_{i,t}$)		0.026		0.016**
		(0.016)		(0.008)
R^2	0.561	0.561	0.510	0.510
N	12,342	12,342	12,342	12,342
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

Notes: This table shows in columns (1) and (2) results from a regression of number of earnings w/ 'new product' or similar bigrams mentioned by firm i in year t on creative and derivative patenting by firm i in year t. Columns (3) and (4) present results from a regression of number of earnings w/ 'new design' or similar bigrams mentioned by firm i in year t on creative and derivative patenting by firm i in year t. Standard errors are clustered by firm. All specifications control for firm and year fixed effects.

Table 2: Validation: Stock returns and creative patenting

Panel A: Stock returns, and creative and derivative patents

	Stock Returns$_{i,t}$ (weekly)				
	(1)	(2)	(3)	(4)	(5)
ihs(creative patenting$_{i,t}$)	0.161***	0.093***	0.085***	0.082***	0.083***
	(0.022)	(0.022)	(0.026)	(0.025)	(0.026)
ihs(derivative patenting$_{i,t}$)			0.009		
			(0.013)		
ihs(derivative patenting$_{i,t}$ - cite wt.)				0.014	
				(0.013)	
ihs(derivative patenting$_{i,t}$ - f/b)					0.011
					(0.013)
R^2	0.074	0.075	0.075	0.075	0.075
N	1,816,951	1,816,951	1,816,951	1,816,951	1,816,951
Controls	N	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y

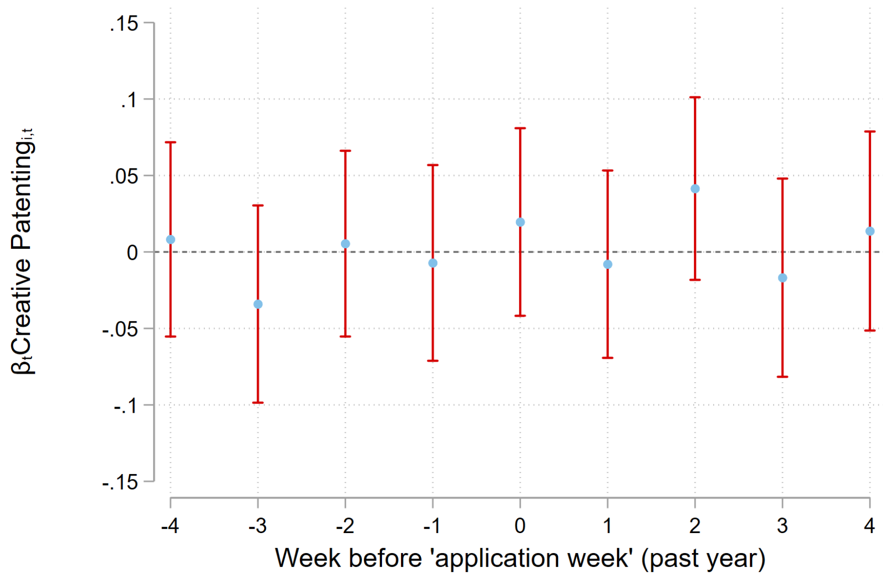
Panel B: Comparison with other measures

	Stock Returns$_{i,t}$ (weekly)				
	(1)	(2)	(3)	(4)	(5)
ihs(creative patents$_{i,t}$)	0.093***	0.100***	0.087***	0.083***	0.088***
	(0.022)	(0.038)	(0.026)	(0.027)	(0.023)
ihs(original patents$_{i,t}$ - bck sim)		0.023			
		(0.060)			
ihs(original patents$_{i,t}$ - cites HHI)			0.011		
			(0.042)		
ihs(original patents$_{i,t}$ - academic citations)				0.015	
				(0.022)	
ihs(original patents$_{i,t}$ - # claims)					0.024
					(0.041)
R^2	0.075	0.062	0.073	0.075	0.075
N	1,816,951	1,214,194	1,706,247	1,816,951	1,816,951
Controls	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y

Notes: Table reports results from a regression of stock returns$_{i,t}$ for firm i over week t on inverse hyperbolic sine of creative and derivative patenting. Patents which have a patent creativity ≥ 2 are classified as creative and rest as derivative. The sample only includes firms which have filed at least one patent during 1991-2014. Specifications in columns 2-5 control for IHS of R&D spending during the previous five calendar years, and CAPM Betas calculated using regression of firm's stock returns on S&P 500. All specifications control for time fixed effects. Standard errors are clustered by firm.

Figure 1: Placebo: Creative patenting and previous year's stock returns

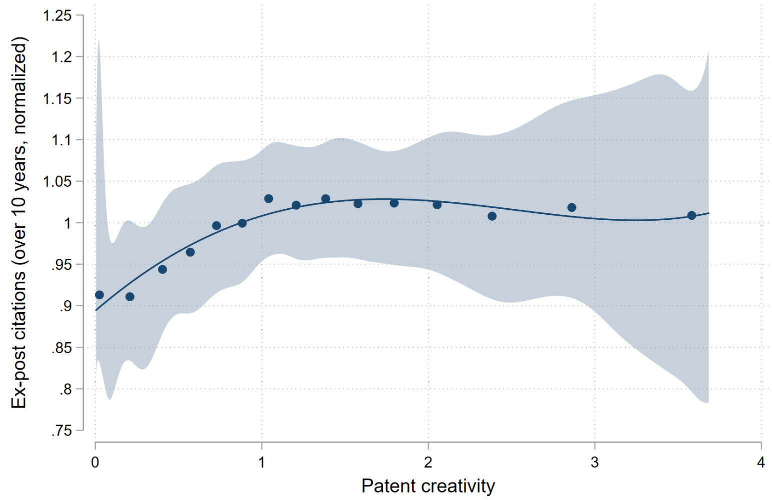
Year before year of patent filing



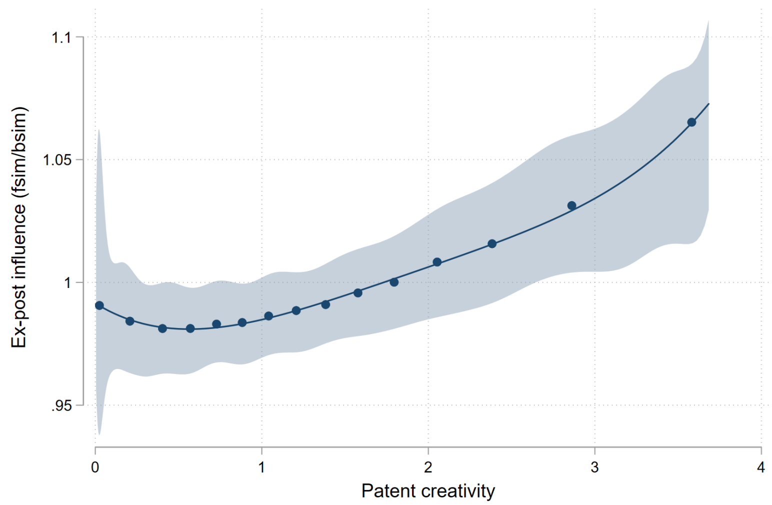
Notes: The table reports coefficients and confidence intervals from a regressions of $\text{stockreturns}_{i,t^{Y-1}}$ of firm i in week t^{Y-1} on $\text{IHS}(\text{creativepatenting}_{i,t^{Y}})$ for firm i in week t^{Y}. Week t^{Y-1} denotes the same calendar week in year $Y-1$ as week t^{Y} in year Y. Specification controls for IHS of R&D spending during the previous five calendar years, and CAPM Betas calculated using regression of firm's stock returns on S&P 500. Detailed specification is provided in equation 3. Standard errors are clustered by firm.

Figure 2: Validation: Patent creativity and follow-on innovations

Panel A: Citations

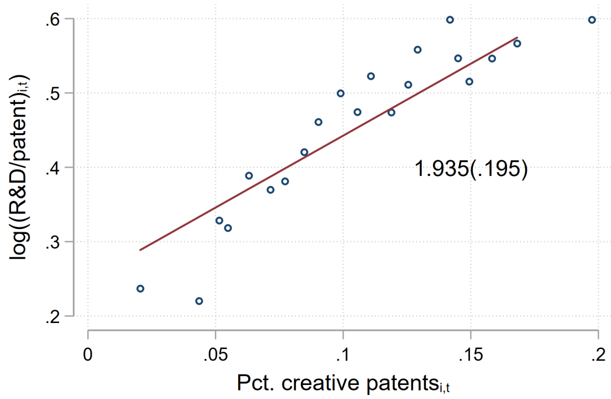


Panel B: Influence - Kelly et al. (2021)



Notes: The figure plots a binned scatter plot of patent creativity$_p$ against citations$_p$ and measure of patent influence(forward/backward similarity$_p$) provided by Kelly et al. (2021). Along with the bins, a polynomial fitted line and confidence intervals for the line have also been added. The sample for this binscatter only includes patents applied for on or before 2000 to allow for enough time to materialize lifetime citations. The regression lines and estimates control for technology class and year fixed effects. Standard errors are clustered by technology class.

Figure 3: Validation: R&D expenditure and creative patenting



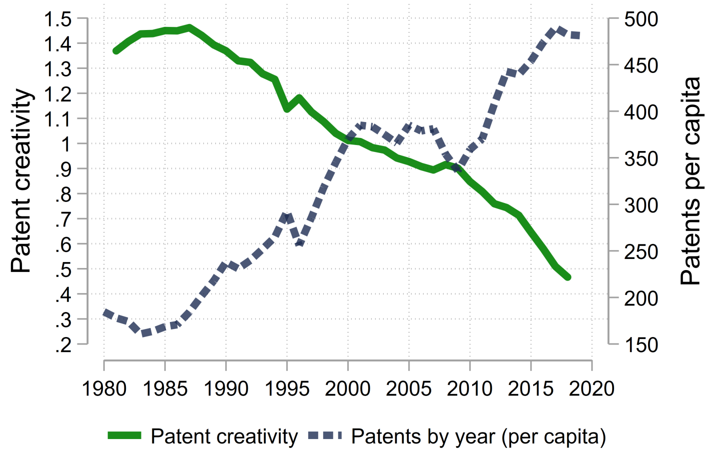
Notes: The figure plots a binned scatter plot of log of R&D expenditure per patent against percentage of creative patents for firm i at time t. R&D expenditure per patent is calculated by dividing yearly R&D expenditure recorded in compustat by the number of patents, and then taking a 5-year moving average. The binscatter controls for 3-digit NAICS industry and year fixed effect. The coefficient of the regression corresponding to the binned scatter plot is reported. Standard errors are clustered by firm.

Table 3: Validation: Patent creativity and academia

	Patent creativity$_p$		
	(1)	(2)	(3)
$1\{\text{Cites academic paper}\}_p$	0.337***	0.236***	
	(0.051)	(0.033)	
$1\{\text{Cites recent academic paper}\}_p$			0.359***
			(0.033)
$1\{\text{Cites older academic paper}\}_p$			–0.026
			(0.023)
Constant	0.913***	0.939***	0.932***
	(0.039)	(0.008)	(0.009)
R^2	0.043	0.078	0.084
N	2,747,115	2,747,115	2,747,115
Year FE	Y	Y	Y
Technology Class FE	N	Y	Y

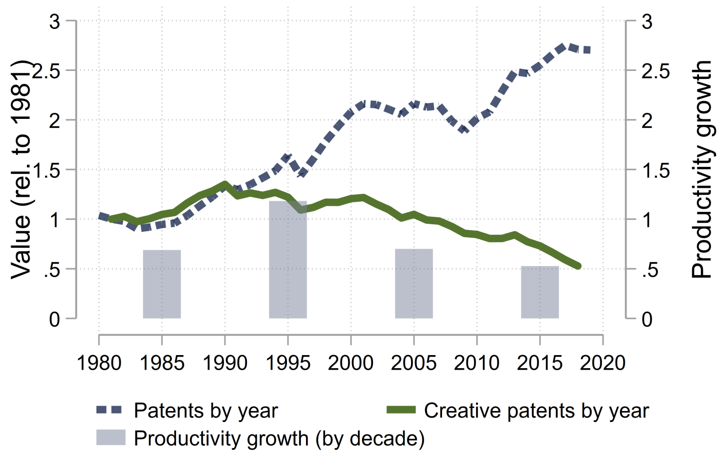
Notes: The table regresses patent creativity for a patent p on a dummy which indicates if the patent cites any academic papers. Column 3 separates academic citations into recent (academic papers published within 5 years before patent filing) and old. Specifications control for 3-digit technology class and filing year fixed effects. Standard error is clustered by firm.

Figure 4: Creativity decline: Average *patent creativity* and number of patents



Notes: The figure plots the number of patents per capita, calculated as patents filed per million people in the US (in blue dashed line), and the average patent creativity of these patents (in green solid line).

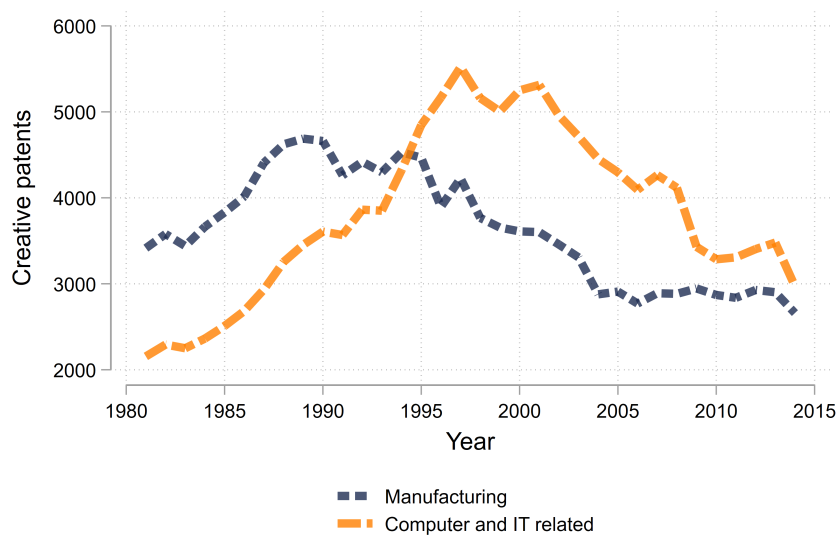
Figure 5: Creativity decline: patents, creative patents, and productivity growth



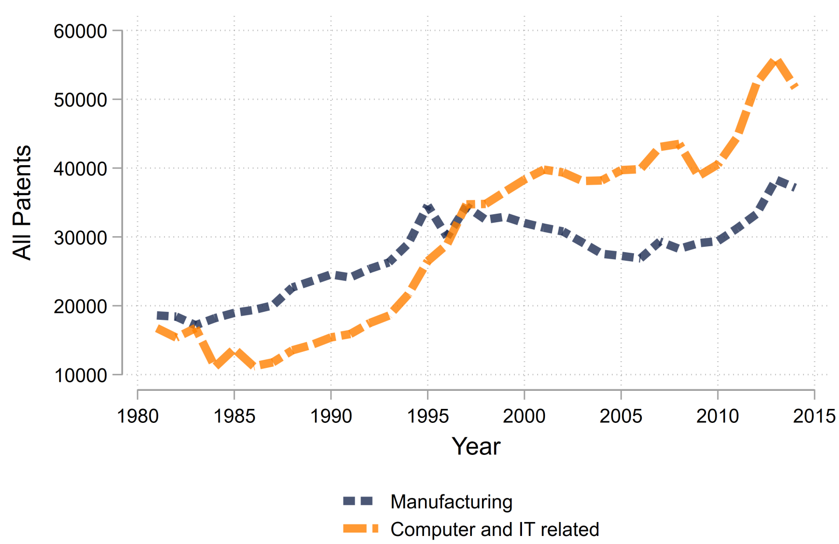
Notes: The figure plots the number of patents per capita (in blue dashed line), the number of creative patents per capita (in green solid line), and US productivity growth by decade. Patents are counted as filings which are eventually granted by year. Patents with patent creativity ≥ 2 are classied as creative, and the rest as derivative. Productivity growth is multi-factor productivity provided by the BEA.

Figure 6: Creative and Overall Patents by Industry

Panel A: Creative Patents



Panel B: All Patents



Notes: The figure plots creative patents (in panel A) and all patents (in panel B) filed year-by-year by U.S. based inventors for computer and IT related industries, and manufacturing (other than computer manufacturing) industries. Industry classification is on the basis of NAICS-4 digit industry codes. Patents with patent creativity ≥ 2 are classied as creative, and the rest as derivative.

Table 4: Patent creativity and firm-level TFP growth

	TFP Growth$_{i,t}$ (5-year differences)					
	(1)	(2)	(3)	(4)	(5)	(6)
ihs(creative patents$_{i,t}$)		0.234***	0.169*	0.215**	0.211**	0.222**
		(0.078)	(0.098)	(0.104)	(0.102)	(0.102)
ihs(derivative patents$_{i,t}$)			0.078	–0.095		
			(0.083)	(0.106)		
ihs(patents$_{i,t}$)	0.164**					
	(0.067)					
ihs(derivative patents - cite wt.$_{i,t}$)					–0.087	
					(0.091)	
ihs(derivative patents - (f/b) wt.$_{i,t}$)						–0.111
						(0.100)
R^2	0.012	0.012	0.012	0.005	0.005	0.005
N	19,020	19,020	19,020	19,012	19,012	19,012
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	N/A	N/A	N/A
Firm FE	N	N	N	Y	Y	Y

Notes: Table reports results from a regression of TFP Growth$_{i,t}$, calculated using 5-year changes in log(TFP) ($log(TFP_{i,t}) - log(TFP_{i,t-5})$), on inverse hyperbolic sine (IHS) of yearly creative and derivative patenting. The sample is a yearly panel of 1,194 manufacturing firms in Compustat which file at least 10 patents during 1991-2014. Creative and derivative patenting is as defined in section 2. All specifications control for IHS of R&D spending during the previous five calendar years, and polynomials of year since initial public offering. Standard errors are clustered by firm.

Table 5: Patent creativity, labor productivity, and investment rate

	$\Delta log(Sales/emp)_{i,t}$		$(I_{i,t}/K_{i,t-1}) * 100$	
	(1)	(2)	(3)	(4)
ihs(CreativePatenting$_{i,t}$)	0.214*	0.214*	0.223***	0.223***
	(0.116)	(0.116)	(0.085)	(0.085)
ihs(DerivativePatenting$_{i,t}$)	–0.166	–0.166	0.037	0.037
	(0.119)	(0.119)	(0.075)	(0.075)
R^2	0.212	0.212	0.377	0.377
N	19,571	19,571	23,070	23,070
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

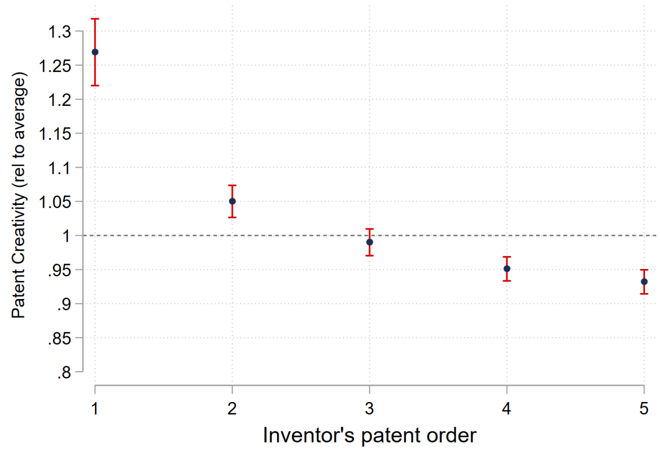
Notes: Table reports results from a regression of $\Delta log(Sales/emp)$ (in cols 1-2) and investment rate $(I_{i,t}/K_{i,t-1}) * 100$ (in cols 3-4) on inverse hyperbolic sine (IHS) of yearly creative and derivative patenting. Investment rate for a firm i in year t is calculated by dividing capital investment and expenditures, and previous year's Property, plant and equipment. The sample is a yearly panel of manufacturing firms in Compustat which file at least 10 patents during 1991-2014. Creative and derivative patenting is as defined in section 2. All specifications control for IHS of R&D spending during the previous five calendar years, and polynomials of year since initial public offering. Standard errors are clustered by firm.

Table 6: Patent creativity and industry-level TFP growth

	TFP Growth$_{i,t}$ (5-year differences)					
	(1)	(2)	(3)	(4)	(5)	(6)
ihs(patents$_{i,t}$)	1.577***					
	(0.323)					
ihs(creative patenting$_{i,t}$)		1.888***	3.315***	1.674**	6.406***	6.278***
		(0.336)	(0.657)	(0.677)	(1.189)	(1.947)
ihs(derivative patenting$_{i,t}$)			–1.518***	–2.773***	–4.517***	–5.812***
			(0.547)	(0.925)	(1.033)	(1.359)
Partial R^2	0.094	0.134	0.146	0.059	0.173	0.097
N	506	506	506	506	506	506
Year FE	N	N	N	Y	N	Y
Industry FE	N	N	N	N	Y	Y

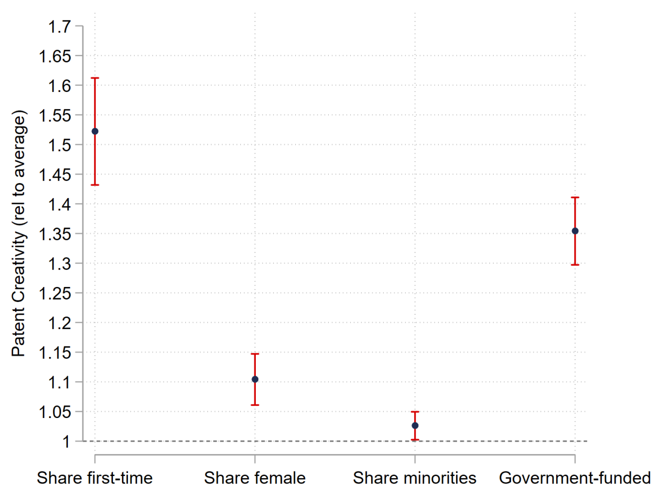
Notes: Table reports results from a regression of TFP Growth$_{i,t}$, calculated using 5-year changes in log(TFP) $(log(TFP_{i,t}) - log(TFP_{i,t-5}))$, on inverse hyperbolic sine (IHS) of yearly creative and derivative patenting. The sample is a yearly panel of industries which file at least 500 patents in the year 2000. Creative and derivative patenting is as defined in section 2. Standard errors are clustered by industry.

Figure 7: Average $PatentCreativity$ by inventor's patenting order



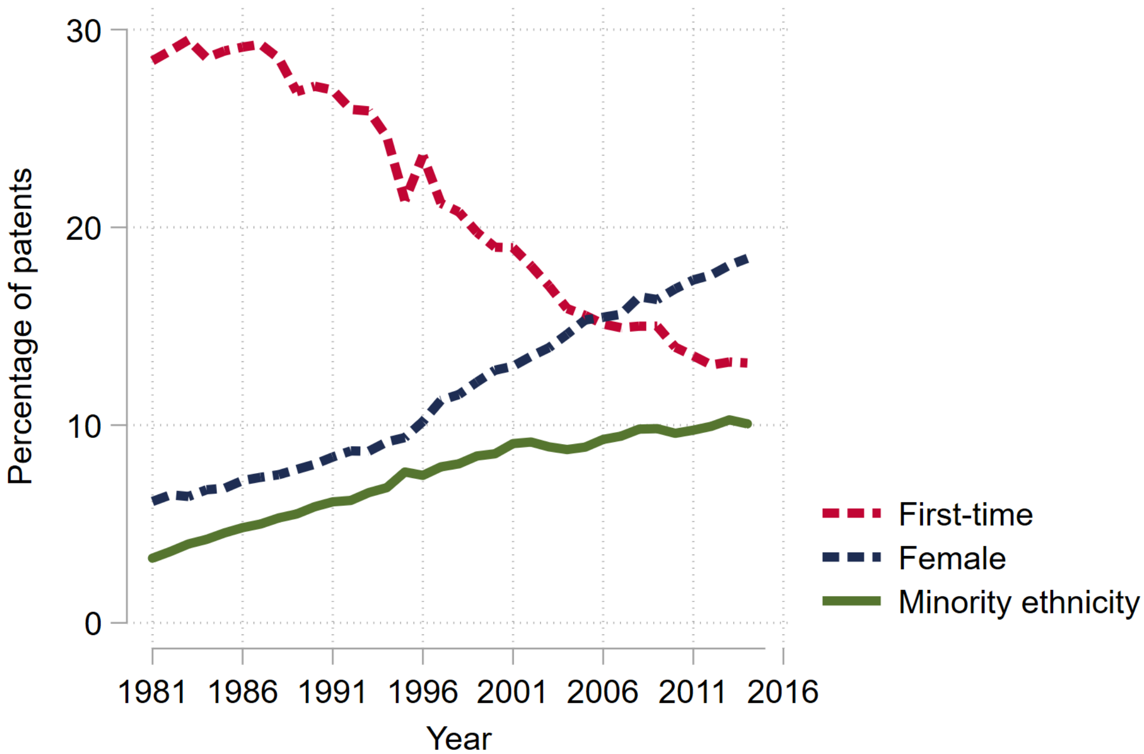
Notes: The figure plots coefficients from a regression of patent creativity on inventors patenting order along with their 95% confidence interval. The first point denotes average creativity of their first patent, second point denotes average creativity of their second patent, and so on. Only inventors who file more than five patents are included in the sample. The regression adds controls for technology class and year fixed effects. Standard errors are clustered by technology class.

Figure 8: $PatentCreativity$: women, minority and government involvement



Notes: The figure plots estimates from a regression of patent creativity on share of female authors, share of minority authors and a dummmy which indicates government involvement in a patent, along with 95% confidence interval for the estimate. The regression adds controls for technology class and year fixed effects. Standard errors are clustered by technology class.

Figure 9: Composition of inventors



Notes: The figure plots the share of patents filed by first-time inventors (in red), share of patents filed by women (in blue) and share of patents filed by inventors of minority ethnicities (in green). The share is weighted by the weight of an inventor in a team of authors. Gender and ethnicity are inferred from inventors names.

Table 7: Model results

	(1) 1950	(2) 1980*	(3) 2010	(4) Chg. 1950-2010	(5) Chg. 1980-2010	(6) Data	(7) Pct. Explained
Prod. Growth	0.0151	0.0148	0.0120	-20.55%	-18.96%	-66%	31.16%
Pct. Creative	0.1222	0.1200	0.0979	-19.84%	-18.39%	-42.86%	42.90%
Entrepreneurs/Innovators per capita	0.1149	0.1200	0.1763	53.49%	46.94%	348.94%	15.33%
Weight of creative technologies	0.8614	0.7808	0.2603	-69.78%	-66.67%	-	-
Adopters	0.0474	0.0475	0.0472	-0.44%	-0.78%	-	-
Avg. creative valuation	8.1678	8.3581	11.6766	42.96%	39.70%	-	-
Avg. derivative valuation	7.0856	6.9750	5.0262	-29.06%	-27.94%	-	-

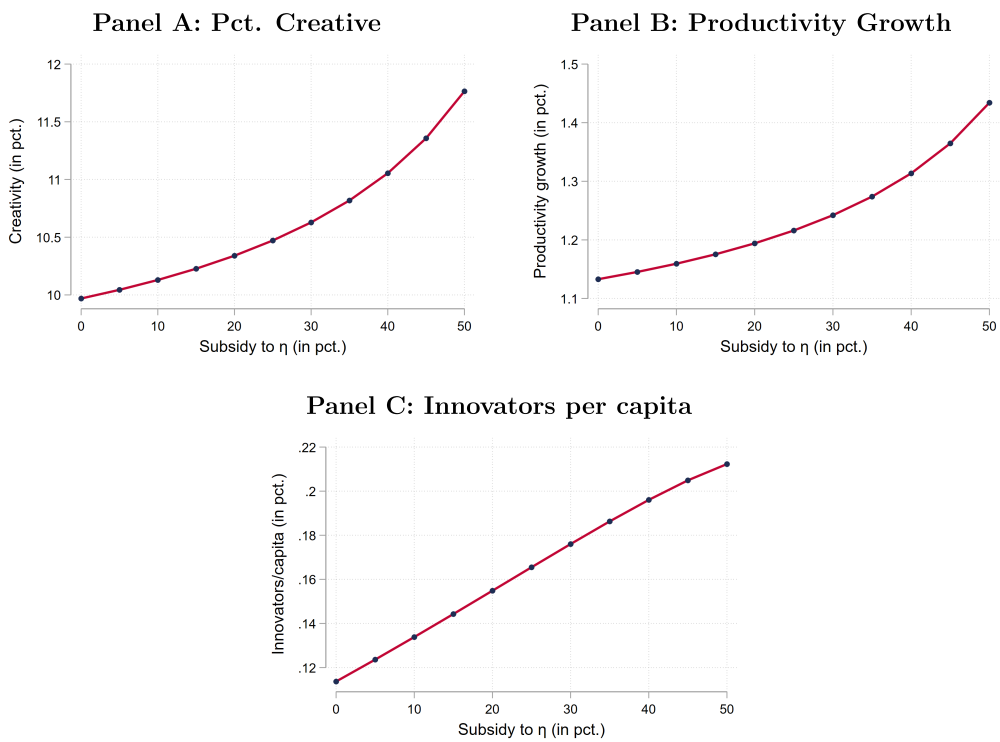
Notes: *** denotes matched cross-section**. The table reports results from decreasing population growth described in section 6. The model is calibrated to match productivity growth, percentage creative entrepreneurs and entrepreneurs per capita during 1980s (col 2), when population growth rate was 2.3%. In column 2 and 3, the results are shown for changing population growth to 2.5% and 0.6%, respectively.

Table 8: Model results - female labor force participation

	(1) 1950	(2) 1980*	(3) 2010	(4) Chg. 1950-2010	(5) Chg. 1980-2010
Participation rate	34%	51%	59%		
Prod. Growth	1.44%	1.48%	1.50%	4.38%	1.27%
Pct. Creative	12.21%	12.53%	12.66%	3.75%	1.08%
Entrepreneurs/Innovators per capita	10.67%	9.82%	9.48%	-11.17%	-3.52%

Notes: *** denotes matched cross-section**. The table reports results from a counterfactual with an increase in labor force participation by women. Column 1 reports the counterfactual productivity growth, creativity and innovators per capita with a labor force participation rate of 34%. In the model that means that 34% of population growth translates into women's labor supply. Columns 2 and 3 evaluate the counterfactual values for increasing values of women's labor supply (51% and 59%).

Figure 10: Model results: government subsidy to technology search cost (η)



Notes: *** denotes matched cross-section**. The figures report results for changing values of government subsidy to *eta* or innovator's fixed cost to search for new technologies. Panel A, plots share of creative innovators, Panel B plots productivity growth, and Panel C plots innovators per capita.

Appendix Tables and Figures

Appendix Table 1: Summary Statistics

	(1) Mean	(2) SD	(3) p01	(4) Median	(5) p99	(6) N
Panel A: Patent level						
Bigrams_p	4003	6202	548	2653	24299	2,749,329
Technical bigrams_p	423	622	3	264	2836	2,749,329
New technical bigrams_p	44	85	0	19	410	2,749,329
Patent creativity_p	1.00	0.96	0.00	0.73	3.86	2,749,329
Panel B: Firm-week level						
Creative $\text{patenting}_{i,t}$	0.03	0.29	0.00	0.00	1.00	1,817,738
Derivative $\text{patenting}_{i,t}$	0.14	0.98	0.00	0.00	3.00	1,817,738
Derivative $\text{patenting}_{i,t}$ (cite-wt)	0.15	1.12	0.00	0.00	4.10	1,817,738
Derivative $\text{patenting}_{i,t}$ (f/b-wt)	0.17	1.20	0.00	0.00	3.62	1,817,738
Stock $\text{returns}_{i,t}$ (weekly, pct.)	0.06	7.51	-23.32	0.00	25.13	1,817,738
Panel C: Firm-year level						
Creative $\text{patenting}_{i,t}$	1.37	7.77	0.00	0.00	28.00	65,811
Derivative $\text{patenting}_{i,t}$	11.10	62.26	0.00	0.00	219.00	65,811
# EC w/ product $\text{introductions}_{i,t}$	1.60	1.46	0.00	1.00	4.00	18,999
$\text{R\&D/Assets}_{i,t}$	0.14	0.24	0.00	0.05	1.26	48,155
$\text{TFPGrowth}_{i,t}$	4.26	8.89	-17.89	3.54	33.06	43,313
$\text{SalesGrowth}_{i,t}$	8.47	17.02	-35.84	6.75	61.50	49,844
$\text{EmpGrowth}_{i,t}$	3.02	12.88	-31.14	2.12	38.30	46,751
Investment $\text{Rate}_{i,t}$	6.30	8.65	0.00	3.91	46.64	62,245

Notes: The table shows summary stats (Mean, standard deviation, 1st percentile, median, 99th percentile and number of observations) for variables used in empirical analysis. Panel A presents summary stats at the patent level. $Bigrams_p$ are the total number of bigrams in a patent. Panel B presents summary stats at the firm-week level used in stock return analysis. Panel C presents summary statistics at the firm-year level.

Appendix Table 2: Top creative patents

Filing year	Assignee	Title	*PatentCreativity*
1997	NGK Insulators, Ltd.	method of producing a polymer lp insulator	11.23
1988	Halliburton Company	slipliner grouting method and system	9.08
2003	The Regents of the University of California	synthesis of libc and hole doped li xbc	8.93
1993	Florida Atlantic University	contracting expanding self sealing **cryogenic tube seal**s	8.91
2003	FireKing International, Inc.	anti prying device for use with a safe	8.82
1989	GTE Products Corporation	method of aligning and gapping arc **lamp electrode**s	8.69
2013	Digimarc Corporation	body worn **phased array antenna**	8.6
1984	Siemens Gammasonics, Inc.	imaging dynodes arrangement	8.55
1992	Helix Technology Corporation	cryopump and cryopanel having frost concentrating device	8.53
1995	George Gordon Associates, Inc.	bulk straw loading system	8.49
1985	Analytic Services, Inc.	satellite continuous coverage constellations	8.45
1989	Teleco Oilfield Services Inc.	method for determining the free point of a stuck drillstring	8.44
1984	Cubic Corporation	**stripline circuit**s isolated by adjacent decoupling **strip portion**s	8.39
2000	Chace Candles, Inc.	flame cover	8.39
2002	Board of Regents, The University of Texas System	devices and methods for **placing wiring** into split loom tubing	8.36
1982	Rosemount Inc.	feedthrough apparatus	8.35
2011	Ford Global Technologies, LLC	electric vacuum pump **backup control** system and method	8.17
2006	Delphi Technologies, Inc.	insulated non halogenated heavy **metal free** vehicular cable	8.14
2003	NXP B.V.	small **hardware implementation** of the subbyte function of rijndael	8.11
1985	Shape Inc.	coined reel leaf spring for a video **tape cassette**	8.07

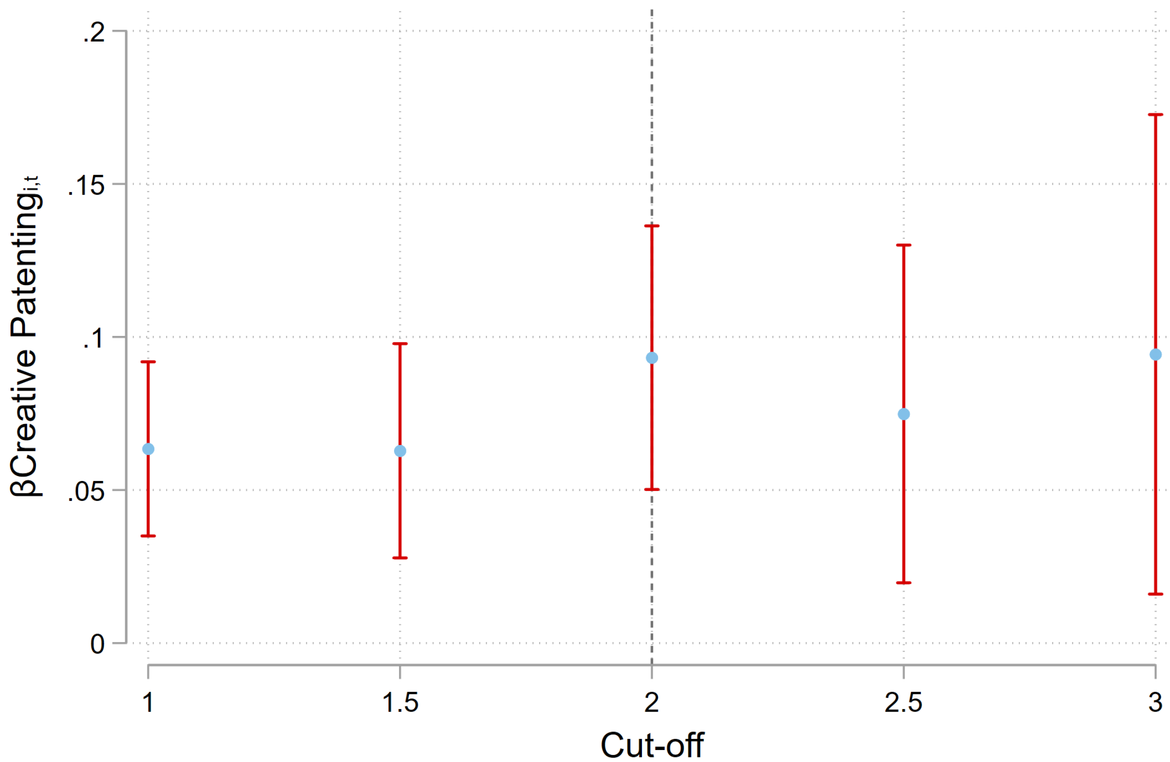
Notes: The table reports top patents by *patent creativity* with their filing year (in column 1), assignee (in column 2), title (in column 3) and *patent creativity* (in column 2). Only patents with at least one creative bigram in the title are reported, and creative bigrams are highlighted in yellow.

Appendix Table 3: Examples of derivative patents

Filing year	Title	Assignee	Citations received
2008	Telepresence robot with a camera boom	INTOUCH TECHNOLOGIES, INC.	75.88
2013	System, method, and apparatus for electric power grid and network management of grid elements	Causam Holdings, LLC	75.36
2012	Shiftable drive interface for robotically-controlled surgical tool	Ethicon Endo-Surgery, Inc.	75.15
2013	Wireless network device	Metrologic Instruments, Inc.	70.07
2013	Using a user's application to configure user scanner	Hand Held Products, Inc.	65.40
2013	Managing data communication between a peripheral device and a host	Honeywell Internation Inc.	65.40
2008	Surgical stapling device having trigger lock and associated lockout mechanism	TYCO Healthcare Group LP	64.92
2011	Structure for attachment of buttress material to anvils and cartridges of surgical stapler	TYCO Healthcare Group LP	64.39
2012	Imaging apparatus having imaging assembly	Welch Allyn Data Collection, Inc.	62.72
2012	Parallel decoding scheme for an indicia reader	Hand Held Products, Inc.	62.00
2011	Surgical stapling apparatus with control features	Ethicon Endo-Surgery, Inc.	60.86
2011	System for using keyword phrases on a page to provide contextually relevant content to users	WordNetworks, Inc.	59.83
2010	System for controlled distribution of user profiles over a network	Cheah IP LLC	59.69
2012	Motor driven surgical cutting instrument	Ethicon Endo-Surgery, Inc.	57.83
2009	Structure for attachment of buttress material to anvils and cartridges of surgical staplers	TYCO Healthcare Group LP	57.54
2008	Methods, systems, and products for gesture-activated appliances	AT&T INTELLECTUAL PROPERTY I, L.P.	56.18
2011	End effector coupling arrangements for a surgical cutting and stapling instrument	Ethicon Endo-Surgery, Inc.	54.92
2012	Articulatable surgical device	Ethicon Endo-Surgery, Inc.	54.81
2010	Adaptor for anvil delivery	TYCO Healthcare Group LP	53.85
2010	Electromechanical driver and remote surgical instrument attachment having computer assisted control capabilities	TYCO Healthcare Group LP	53.42

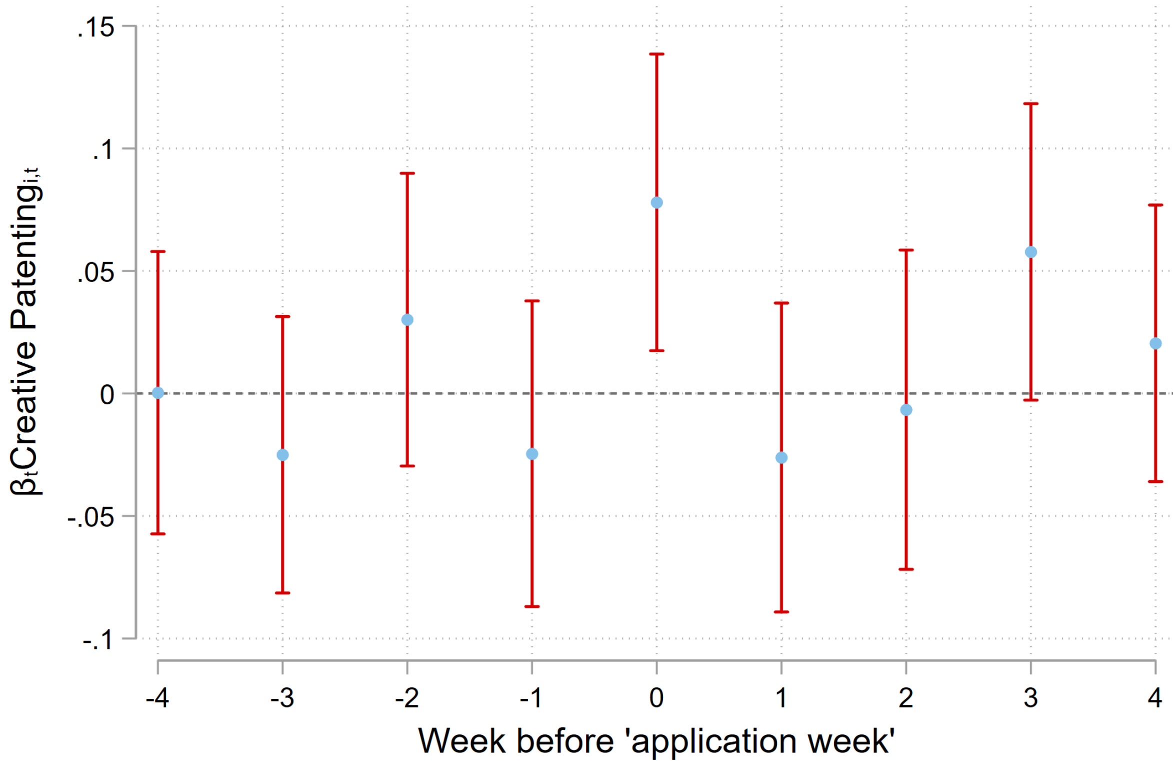
Notes: The table reports derivative patents with zero patent creativity with their filing year (in column 1), assignee (in column 2), title (in column 3) and citations received (in column 4).

Appendix Figure 1: Robustness: Stock returns and creative patenting calculated using different cut-offs on patent creativity



Notes: This figure plots coefficients from a regression of stock returns$_{i,t}$ on creative patenting, calculated using changing cut-offs on patent creativity. Aggregation of patent creativity in creative patenting as described in 2. The coefficients are plotted with their confidence intervals. The specification and sample is same as in table 2. Standard errors are clustered by firm.

Appendix Figure 2: Placebo: Creative patenting and stock returns



Notes: This figure plots coefficients from a regression of stock returns$_{i,t}$ on leads and lags of creative patenting. The coefficients of leads and lags are plotted with their confidence intervals. The specification and sample is same as in table 2. Standard errors are clustered by firm.

Appendix Table 4: Robustness: Stock returns and variations of patent creativity measure

	Stock Returns$_{i,t}$ (weekly)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ihs(creative patenting$_{i,t}$)	0.093***						
	(0.022)						
1{creative patenting $> 0\}_{i,t}$		0.106***					
		(0.028)					
Ihs(total patent creativity$_{i,t}$)			0.042***				
			(0.010)				
Ihs(creative patenting$_{i,t}$ - using title)				0.069***			
				(0.020)			
Ihs(creative patenting$_{i,t}$ - using abstract)					0.070***		
					(0.020)		
Ihs(creative patenting$_{i,t}$ - using desc.)						0.078***	
						(0.021)	
Ihs(creative patenting$_{i,t}$ - using claims)							0.070***
							(0.021)
R^2	0.075	0.075	0.075	0.075	0.075	0.075	0.075
N	1,816,951	1,816,951	1,816,951	1,816,951	1,816,951	1,816,951	1,816,951
Time FE	Y	Y	Y	Y	Y	Y	Y

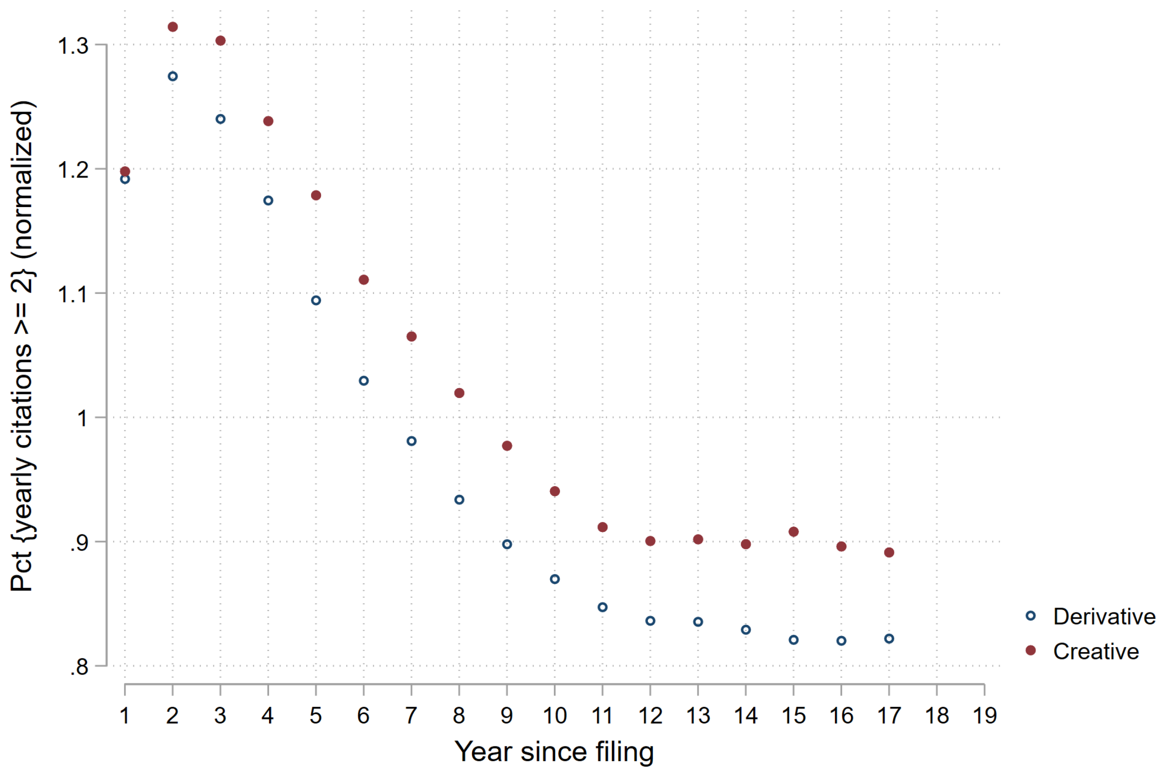
Notes: Table reports regression of stock returns for firm i in week t on variations of measures of creative patenting with the same specification and sample as in Table 2. In col 1, creative patenting$_{i,t}$ is the baseline measure where creative patenting is the number of patents with creativity more than twice the average; in col 2, 1{creative patenting$_{i,t} > 0$} is an indicator for firm granted any created patent in week t; in col 3, total patent creativity$_{i,t}$ is the sum of patent creativity for all patents granted to firm i in week t. In columns 4-7, I calculate creative patenting using different sections of the patent and following the same steps as in section 2. Standard errors are clustered by firm.

Appendix Table 5: *CreativePatenting* and R&D Expenditure

	$(R\&D_{i,t}/Patent_{i,t})$			
	(1)	(2)	(3)	(4)
Creativity per patent$_{i,t}$	0.981***	2.070***	1.935***	0.529***
	(0.189)	(0.213)	(0.195)	(0.153)
R^2	0.015	0.104	0.241	0.866
N	13,010	13,010	13,007	12,869
Year FE	N	Y	Y	Y
Industry FE	N	N	Y	N/A
Firm FE	N	N	N	Y

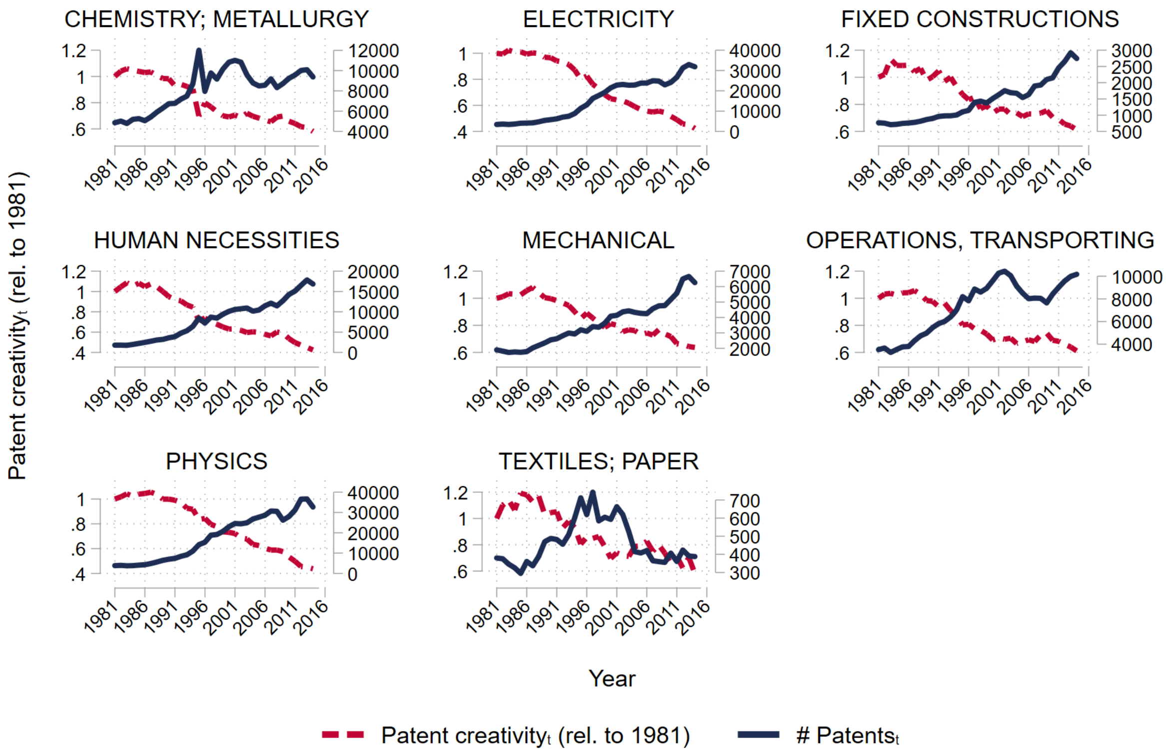
Notes: The table regresses log of R&D expenditure per patent against average creativity per patent for a firm i at time t. R&D expenditure per patent is calculated by dividing yearly R&D expenditure recorded in compustat by the number of patents, and then taking a 5-year moving average. Creativity per patent is calculated as the average creativity of the patents registered by a firm i at time t. The regressions separately control for 3-digit NAICS industry, firm and year fixed effects. Standard errors are clustered by firm.

Appendix Figure 3: Citation patterns of *creative* and *derivative* patents



Notes: The figure plots percentage of patents which receive more than two normalized citations received by a patent year-by-year since filing. To calculate year normalized citations, I normalize citations received by patents year by year by technology class and year. Creative patent is defined as those with a patent creativity twice the technology class average, and other patents are derivative patents.

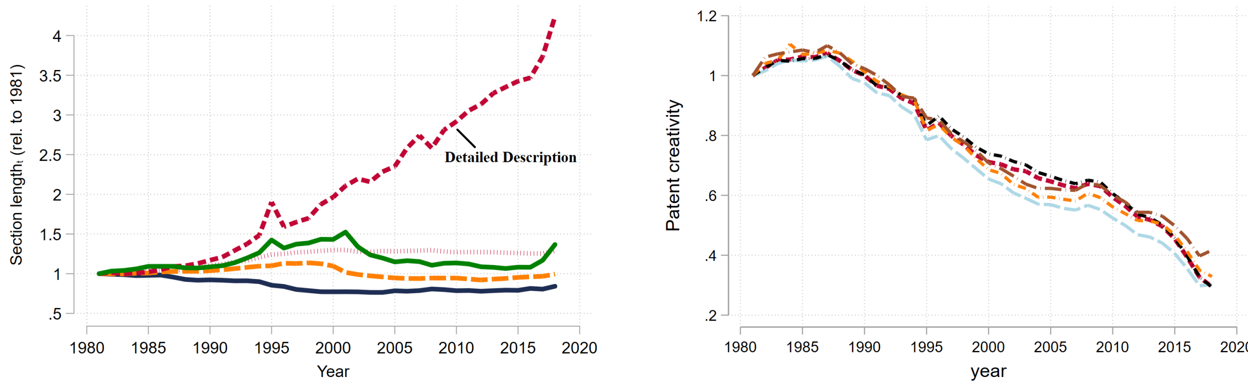
Appendix Figure 4: Robustness: Average *PatentCreativity* by technology class



Notes: The figure plots year-by-year and by primary technology class, the number of patents (in blue solid line) applied, and the average *PatentCreativity* of these patents (in red dashed).

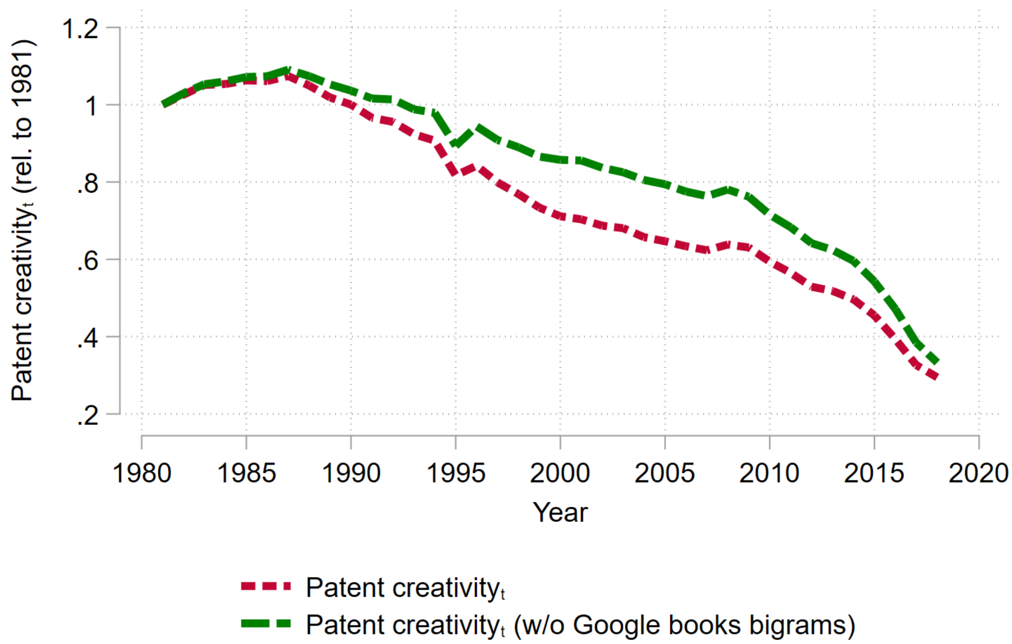
Appendix Figure 5: Robustness: Average *PatentCreativity* calculated using different patent sections

Panel A: Patent section lengths **Panel B: Patent creativity, by section**



Notes: The figure plots the average *PatentCreativity* of these patents applied for year-by-year by U.S. based inventors calculated separately for each section in a patent.

Appendix Figure 6: Robustness: Average *PatentCreativity* without language trends



Notes: The figure plots the average *PatentCreativity* of these patents applied for year-by-year by U.S. based inventors calculated by removing any bigram mentioned in any book published five years before a patent is filed. The set of books is downloaded from publicly available Google books dataset.

Appendix Table 6: Comparison: Patent Creativity, TFP Growth, and other measures of originality

	TFP Growth$_{i,t}$ (5-year differences)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ihs(creative patents$_{i,t}$)		0.268*		0.221		0.229**		0.219*
		(0.154)		(0.181)		(0.116)		(0.117)
ihs(original patents$_{i,t}$ - bck sim.)	–0.047	–0.145						
	(0.158)	(0.168)						
ihs(non-original patents$_{i,t}$ - bck sim.)	–0.019	–0.099						
	(0.129)	(0.140)						
ihs(original patents$_{i,t}$ - cites HHI)			–0.252	–0.297*				
			(0.182)	(0.179)				
ihs(non-original patents$_{i,t}$ - cites HHI)			0.026	–0.061				
			(0.166)	(0.195)				
ihs(original patents$_{i,t}$ - acad. cites)					–0.033	–0.088		
					(0.129)	(0.133)		
ihs(original patents$_{i,t}$ - acad. cites)					0.054	–0.017		
					(0.093)	(0.101)		
ihs(original patents$_{i,t}$ - claims)							0.092	0.056
							(0.124)	(0.128)
ihs(original patents$_{i,t}$ - claims)							–0.013	–0.088
							(0.099)	(0.110)
R^2	0.313	0.313	0.369	0.369	0.235	0.235	0.235	0.235
N	11,881	11,881	8,127	8,127	18,832	18,832	18,832	18,832
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes:Table reports results from a regression of TFP Growth$_{i,t}$, calculated using 5-year changes in log(TFP) ($log(TFP_{i,t}) - log(TFP_{i,t-5})$), on inverse hyperbolic sine (IHS) of yearly creative patenting along with other measures of patent originality. Original patent are defined using previously proposed measures of patent originality: In col 1-2, backward looking text similarity (Kelly et al. (2021)); in col 3-4, distribution of citations across technology classes (Hall et al. (2001)); in col 5-6, number of academic citations (Watzinger and Schnitzer (2019)); in col 7-8, number of claims of invention in a patent (Lanjouw and Schankerman (2004)). Similar to a creative patent, for a continuous measure of originality, an original patent is defined as one which has originality twice the average in its technology class. The sample is a yearly panel of firms which file at least 10 patents during 1991-2014. Creative and derivative patenting is as defined in section 2. All specifications control for IHS of R&D spending during the previous five calendar years, and polynomials of year since initial public offering. Standard errors are clustered by firm.

Appendix Table 7: Robustness: Creative patenting, and investment rate

	$(I_{i,t}/K_{i,t-1}) * 100$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ihs(creative patents$_{i,t}$)		0.440***	0.265***		0.241***	0.223***	0.186**	0.213**
		(0.079)	(0.085)		(0.089)	(0.085)	(0.089)	(0.086)
ihs(derivative patenting$_{i,t}$)			0.202***			0.037		
			(0.065)			(0.075)		
ihs(patenting$_{i,t-1}$)	0.328***			0.116				
	(0.059)			(0.076)				
ihs(derivative patenting - cite wt.$_{i,t}$)							0.112*	
							(0.066)	
ihs(derivative patenting - (f/b) wt.$_{i,t-1}$)								0.057
								(0.072)
R^2	0.181	0.181	0.182	0.377	0.377	0.377	0.377	0.377
N	23,070	23,070	23,070	23,070	23,070	23,070	23,070	23,070
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	N/A	N/A	N/A	N/A	N/A
Firm FE	N	N	N	Y	Y	Y	Y	Y

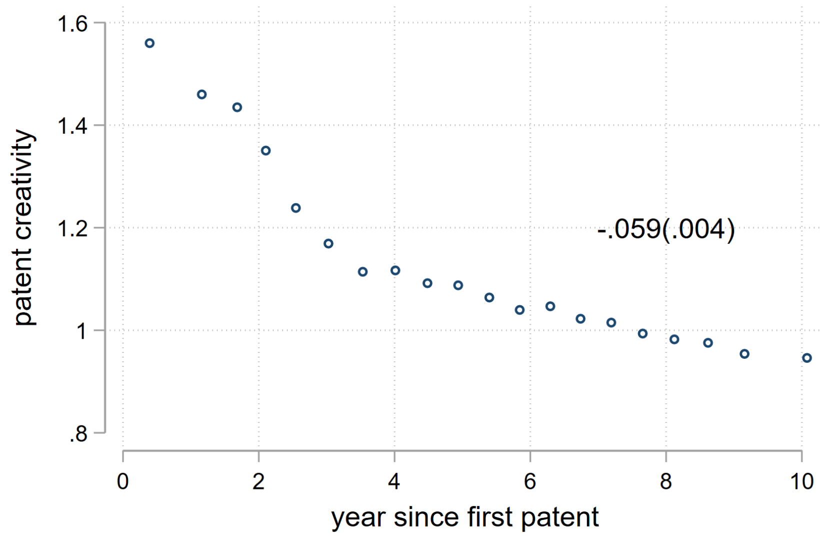
Notes: Table reports results from a regression of investment rate $(I_{i,t}/K_{i,t-1}) * 100$ on inverse hyperbolic sine (IHS) of yearly creative and derivative patenting. Investment rate is calculated by dividing capital investment and expenditures, and past year's Property, plant and equipment. The sample is a yearly panel of manufacturing firms which file at least 10 patents during 1991-2014. Creative and derivative patenting is as defined in section 2. All specifications control for IHS of R&D spending during the previous five calendar years, and polynomials of year since initial public offering. Standard errors are clustered by firm.

Appendix Table 8: Robustness: Patent creativity, employment growth, and sales growth

	$\Delta log(Emp_{i,t})$		$\Delta log(Sales_{i,t})$	
	(1)	(2)	(3)	(4)
ihs(CreativePatents$_{i,t}$)	0.586***	0.586***	0.716***	0.716***
	(0.153)	(0.153)	(0.197)	(0.197)
ihs(DerivativePatents$_{i,t}$)	1.145***	1.145***	0.942***	0.942***
	(0.162)	(0.162)	(0.214)	(0.214)
R^2	0.426	0.426	0.379	0.379
N	19,724	19,724	20,679	20,679
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

Notes: Table reports results from a regression of employment growth and sales growth on inverse hyperbolic sine (IHS) of yearly creative and derivative patenting. Employment growth and sales growth is calculated using 5-year changes in log(emp) and log(sales) ($log(emp_{i,t}) - log(emp_{i,t-5})$). The sample is a yearly panel of manufacturing firms which file at least 10 patents during 1991-2014. Creative and derivative patenting is as defined in section 2. All specifications control for IHS of R&D spending during the previous five calendar years, and polynomials of year since initial public offering. Standard errors are clustered by firm.

Appendix Figure 7: Robustness: Average patent creativity by year since first patent



Notes: The figure plots a binned scatter plot of patent creativity for inventors against year since their filed their first patent. The plot controls for technology class and year fixed effects.

Appendix Table 9: Public funding and *patent creativity*

	Patent creativity$_p$			
	(1)	(2)	(3)	(4)
Government owned$_p$	0.487***			
	(0.027)			
Government funded$_p$		0.335***		
		(0.025)		
Cites govt owned patent$_p$			–0.026***	
			(0.009)	
Cites govt funded patent$_p$				–0.019***
				(0.001)
$Partial R^2$	0.012	0.020	0.002	0.007
R^2	0.120	0.128	0.111	0.116
N	478,798	478,798	478,798	478,798
Year FE	Y	Y	Y	Y
Technology-class FE	Y	Y	Y	Y

Notes: Table reports results from a regression of Patent creativity$_p$ on status of government involvement in the patent. Government owned$_p$ indicates if the patent is assigned to a government entity, and Government funded$_p$ indicates if the patent received a government funding. Cites govt owned patent$_p$ and cites govt funded patent$_p$ indicates if the patent cites a government owned patent or government funded atent. Standard errors are clutered by technology class.

Appendix Table 10: Robustness: First-patent and patent creativity by decade

	Patent creativity$_p$			
	(All)	(1980s)	(1990s)	(2000s)
	(1)	(2)	(3)	(4)
First-time patent$_p$	0.434***	0.429***	0.441***	0.420***
	(0.026)	(0.033)	(0.025)	(0.030)
Constant	0.884***	1.325***	1.034***	0.777***
	(0.005)	(0.010)	(0.006)	(0.005)
R^2	0.099	0.083	0.082	0.052
N	5,641,924	465,570	1,387,335	3,789,019
Year FE	Y	Y	Y	Y
Technology-class FE	Y	Y	Y	Y

Notes: Table reports results from a regression using inventor x patent level sample of patent creativity$_p$ on a dummy which indicates whether p is the inventor's first patent. Columns (2), (3) and (4) repeat the regression restricting the sample decade by decade. Standard errors are clustered by technology class.

Appendix Table 11: Robustness: Stock returns, new-entry patents and patent creativity

	Stock returns$_{i,t}$ (weekly)			
	OLS			IV
	(1)	(2)	(3)	(4)
Ihs(creative patents$_{i,t}$)	0.093***		0.077***	0.121***
	(0.022)		(0.030)	(0.036)
Ihs(new-entry patents$_{i,t}$)		0.072***	0.026	
		(0.020)	(0.028)	
R^2	0.075	0.075	0.075	0.000
N	1,816,951	1,816,951	1,816,951	1,816,951
Controls	Y	Y	Y	Y
Week FE	Y	Y	Y	Y

Notes: Table reports results from a regression of Patent creativity$_p$ on status of government involvement in the patent. Government owned$_p$ indicates if the patent is assigned to a government entity, and Government funded$_p$ indicates if the patent received a government funding. Cites govt owned patent$_p$ and cites govt funded patent$_p$ indicates if the patent cites a government owned patent or government funded atent. Standard errors are clutered by technology class.

Appendix Table 12: Drivers of patent creativity

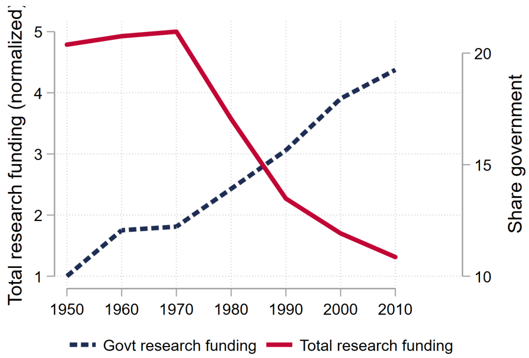
	Patent creativity$_p$				
	(1)	(2)	(3)	(4)	(5)
Share first-time authors$_p$	0.632***				0.618***
	(0.046)				(0.044)
Share female author$_p$		0.109***			0.058***
		(0.022)			(0.016)
Share minority authors$_p$			0.031***		0.027***
			(0.012)		(0.010)
Government owned patent$_p$					
Constant	0.891***	0.994***	0.998***	0.984***	0.872***
	(0.008)	(0.001)	(0.001)	(0.001)	(0.008)
$Partial R^2$	0.045	0.001	0.000	0.007	0.051
R^2	0.136	0.095	0.095	0.101	0.140
N	2,315,429	2,315,429	2,315,429	2,315,429	2,315,429
Year FE	Y	Y	Y	Y	
Technology Class FE	Y	Y	Y	Y	

Notes: Table reports results from a patent creativity$_p$ on the share of women authors (column 1) and the share of minority authors (column 2). Columns 3 and 4, add interactions of share of minority and women authors with a dummy of whether the patent is a first-patent of the inventor. All specifications control for technology class and year fixed effects. Standard errors are clustered by technology class.

Appendix Figure 8: Declining share of public R&D

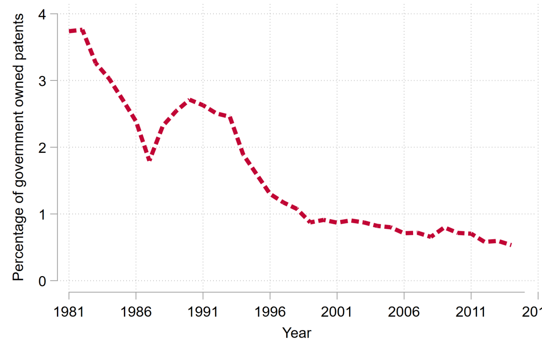
Panel A

Government and private R&D funding



Panel B

Pct. govt. owned patents



Notes: The figure plots (in Panel A) government and total R&D funding accounted by the National Science Foundation. Total R&D spending in 1950 is normalized to 1. In Panel B, the figure shows the percentage of patents which are assigned to government entities.