Heterogeneous Innovation over the Business Cycle*

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Abstract: Schumpeter (1939) claims that recessions are periods of "creative destruction," concentrating innovation that is useful for the long-term growth of the economy. However previous research finds that standard measures of firms' innovation, such as R&D expenditures or raw patent counts, concentrate in booms. We argue that these simple measures do not capture shifts in firms' innovative search strategies. We introduce a model of firms' choice between exploration vs. exploitation over the business cycle and find evidence with more nuanced measures of patent characteristics that firms shift towards exploration during contractions and exploitation during expansions, with a stronger effect for firms in more cyclical industries.

Keywords: Innovation, Business Cycles, Patents

JEL Codes: O31, O32

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1. Introduction

Schumpeter (1939) argues that recessions are times of creative destruction, during which increased innovation fuels enhancements in productivity and the retirement of old technologies. A large body of theoretical work – including Cooper and Haltingwanger (1993), Caballero and Hammour (1994), Aghion and Saint-Paul (1998), and Canton and Uhlig (1999) – has formalized Schumpeter's thesis. This literature typically builds upon the simple idea that the opportunity cost of firms' innovative activities, i.e. the foregone sales that could have been achieved instead, drops in recessions. Stated another way, during recessions, firms should focus on long-run investments since expected profits in the short run are low anyways. During expansions, firms should focus on satisfying current customers' demands and consolidating and harvesting their current technology trajectory.

A number of famous anecdotes about firms' innovations are often adduced to support the Schumpeterian image of creative destruction. Dupont's dominance in the mid 20th century can be directly traced to the inventions from Wallace Caruthers' lab and others during the depression, including neoprene (1930), nylon (1935), teflon (1938), and polyester (1941). Following WWII and the accompanying downturn, Percy Spencer invented the microwave oven in 1946, and in 1947 Shockley, Bardeen, and Brattain at Bell Labs invented the transistor, which in turn enabled the electronics, information, and artificial intelligence revolutions. Schumpeterian thinking would also predict the flip side of incremental and steady development during expansions, though such innovations, while important, provide less compelling images.

Despite the plausible models and salient anecdotes, much systematic evidence suggests that firms do not take the opportunity to replenish the stock of productivity enhancing innovations during downturns. Typically measured by R&D expenditures and raw patent counts, most empirical work to date finds innovative activities to be procyclical (Griliches 1990, Geroski and Walters 1995, Fatas 2000, Rafferty 2003, Walde and Woitek 2004, and Comin and Gertler 2006, Kopytov, Roussanov, and Taschereau-Dumouchel, 2018). Field (2003) offers rare evidence in favor of the Schumpeterian hypothesis with time series measures of productivity. Yet most of the empirical work presents a conundrum; based on measures of R&D spending and patent counts, the data clearly reject the theoretical predictions of countercyclical innovation.

A variety of explanations have been proposed to explain the contrary evidence, for example, that firms invent in downturns but delay the commercialization of their inventions until demand increases (Schleifer 1986, Francois and Lloyd-Ellis 2003), that fear of appropriation encourages pro-cyclical innovation (Barlevy 2007), that credit constrained firms are less likely to invest in counter-cyclical innovation (Aghion et al. 2012), that pro-cyclical innovation is more likely in industries with faster obsolescence and weak intellectual property protection (Fabrizio and Tsolmon 2014), and that inventors become less productive during downturns, due to a deterioration in their household balance sheet (Bernstein, McQuade, and Townsend 2018).

To resolve this conundrum, we model innovative search as a tension within firms between exploration (the pursuit of novel to the firm approaches) versus exploitation (the refinement of existing technology that is known to the firm). Confirming and building upon recent work (Fabrizio and Tsolmon 2014), we observe this tension empirically with a patent-based measure of technological proximity (derived from Jaffe 1989) across time within each firm. Firms shift their search strategies towards exploration during downturns and exploitation during expansions. The results hold with and without controls and are robust to alternate models and measures of proximity and search.

The model begins with the assumption that innovation results from experimentation with new ideas (Arrow 1969). The central tension that arises in experimentation lies between exploration and exploitation (March 1991). Exploration involves search, risk-taking and experimentation with new technologies or new areas of knowledge. Exploitation, on the other hand, is the refinement of existing and familiar technologies. Exploration is more expensive due to an increased probability of failure and the learning that it requires to commercialize new technologies. Because the opportunity cost of exploratory activities – the additional output or sales that could have been achieved instead by a slightly refined product – is lower in recessions, firms have incentives to undertake such activities in downturns. At the same time, during booms, firms have incentives to engage in exploitation, to avoid losing profits from the high sales of its current products. As a consequence, the model predicts that exploration is countercyclical while exploitation is procyclical. Moreover, results should be more pronounced in cyclical industries.

The model and predictions are related to the literature on incentives for innovation (e.g. Holmstrom 1989; Aghion and Tirole 1994). Modelling the innovation process as a simple bandit problem, Manso (2011) finds that tolerance for early failure and reward for long-term success is optimal to motivate exploration. A similar principle operates in our model. During recessions, profit is low regardless of the action pursued, and thus the firm is more tolerant of early failures. Moreover, future profits look more promising than the present, and thus there will be increased rewards for long-term success. Our model starts from the perspective of an individual firm and asks when it is more or less likely to leave already known to the firm paths.

To measure exploration and exploitation we rely on patent data. However, we differentiate between patents filed in new to the firm technology classes and patents filed in known to the firm technology classes. We observe the distribution of the number of patents (in year of application) per technology class and firm. Consistent with Jaffe (1989) and Bloom et al. (2013), we then calculate the similarity between the distribution of patents across technology classes applied by a given firm in year *t* and the same firm's prior distribution of patents across technology classes. The technological profiles of firms that exploit will look more similar to their past profiles; those that explore will look more different from year to year. Using this more nuanced view of innovation and within firm search strategy, we predict and find that innovative exploration is countercyclical while exploitation is procyclical within our sample of patenting firms observed from 1958 through 2008. Moreover, we predict and find stronger results for firms in more cyclical industries. While the results are not causal, in the sense that they rely on historically observed business cycles, the results remain robust to a wide variety of estimations, alternative measures, and data cuts.

Moving beyond the model's immediate predictions, we explore the mechanisms and implications of how firms shift their innovation search strategies over the business cycle. We find that the proportion of new to the firm inventors increases during recessions, and that inventors' patents are more likely to be in classes they had not previously invented in personally. Consistent with a technology life cycle model, and providing an analogy to exploration and exploitation, innovation shifts towards product innovation during recessions and process innovation during expansions. The influence of the business cycle on innovative search strategies appears to be less in high appropriability industries (Fabrizio and Tsolmon 2014). Turning to implications, while firms may patent less during downturns, the average value of their patents (as measured by future prior art citations) increases. The exploration shift induced by the business cycle also induces patents that contribute greater increases in a firm's labor and sales productivities.

This work joins a growing and more sophisticated literature that looks beyond R&D expenditure or patent and citation counts to measure different types and nuances of innovation. For example, Akcigit and Kerr (2018) develop a growth model to analyze how different types of innovation contribute to economic growth and how the distribution of firm size can have important consequences for the types of innovations realized. Babina and coauthors (2019) find that while the volume of patenting declined in the Great Depression, the quality did not. They document a mechanism whereby eminent independent inventors moved inside of surviving firms, particularly within distressed regions. Kelly et al. (2018) construct a quotient where the numerator compares a patent's lexical similarity to future patents and the denominator to past patents. This explicitly incorporates future development of successful search and novelty and clearly identifies technological pivots and breakthroughs. Patents which score highly on this metric correlate with future productivity of the firm, sector, and firm. Brav et al. (2018) use overlap in citation data to characterize exploratory patents and Balsmeier, Fleming and Manso (2017) use several simple patent-based measures to show that independent boards shift a firm towards exploitation strategies.

One conceptual difference of our work compared to many others on heterogeneous innovation is the within firm perspective. We model innovative search as the tension between exploration and exploitation within firms. This implies that some type of exploratory innovative search from a firm's perspective might not be exploratory from another firm's perspective, or novel to the world. We assume that firms that move out of their known territory are more likely to work on new to world inventions but it is worthwhile to note that neither our model nor our empirics make explicit claims about this.

The results ultimately imply that changes within firms' search strategies can bolster economic resiliency and perhaps cast a more positive view of the welfare effects of macroeconomic fluctuations. If negative economic shocks indeed encourage growth-enhancing exploration, economic recessions would tend to be shorter and less persistent than they would be otherwise. This positive contribution might be even more important, if there exists an inherent bias towards exploitation, for example, due to the imperfect protection of property rights, or the difficulty of commercializing new technologies and appropriating their profits for the inventing firm.

2. Theoretical Motivation

We introduce, in the appendix, a simple model of exploration and exploitation over the industry business cycle. The model is based on the simple two-armed bandit problem studied in Manso (2011), but incorporates macroeconomic shocks. We formally derive the hypotheses in this section as propositions in the appendix.

In the model, a representative firm can explore a new technology or exploit a conventional technology. When the firm explores a new technology, it sacrifices short-term payoffs since the new technology has a lower chance of success. At the same time, such experimentation with a new technology provides the firm with useful knowledge that enhances firm profits in the long-run. Exploitation, on the other hand, guarantees reasonable profits both in the short- and long-run, but induces a lower learning rate.

The economy fluctuates between two macroeconomic states: booms and recessions. During recessions, sales are low regardless of the technology adopted. As such, the opportunity cost of experimentation is also low. At the same time, future sales are expected to be higher when the economy leaves a recession, making any knowledge obtained currently more valuable. Therefore, firms have incentives to prioritize exploration in recessions.

During booms, sales are high. As such, the opportunity cost of experimentation is also high. Therefore, firms have incentives to stick to their proven technologies, making only small adjustments to (essentially just fine-tuning) their products. They focus on sales and fulfilling current orders, rather than researching and designing new products. Given that profits can be quickly and immediately harvested in booms, firms reap and exploit the benefits from prior exploration.

Hypothesis 1: Firms are more prone to explore in recessions than in booms.

How should results vary with industry cyclicality? More cyclical industries respond more strongly and significantly to the macroeconomic conditions. This amplifies the sensitivity of a firm's innovation strategy to the business cycle, argued in Hypothesis 1.

Hypothesis 2: The innovation strategies of firms in cyclical industries are more sensitive to business cycles.

3. Empirics

3.1. Data

The empirical analysis is based on the joint availability of firm level data from three sources: 1) public US based firms in Compustat, 2) disambiguated patent assignee data from Kogan et al. (2017), the United States Patent and Trademark Office, and the Fung Institute at UC Berkeley (Balsmeier et al. 2018), and 3) the NBER-CES Manufacturing Industry Database (Bartelsman & Gray, 1996). We build firm level patent portfolios by aggregating eventually granted US patents from 1958 (first year of availability of the NBER-CES industry data) through 2011 inclusive (last year of availability of the NBER-CES industry data). As we base our analysis on measures that have no obvious value in case of non-patenting activity or first time patenting activity, we only include firms in the analysis that applied for at least one patent in a given year, and patented at least once in any previous year, taking all patents granted to a given firm back to 1926 into account when calculating a firm's known classes. The match with the NBER-CES database reduces the sample to manufacturing industries. While this misses recent shifts in the innovative economy towards software and services, manufacturing firms still account for about 70 to 80% of the economy wide R&D spending since 1990 and about 90% beforehand (Barlevy, 2007). Finally, we restrict the sample to firms that we observe at least twice and have non-missing values in any control variable. The final dataset is an unbalanced panel of 24,419 firm year observations on 2,130 firms in 123 manufacturing industries, observed between 1958 and 2011.

Following Barlevy (2007), we measure industry output at the 4-digit SIC industry level.[1] We take the same measure of industry output as our predecessors, namely the value added and material costs per industry, deflated by each industries' shipments deflator as provided by the

[1] Results are robust to higher aggregation to the 3-digit SIC industry level (see Appendix table A12). This level is less precise but also less likely to pick any unobserved time-varying change in firm characteristics.

NBER-CES database.[2] R&D expenses, sales and capital are deflated by the official IMF US price inflation index. Table 1 presents summary statistics and Table 2 provides correlations.

Table 1 – Summary statistics

Variable	N	mean	Median	sd	min	max
Innovative Search	24419	0.40	0.32	0.32	0.00	1.00
Patents	24419	42.15	7	133.47	1	2544
Log(R&D)$_{t-1}$	24419	2.25	2.14	2.04	-4.90	8.80
Log(Sales)$_{t-1}$	24419	12.53	12.64	1.44	1.44	19.10
Log(Employees)$_{t-1}$	24419	1.77	1.50	1.41	0	6.78
Log(Capital)$_{t-1}$	24419	4.19	4.12	2.45	-4.82	11.52
Log(Output)$_{t-1}$	24419	9.59	9.39	1.74	3.09	15.38

Notes: This table reports summary statistics of variables used in the study. Sample covers all public US firms covered by Compustat that patented at least twice between 1958 and 2008. Innovative search is the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). R&D, sales and capital (property, plant, and equipment) are from Compustat and deflated by the IMF price index. Output is value added and material costs per SIC 4-digit manufacturing industry, deflated by each industries' shipments deflator as provided by the NBER-CES database.

Table 2 - Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	Innovative Search	1.000					
(2)	Patents	-0.254	1.000				
(3)	Log(R&D)$_{t-1}$	-0.342	0.421	1.000			
(4)	Log(Sales)$_{t-1}$	-0.163	0.347	0.532	1.000		
(5)	Log(Employees)$_{t-1}$	-0.190	0.383	0.529	0.903	1.000	
(6)	Log(Capital)$_{t-1}$	-0.197	0.364	0.560	0.931	0.909	1.000
(7)	Log(Output)$_{t-1}$	-0.134	0.202	0.316	0.171	0.117	0.192

Notes: This table reports pairwise correlations of the variables used in the study. Sample covers all public US firms covered by Compustat that patented at least twice between 1958 and 2011. Innovative search is the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). R&D, sales and capital (property, plant, and equipment) are from Compustat and deflated by the IMF price index. Output is value added and material costs per SIC 4-digit manufacturing industry, deflated by each industries' shipments deflator as provided by the NBER-CES database.

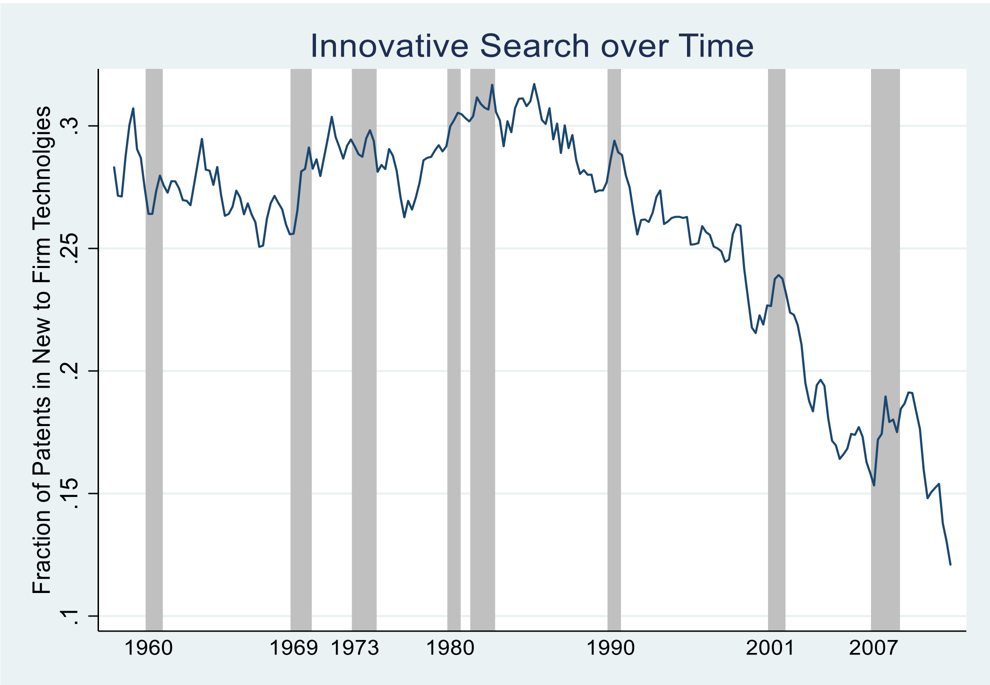
3.2. Descriptive analysis

Before econometric analyses we provide two descriptive and motivating illustrations. We define a patent as explorative if its main technology class is new to the firm and exploitative if its main technology class is known to the firm, taking all patenting of a given firm during the

[2] Results are robust to measure industry output by total shipments (see Appendix table A11).

5 years prior to the year a given patent is applied for (we demonstrate similar results with a variety of robustness checks in Appendix B). Figure 1 illustrates how the average fraction of explorative patenting per firm varies over our sampling period from 1958 thru 2011, for listed firms with at least 10 patents filed in a given year to reduce noise. Measures are calculated on a quarterly basis and smoothed over three quarters. The gray shaded areas mark recessions as defined by the NBER. Though the relationship remains noisy, Figure 1 indicates that firms are more likely to increase their exploration efforts during recessions. Even more clearly, firms decrease their exploration during expansions, especially since 1980.

Figure 1

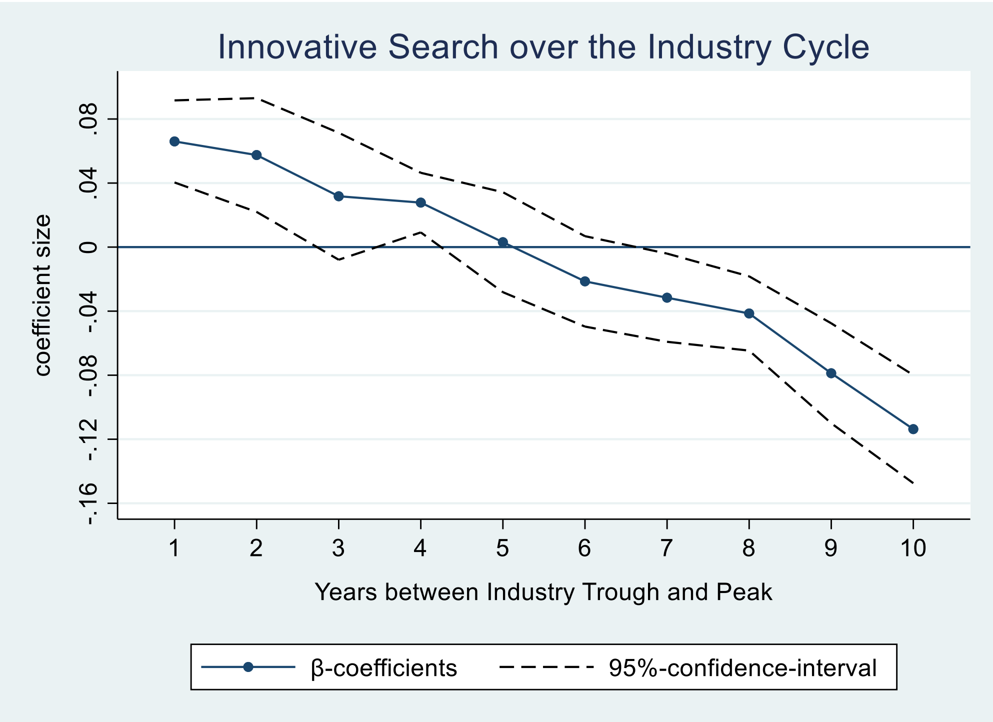


Notes: Average fraction of explorative patenting per firm, for listed firms with at least 10 patents. Measures calculated on quarterly basis and smoothed over three quarters. Gray shading corresponds to recessions as defined by the NBER. Though the relationship is noisy, the degree of exploration often increases during recessions.

Figure 2 illustrates how firms' search strategies change as an industry cycle progresses. It illustrates how the average fraction of explorative patents shifts from the beginning to the 10th year of an industry-specific cycle. We define the industry-specific cycle based on the NBER-CES data that provides yearly industrial output at the four digit SIC level. Resembling the

NBER definition of the macroeconomic cycle, expansion periods start with the first year of positive growth after a year or period of negative growth in industrial output. Values are derived from regressing the fraction of explorative patents per firm on dummies for each year within the industry-specific cycle.

Figure 2



Notes: The average fraction of explorative patents within firms, from the beginning to the end of an industry specific cycle. Industry cycles based on NBER-CES definitions at the four digit SIC level. Expansions start with the first year of positive growth after a year or longer period of negative growth in the industry's output. Estimates are derived from a regression of the fraction of explorative patents per firm on indicators for each year, within the industry-specific cycle.

3.3. Methodology and econometrics

In order to distinguish firms in any given year based on their relative focus on exploitation of known to the firm technologies, versus exploration of new to the firm technologies (which measures the firm's search strategy and is labeled *innovation search*), we draw on the original technology classes that USPTO examiners assigned to each patent.[3] Our measure examines the degree of overlap between patents granted to the firm in year t and the existing patent portfolio held by the same firm up to year $t-1$. In particular, we employ the following variant of the Jaffe (1989) technological proximity measure (see also Mowery et al. 1998; Silverman 1999; Benner and Waldfogel 2008; Bloom, Schankerman & van Reenen, 2013) to estimate similarity in technological space of firm i's patents applied in year t (patent flow f) and its pre-existing patent stock g accumulated between $t-5$ and $t-1$, using patent counts per USPTO three-digit technology classes k:

$$Internal\ Search\ Proximity_{i,t} = 1 - \frac{\sum_{k=1}^{K} f_{i,k,t}\, g_{i,k,t-1\ldots t-5}}{\left(\sum_{k=1}^{K} f_{i,k,t}^2\right)^{\frac{1}{2}} \left(\sum_{k=1}^{K} g_{i,k,t-1\ldots t-5}^2\right)^{\frac{1}{2}}} \qquad (1)$$

where $f_{i,k,t}$ is the fraction of patents granted to firm i in year t that are in technology class k such that the vector $f_{i,t} = \left(f_{i,1,t} \cdots f_{i,K,t}\right)$ locates the firm's year t patenting activity in K-dimensional technology space and $g_{i,k,t-1\ldots t-5}$ is the fraction of all patents granted to firm i between $t-5$ and up to and including year $t-1$ that are in technology class k such that vector $g_{i,t-1} = \left(g_{i,1,t-1\ldots t-5} \cdots g_{i,K,t-1\ldots t-5}\right)$ locates the firm's patent stock in K-dimensional technology space.[4] $Innovative\ Search_{i,t}$ is basically one minus the cosine angle between both vectors and would be one for a given firm-year when there is no overlap of patents' technology classes in year t compared to the previous five years; $Innovative\ Search_{i,t}$ will equal zero when the distribution of firm i's patents across technology classes in a given year is identical to the distribution of patents across technology classes accumulated in the previous five years. When firms search for new technologies extensively, i.e. patent *only* in new to the firm technology classes, the measure would be one. Therefore, we classify firms as being relatively

[3] If there is more than one technology class assigned to a patent we take the first one mentioned on the patent grant. Results are robust to taking all mentioned patent classes into account, please see Appendix B.
[4] Results are robust to taking all prior patents applied by the given firm into account, changing the threshold value from 5 to 10 years, and applying a 15% depreciation rate to a firm's past patent stock per technology class when calculating the innovative search measure.

more focused on exploration (exploitation) when they have a high (low) $Innovative\ Search_{i,t}$ score.

Bloom et al. (2013) use a similar approach to measure technological similarity across firms rather than within firms over time. They also study and discuss alternative measures of technological similarity in detail but find little differences in their results. Our results are robust to a variety of consistent measures, detailed in Appendix B, including the fraction of new to the firm patents, a firm's self and backward citations, taking all mentioned technology classes on a patent into account (max 23), excluding firms with fewer than 2, 5 or 10 patents where single patents may have an overly strong effect on our measure, or excluding firms with very large patent portfolios (min 100 patents). Note that all our measures are compositional measures. Separately analyzing the level of patenting in new vs. known to firm technological areas indicate an increase in new to firm patenting and a decrease in known to the firm patenting areas during recessions, where the latter effect is stronger in absolute terms than the former.

We follow Fabrizio and Tsolmon (2014) in adapting the classic patent production model (Hall, Griliches, & Hausman, 1986, and Pakes & Griliches, 1980) to estimate the effect of changes in industry demand on within firm changes in innovative search. Specifically, we estimate the following equation in OLS: [5]

$$IS_{ikt} = \alpha_0 + \beta_1 D_{kt-1} + \beta_2 X_{it-1} + f_i + \delta_t + \varepsilon_{ikt}, \tag{2}$$

where IS_{ikt} is the innovative search focus of firm *i* in industry *k* and year *t*, D_{kt-1} is the output in industry *k* in year *t-1*, X_{it-1} is a vector of one-year lagged firm level controls, and f_i controls for time-invariant unobserved firm characteristics. Besides reducing endogeneity concerns, the latter resembles the theoretical prediction of shifts towards more or less exploration

[5] Alternatively estimating a quasi-fixed effects Tobit model in the spirit of Chamberlain (1986) and proposed by Wooldridge (2002, p. 538f.) reveals qualitatively the same results.

(exploitation) *within* firms. Since firms do not switch industries over time, f_i effectively absorbs all unobserved time invariant heterogeneity at the industry level as well. δ_t denotes a full set of year fixed effects that absorb aggregate changes in industry demand due to varying macroeconomic conditions, and ε_{ikt} is the error term.

If industry specific output strongly co-varies with the macro economy, however, this may leave little unique variation to identify how firms change their innovative search in response to changes in macroeconomic conditions. We thus follow Barlevy (2007) and estimate a model without time fixed effects in addition.[6] This empirical model should reflect firms' reactions to macroeconomic shocks more accurately, however, it has the unavoidable downside of being potentially confounded by aggregate changes in policies or subsidies that affect all firms and industries at a given point of time.

As in Fabrizio and Tsolmon (2014) the vector X_{it-1} contains controls for R&D spending, sales, employment and property, and plant and equipment per firm. Controlling for firms' sales should reduce concerns that the output measure captures the firm specific change in sales, and controlling for employment should capture firm size variation over the business cycle, and property, plant and equipment should capture changes in physical capital. A positive (negative) estimated coefficient on D_{kt-1} would indicate that, controlling for any change in R&D spending, firms focus more on exploration (exploitation) when industry output increases. Observed changes in innovative search are thus not just driven by the procyclical changes in R&D as shown in Barlevy (2007). For a graphical inspection of the linearity assumption, estimates without firm fixed effects and with and without covariates, secular industry specific

[6] Alternatively, we also estimated models where δ_t is replaced by linear or log-linear cycle trend, drawing on the NBER US Business Cycle Expansions and Contractions data, where the trend variable takes the value zero in recession periods and values 1, 2, …, N, for the first, second, …, and Nth year of each expansion period. Results remain unchanged. The trend itself is significantly positive, and taking just recession dummies instead of a trend indicates an increase in exploration during recession periods.

trends, a forward term test, and a wide variety of other robustness and specification tests, please see Appendix B.

The lag between research and patent application could in principle make it hard to find results with more nuanced patent measures. If there is a long lead time from initiating research to patenting, we may not find countercyclical exploration in the patent application data even if firms were to start exploring new areas during recessions. However, Griliches (1990) finds that "patents tend to be taken out relatively early in the life of a research project," and that the lag between initial research and patent application is typically short. Furthermore, firms typically work simultaneously on exploratory as well as exploitative inventions. What we study here and what our model implies is a shift in focus towards more or less exploration, not necessarily a complete abandonment of either of the two. With respect to patenting activity, this implies that a shift of focus should be observable in patenting activity since firms will not need to start from scratch but rather focus more on specific and particular yet ongoing exploratory activities. The delay between a shift in strategic choice and patenting probably varies between industries, for example, the pharmaceutical industry probably experiences a longer lead time from the initiation of search to the discovery of a patentable compound. Industry fixed effects models help to isolate these differences within models and Appendix B illustrates robust results that exclude more stable and long horizon industries.

3.4. Baseline results

We first confirm the pro-cyclicality of R&D spending (Barlevy, 2007), and patenting (Fabrizio and Tsolmon, 2014), with our longer time series (though smaller dataset, due to the patenting criterion for inclusion). As can be seen in Table 3, columns (a) and (b) for R&D spending, and (c) and (d) for patenting, these measures correlate positively with increases in aggregate output per industry. As expected, and similar to the prior results, the impact weakens if we control for changes in the macro economic conditions that affect all firms and industries in the same way, through the inclusion of year fixed effects. Table 3, columns (e) and (f), show the results of estimating our main model as introduced above, first without (e) and then with time fixed effects (f). The negative coefficients for the output variable support the prediction of our theoretical model - that firms tend to explore less, i.e. search amongst known technologies, the better the economic conditions.

The magnitude of the effects is not only statistically but also economically significant. A one standard deviation increase in output corresponds to a 0.31 (model a) (0.10 [model b]) standard deviation increase in R&D spending, a 0.18 (model c) (0.23 [model d]) standard deviation increase in patenting, and a -0.14 (model e) (-0.12 [model f]) standard deviation decrease in innovative search/exploration.

Table 3 – Industry growth, R&D, patents and innovative search

	R&D spending		Patents		Innovative search	
	a	b	c	d	e	f
$Log(R\&D)_{t-1}$			0.000	0.060***	-0.003	-0.007*
			(0.011)	(0.014)	(0.003)	(0.004)
$Log(Sales)_{t-1}$	0.215***	0.142***	-0.047**	-0.008	0.004	0.005
	(0.058)	(0.034)	(0.019)	(0.020)	(0.007)	(0.007)
$Log(Employees)_{t-1}$	0.403***	0.345***	0.402***	0.462***	-0.033***	-0.045***
	(0.115)	(0.061)	(0.051)	(0.047)	(0.009)	(0.009)
$Log(Capital)_{t-1}$	0.389***	0.255***	0.097***	0.070**	-0.020**	-0.015*
	(0.044)	(0.034)	(0.031)	(0.027)	(0.008)	(0.008)
$Log(Output)_{t-1}$	0.356***	0.111***	0.143***	0.188***	-0.025***	-0.021***
	(0.108)	(0.027)	(0.046)	(0.040)	(0.005)	(0.005)
N	24419	24419	24419	24419	24419	24419
Year fixed effects	No	Yes	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.830	0.866	0.800	0.814	0.458	0.464

Notes: This table presents OLS regression of firms' log(R&D spending), a and b, log(no. patents +1), c and d, and innovative search, e and f, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

3.5. Pro-cyclical industries

Our theory further implies that the decreasing focus on exploration over the business cycle is stronger for firms in particularly pro-cyclical industries as opposed to less cyclical industries. To test this prediction empirically we measure each industries' cyclicality with the correlation of the industry-specific output growth as measured by the NBER-CES with the economies GDP growth as measured by the BEA. Specifically, we run separate regressions of each industries output growth ($\log(D_{kt}) - \log(D_{kt-1})$) at the 4-digit SIC level on the nations GDP growth. The coefficients of GDP growth from these regressions, named $\hat{\beta}_{k,cyc}$, then reflect the degree to which output growth per industry *k* co-varies with the nation's business cycle.

We test our theories prediction by estimating a slightly abbreviated version of our baseline model:

$$IS_{ikt} = \alpha_0 + \beta_1 X_{it-1} + \beta_2 X_{it-1} \times Cyc_k +$$

$$\beta_3 D_{kt-1} + \beta_4 D_{kt-1} \times Cyc_k + f_i + \delta_t + \varepsilon_{ikt} \quad (3)$$

where we keep everything as introduced above but add an interaction of industry demand D_{kt} and an indicator for strong industry cyclicality Cyc_k, i.e. a $\hat{\beta}_{k,cyc}$ value above the median. For easier comparison we keep $D_{kt-1} \times Cyc_k$ where Cyc_k is equal to one and replace all values of D_{kt-1} with zero if Cyc_k is equal to zero such that the size of β_3 is the estimated elasticity of demand and innovative search in weakly pro-cyclical or counter cyclical industries and β_4 is the estimated elasticity of demand and innovative search in strongly pro-cyclical industries. Note that the main effect of Cyc_k is fully absorbed by f_i. We also added interactions of each covariate with Cyc_k to control for differing confounder influences. A larger estimated β_4 than β_3 would support our prediction of stronger decrease in exploration over the business cycle in particular for pro-cyclical industries. Again, we estimate the equation once with and without year fixed effects to allow an estimation of the effect of industry specific cyclicality beyond the macroeconomic cycle, as opposed to macroeconomic changes that influence innovative search.

Table 4, columns (a) and (b), present the results of estimating (3). The results provide further support for the theoretical predictions. Firms tend to decrease their focus on exploration almost twice as much if they operate in stronger pro-cyclical industries (an F-test of $\beta_3 - \beta_4 = 0$, is statistically significant in the baseline at $p < 0.07$ (a) and $p < 0.06$ (b), respectively, if we reduce noise by excluding firm-year observations where firms applied for just one patent). In pro-cyclical industries we estimate that a one standard deviation increase in output corresponds to a -0.45 (model a, [-0.46, model b]) decrease in standard deviation of innovative search, while in weakly pro-cyclical and counter-cyclical industries, a one standard deviation increase in output corresponds to a -0.09 (model a, [-0.08, model b]) standard deviation decrease in innovative search.

Table 4 – Industry growth, innovative search and cyclicality

	Innovative search	
	a	b
Log(Output)_{t-1} x Cyc	-0.031***	-0.032**
	(0.012)	(0.012)
Log(Output)_{t-1}	-0.018***	-0.015***
	(0.003)	(0.004)
N	24419	24419
Year fixed effects	No	Yes
Firm fixed effects	Yes	Yes
R^2	0.459	0.465

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). *Cyc* is a dummy that indicates strongly pro-cyclical industries as defined above. All models are estimated with the previously used set of controls: $\text{Log(R\&D)}_{t-1}$, Log(Sales)_{t-1}, $\text{Log(Employees)}_{t-1}$, $\text{Log(Capital)}_{t-1}$ and the full set of interactions with *Cyc*. The main effect of *Cyc* is fully absorbed by the firm fixed effects. Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

3.6. Robustness checks (details in Appendix B)

Results remain robust to a variety of additional analyses including 1) many alternate measures of exploration, including the fraction of patents in new to the firm technologies, backward citations, self-citations, fraction of self-citations, taking all tech classes mentioned on a patent into account when calculating the Jaffe measure, and the absolute number (as opposed to the fraction) of patents in new to the firm classes, 2) including linear or log-linear industry specific trends that capture the co-movement of secular trends in patenting and industrial expansion, 3) the number of patents, 4) models without fixed effects, 5) mergers and acquisitions, 6) graphical test of linearity assumption, 7) intensive vs. extensive margin, i.e., results are not driven by firm entry, 8) forward term, 9) influence of control variables, 10) different lags, 11) excluding the first five years after a firm first patents, which might overstate the exploratory nature of patenting early in a firm's lifecycle, 12) taking moving averages of the proximity measure to account for potential time variation due to measurement issues, 13) assuming that firms explore radically when not patenting, which remains unobservable in patenting data, 14) excluding firm-year observations when firms obtained only a few patents, which might cause overly high or low exploration scores, 15) excluding firms with large patent portfolios, 16) excluding the years after 1999 and bust of the dot-com bubble, which might have influenced firms' innovative search strategies differently than in other recessions, 17) alternate measures of industries and industry aggregation, 18) including a control for competition within industries, 19) exclusion of stable and long horizon industries (such as pharmaceuticals). Please see corresponding numbered sections in Appendix B for details.

4. Additional results on underlying mechanisms and implications of shifts in search strategy

While not directly predicted by our theoretical model, we further explore underlying mechanisms in this section, as well as plausible implications of firms' shifting search strategies. For mechanisms, we illustrate the influence of hiring and workforce redirection, product vs. process innovation, and industry appropriability. For implications, we illustrate an increase in patent value and resulting productivity improvements. Note that these results, like the baseline results, rely on historical trends and do not provide causal evidence for the described mechanisms and implications.

4.1. Hiring and inventor redirection as search strategies over the business cycle

Firms can change their innovative search focus through their hiring, for example, firms can explore by hiring and learning from outside inventors (March 1991); unless an inventor's distribution of prior technologies exactly matches that of the hiring firm (which though not impossible is likely to be very rare), this will by definition and by varying degrees cause the firm to explore. Firms can also redirect their current workforce, employing them to work and invent in new fields.

To explore these possibilities, we first run the baseline model again but exchange the dependent variable with the fraction of newly patenting inventors as measured by the number of inventors that appear for the first time on a given patent filed by a given firm, divided by the total number of inventors that appear on all patents filed by a given firm in a given year (disambiguated inventor data comes from Balsmeier et al. 2018, starting in 1976). Table 5, columns (a) and (b), indicates that the relative proportion of new hires is counter-cyclical, that is, firms hire relatively more new inventors during recessions, such that the proportion of newly hired inventors rises (this assumes that the bulk of first appearances within the firm have been recently hired externally).

Table 5 also reports regressions where the unit of observation is an inventor-patent-year combination. In columns (c) and (d) we estimate a regression similar to (2) where the dependent variable is a dummy indicating whether a given patent falls into a new to the inventor tech class, taking all patents filed by the given inventor from t-1 to t-5 into account (it is an analogous measure to the new to the firm level measure, but at the individual inventor level). As can be seen, inventors are less likely to invent in a new class during expansions. Finally, in columns (e) and (f), we use a dummy that indicates whether a given patent is not only new to the inventor but also new to the firm. While the coefficient decreases, it remains highly significant, indicating that inventors' personal exploration during downturns provides one mechanism of firms' exploration.

Consistent with Babina et al. (2019), firm rely more on new to the firm inventors during recessions. Furthermore, during downturns, firms also appear to redirect their current workforce towards new to the firm technologies. Both of these mechanisms appear to shift firms' search strategies in favor of exploration, during downturns. Keep in mind that these results only speak to inventors employed by public firms, and do not consider lone inventors (whose patents are not assigned to a public firm) or those working for universities and non-public firms. While beyond the scope of the current paper, it would be interesting to investigate how the business cycle influences those inventors' search strategies.

Table 5 – Newly hired inventors and inventor level regressions

	Share new Inventors		Patent falls into new to inventor tech class		Patent falls into new to inventor and new to firm tech class	
	a	b	c	d	e	f
Log(Output)$_{t-1}$	-0.020***	-0.007**	-0.027***	-0.019***	-0.008***	-0.005**
	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
N	19020	19020	879695	879695	879695	879695
Year FEs	No	Yes	Yes	Yes	No	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.761	0.771	0.054	0.056	0.124	0.125

Notes: This table presents OLS regression of firms' log(no. new inventors +1), a and b. Models c to f are based on inventor level data and the dependent variable is a dummy indicating if a patent falls into a new to inventor tech class, c and d, and a dummy indicating if a patent falls into a new to inventor and new to the firm tech class, e and f, taking all patents from t-5 to t-1 into account. All models are estimated with the previously used set of controls: Log(R&D)$_{t-1}$, Log(Sales)$_{t-1}$, Log(Employees)$_{t-1}$, Log(Capital)$_{t-1}$. Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

4.2. Product vs. process innovation as search strategies over the business cycle

The technology life cycle is typically thought to start with product innovation and then progress to process innovation, and the focus of engineering and innovative effort has been argued to follow this progression as well (Utterback and Abernathy 1975). When demand for current products is strong, then firms will focus on making and shipping existing designs, and have less time and motivation to create new designs. This provides a simple analogy to exploration and exploitation; when demand for current products is strong, firms focus on exploitation and process innovation, and have less time and motivation to explore new designs and innovate new products.

This tension between exploration and exploitation should be observable in a firm's focus on product development as opposed to process refinement. Recent advances in natural language processing have allowed researchers to classify each claim of a patent into whether it contains a process or product invention. To operationalize and test these ideas, we draw on Seliger et al. (2019), who provide an extensive set of robustness and validation checks of their measure.

Their approach is similar to Bena, Ortiz-Molina, and Simintzi (2018), Bena and Simintzi, (2019) and Ganglmair and Reimers (2019).

We create two measures based on the Seliger et al. (2019) work. First, we classify patents into product and process patents according to whether they comprise exclusively only product related independent claims or only process related claims. Then we calculate the fraction of new product patents over all product and process patents filed by a given firm in a given year. Second, we take the average of all new product claims out of all patents filed in given year by a given firm, including patents that contain process and product related claims and could thus not be classified as pure product or process patents. Table 6 shows the corresponding results, with and without year fixed effects, suggesting that firms are relatively more likely to work on new products during recessions than during booms.

Table 6 – New products versus new processes

	Share of new product patents		Share of new product patent claims	
	a	b	c	d
Log(Output)$_{t-1}$	-0.038***	-0.014**	-0.030***	-0.009*
	(0.007)	(0.006)	(0.005)	(0.005)
N	19020	19020	19020	19020
Year fixed effects	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
R^2	0.425	0.483	0.451	0.534

Notes: This table presents OLS regression of firms' of the share of firms' new product patents over the total of firms' new product and new process patents (models a and b) and the share of firms' new product patent claims over all patent claims (models c and d). All models are estimated with the previously used set of controls: Log(R&D)$_{t-1}$, Log(Sales)$_{t-1}$, Log(Employees)$_{t-1}$, Log(Capital)$_{t-1}$. Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

4.3. The influence of appropriability on search strategies over the business cycle

Fabrizio and Tsolmon's (2014) found that patenting is more procyclical in industries with weaker IP protection (where imitation poses a greater threat of imitation). Industries also vary in the effectiveness of patent protection and the ability of firms to appropriate returns to their innovation (Cohen et. al. 2000). Firms might patent strategically by withholding exploration patents until an optimal time, for example, when rivals might be less able to copy the exploration invention.

We differentiate between high low appropriation risk using data provided in Cohen et al. (2000), [7] where managers rated the effectiveness of patent protection in their industry. Industries with below or equal to median ratings are considered industries with high appropriation risk while industries with effectiveness ratings above the median are considered low appropriation industries. We then re-estimate model 3 but exchange the cyclicality indicator with an indicator equal to one for low appropriation risk. Table 7 presents the results and indicates that firms in industries with low appropriation risk are less likely to explore in expansions (differences are statistically significant at $p < 0.01$ (a) and $p < 0.02$ (b), respectively). Stated another way, it would appear that the influence of the business cycle on exploration is less in high appropriability industries. Firms are less influenced by the business cycle in high appropriability industries, perhaps because they are more worried about their ideas getting stolen.

Table 7 – High vs. low appropriation risk

	Innovative search	
	a	b
Log(Output)_{t-1} x low	-0.047***	-0.042***
appropriation risk	(0.010)	(0.012)
Log(Output)_{t-1}	-0.013***	-0.014***
	(0.004)	(0.004)
N	20314	20314
Year fixed effects	No	Yes
Firm fixed effects	Yes	Yes
R^2	0.467	0.473

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Low appropriation risk is a dummy that indicates firms that operate in industries where mangers reported an above median patent effectiveness in the CNW 2000 survey. All models are estimated with the previously used set of controls: $\text{Log(R\&D)}_{t-1}$, Log(Sales)_{t-1}, $\text{Log(Employees)}_{t-1}$, $\text{Log(Capital)}_{t-1}$ and the full set of interactions with low appropriation risk dummy. The main effect of low appropriation risk is fully absorbed by the firm fixed effects. Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

[7] We thank an anonymous reviewer for suggesting this mechanism and Wesley Cohen for providing these data.

4.4. Invention quality over the business cycle

Though the relationship between exploration and a patent's value is complex (Fleming, 2001), anecdotes of breakthrough inventions (such as neoprene, Teflon, polyester, and the transistor described in the introduction) would imply that firms are more likely to invent higher value patents during recessions. While exploration of new technologies might result in more failures, it might also result in more breakthroughs as well (March, 1991; Manso 2011), such that the average value of patents increases during a recession.

We test this conjecture by re-estimating our baseline model with the dependent variable of the average amount of citations that a firm's patents applied for in year *t* receive from future patents. Table 8 shows that the patents applied for during expansions receive on average fewer future cites, thus implying that patents applied for during recessions are more highly cited. The overall picture that emerges is that firms apply for fewer patents (see baseline results, table 3, above) but that those patents are more likely to fall into new to the firm tech classes -- and receive more future cites.

Table 8 – Future cites

	Average future cites	
	a	b
$Log(Output)_{t-1}$	-1.206*	-0.681**
	(0.712)	(0.264)
N	24419	24419
Year fixed effects	No	Yes
Firm fixed effects	Yes	Yes
R^2	0.548	0.595

Notes: This table presents OLS regression of the average amount of citations that a firm's patents applied for in year t receive from future patents. All models are estimated with the previously used set of controls: $Log(R\&D)_{t-1}$, $Log(Sales)_{t-1}$, $Log(Employees)_{t-1}$, $Log(Capital)_{t-1}$. Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

4.5. Future productivity and inventions over the business cycle

While a study of the causal impact of innovative search on productivity lies well beyond the scope of the present paper, we estimate some simple regressions of revenue-based labor productivity and capital productivity on innovative search. Consistent with recent arguments (Akcigit and Kerr 2018), our theory, and the previously reported higher future citation rates of patents filed in recessions, Table 9 indicates that it is only the exploration conducted during recessions (patents filed then or one year later) that is positively related to future improvements in (t+1, t+2, t+3) of labor and capital productivity. The differences in estimated coefficients over the business cycle are not causal estimates but will hopefully motivate future research.

Table 9 – Innovative search and productivity

	Lab. Prod.$_{t+1}$ a	Lab. Prod.$_{t+2}$ b	Lab. Prod.$_{t+3}$ c	Cap. Prod.$_{t+1}$ d	Cap. Prod.$_{t+2}$ e	Cap. Prod.$_{t+3}$ f
Log(R&D)	0.043**	0.039*	0.031*	-0.060***	-0.044***	-0.022*
	(0.020)	(0.020)	(0.017)	(0.017)	(0.015)	(0.013)
Innovative Search	0.046***	0.023	0.045**	0.042**	0.045**	0.081***
(in recessions)	(0.016)	(0.018)	(0.018)	(0.017)	(0.021)	(0.018)
Innovative Search	-0.029**	-0.007	-0.040*	-0.001	-0.014	-0.070**
(in booms)	(0.014)	(0.014)	(0.020)	(0.024)	(0.019)	(0.030)
N	21,021	20,071	18,867	21,390	20,316	19,081
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.755	0.759	0.762	0.745	0.746	0.747

Notes: This table presents OLS regression of the firms' labor productivity, defined as the log of (sales/employee), winsorized yearly at the 1% and 99% values (models a to c) and firms' capital productivity, defined as the log of (sales/property, and plant and equipment), winsorized yearly at the 1% and 99% values. Innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

5. Discussion

The pro-cyclicality of R&D and raw patenting is clear from many analyses, including ours, and many explanations have been offered for this departure from theoretical expectations (based on changes in opportunity costs), including credit constraints (Aghion et al. 2012), potentially strategic delay (Schleifer 1986, Francois and Lloyd-Ellis 2003), externalities in R&D (Barlevy

2007), and competition or obsolescence (Fabrizio and Tsolmon 2014). More practically, and consistent with our theoretical model, most research and development spending focuses on development, getting products into manufacturing, and ramping up production. Less spending goes into fundamental research (Barlevy 2007).[8] While patenting might be thought to be fundamental and a good measure of novelty, much (even most of it) of it is often done to flesh out already discovered opportunities. For example, firms often patent incremental inventions designed to build defensible portfolios or thickets (Shapiro 2001). Such defensive patenting fits the definition of exploitation and can be measured by the rate of self and backward cites in addition to the profile measure used here.

While we do not incorporate our simple theory into a macroeconomic framework, it is related to recent advances in applied growth theory (e.g. Klette and Kortum 2004, Lentz and Mortensen 2008, Acemoglu et al. 2018, Akcigit and Kerr 2018) due to its emphasis on heterogeneous types of innovation and potential implications for macroeconomic stability. Our data also share some regularities modelled and observed for the whole economy, e.g. a negative correlation between firm size and exploration (see Akcigit and Kerr 2018 and their 2010 working paper version). Given that Akcigit and Kerr (2018) calculate that 54.5% of the economic growth due to innovation comes from exploratory (external in their parlance) efforts as opposed to exploitation (refinement or internal) efforts, our results imply that economic downturns might have benefits in the long-run. Such an idea is at odds with macroeconomic policy whose goal is stability.

Our model remains consistent with the organizational realities of high technology firms. During expansions, firms must respond to increased sales and manufacturing pressures. When these pressures are most intense (for example, inordinate sales demand or a yield crash), managers

[8] https://www.nsf.gov/statistics/2018/nsb20181/report/sections/overview/r-d-expenditures-and-r-d-intensity.

of sales and manufacturing organizations will seek additional resources -- and the research and development organizations provide tempting repositories of highly talented and immediately effective help. Rather than increase head count and go through the laborious process of hiring and training new employees, a manager will often prefer to request help from his or her upstream functions. In a stable firm with low turnover, that manager will often know and have worked with the same R&D engineers who invented and perfected the challenged product. Particularly during a sales or yield crisis, the R&D manager will find it difficult to avoid demands to help his or her manufacturing counterpart. The pressures to siphon off exploration talent in order to meet sales demands should also be greater in cyclical industries, as for example, in semiconductors. Unsolved manufacturing problems can lead to cross functional friction and the temporary re-assignment of R&D engineers to the fab floor, and that temporary re-assignment delays research. Such temporary assignments will in turn delay exploration of new opportunities – and increase the firm's attention on current technologies.

Other realities are also consistent with the model and will drive the results reported here. Defensive patenting (Shapiro 2001) consolidates and protects market share and should rise when firms think that the cost and delay in patent pendency can warrant the investment. This investment requires legal time and money and cannot ignore the non-trivial demand on inventors' time as well. Despite well-trained patent lawyers, inventors cannot avoid spending time in crafting even minor patents and this time distracts them from exploring new ideas and technologies. Firms also need to consider the delay in getting patent approval; patent "pendency" typically lasts one to three years. All of these costs are easier to justify with the expectation of a growing and robust market. In contrast, with a shrinking or stagnant market, searching for new markets becomes relatively more attractive.

6. Conclusion

Schumpeter and others have argued that innovative activities should concentrate in recessions. However, using common measures of innovation, such as R&D expenditures and raw patent counts, previous research found that innovation is instead procyclical. We propose a solution to this puzzle by modelling innovative search as a within the firm tension between exploration and exploitation. We rely on changes in the distribution of a firm's patenting across new and old to the firm technology classes to separate and measure exploration and exploitation. Consistent with the model, and considering observed business cycles since 1958, exploitation strategies are procyclical while exploration strategies are countercyclical. The results are stronger for firms in more cyclical industries.

Investigating the empirical mechanisms behind the observed compositional shifts of firms' search strategies, we found that firms employ a greater proportion of new inventors in recessions and that inventors are more likely to work in new to the firm technologies. Product innovation, as measured by a natural language processing metric, becomes more dominant in recessions and process innovation more dominant in expansions. The cyclical effects are weaker in industries with high appropriation risk. Finally, exploration patents are more highly cited and search during recessions correlates positively with future productivity improvements.

This work investigated how economic conditions that are largely out of control of a focal firm can influence firms' innovation strategies and in particular, how macro-economic conditions might motivate different types of innovative search within the firm. Future work could look at how search strategies influence profitability, growth, and productivity changes. For example, do exploitation strategies lead to short term profits and meager productivity improvement, and exploration to lagged profits and fundamental improvements? Can firms appropriate exploitation patents more easily, even though the gains are smaller? Alternately, are the gains larger with exploration patents, yet more likely to leak to competitors? Future work could also consider differences across countries, for example, does an isolated downturn in one country shift the patenting of domestic firms more radically than foreign firms that also patent in that country? It also appears that exploitation has been steadily increasing since the 1980s. The U.S. economy expanded for most of those years, however, hence raising the important question of whether the nature of innovative search has fundamentally changed (Arora et. al. 2017). Establishing a causal link between innovative search and productivity lies beyond the scope of the present paper, though our descriptive regressions point to an important path for future research once proper identification becomes available.

As Schumpeter (1939) argues, macroeconomic fluctuations may facilitate creative destruction and growth-enhancing exploration by firms that would otherwise not take place in the economy. Our results provide evidence supporting this view. If creative destruction and exploration during recessions are indeed important, there could be potential costs related to pursuing macroeconomic stability. Further investigation on this issue could be fruitful.

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Appendix A: Theoretical model

A1.1 The Base Model

We introduce a simple model of exploration and exploitation over the industry business cycle. The model is based on the simple two-armed bandit problem studied in Manso (2011), but incorporates macroeconomic shocks.

The economy exists for two periods. In each period, the representative firm in the economy takes either a well-known or a novel action. The well-known action has a known probability p of success (S) and $1-p$ of failure (F) with $S > F$. The novel action has an unknown probability q of success and $1-q$ of failure (F). The only way to learn about q is by taking the novel action. The expected probability of success when taking the novel action is $E[q]$ when the action is taken for the first time, $E[q|S]$ after experiencing a success with the novel action, and , $E[q|F]$ after experiencing a failure with the novel action. From Bayes' rule, $E[q|F] < E[q] < E[q|S]$.

We assume that the novel action is of exploratory nature. This means that when the firm experiments with the novel action, it is initially not as likely to succeed as when it conforms to the conventional action. However, if the firm observes a success with the novel action, then the firm updates its beliefs about the probability q of success with the novel action, so that the novel action becomes perceived as better than the conventional action. This is captured as follows:

$$E[q] < p < E[q|S].$$

The macroeconomic state m can be either high (H) or low (L). If the macroeconomic state is currently m it remains in the same state next period with probability μ. Alternatively, it transitions into the other state n next period. Industry demand in macroeconomic state m is d_m with $d_H > d_L$. Given the macroeconomic state m, firm profit in each period is given by $d_m S$ in case of success and $d_m F$ in case of failure.

For simplicity, we assume risk-neutrality and a discount factor of δ. There are only two action plans that need to be considered. The first relevant action plan, exploitation, is to take the well-known action in both periods. This action plan gives the payoff $\pi(m, exploit)$ if the macroeconomic state is m:

$$pd_{\mathrm{m}}S + (1-p)d_mF + \delta\,\mu\,(pd_mS + (1-p)d_mF) + \delta(1-\mu)(pd_nS + (1-p)d_nF)$$

The other relevant action plan, exploration, is to take the novel action in the first period and stick to it only if success is obtained. This action plan gives the payoff $\pi(m, explore)$ if the macroeconomic state is m:

$$\begin{aligned}&E[q]d_mS + (1-E[q])d_mF\\&+\delta\mu\left(E[q](E[q|S]d_mS + (1-E[q|S]))d_mF) + (1-E[q])(p\,d_mS + (1-p)d_mF)\right)\\&+\delta(1-\mu)(E[q](E[q|S]d_nS + (1-E[q|S])d_nF) + (1-E[q])(pd_nS + (1-p)d_nF))\end{aligned}$$

The total payoff from exploration is higher than the total payoff from exploitation if:

$$E[q] \geq \frac{d_m}{d_m(1+\delta\,(E[q|S]-p)\mu\,) +\; d_n\,\delta\,(E[q|S]-p)(1-\mu\,)}\;p$$

If the firm tries the novel action, it obtains information about q. This information is useful for the firm's decision in the second period, since the firm can switch to the conventional action if it learns that the novel action is not worth pursuing. The fraction multiplying p in the inequality above is less than 1. Therefore, the firm may be willing to try the novel action even though the initial expected probability $E[q]$ of success with the novel action is lower than the probability p of success with the conventional work method.

Proposition 1: Firms are more prone to explore in recessions than in booms.

Proof: The coefficient multiplying p on the right-hand side of equation (1) is increasing in d_m and decreasing in d_n. Since $d_H > d_L$, the firm is more prone to explore in bad times ($m = L, n = H$) than in a good times ($m = H, n = L$). ■

The intuition for the result is that in a recession, the future is more important than the present, since current industry demand is low. Therefore, the firm is more forward-looking and is willing to explore for a larger set of opportunities. In an expansion, the present is more important than the future, since current industry demand is high. Hence, the firm is more focused on the present and prefers to exploit their current set of opportunities.

A1.2 Industry Cyclicality

How do results vary with industry cyclicality? More cyclical industries respond more quickly to the macroeconomic state (higher d_H and lower d_L). The following proposition studies this comparative statics.

Proposition 2: The innovation strategies of firms in cyclical industries are more sensitive to business cycles.

Proof: Since the coefficient multiplying p on the right-hand side of equation (1) is increasing in d_m, decreasing in d_n, and $d_H > d_L$, more cyclical firms are more prone to exploration than less cyclical firms during recessions. Conversely, more cyclical firms are less prone to exploration than less cyclical firms during booms. ■

The intuition is that, for more cyclical firms, fluctuations caused by the business cycle are exaggerated. This amplifies the dependence of innovation strategy on the business cycle, derived in Proposition 1.

Appendix B: Robustness checks

Here we present tables that report a wide variety of robustness checks, alternate measures, and deeper analyses:

- B1: Alternate measures of exploration
- B2: Industry specific trends
- B3: The number of patents
- B4: OLS without fixed effects
- B5: Mergers and acquisitions
- B6: Graphical test for linearity
- B7: Intensive vs extensive margin
- B8: Forward term
- B9: Influence of control variables
- B10: Different lags
- B11: Excluding first 5 years of firms' patenting activity
- B12: Two year moving averages
- B13: An assumption of exploration in periods of no patenting
- B14: Excluding firms with little patenting activity
- B15: Excluding firms with large patent portfolios
- B16: Limiting analysis from 1958 to 1999
- B17: Alternative industry measure and 3-digit-SIC aggregation
- B18: HHI control for competition
- B19: Exclusion of stable and long horizon industries
- B20: Summary of robustness checks

B1: Alternate measures of exploration

Estimations in the body of the paper rely upon the internal search proximity measure in (1), which calculates the correlations in firms' patent portfolios from year to year. Here we re-estimate the baseline model with alternative dependent variables, including the simple fraction of new to the firm patents, the number of backward citations, self-backward citations, and fraction self-backward citations out of all backward citations. The alternative measures correlate with a broad battery of exploration and exploitation measures (Balsmeier, Fleming, and Manso 2017) and are similar to traditional measures in the literature (Jaffe 1989, Mowery et al. 1998; Silverman 1999; Benner and Waldfogel 2008; Bloom, Schankerman & van Reenen, 2013).

We exchanged the abbreviated Jaffe measure with the simple fraction of patents in new to the firm technology classes. This measure is inferior to the proximity measure in that it will miss any shifts of patenting within technology classes already known to firm. In that sense, the fractional measure puts more emphasis on entering new to the firm technology classes. Consistent with a decreased focus on exploration over the business cycle, Table B1 illustrates a decrease in the simple fraction of new to the firm patents during expansions.

Increased backward citations indicate a more crowded space in prior art and self-citations indicate that a firm is building directly upon its own existing patents, rather than exploring new areas. Table B2 illustrates increased rates of backward and self-backward citations during expansions.

Finally, we re-calculated the abbreviated Jaffe measure taking all technology classes mentioned on a patent into account, weighing each tech class equally with the inverse of the total number of tech classes mentioned on a given patent. Taking all tech classes into has the advantage of potentially more accurately reflecting in which technological area a firm is active. It has hase the downside, however, of potentially reducing accuracy by taking tech classes into account that are only loosely related to a given firm's actual focus, if they are only mentioned as additional tech classes down to the 23rd place (23 is the maximum number of classes in the data). Table B3 illustrates that the abbreviated Jaffe measure, taking all tech classes into account, reveals no material impact on our baseline estimates.

Table B1 – Alternative measures of innovative search – Fraction of new to the firm patents

	% new tech patents	
	a	b
Log(R&D)$_{t-1}$	-0.704**	-0.659*
	(0.332)	(0.392)
Log(Sales)$_{t-1}$	-1.007**	-0.335
	(0.478)	(0.611)
Log(Employees)$_{t-1}$	-1.607*	-2.282**
	(0.915)	(0.885)
Log(Capital)$_{t-1}$	-2.697***	-2.537***
	(0.566)	(0.603)
Log(Output)$_{t-1}$	-2.803***	-1.874***
	(0.369)	(0.378)
N	24419	24419
Year fixed effects	No	Yes
Firm fixed effects	Yes	Yes
R^2	0.366	0.371

Notes: This table presents OLS regression of firms' innovative search focus, defined as the fraction of patents filed in year *t* that are assigned to an original USPTO tech class where the given firm has not patented within the last 5 years. Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

Table B2 – Alternative measures of innovative search – backward and self-citations

	Backward citations		Self-back-citations		% of Self-back cites	
	a	b	c	d	e	f
Log(R&D)$_{t-1}$	0.165***	0.069***	0.161***	0.091***	0.330***	0.024
	(0.019)	(0.017)	(0.021)	(0.021)	(0.125)	(0.114)
Log(Sales)$_{t-1}$	0.012	0.006	-0.086***	0.040*	0.337**	0.861***
	(0.042)	(0.027)	(0.031)	(0.022)	(0.144)	(0.139)
Log(Employees)$_{t-1}$	0.384***	0.569***	0.183**	0.367***	-1.250***	-1.075***
	(0.091)	(0.070)	(0.085)	(0.065)	(0.370)	(0.339)
Log(Capital)$_{t-1}$	0.156***	0.067*	0.237***	0.071**	0.682***	0.223
	(0.043)	(0.036)	(0.049)	(0.031)	(0.144)	(0.145)
Log(Output)$_{t-1}$	0.292***	0.149***	0.253***	0.162***	0.583	0.418***
	(0.059)	(0.034)	(0.074)	(0.037)	(0.388)	(0.142)
N	24419	24419	24419	24419	24419	24419
Year fixed effects	No	Yes	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.718	0.751	0.670	0.754	0.374	0.404

Notes: This table presents OLS regression of the log of firms' backward citations +1 (models a and b), the log of firms' back citations to own patents (models c and d), and the percentage of back citations to own patents out of all back citations. Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

Table B3 – Alternative measure of innovative search – Jaffe measure taking all tech classes mentioned on a patent into account

	Innovative search	
	a	b
$Log(R\&D)_{t-1}$	-0.002	-0.006*
	(0.003)	(0.003)
$Log(Sales)_{t-1}$	0.005	0.005
	(0.005)	(0.005)
$Log(Employees)_{t-1}$	-0.032***	-0.043***
	(0.009)	(0.008)
$Log(Capital)_{t-1}$	-0.022***	-0.017**
	(0.007)	(0.007)
$Log(Output)_{t-1}$	-0.018***	-0.014***
	(0.006)	(0.005)
N	24419	24419
Year fixed effects	No	Yes
Firm fixed effects	Yes	Yes
R^2	0.479	0.485

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989), taking all tech classes assigned to a patent by the USPTO with an equal weight into account. Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

The baseline Jaffe measure as well as the fraction of new to the firm patents are compositional measures. Here we separately analyze the level of patenting in new vs. known to firm technological areas, first for all companies (Table B4) and second for those firms that filed at least 10 patents in a given year (Table B5). Results indicate an increase in new to firm patenting and a decrease in known to the firm patenting areas during recessions, where the latter effect is stronger in absolute terms than the former. These differences in the levels are more pronounced for firms with at least 10 patents.

All measures remain imperfect, however, the consistency of the results supports the theoretical arguments.

Table B4 – Level of new vs. known to firm patenting

	New patents		Known patents	
	a	b	c	d
Log(R&D)$_{t-1}$	-0.036***	0.005	0.009	0.066***
	(0.009)	(0.008)	(0.014)	(0.017)
Log(Sales)$_{t-1}$	-0.047***	0.008	-0.033	-0.006
	(0.014)	(0.022)	(0.022)	(0.020)
Log(Employees)$_{t-1}$	0.181***	0.200***	0.427***	0.492***
	(0.044)	(0.035)	(0.051)	(0.048)
Log(Capital)$_{t-1}$	0.034*	0.021*	0.125***	0.097***
	(0.019)	(0.012)	(0.033)	(0.032)
Log(Output)$_{t-1}$	-0.053**	0.014	0.175***	0.205***
	(0.022)	(0.015)	(0.043)	(0.039)
N	24419	24419	24419	24419
Year fixed effects	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
R^2	0.464	0.488	0.797	0.808

Notes: This table presents OLS regressions of the log of patents in new to the firm technological areas (a and b) and log of patents in new to the firm technological areas (c and d) filed in year *t* and compared against the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

Table B5 – Level of new vs. known to firm patenting, min. 10 patents

	New patents		Known patents	
	a	b	c	d
Log(R&D)$_{t-1}$	-0.025**	0.003	-0.000	0.046***
	(0.011)	(0.011)	(0.013)	(0.015)
Log(Sales)$_{t-1}$	-0.105***	0.028	-0.015	0.041
	(0.031)	(0.042)	(0.058)	(0.064)
Log(Employees)$_{t-1}$	0.074	0.052	0.263***	0.321***
	(0.073)	(0.052)	(0.078)	(0.071)
Log(Capital)$_{t-1}$	0.093**	0.053*	0.187***	0.135***
	(0.041)	(0.028)	(0.057)	(0.050)
Log(Output)$_{t-1}$	-0.107***	-0.047**	0.180***	0.193***
	(0.019)	(0.023)	(0.033)	(0.038)
N	10524	10524	10524	10524
Year fixed effects	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
R^2	0.384	0.420	0.785	0.800

Notes: This table presents OLS regressions of the log of patents in new to the firm technological areas (a and b) and log of patents in new to the firm technological areas (c and d) filed in year *t* and compared against the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B2: Controlling for industry specific trends

Table B6 illustrates how results remain robust to adding linear or log-linear industry specific trends, which should ameliorate concerns that the results are driven by secular trends.

Table B6 – Controlling for industry specific trends

	Innovative search			
	a	b	c	d
Log(R&D)$_{t-1}$	-0.003	-0.007***	-0.005**	-0.007***
	(0.002)	(0.003)	(0.002)	(0.003)
Log(Sales)$_{t-1}$	0.005	0.005	0.004	0.004
	(0.007)	(0.007)	(0.006)	(0.007)
Log(Employees)$_{t-1}$	-0.029***	-0.041***	-0.030***	-0.042***
	(0.010)	(0.010)	(0.010)	(0.010)
Log(Capital)$_{t-1}$	-0.020***	-0.016**	-0.019**	-0.014*
	(0.008)	(0.007)	(0.008)	(0.007)
Log(Output)$_{t-1}$	-0.032***	-0.034***	-0.033***	-0.029***
	(0.005)	(0.006)	(0.005)	(0.005)
N	24419	24419	24419	24419
Year fixed effects	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
R^2	0.465	0.470	0.465	0.470

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Models a and b estimated including 3-digit-SIC linear trends and models c and d are estimated including 3-digit-SIC log-linear trends. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B3: Controlling for number of patents

Table B7 illustrates how results remain robust to adding patent counts as a control.

Table B7 – Controlling for patent count

	Innovative search	
	a	b
No. patents	-0.002***	-0.002***
	(0.001)	(0.001)
Log(R&D)$_{t-1}$	-0.002	-0.005
	(0.003)	(0.004)
Log(Sales)$_{t-1}$	0.003	0.004
	(0.007)	(0.007)
Log(Employees)$_{t-1}$	-0.027***	-0.039***
	(0.009)	(0.009)
Log(Capital)$_{t-1}$	-0.019**	-0.015*
	(0.007)	(0.008)
Log(Output)$_{t-1}$	-0.019***	-0.016***
	(0.005)	(0.005)
N	24419	24419
Year fixed effects	No	Yes
Firm fixed effects	Yes	Yes
R^2	0.461	0.466

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B4: OLS without firm fixed effects

Table B8 illustrates that results remain robust to models without firm fixed effects.

Table B8 – OLS without firm fixed effects

	Innovative search	
	a	b
Log(R&D)$_{t-1}$	-0.028***	-0.029***
	(0.005)	(0.004)
Log(Sales)$_{t-1}$	0.020***	0.020***
	(0.006)	(0.006)
Log(Employees)$_{t-1}$	-0.041***	-0.042***
	(0.009)	(0.009)
Log(Capital)$_{t-1}$	-0.022***	-0.021***
	(0.006)	(0.006)
Log(Output)$_{t-1}$	-0.029***	-0.023***
	(0.006)	(0.007)
N	24419	24419
Year fixed effects	No	Yes
Firm fixed effects	No	No
R^2	0.189	0.199

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B5: Mergers and acquisitions as exploration strategies over the business cycle

Firms can shift their innovative search focus in a number of ways, for example, by acquiring or merging with other firms. One would expect, by definition of the measure, that mergers and acquisitions should either not affect or more likely, increase a firm's innovative search, because it is very unlikely that two firms would ever possess the exact same technology portfolio, as defined in (1).

Though difficult to track over time, the DISCERN data from Arora et al. (2020) enables identification and assignment of patents from M&As for all listed firms from 1980 onwards. Using these data we recalculate our innovative search score taking all patents acquired through M&As into account. Table B9 illustrates how results hold even taking into account mergers and acquisitions.

Table B9 – Innovative search taking M&A into account

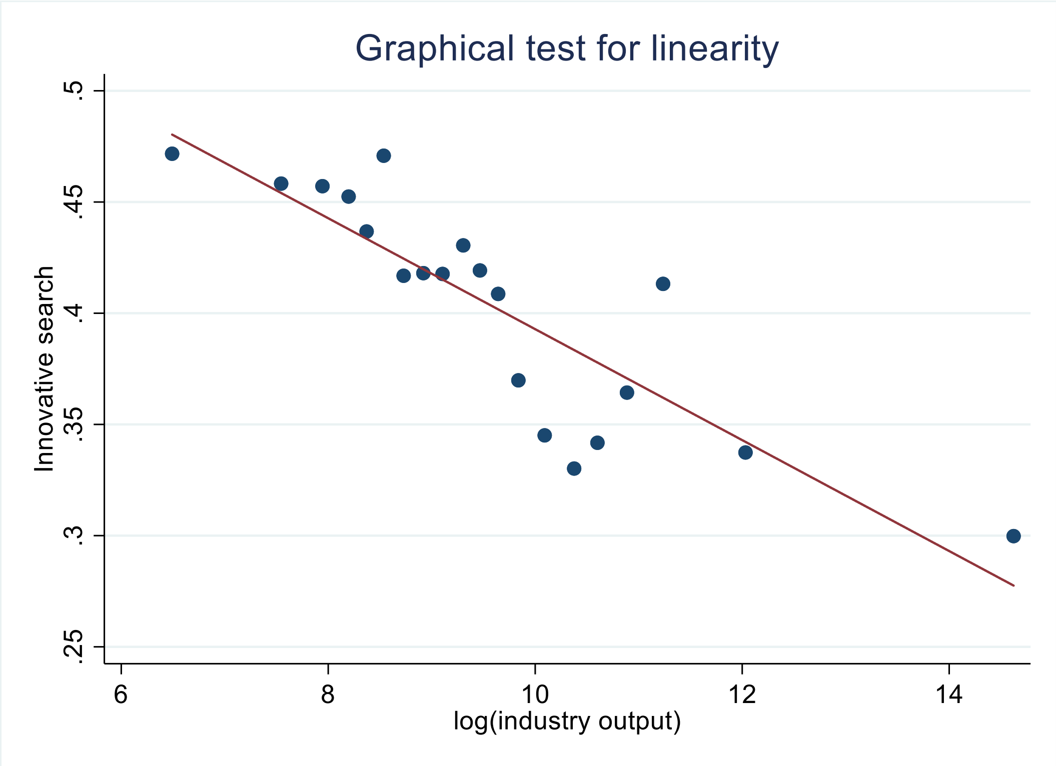
	Innovative search	
	a	b
Log(Output)$_{t-1}$	-0.106***	-0.082***
	(0.036)	(0.025)
N	14622	14622
Year fixed effects	No	Yes
Firm fixed effects	Yes	Yes
R^2	0.464	0.469

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989), taking M&A deals from 1980 to 2011 into account. All models are estimated with the previously used set of controls: Log(R&D)$_{t-1}$, Log(Sales)$_{t-1}$, Log(Employees)$_{t-1}$, Log(Capital)$_{t-1}$. Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B6: Graphical test for linearity

Figure B10 illustrates a roughly linear relationship between log of industry output and innovative search.

Figure B10 – Graphical test for linearity



Notes: This illustrates the relationship between log(industry output) and firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). The red line represents the relationship estimated with a standard OLS regression. For easier graphical inspection the data is sorted into 20 equal bins and each dot represent the mean of each bin.

B7: Intensive vs extensive margin

Table B11 splits the data into old vs. young firms (</> 26 years in the data), reveals no significant differences, and implies that the results are not driven by differences in sample composition over time.

Table B11 – Intensive vs extensive margin

	Firms < 26 year of data		Firms >= 26 years of data	
	a	b	c	d
Log(R&D)$_{t-1}$	-0.001	-0.004	-0.002	-0.008**
	(0.006)	(0.006)	(0.003)	(0.004)
Log(Sales)$_{t-1}$	0.003	0.003	-0.005	0.004
	(0.008)	(0.009)	(0.021)	(0.022)
Log(Employees)$_{t-1}$	-0.023	-0.030*	-0.025	-0.045**
	(0.016)	(0.017)	(0.017)	(0.020)
Log(Capital)$_{t-1}$	-0.018**	-0.016*	-0.027*	-0.020
	(0.009)	(0.009)	(0.015)	(0.015)
Log(Output)$_{t-1}$	-0.020***	-0.019***	-0.025***	-0.022***
	(0.005)	(0.006)	(0.007)	(0.007)
N	15463	15463	8956	8956
Year fixed effects	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
R^2	0.437	0.442	0.481	0.491

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B8: Forward term test

Adding a forward term of industrial output to the model shows that explanatory power comes from the one year lagged industry output, suggesting that we are unlikely to be picking up any unobserved trends.

Table B12 – Forward term test

	Innovative search	
	a	b
Log(R&D)$_{t-1}$	-0.003	-0.007*
	(0.003)	(0.004)
Log(Sales)$_{t-1}$	0.006	0.007
	(0.007)	(0.007)
Log(Employees)$_{t-1}$	-0.035***	-0.047***
	(0.009)	(0.009)
Log(Capital)$_{t-1}$	-0.021**	-0.016*
	(0.008)	(0.008)
Log(Output)$_{t+1}$	-0.021**	0.005
	(0.010)	(0.010)
Log(Output)$_{t-1}$	-0.006	-0.025***
	(0.010)	(0.009)
N	23911	23911
Year fixed effects	No	Yes
Firm fixed effects	Yes	Yes
R^2	0.459	0.464

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B9: Influence of control variables

Table B13 illustrates how results are (not substantively) influenced by the inclusion of control variables.

Table B13 – Influence on control variables

	Innovative search					
	a	b	c	d	e	f
Log(R&D)$_{t-1}$			-0.016***	-0.011***	-0.008**	-0.007*
			(0.004)	(0.004)	(0.004)	(0.004)
Log(Sales)$_{t-1}$				-0.019***	-0.001	0.005
				(0.006)	(0.006)	(0.007)
Log(Employees)$_{t-1}$					-0.056***	-0.045***
					(0.009)	(0.009)
Log(Capital)$_{t-1}$						-0.015*
						(0.008)
Log(Output)$_{t-1}$	-0.046***	-0.031***	-0.027***	-0.024***	-0.022***	-0.021***
	(0.008)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
N	24419	24419	24419	24419	24419	24419
Year fixed effects	No	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.454	0.459	0.461	0.462	0.464	0.464

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B10: Influence of different lags

Table B14 illustrates how results remain robust to the inclusion/exclusion of different lags.

Table B14 – Influence of different lags

	Innovative search					
	a	b	c	d	e	f
$Log(R\&D)_{t-1}$	-0.007*			-0.006*	-0.006*	-0.005
	(0.004)			(0.004)	(0.004)	(0.004)
$Log(Sales)_{t-1}$	0.005			-0.002	-0.002	0.000
	(0.007)			(0.007)	(0.007)	(0.007)
$Log(Employees)_{t-1}$	-0.045***			-0.029*	-0.028	-0.029
	(0.009)			(0.017)	(0.017)	(0.018)
$Log(Capital)_{t-1}$	-0.015*			0.001	0.001	0.003
	(0.008)			(0.009)	(0.008)	(0.008)
$Log(R\&D)_{t-2}$		-0.007*		-0.002	-0.002	-0.001
		(0.004)		(0.004)	(0.004)	(0.004)
$Log(Sales)_{t-2}$		0.005		0.007	0.006	-0.006
		(0.008)		(0.009)	(0.009)	(0.011)
$Log(Employees)_{t-2}$		-0.044***		-0.017	-0.018	-0.000
		(0.009)		(0.017)	(0.017)	(0.022)
$Log(Capital)_{t-2}$		-0.017**		-0.017**	-0.017**	-0.013*
		(0.007)		(0.008)	(0.008)	(0.007)
$Log(R\&D)_{t-3}$			-0.007*			-0.003
			(0.004)			(0.003)
$Log(Sales)_{t-3}$			0.004			0.011**
			(0.008)			(0.005)
$Log(Employees)_{t-3}$			-0.046***			-0.021
			(0.009)			(0.017)
$Log(Capital)_{t-3}$			-0.012*			-0.005
			(0.006)			(0.007)
$Log(Output)_{t-3}$			-0.020***			0.001
			(0.006)			(0.016)
$Log(Output)_{t-2}$		-0.019***			0.014	0.008
		(0.005)			(0.015)	(0.020)
$Log(Output)_{t-1}$	-0.021***			-0.021***	-0.034**	-0.032**
	(0.005)			(0.006)	(0.015)	(0.016)
N	24419	22951	21669	22951	22951	21532
Year fixed effects	No	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.464	0.472	0.476	0.472	0.472	0.478

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B11: Excluding first 5 years of firms' patenting activity

Table B15 excludes the first five years of patenting by each firms, where the measure might be particular noisy.

Table B15 – Excluding first 5 years of firms' patenting activity

	Innovative search	
	a	b
$Log(R\&D)_{t-1}$	-0.003	-0.008**
	(0.003)	(0.004)
$Log(Sales)_{t-1}$	-0.002	-0.002
	(0.009)	(0.010)
$Log(Employees)_{t-1}$	-0.034***	-0.046***
	(0.012)	(0.012)
$Log(Capital)_{t-1}$	-0.011	-0.004
	(0.009)	(0.009)
$Log(Output)_{t-1}$	-0.027***	-0.024***
	(0.007)	(0.006)
N	19537	19537
Year fixed effects	No	Yes
Firm fixed effects	Yes	Yes
R^2	0.485	0.491

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B12: Two year moving averages

Table B16 illustrates robust results if we consider 2-year moving averages of our innovative search score.

Table B16 – Two year moving averages

	Innovative search	
	a	b
Log(R&D)$_{t-1}$	-0.003	-0.007**
	(0.002)	(0.003)
Log(Sales)$_{t-1}$	0.007	0.011*
	(0.005)	(0.006)
Log(Employees)$_{t-1}$	-0.035***	-0.049***
	(0.010)	(0.009)
Log(Capital)$_{t-1}$	-0.022***	-0.016**
	(0.007)	(0.008)
Log(Output)$_{t-1}$	-0.026***	-0.019***
	(0.005)	(0.004)
N	21671	21671
Year fixed effects	No	Yes
Firm fixed effects	Yes	Yes
R^2	0.593	0.601

Notes: This table presents OLS regression of firms' innovative search focus, defined as the 2-year moving average of technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B13: An assumption of exploration in periods of no patenting

As we cannot observe firm search behavior when the firm does not patent, we assume they explore completely (innovative search is set to 1). The results in Table B17 should alleviate concerns that the results are driven by the reduction of the sample to firm-year observations in which firms file one or more patents.

Table B17 – Assuming exploration in periods of no patenting

	Innovative search	
	a	b
Log(R&D)$_{t-1}$	-0.011***	-0.014***
	(0.003)	(0.003)
Log(Sales)$_{t-1}$	0.008**	0.003
	(0.003)	(0.003)
Log(Employees)$_{t-1}$	-0.067***	-0.076***
	(0.008)	(0.007)
Log(Capital)$_{t-1}$	-0.013***	-0.011***
	(0.002)	(0.002)
Log(Output)$_{t-1}$	-0.010*	-0.020***
	(0.006)	(0.006)
N	76804	76804
Year fixed effects	No	Yes
Firm fixed effects	Yes	Yes
R^2	0.635	0.639

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B14: Excluding firms with little patenting activity

Filing only a few patents in a given year may create noisy and inaccurate measurements. Table B18 estimates models where the sample is restricted to firm-year observations, for firms that applied for at least 2/5/10 patents. Results remain robust to these restrictions.

Table B18 – Excluding firms with little patenting activity

	Innovative Search					
	Min 2 Patents		Min 5 Patents		Min 10 Patents	
	a	b	c	d	e	f
Log(R&D)$_{t-1}$	-0.003	-0.005	-0.003	-0.006*	-0.003	-0.004
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Log(Sales)$_{t-1}$	-0.001	0.003	-0.002	0.006	0.006	0.014*
	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Log(Employees)$_{t-1}$	-0.029***	-0.043***	-0.018*	-0.036***	-0.011	-0.029**
	(0.010)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)
Log(Capital)$_{t-1}$	-0.019***	-0.013*	-0.020**	-0.013	-0.027***	-0.020**
	(0.007)	(0.007)	(0.009)	(0.008)	(0.009)	(0.009)
Log(Output)$_{t-1}$	-0.023***	-0.015***	-0.019***	-0.012**	-0.020***	-0.014**
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)
N	20894	20894	14832	14832	10524	10524
Year fixed effects	No	Yes	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.487	0.495	0.512	0.521	0.530	0.539

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B15: Excluding firms with large patent portfolios

Some firms have very large patent portfolios that may have material effect on results and our measure. Hence, we re-estimate our baseline model excluding firms that filed more than 1000 or 100 patents, respectively, and also estimate a model based only on firms that filed between 10 and 100 patents where our measure is probably best suited to measure firms' innovative search focus. Results remain robust to these restrictions.

Table B19 – Excluding firms with large patenting activity

	Innovative Search					
	Max 1000 Patents		Max 100 Patents		Min 10 and max 100 Patents	
	a	b	c	d	e	f
Log(R&D)$_{t-1}$	-0.003	-0.007*	-0.003	-0.007	-0.004	-0.004
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
Log(Sales)$_{t-1}$	0.004	0.005	0.006	0.008	0.014*	0.023***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)
Log(Employees)$_{t-1}$	-0.034***	-0.047***	-0.036***	-0.048***	-0.021	-0.038***
	(0.010)	(0.009)	(0.011)	(0.011)	(0.015)	(0.015)
Log(Capital)$_{t-1}$	-0.020**	-0.015*	-0.018**	-0.014*	-0.023**	-0.019*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)
Log(Output)$_{t-1}$	-0.026***	-0.022***	-0.025***	-0.021***	-0.023***	-0.017**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)
N	24329	24329	22214	22214	8314	8314
Year fixed effects	No	Yes	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.487	0.495	0.512	0.521	0.530	0.539

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B16: Limiting analysis from 1958 to 1999

Results are also robust to taking out the 2000s years, which might be particularly influential due to the bust of the dotcom bubble (see Table B20).

Table B20 – Limiting analysis from 1958 to 1999

	Innovative search	
	a	b
Log(R&D)$_{t-1}$	-0.002	-0.008**
	(0.002)	(0.003)
Log(Sales)$_{t-1}$	0.007	0.012
	(0.008)	(0.008)
Log(Employees)$_{t-1}$	-0.008	-0.028**
	(0.013)	(0.013)
Log(Capital)$_{t-1}$	-0.040***	-0.036***
	(0.009)	(0.009)
Log(Output)$_{t-1}$	-0.024***	-0.021***
	(0.007)	(0.007)
N	17225	17225
Year fixed effects	No	Yes
Firm fixed effects	Yes	Yes
R^2	0.478	0.484

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B17: Alternative industry measure and 3-digit-SIC aggregation

Table B21 reports results with the industry output measure with total shipments per sector as measured by the NBER productivity database. Table B22 estimates models with higher aggregated output measures at the 3-digit-level. The higher aggregation should lessen concerns that measurement error with respect to the relevant industries confound our results, because firms are active in more than one 4-dgit SIC industry.

Table B21 – Aggregated industry measure

	Innovative search	
	a	b
$Log(R\&D)_{t-1}$	-0.003	-0.007*
	(0.003)	(0.004)
$Log(Sales)_{t-1}$	0.004	0.005
	(0.007)	(0.007)
$Log(Employees)_{t-1}$	-0.033***	-0.045***
	(0.009)	(0.009)
$Log(Capital)_{t-1}$	-0.020**	-0.015*
	(0.008)	(0.008)
$Log(Shipments)_{t-1}$	-0.025***	-0.021***
	(0.005)	(0.005)
N	24419	24419
Year fixed effects	No	Yes
Firm fixed effects	Yes	Yes
R^2	0.458	0.464

Notes: OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

Table B22 – 3-digit-SIC aggregation

	Innovative search	
	a	b
Log(R&D)$_{t-1}$	-0.005*	-0.008**
	(0.003)	(0.003)
Log(Sales)$_{t-1}$	0.001	0.004
	(0.006)	(0.008)
Log(Employees)$_{t-1}$	-0.032***	-0.045***
	(0.010)	(0.009)
Log(Capital)$_{t-1}$	-0.023**	-0.017*
	(0.009)	(0.010)
Log(Output)$_{t-1}$	-0.013**	-0.009**
	(0.005)	(0.004)
N	24419	24419
Year fixed effects	No	Yes
Firm fixed effects	Yes	Yes
R^2	0.457	0.463

Notes: OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B18: HHI control for competition

Because change in innovative search might be driven by changes in competition, we ran additional models which control for the sales based Herfindahl index per 4-digit SIC industry, once with a linear term and once with the squared term included. Table B23 illustrates that the main results remain unchanged.

Table B23 – HHI control for competition

	Innovative Search		Innovative Search	
	a	b	c	d
Log(R&D)$_{t-1}$	-0.003	-0.007*	-0.003	-0.007*
	(0.003)	(0.004)	(0.003)	(0.004)
Log(Sales)$_{t-1}$	0.004	0.005	0.004	0.005
	(0.007)	(0.007)	(0.007)	(0.007)
Log(Employees)$_{t-1}$	-0.034***	-0.047***	-0.035***	-0.047***
	(0.009)	(0.009)	(0.009)	(0.009)
Log(Capital)$_{t-1}$	-0.020**	-0.015*	-0.020**	-0.015*
	(0.008)	(0.008)	(0.008)	(0.008)
HHI$_{t-1}$	0.026	0.027	0.059	0.049
	(0.030)	(0.033)	(0.093)	(0.081)
HHI squared$_{t-1}$			-0.034	-0.024
			(0.090)	(0.077)
Log(Output)$_{t-1}$	-0.024***	-0.020***	-0.023***	-0.020***
	(0.005)	(0.005)	(0.005)	(0.005)
N	24419	24419	24419	24419
Year fixed effects	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
R^2	0.458	0.464	0.458	0.464

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Standard errors clustered at the industry level appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B19: Exclusion of stable and long horizon industries

In order to control for different lags between research and patenting, we exclude stable and long horizon industries (as defined by Hall and Vopel 1997), with no changes in results. Similarly, excluding pharmaceutical patents, which might have particularly long lead time from research to patenting a promising molecule, does not change results. Stable and long horizon industries demonstrate no significant result in Table B24, consistent with the cyclicality result.

Table B24 – Long and stable industries vs. short and mid-term

	Innovative search			
	Long and stable industries		Short and mid-term industries	
	a	b	c	d
Log(R&D)$_{t-1}$	0.005	-0.005	-0.007**	-0.009*
	(0.003)	(0.006)	(0.004)	(0.005)
Log(Sales)$_{t-1}$	0.037**	0.032	0.001	0.001
	(0.018)	(0.026)	(0.007)	(0.007)
Log(Employees)$_{t-1}$	-0.026	-0.019	-0.032***	-0.043***
	(0.035)	(0.040)	(0.010)	(0.010)
Log(Capital)$_{t-1}$	-0.077***	-0.077***	-0.011	-0.006
	(0.013)	(0.013)	(0.008)	(0.008)
Log(Output)$_{t-1}$	-0.028	-0.035	-0.026***	-0.022***
	(0.023)	(0.028)	(0.006)	(0.005)
N	4995	4995	19424	19424
Year fixed effects	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
R^2	0.454	0.465	0.459	0.466

Notes: This table presents OLS regression of firms' innovative search focus, defined as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.

B20: Summary of robustness checks

This table presents how results change with respect to different ways of estimation, different ways of calculating innovative search, and different sample compositions; for details please see individual tables in appendix. Order of presentation in the table resembles order of presentation in the appendix.

Table B25 – Summary of robustness checks

Baseline	-0.021*** (0.005)	*Log(Output) t-1,t-2 controls t-1, t-2*	-0.034** (0.015)
Alt. measure % new to the firm patents	-1.874*** (0.378)	*Log(Output) t-1,t-2,t-3 controls t-1, t-2,t-3*	-0.032** (0.016)
Alt. measure backward cites	0.149*** (0.034)	*Excluding first 5 years of patenting*	-0.024*** (0.006)
Alt. measure self-backward cites	0.162*** (0.037)	*Two year moving average*	-0.019*** (0.004)
Alt. measure % self-backward cites	0.418*** (0.142)	*Assuming exploration when no patenting*	-0.020*** (0.006)
Alt. measure all tech classes	-0.014*** (0.005)	*Only firms min 2 patents*	-0.015*** (0.005)
Controlling for industry specific trends	-0.034*** (0.006)	*Only firms min 5 patents*	-0.012** (0.005)
Controlling for no. of patents	-0.016*** (0.005)	*Only firms min 10 patents*	-0.014** (0.006)
Standard OLS w/o firm fixed effects	-0.023*** (0.007)	*Only firms <1000 patents*	-0.022*** (0.005)
Taking M&A into account (1980-2011)	-0.082*** (0.025)	*Only firms <100 patents*	-0.021*** (0.005)
Only firms <= 25 years of data	-0.019*** (0.006)	*Only firms >=10 & <=100 patents*	-0.017** (0.008)
Only firms > 25 years of data	-0.022*** (0.007)	*Excluding dot com bubble (1958 to 1999)*	-0.021*** (0.007)
No control variables	-0.031*** (0.006)	*Alternative output measure shipments*	-0.021*** (0.005)
Log(Output)t-1, controls t-2	-0.019*** (0.005)	*Alternative output measure at 3-digit SIC*	-0.009** (0.004)
Log(Output) t-1, controls t-3	-0.020*** (0.006)	*Control for HHI*	-0.020*** (0.005)
Log(Output) t-1,t-2, controls t-1, t-2	-0.021*** (0.006)	*Only short and midterm industries*	-0.022*** (0.005)

Notes: This table presents OLS regression of firms' innovative search focus, defined, if not otherwise mentioned, as the technological proximity between the patents filed in year *t* to the existing patent portfolio held by the same firm from year *t*-5 up to year *t*-1, calculated according to Jaffe (1989). Reported are coefficients of Log(Output)$_{t-1}$. All models are estimated with year fixed effects and, if not otherwise mentioned, firm fixed effects and controls: Log(R&D)$_{t-1}$, Log(Sales)$_{t-1}$, Log(Employees)$_{t-1}$, Log(Capital)$_{t-1}$. Full output tables for each regression are presented in the appendix. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively.