Sailing in all Winds:
Technological Search over the Business Cycle

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Keywords: innovation; technological change; business cycle; patent indicators.

JEL classification: E32, O32; O33

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1. Introduction

The Global Financial Crisis of 2007-2009 has shown how deep recessions affect the ability of firms to persistently invest in innovation, with important consequences for long-term competitiveness and economic growth (OECD, 2012). Despite the heterogeneous response across countries and sectors, many firms have curtailed their R&D expenses, calling for a deeper understanding of the effects of economic shocks on the innovative strategies of firms (Filippetti and Archibugi, 2011). The scholarly debate has identified a procyclical relationship between business cycles and innovation and the centrality of financial constraints in the R&D investment decisions of firms (Aghion and Saint-Paul,1998; Campello et al., 2010; Aghion et al., 2012).

In this study we extend this line of research by exploring the relationship between the nature of the inventive process and the business cycle. Compared to previous works, which look at the rate of innovation during economic crises, this study elaborates on the direction of innovation undertaken along the business cycle by measuring the degree of novelty embodied in inventions. We argue that the business cycle not only affects the propensity of firms to invest in R&D and, in turn, the rate of inventions produced, but also the type of inventions being generated. Inventions departing from conventional technological paradigms, pointing to more explorative routes, have in fact a fundamental impact on the economy and society as a whole (Dosi, 1982). Along these lines, we argue that understanding the patterns of technological novelty embedded in inventions, and not only its rate, may have important implications for firms' market value and for their ability to sustain a competitive advantage along the cycle.

To capture the degree of technological novelty of patents, we introduce a new measure based on relatedness of knowledge components, i.e. patent classes, recombined in inventions that measure the extent to which inventions are the result of unconventional combinations (Teece et al., 1994; Della Malva and Riccaboni, 2015). We define as unconventional those patents in which unusual combinations of classes appear. To study how the degree of conventionality of patents changes along the business cycle, we analyze the patents granted by the United States Patent and Trademark Office (USPTO) between 1980 and 2000. We merge patent data (Li et al., 2014) with financial information of firms listed in Compustat, and industry specific business cycle data from the NBER-CES Manufacturing Industry database.

The relationship between the business cycle and the unconventionality of patents is investigated both at the level of single patents and at the firm level. The first approach enables us to examine the extent to which the type of inventions produced by firms changes along the business cycle. Unlike previous studies, which used measures of innovation input and output aggregated at the level of countries or sectors, our approach relates individual patent inventions, and their characteristics, to the phases of the business cycle, allowing for a finer analysis of the relationship. The second approach takes on the perspective of the firm to assess the economic and technological implications of the changes in patent unconventionality along the business cycle.

We find that upturns are not only associated with an increase in R&D expenditures and patent production, but also with an increase in the degree of unconventionality of the inventions generated, i.e. inventions being the result of recombination of more distant technological components. This is indicative of the re-composition of the patent portfolio of firms along the business cycle, with more novelty being produced during upturns. Our results also show that financially resilient firms and multi-segment firms produce on average more patents and more unconventional ones. We further investigate the contribution of unconventional patents to the technological impact and market value of firms and find that patent unconventionality is associated with higher technological impact and firm market value. However, although technological unconventionality is procyclical, unconventional inventions have a higher potential for technological and firm market value when produced during the contractive phases of the business cycle. Finally, we compare our measure of patent unconventionality with the measure of patent novelty, as defined in Verhoeven et al. (2016).

The remainder of the paper is organized as follows. The next section presents a review of the literature on the relationship between innovation and business cycle. Section 3 provides an overview of the data and our methodological approach, whereas results are presented and discussed in section 4. Section 5 concludes with a summary of the main findings and a discussion of the implications of our work.

2. Innovation and the Business Cycle

This study contributes to the extensive scholarly debate on the cyclicality of innovation, which has mainly dealt with the impact of recessions on R&D expenditures (Barlevy, 2004, 2007; Ouyang, 2011; Aghion et al., 2012; Amore, 2015; Paunov, 2012; Filippetti and Archibugi, 2011). Two competing arguments regarding the relationship between business cycle and innovation have emerged in the literature.

A first view states a counter-cyclical relationship between business cycle and innovation, i.e. innovation increases during downturns. The underlying argument is that firms face lower opportunity costs for investing in innovation during recessions (Saint-Paul, 1997; Aghion and Saint-Paul, 1998). As returns from existing product lines and activities decline, firms are more prone to search for new market niches less affected by the downturn, reducing the risks through diversification. Accordingly, firms have higher incentives to allocate internal resources to the development of new products (Berchicci et al., 2013). Geroski and Walters (1995) suggest that firms have higher incentives to innovate when the loss associated with a decline in current activities is larger than the relative returns to be gained from implementing new processes. The introduction of new products during downturns enables firms to establish a leading position in the eyes of consumers when the demand recovers (Steenkamp and Fang, 2011). Moreover, firms have higher incentives to introduce cost-saving process innovations to curtail the costs of production and therefore match the lower demand. As for new products, the advantages stemming from more efficient production processes can provide firms with an advantage when the economy recovers (Saint-Paul, 1997).

A second perspective theorizes a procyclical relationship due to higher availability of resources to allocate to innovation activities when production grows. Following this argument, profit-maximizing firms time their innovation activities to periods of high-demand in order to capture higher profits (Schleifer, 1986). As the demand for goods and services grows during upswings, firms usually experience an increase in profits. Higher profitability translates in a higher availability of resources, especially liquidity, which enable firms to expand their investment in innovation (Barlevy, 2007; Fabrizio and Tsolmon, 2014). Moreover, the availability of external resources to finance innovation, such as bank loans, increases as financial institutions may be more keen to finance risky projects (Aghion et al., 2012).

The empirical evidence has mostly documented a procyclical relationship between industry-specific fluctuations and input/output measures of innovation (Barlevy 2007; Geroski and Walters, 1995; Ouyang, 2011; Fabrizio and Tsolmon, 2014). Using data for manufacturing sectors over four decades, Ouyang (2011) finds that the cyclical pattern of R&D investments is due to the existence of financial constraints that limit the ability of firms to sustain R&D during downturns. However, the author finds that sectors react negatively to positive shocks in the economy, advancing that the opportunity cost argument, despite not being predominant, is also in place. Using a sample of French firms, Aghion et al. (2012) complement these findings by showing that the effect of financial constraints is not uniform across firms and sectors. The relationship between R&D and business cycle is procyclical for firms with higher dependence on external capital and fewer collaterals and in more exposed sectors. Moreover, the authors find that the ratio of R&D to total investments is counter-cyclical, supporting the view that firms limit the negative effects of cash-flow fluctuation on R&D by relying on internal reserves of cash (Himmelberg and Petersen, 1994). Using patents as measure of output, Geroski and Walters (1995) find that in the UK, for a time window of 40 years, patent output clusters around periods of boom. This result suggests that economic fluctuations drive inventive activities, in line with the view that firms time their innovative activities with periods of high customer demand. Fabrizio and Tsolmon (2014) use firm data from 1975 to 2002 showing that the relationship between business cycles and patenting differs across sectors. The authors contend that the relationship is positively moderated by the likelihood of imitation and the rate of product obsolescence of sectors. Berchicci et al. (2013) investigate the relationship between industry fluctuation and types of innovation, namely product and process innovation. They argue that the opportunity cost and the financial constraint arguments co-exist when product and process innovations are considered separately. The authors show that, for a panel of Italian firms, product innovation is most likely to occur during downturns, therefore supporting the counter-cyclical argument. During industry downturn, firms engage in product innovation while holding back on process innovation since it may be not profitable to improve the efficiency of producing existing lines of products whose value is declining (Berchicci et al., 2013). Process innovation is thus more likely to coincide with upturns, as the financial constraint argument indicates (Devinney, 1990).

Against this background, in this paper we investigate the relationship between innovation activities and the business cycle by focusing on the nature of patent inventions whereas the literature has considered R&D investments or patent count.[1] Schumpeter (1911; 1939; 1942) has advanced that not only technological change is responsible for variations in the business cycle, but that innovative activities are influenced by the stages of the business cycle. Leveraging on the availability of credit from the banking sector, the author theorized that during upturns incumbent firms invest in innovation along consolidated trajectories and developed routines (Schumpeter 1942). Conversely, during downturns, when established sectors and technologies are shaken out, firms seek for new technological opportunities by investing in new domains (Schumpeter, 1911). The author also advocated the view of major economic crises as “the gale of creative destruction” referring to the opportunities for addressing inefficiencies and for a general re-organization of R&D activities. Therefore, Schumpeter suggests that unconventional innovations, those departing from established patterns and routines, carrying forward the highest impact, are produced during recessions.

A more recent stream of literature has instead argued in favor of a procyclical relationship between innovation and the business cycle (Berchicci et al., 2013; Cincera et al., 2010; Ouyang, 2011; Fabrizio and Tsolmon 2014). Based on this line of argument, during upturns managers may have more incentives to embark in novel inventive activities to captures higher rents from growing demand

[1] The only exception we are aware of is Manso et al. (2017) who use a battery of patent-based measures to capture the different dimensions of firms’ innovation strategies over the business cycle.

compared to period of downturns. Conversely, a reduced profitability and the lower availability of resources that firms face when economy shrinks affect their investment decisions not only at the *extensive* margin (total patent production) but also at the *intensive* margin (the riskiness of the inventive projects being pursued, expressed by the degree of unconventionality in the patent portfolio) as predicted by the behavioral theory of the firm and the literature on the role of slack resources (Cyert and March, 1963; Troilo et al., 2014). An increase in uncertainty following challenging economic conditions shortens the time horizon of investment decisions (Kahneman and Lovallo, 1993), especially with regards to innovation, as firms prefer to invest in projects whose returns are more predictable (Garicano and Steinwender, 2016; Peia, 2016). Summarizing, fewer prospects for payoffs during downturns refrain firms from high-risk unconventional R&D activities. Conversely, the large amount of liquidity and a lower perceived risk, motivates firms in the pursuit of more radical approaches to innovation during upturns (Bovha Padilla et al., 2009). Therefore, the pro-cyclical perspective described in the empirical literature relying on patent count and R&D is also likely to affect the relationship between the degree of patent unconventionality and the business cycle. Reconciling the two views, the pro-cyclical argument with the Schumpeterian perspective, we argue that the technological and economic impact of unconventional inventions is higher during recessions, although being mostly produced during upturns. This is our main research hypothesis that will be investigated in the following sections.

3. Data and methodology

Our research strategy is to track the degree of unconventionality embedded in inventions along the different stages of the business cycle of the industry in which firms operate.[2] We use data on utility patents granted by the USPTO between 1980 and 2000 (Li et al., 2014).[3] The database includes procedural information about patents (i.e. publication and application number, grant and application date, claims), together with inventor and assignee data, as well as complete references to the technological classes according to the US Patent Classification (USPC) system. The USPC system is articulated in more than 400 classes, representing broad technological fields, and about 100,000 subclasses, that point to specific technological divisions within each class. Patent subclasses identify, in our framework, the knowledge components available for the search and recombination process

[2] This section presents the data and the construction of the variables. The description of the variables and data sources are reported in Table B1 for patent level variables and B2 for firm level variables, respectively.
[3] The 2007-2009 financial crisis motivated this study, however due to data constraints, our analysis only includes the period 1980-2000. The measure of unconventionality that we use in this study to assess the recombination process only includes inventions up to 2000, before the introduction of new technological classes in the USPC to avoid biases in the construction of the measure. We consider only granted patents between 1980 and 2000 to guarantee consistency in the unconventionality measure used in this study. Details on the derivation of the measure are provided in the Appendix A.

(Fleming, 2001). We complement the dataset with the relational table of patents and firms from Orbis Bureau Van Dijk that provides information on about 70,000 listed companies. First, we matched patents with firms' financial accounts database and we used companies' main sector of operation to retrieve sector-level information.[4] We thus combine firm-level data with the NBER-CES Manufacturing Industry Database, which contains annual industry-level data (i.e. number of workers, total payroll, value added) for the U.S. manufacturing sector from 1958 to 2009 (Becker et al., 2013).[5] Our final dataset comprises 166,168 patent observations belonging to 1,076 US firms having at least one listed activity and operating in the manufacturing sector between 1980 and 2000.

3.1. Unconventionality and the business cycle

Inventions are the result of a process of search and recombination of knowledge into new domains of applications or reconfiguration of existing knowledge into novel combinations (Fleming, 2001). The search for novel combinatorial possibilities usually occurs in the proximity of firms' competences through local search, characterized by lower levels of risks and uncertainty as it builds on past failures, extant competences and previous successful solutions (Cyert and March, 1963; Simon, 1978). However, connections of related or complementary pieces of knowledge are likely to hinder the possibility of producing impactful inventions (Perkins, 1995). Unlike local search, distant search explores new and unfamiliar technological domains, with greater possibilities of extending the range of combinatorial alternatives (Katila and Ahuja, 2002). The ultimate result of this process is that inventions are more likely to include new or original relationships characterized by higher level of unconventionality (Levinthal and March, 1993; Simonton, 1999; Schilling, 2005; Katila and Chen, 2008). Compared to local, distant search is a costly activity, characterized by higher levels of uncertainty and failures, as it requires more efforts in the selection and integration of relevant knowledge (Fleming, 2001). Although inventions resulting from local search have a positive impact on productivity growth (Baumol, 2002), novel innovations, resulting from distant search, prevent from core rigidities traps with positive impact on performances and long term competitiveness (March, 1991; Leonard-Barton, 1992).

Therefore our main dependent variable is the degree of unconventionality of a patent (*unconventionality*), namely the extent to which an invention is the result of a search and recombinant

[4] The exclusion from Compustat of non-listed firms may generate possible sample selection bias of small firms, most of which are not included. However, the potential bias is mitigated by the fact that US firms have a high recourse to stock markets and R&D is concentrated in publicly listed firms. Compustat provides reliable coverage on long historical data and extensive financial and operating accounts.

[5] Around 70%-80% of total R&D investments are made by firms in the manufacturing sector (Barlevy, 2007).

process that departs from established and conventional practices.[6] Leveraging on the concept of relatedness, previously used to assess the diversification of business activities (Teece et al., 1994) and technological portfolios of firms (Breschi et al., 2003; Nesta and Saviotti 2005), we define as unconventional those combinations of knowledge components (i.e. patent subclasses) that are distant in the knowledge space. We conceptualize distance as the strength of the relationship among the components underlying inventions as measured by the frequency of the joint occurrence of each pair of patent classes within the focal patent in the USPTO collection of patents granted in the previous five years:

$$J_{ij} = \sum\nolimits_{k} C_{ik}\, C_{jk} \tag{1}$$

where J_{ij} provides the number of patents having simultaneously membership in class i and class j. Raw counts of the number of inventions having membership in each couple of patent classes, however, cannot be taken directly as a measure of relatedness. Conventional combinations of patent classes are those which are overexpressed as compared to an appropriate random benchmark. Following Teece et al. (1994), we modeled the random co-occurrence of each possible combination of patent classes by means of the hypergeometric distribution.[7] The difference between J_{ij} and the expected value of the random variable provides the basis for the measure of conventionality of a given combination of patent classes:

$$\tau_{ij} = \frac{J_{ij} - \mu_{ij}}{\sigma_{ij}} \tag{2}$$

where the difference between the observed and the expected occurrence of the couple of classes (J_{ij}-μ_{ij}) is divided by the standard deviation. Large values of the difference in eq. (2) are associated with combinations of patent classes which are systematically recombined and over-represented in the USPTO patent collection, thus identifying local search strategies. Conversely, small or even negative values of conventionality indicate that unexpectedly few inventions have successfully combined

[6] Similar concepts have been used in the literature as for example: novelty (Fleming 2001; Verhoeven et al., 2016) and originality (Trajtenberg et al., 1997). For the construction of the unconventionality measure, we rely on previous work by Della Malva and Riccaboni. (2015). This measure does not identify uniquely the very first combination of patent classes but it takes into account the actual state of relationship between the elements recombined in the invention along the entire technological space, considering also the relative distance among the fields that are recombined within the invention.

[7] Note that we identify the joint occurrence of the components at year t and observe the recombination of the components with other technological classes in the knowledge space in the previous 5 years. See Appendix A for details on the derivation of the measure. As an example, the patent "US6180351", assigned to Agilent Technologies Inc., has a high degree of unconventionality in the knowledge recombination process. In 1999 (application year) this patent recombined two components, i.e. database maintenance principles [class 707/200] and nucleic acid base hybridization processes [class 435/6 for molecular biology and microbiology], that at the time were predominantly used in different patents and rarely combined in a single invention.

patent classes *i* and *j*, suggesting that the combination thereof departs from a systematic recombination process as it connects unrelated pieces of knowledge through distant search.

From eq. (2), we derive the degree of conventionality of a patent as the median value of conventionality of all pairs of its patent classes. In our analysis the negative of patent conventionality is used as a measure of patent unconventionality.

Table 1 reports the descriptive statistics of the unconventionality measure. Unconventionality increases over time suggesting that recent patents are characterized by combinations of technological classes that are, on average, more atypical or unconventional[8]. This trend may depend on the grow of interdisciplinary research and the increasing availability of general purpose technologies that allow firms to carry on distant search in a more efficient way. However, the increase in dispersion over time suggests that the tendency to recombine knowledge in an unconventional way builds on top of more traditional patent production to exploit already established combinations. Large firms produce more unconventional inventions since, compared to small firms, they better diversify risks and exploit greater economies of scale and scope.[9]

[Table 1 about here]

The distribution of unconventionality across technological categories confirms the common wisdom that ICT related inventions and pharmaceutical innovations are more unconventional as compared to inventions in more traditional domains, like for example agriculture and transportation. The summary statistics of unconventionality at the sectoral level show that semiconductors and related device have the highest value of unconventionality.

In our analysis, our main goal is to investigate the relationship between patent unconventionality and the business cycle. Therefore, for all industrial sectors (SIC 3 digit level) we measure the business cycle by the value of real output over time as included in the NBER Manufacturing and Productivity database (Bartlesman and Gray, 1996). In particular, drawing on prior studies on the relationship between patents and business cycles (Barlevy, 2007; Fabrizio and Tsolmon, 2014), we use the logarithm of the annual real gross output (*ln Output*), calculated as the sum of annual value added and material costs, divided by the shipment deflator.

[8] This trends is confirmed when we recomputed the time evolution of unconventionality for selected technologies.
[9] Note that the sample includes Compustat firms so size has to be understood in the context of firms having their activities listed on the financial markets. Firm size is measured by the natural log of the number of patents of the focal firm. The average size of firms is 5.7. Small firms are capped at 3 while large firms have a size equal or greater than 7. Similar trends are found when using the log of the number of employees as a proxy of firm size.

3.2 Control variables at patent and firm level

In our empirical analysis we include a battery of controls for the characteristics of inventions. We consider the extent to which the focal patent builds on prior knowledge, as proxied by the natural logarithm (plus one) of the number of backward citations to prior art (*citations*). Original recombination of components, however, might be the result of completely new combinations which are not based on pre-existing knowledge (Ahuja and Lampert, 2001). Hence, the model also accounts for the possibility that inventions do not cite prior art (*no prior citations*). The degree of novelty characterizing each invention is a positive function of the number of knowledge components which are recombined. In our framework, the *number of technological components* is (the natural log of) the number of technological classes on which the patent is based. Drawing on the organizational literature, we also include a set of controls for the inventive process at the level of inventive teams. Since knowledge is distributed among individuals, teams may facilitate the recombination of competences and hence draw solutions from a more diversified pool (Singh and Fleming, 2010). We control for the composition of teams by considering the number of inventors in every patent (*team*). Finally, we also control for the experience of inventors by taking into account (the natural logarithm of) the total number of patents of the most prolific inventor in the team (*experience*).

Innovation is characterized by inherent uncertainty which makes it challenging for firms to finance radically new projects through external sources of capital (Amore et al., 2013; Hall and Lerner, 2010; Peia, 2016). This problem is exacerbated during downturns, when profitability and availability of internal finance decrease and the financial sector is expected to lend a lower share of their total asset (Himmelberg and Petersen, 1994). We measure the dependence of firms on external finance by the Kaplan and Zingales (KZ) Index[10]. The KZ Index is a linear combination of cash flow, market value, debt, dividends, cash holding and assets. Firms with fewer availability of liquid assets, lower ratio of cash flow and dividends to assets, higher ratio of debt to assets and Tobin's Q are expected to be more

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[10] The Kaplan and Zingales Index is defined as:

$$KZ_{it} = -1.002\frac{CF_{it}}{PPENT_{it-1}} - 39.368\frac{Div_{it}}{PPENT_{it-1}} - 1.315\frac{CHE_{it}}{PPENT_{it-1}} + 3.139LEV_{it} + 0.283Q_{it}$$

where cash flow (*CF*) is the sum of income before extraordinary items and depreciation and amortization (Compustat IB+ DP items), dividends (*Div*) common and preferred (Compustat DVC+DVP items), *CHE* refers to cash and short term investment. These variables are normalized by lagged Property Plant and Equipment (PPENT). Leverage (*LEV*), is the ratio of long term debt (DLTT item) and debt in current liabilities (DLC item) to stockholders equity (SEQ item). Tobin's Q (*Q*) is the ratio of total asset (AT), Market Value of Equity (CSHO*PRCC_F) minus the book value of equity (CEQ) and deferred taxes (TXDB) to total assets. According to Kaplan and Zingales (1997) firms are financially constrained as the wedge between internal and external funds increases with increasing cost in rising external sources of capital. Appendix C reports robustness checks using the Size and Age index as an alternative measure of financial constraints.

financially constrained and hence are likely to have more difficulties in financing their ongoing operations when economic conditions tighten. Therefore, high values of the KZ Index (*financial constraints*) indicate firms that rely heavily on external sources of funds and are characterized by high debt, low cash-flow and low dividends. Lower values are instead associated with more resilient firms.

Another firm-level characteristic that we explore is the degree of diversification across sectors, (*multiple segments*). Firms that operate in multiple segments may in fact be in a better position to diversify risks during sector-specific contractions. By operating in multiple segments, firms can shift resources to other segments that are performing relatively better. Conversely, single-segment firms are expected to be more exposed to business fluctuations as they cannot edge risk by moving resources across sectors.

Other firm-level characteristics that may influence the propensity to engage in novel search strategies are also included in the model. In particular, large firms have been found to be path dependent, usually confined within their established routines and practices showing resistance towards new or more radical solutions (Hill and Rothaermel, 2003). Yet, they also build on a larger knowledge base from which they can easily diversify their technological portfolio (Leten et al., 2007). Hence, we control for the firm inventive size (*assignee size*) computed as the (log plus one) of the total number of patents at the USPTO in the year of the focal invention.[11] The concentration of R&D activities within firms may affect the knowledge recombination process. Therefore, we control for the technological *concentration* of firms over technological classes by computing the Herfindahl index of concentration. This measure takes large values for firms having patent portfolios concentrated in a handful of patent classes, whereas it approaches zero for technologically diversified firms. We finally introduce a set of time and technology dummies to capture trends in unconventionality over time and across technologies.

4. Results

We analyze the relationship between innovation and the business cycle at the patent level (section 4.1) and at the firm level (section 4.2). In the patent level analysis, we explore the relationship between unconventionality and business cycle at the intensive margin, i.e. the degree of unconventionality of each and every patent, irrespective of the change in size of the patent portfolio of the firm. In the firm level analysis we complement the patent level perspective by taking into account the extensive margin, i.e. the changes in the size of the patent portfolio. The purpose is

[11] In separate regression we use the log (+1) of the number of employees as a proxy of size. Estimations using this alternative specification are consistent.

twofold. First, we want to provide a better understanding of the extent to which changes in the degree of unconventionality of inventions are related to variations in the production of patents along the business cycle; second, we want to consider the technological and economic implications of our findings for the firm. At the firm level we also consider the technological impact of patents (as measured by forward patents citations) and the market value of firms (market to book value and Tobin's Q).

4.1. Patent level analysis

In the patent level analysis we estimate the following equation model:

$$Unconventionality_i = \beta_1 * Ln\ Output_{k,t-1} + \gamma_1 * X_i + \tau_t + \theta_z + \varepsilon_{i,t} \qquad (3)$$

where Ln Output is the one-year lagged natural log of Output in industry k (SIC 3 digit level), X is the vector of controls of the focal patent i as described in section 3, τ_t and θ_z the two sets of time and technology dummies. Summary statistics and the correlation table of the variables used in the patent level analysis are reported in Table 2.[12]

Table 3 shows the results of our main analysis on the effect of business cycles on the degree of unconventionality embedded in inventions. In all models the coefficient of the natural logarithm of output is positive and statistically significant, indicating that higher levels of output are associated with more unconventional inventions. Higher values of the output in fact, are not only associated with an increase in R&D expenditures and patent production, as extensively discussed in literature (Fabrizio and Tsolomon, 2014; Barlevy 2007), but also with an increase in the degree of unconventionality of the inventions being generated, i.e. inventions being the result of recombination of more distant technological components. During upturns, managers may be willing to undertake risky investments, such as those relative to original innovative projects. Conversely, during recessions, firms are reluctant to pursue innovative projects based on the recombination of distant technological domains (Cyert and March, 1963; Troilo et al., 2014). They are more likely to focus on recombination processes that leverage on established knowledge domains and on the exploitation of existing solutions. Model 2 and 3 further investigate the mechanisms behind the reconfiguration of patent portfolios along the business cycle. Namely, model 2 includes a control for multi-segment firms whereas model 3 contains the coefficient on the dependence of firms on financial resources.[13]

[12] Table B1 and B2 in Appendix B provide a description of all variables used in the patent and firm level analyses.
[13] In models 3 and 4 there is a reduction in the number of observation due to missing information in the computation of the KZ financial constraints index. In non-reported analysis we replicated model 1 and 2, excluding the observations with missing data of KZ, obtaining very similar results.

The results indicate that the relationship between business cycle and innovation is not significantly affected by the diversification of the firm across different segments. Also financial constraints at the firm level are not significant.

The effect of the remaining controls is in line with expectations. Inventions based on a larger number of components recombine more distant elements in the technological space, providing possibilities for more novel solutions. Unconventionality is negatively associated with the number of backward citations in patents and larger teams tend to produce more conventional patents, even though this effect is no more significant in our full model. This result, surprisingly at first, can be explained by the fact that larger teams have the advantage of recombining components from a broad set of competences, but they also require a common ground to combine very distant domains. Finally, firms whose technological competences are highly concentrated have lower possibilities to recombine in a more unconventional way fields that are distant to each other in the knowledge space.

[Table 2 about here]

[Table 3 about here]

4.2. Firm-level analysis

In the patent level analysis, we have explored the relationship between unconventionality and business cycle at the intensive margin, i.e. the degree of unconventionality of the inventions irrespective of the size of the patent portfolio. In this section we provide a comprehensive analysis by taking into account the extensive margin, that is the change in the number of patents. In particular, we estimate the models for the patent count and unconventionality (section 4.2.1) as well as the models for technological impact and the firm market value (section 4.2.2).

In the analysis of patent production we consider both the simple patent count and the one weighed by unconventionality. In the first model *patent production*, measured as the log of the number of patents filed in each year (extensive margin), is the dependent variable as expressed in the following equation:

$$Patent_j = \beta_2 * Ln\ Output_{k,t-1} + \gamma_2 * Z_{j,t-1} + \tau_t + \sigma_j + \varepsilon_{j,t} \qquad (4)$$

where, next to the one-year lag of the logarithm of output at the level of the industry *k*, Z represents the set of controls at the level of the firm *j*, τ and σ the two sets of time and firm dummies.

In a second model, we weigh the number of patents by unconventionality to take into account possible changes in the aggregated unconventionality by considering the log of the count of patents weighed by their *unconventionality*, whereby patents with higher levels of unconventionality have a higher weight than those that are more conventional as in the following equation:

$$Unconventionality_j = \beta_2 * Ln\ Output_{k,t-1} + \gamma_2 * Z_{j,t-1} + \tau_t + \sigma_j + \varepsilon_{j,t} \qquad (5)$$

As reported in the equations above, we use the logarithm of the annual real gross output (*ln Output*) as independent variable while including an array of controls to account for differences in knowledge and profitability of the firm. Namely, we include *sales* as a control for firm profitability, *R&D stock* to account for the firm innovative efforts as well as *total asset* used as a proxy of firm size **(**all variables are in log and lagged by one year). We also use time and firm dummies, as well as dummies for missing information about firm asset, R&D stock and sales.

In addition to the estimation models described above, we also consider the technological impact of patents and the firms' market value. To assess the technological impact of possible changes of unconventionality along the business cycle we rely on the number of forward citations of the patent portfolio of the firms (*technological impact*, see Hall et al., 2001) by estimating the following equation:

$$\begin{aligned} Citations_j = {} & \alpha_3 * Unconventionality_{j,t} + \beta_3 * Ln\ Output_{k,t-1} + \delta_3 \\ & * Unconventionality_{j,t} * Ln\ Output_{k,t-1} + \gamma_3 * W_{j,t-1} + \tau_t \qquad (6) \\ & + \sigma_j + \varepsilon_{j,t} \end{aligned}$$

where we include the logarithm of the output (one-year lag) at the level of the industry *k*, as already described in section 3. As in previous estimation models, we add the set of controls W at the level of the firm *j*, as well as two sets of time (τ) and firm dummies (σ). To control for firm's characteristics we consider also the firm *R&D intensity* (R&D to assets ratio) providing an idea of firm investments in innovation as well as *profitability* computed as the ratio of sales to assets and the *patent intensity* (patent to R&D ratio).

Lastly, we analyze the impact of patent unconventionality on firm *market to book value*, (natural logarithm of the ratio of market to book value), considered in the literature a measure of long term profitability of firms (e.g. Arora et al., 2015). We estimate the following equation:

$$Market\ Value_j = \alpha_4 * Unconventionality_{j,t} + \beta_4 * Ln\ Output_{k,t-1} + \delta_4 * Unconventionality_{j,t} * Ln\ Output_{k,t-1} + \gamma_4 * Y_{j,t-1} + \tau_t + \sigma_j + \varepsilon_{j,t} \quad (7)$$

where, next to the logarithm of the output (one-year lag) at the level of the industry *k*, we include the set of controls Y at the level of the firm *j*, and the two sets of time (τ) and firm dummies (σ). In this estimation model we control for the stock of existing knowledge in the previous year, *patent stock*, measured as the log of the firm cumulated patent counts lagged by one year, as well as *R&D stock* to consider the firms' innovative efforts. Finally, to account for firm size we included *sales* and *total asset* (all variables are in log and are lagged by one year). We also built additional dummies to control for missing information on R&D and patent data. As an additional proxy of firm value, we replicated the same model also on firms' *Tobin's Q*.

As for the patent level approach (section 4.1), we identify financially constrained firms by means of the Kaplan-Zingales Index and we control for the effect of firm diversification by means of a dummy which indicates firms operating in multiple segments. Tables 4 shows the summary statistics of the firm level variables whereas table 5 reports the correlation table.

[Table 4 about here]

[Table 5 about here]

4.2.1. Patent production and unconventionality along the business cycle

Table 6 shows the main determinants of firm patent production. We find a procyclical relationship between the production of patents and industry real output: a 1% increase in real output at the industry level generates an increase of 0.08-0.10% in patent production. This result, combined with the findings from the analysis at the level of patents, suggests that during upturns firms not only produce more inventions but they also recombine patent classes in a more unconventional manner. In table 7 we combine these two dimensions (unconventionality at the patent level and the number of patents in the portfolio of the firm) by considering the log of the sum of patent unconventionality of the firm. From this analysis we conclude that the increase in patent production at the extensive margin in the expanding periods of the cycle is paired with an increase at the intensive margin, i.e. on the degree of unconventionality of inventions.

Models 2 and 4 show that firms in multiple segments produce on average more patents (table 6) which are also more unconventional (table 7). We argue that firms that are active in multiple sectors have diversified technological competences that enable them to effectively recombine components in a more unconventional manner. Models 3 and 4 show that financially constrained firms produce less patents and less unconventional ones during upturns. This finding supports the view that, on average, firms that have a lower availability of financial or slack resources decrease the number of patent produced and are less likely to engage in innovative activities characterized by distant search. The availability of slack resources is in fact a critical factor for the pursuit of novel activities that are based on the unconventional recombination of distant components. Conversely, firms with higher slack resources are more likely to engage in more unconventional inventive processes as they are less concerned about immediate returns (Danneels, 2008; Levinthal and March, 1981). Along this line, Nohria and Gulati (1996) argue that slack resources allow firms to pursuit innovative projects associated with higher levels of uncertainty but also with expected higher pay-offs.[14]

As for the controls, they are in line with expectations: size, proxied by firms' assets, profitability, expressed in sales, and R&D stock are all positively associated with unconventionality and patent production.

[Table 6 about here]

[Table 7 about here]

4.2.2. Technological Impact and Market Value

The analysis so far has highlighted a decrease in the level of patent production and patent unconventionality during downturns. In this section we shed light on the technological and economic implications of these findings. First, we consider the relationship between business cycle and the technological impact of the inventions produced by firms by means of forward citations (Trajtenberg, 1990). Then, we analyze the impact of unconventionality along the business cycle on the market value and the Tobin's Q of firms.

[14] Financially constrained firms not only may be at a disadvantage with regards to the ability to deploy financial resources for innovative activities; they might also face difficulties in hiring and retaining inventors. In this regards, Hombert and Matray (2016) found that financially constrained firms are more likely to experience a loss of human capital (i.e. inventors) when they are hit by credit shocks.

Table 8 (model 1) shows that, as expected, upturns are positively associated with forward citations due to the procyclical relationship between patent production and unconventionality discussed in the previous section. The interaction term between the degree of unconventionality and industry real output indicates that although unconventionality is generally associated with an increase in forward citations, unconventional inventions generated during the upturns receive proportionally less citations by future patents.[15] Put differently, unconventional inventions have the highest impact when they are produced during downturns. This finding suggests that unconventional innovations during upturns are less cited, probably due to the increase in the number of citable patents in the expansive phase of the cycle. As the relationship between unconventionality and output is procyclical, during upturns there is a higher number of unconventional patents that can be possibly cited. As a consequence, unconventional inventions during the upturn phases of the cycle are a less rare event resulting on average in a lower impact in terms of citations. In models 3 and 4 the effects are maintained, although weaker in magnitude, but we do not find any statistically significant impact of multiple segments and financial constraints variables.

Table 9 focuses on the implications of the inventive outcomes on the market to book value of firms. Model 1 shows that unconventional inventions are associated with an increase in the market to book value of firms. The model also shows that the market to book value of the firm increases in upturns: a 10% increase in the industry real output translates in an increase of 5% of the value of the firms. The interaction term between unconventionality and output shows that unconventionality bears a different impact depending on the phases of the business cycle in which unconventional patents are generated. Unconventional inventions generated in upturns are associated with a decrease in market value indicating a discount in the value of the firm relative to the generation of more innovative inventions when economy expands. In other words, unconventional inventions carry their highest contribution to the market to book value of the firm when they are developed during the recessive phases of the industry, in line with the finding relative to the technological impact of inventions. Models 2 and 3 confirm the positive association between market value unconventionality and output but do not show any significant effect from the financial structure and firms' diversification. Results hold also when we turn to Tobin's Q as a measure of firm value (table 10). Compared to previous estimations, Model 3 shows a negative effects of the financial constraints on the firm's Tobin's Q which is maintained in the full model.

[15] The results relative to the technological impact and the value of the firms are robust and slightly stronger in magnitude when using the unconventionality lagged by 1 year.

All in all, we find that unconventionality is positively related to technological impact and market value, especially when it is generated during downturns. However, our results on the relationship between patent unconventionality and firm value must be interpreted with caution since reverse causality might be present. Such a relationship should be further investigated in future work to better ascertain how patent unconventionality contributes to the value of the firm.

[Table 8 about here]

[Table 9 about here]

[Table 10 about here]

4.2.3. Patent novelty and patent unconventionality

This section replicates our analysis by using a measure of patent novelty (Verhoeven et al., 2016) which considers as novel those inventions recombining for the first time a given combination of technological classes.[16, 17] More precisely, we use the logarithm of the number of new combinations embodied in each patent (plus 1) (*Ln novelty in recombination, ln_NR*) as measure of patent novelty. Measures of patent unconventionality and patent novelty are logically different: patents are novel if they contain completely new combinations of patent classes whereas unconventional patents comprise rare and unusual (but maybe not totally new) combinations of classes. In fact, the two measures are not strongly correlated: there is almost no correlation at the patent level while at the firm level the correlation is 0.7 (significant at 5% level), mostly driven by the production of patents.

Table 11 replicates our analysis at the patent level showing that the business cycle has a weaker effect on patent novelty. Overall, the results confirm that novelty is procyclical but the coefficients are much smaller in magnitude and weakly significant in models 1 and 3. By considering only the new combinations, the measure of patent novelty flags as novel only about 2.84% of the patents in our sample.[18] Conversely, our measure of unconventionality identifies more patent as unconventional

[16] Additional robustness tests are reported in Appendix C.

[17] The novelty measure by Verhoeven et al. (2016) adopts a combination of constructs: a) the newness of the combination (Novelty in Recombination, NR); b) the citations to previously unconnected scientific fields (Novelty in Knowledge Origins, NSO) and c) originality in technological classes (Novelty in Technological Knowledge Origins, NTO). The robustness checks presented in this section only show the estimations based on the NR construct which is closer to our approach. Non reported estimations on the NTO and NSO constructs in the patent level robustness checks are (respectively) not significant and only weakly significant. In the firm level regressions instead, NTO and NSO constructs are strongly significant and positively associated with technological impact as well as market value of the firm.

[18] In our sample about 9% of patents are in the decile with the highest degree of unconventionality.

thus improving the predictive power of the model. Table 12 shows the results of the firm level. The procyclical relationship between novelty and output is in line with the findings in table 7, even though effects are weaker in magnitude for novelty. As for the unconventionality measure we find that multiple segment company produce more novel patents. Conversely financial constraints are no more significant.

[Table 11 about here]

[Table 12 about here]

5. Discussion and concluding remarks

This study contributes to the debate on the cyclicity of innovation by showing that firms react to business cycles by modifying both the amount and the type of innovation being generated. Not only business cycles affect the incentives to undertake R&D and produce inventions, but also to steer innovation strategies towards more unconventional projects. Therefore, changes in innovation strategies during the business cycle affect the innovative portfolio of firms at the extensive margin and at the intensive margin.

We found that the expanding phases of the business cycle are not only associated with investments in R&D and patent production, as extensively documented in the literature, but also with inventions characterized by higher degree of unconventionality, in line with the procyclical hypothesis. Financially constrained firms produce fewer patents showing also a decrease in the degree of unconventionality embedded in patents. This suggest that financially resilient firms are in a better position since they can leverage on the availability of financial resources that can potentially be mobilized among projects, especially in multiple segment companies. Indeed, we also find that multi-business firms are in an advantageous position with regards to both patent production and production of more unconventional patents. Finally, our results suggest that unconventional patents have a greater technological and economic impact. However, there is a discount in both dimensions related to upturns, suggesting that unconventional inventions are associated with a higher technological impact during recessions, and that during the latter unconventional inventions have a greater market value. On average the propensity to invest in innovation, in particular more unconventional projects, decreases during recessions.

All in all, our findings imply that firms tend to be more risk averse when the economy contracts, showing higher preferences for local search, i.e. knowledge components recombined among familiar and less risky technological domains. Reduced profitability from ongoing projects, lower availability of external funding and higher level of uncertainty may affect the decisions with regards to R&D investments and innovation search strategies at large.

This study is not without limitations. As recognized in the literature, patents data have the major drawback of capturing only successful inventions. Besides, they do not have a uniform value and not all sectors are equally patents intensive (Cohen et al., 2000). Yet, patent data reveal major and important innovations patterns. Moreover, the patent classification system is rather stable over time and regularly updated, making it a reliable source for the computation of the level of unconventionality in the recombination of knowledge. Another limitation is that we analyze only firms listed in the US stock market by means of Compustat data, leaving out a large majority of small and medium sized companies that are more subjected to the fluctuations of the business cycle. In addition, R&D data in standard dataset as Compustat may suffer from misclassification and reporting problems, as acknowledged in Koh and Reeb (2015).

In our analysis we try to identify the heterogeneity of firms reactions to variation in the level of output although other sources of heterogeneity can play a role in shaping the relationship between innovation and the business cycle. Therefore, the scope of future research is to provide further insights on how firm innovation strategies and market value change along the business cycle. It is interesting to consider potential premia associated with better performances (i.e. sales) in the aftermath of downturns for firms that are able to sustain adequate levels of technological innovation. Research in this direction should focus on a better understanding of the extent to which firms reshape their patent portfolio since firms with limited availability of resources may reduce their involvement in riskier projects thus focusing on inventions with more certain outcome (Almeida et al., 2013). Novelty, and the uncertainty underlying it, is usually associated with inventions having both a higher failure rate but also a higher impact. Thus, future research should tease out whether firms, especially those with limited access to financial resources, are more selective in the pursuit of novel projects. Future research should also further investigate the role of market concentration on the degree of unconventionality. This aspect is driven by the rationale that during expansion competition may boost innovation because firms have incentives to increase their technological lead over rivals (Aghion and Saint-Paul, 1998). However, a decrease in competition during the contractive phases may translate in a decline of patent race pushing more resilient firms to invest in unconventional innovations.

The impact of economic recessions on innovation is not homogeneous across industries. In complex industries as the information technologies, economic crises may serve as an opportunity to reallocate resources to new projects and to build a forthcoming market demand for more radical products. Thus, a line of research should provide insights in the relation between search process and business cycle in different industries.

Although its limitations, this study contributes to a stream of research aiming at advancing the understanding of innovation along the business cycle, a topic that has important implications for economic growth and firm competitiveness.

Reference List

Aghion, P., Askenazy, P., Berman, N., Cette, G. and Eymard, L., 2012. Credit constraints and the cyclicality of R&D investment: Evidence from France. *Journal of the European Economic Association*, *10*(5), pp.1001-1024.

Aghion, P. and Saint-Paul, G., 1998. Virtues of bad times interaction between productivity growth and economic fluctuations. *Macroeconomic Dynamics*, *2*(3), pp.322-344.

Ahuja, G. and Morris Lampert, C., 2001. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal*, *22*(6-7), pp.521-543.

Almeida, H., Hsu, P.H. and Li, D., 2013. Less is more: Financial constraints and innovative efficiency.

Amore, M.D., 2015. Companies learning to innovate in recessions. *Research Policy*, *44*(8), pp.1574-1583.

Amore, M.D., Schneider, C. and Žaldokas, A., 2013. Credit supply and corporate innovation. *Journal of Financial Economics*, *109*(3), pp.835-855.

Arora, A., Belenzon, S. and Patacconi, A., 2015. *Killing the golden goose? The decline of science in corporate R&D* (No. w20902). National Bureau of Economic Research.

Barlevy, G., 2007. On the cyclicality of research and development. *American Economic Review*, *97*(4), pp.1131-1164.

Barlevy, G., 2004. The cost of business cycles under endogenous growth. *American Economic Review*, *94*(4), pp.964-990.

Bartlesman, E. and Gray, W.B., 1996. The NBER manufacturing productivity database.

Baumol, W.J., 2002. *The free-market innovation machine: Analyzing the growth miracle of capitalism*. Princeton university press.

Becker, R., Gray, W. and Marvakov, J., 2013. Nber-ces manufacturing industry database: Technical notes. *NBER Working Paper*, *5809*.

Berchicci, L., Tucci, C.L. and Zazzara, C., 2013. The influence of industry downturns on the propensity of product versus process innovation. *industrial and Corporate Change*, *23*(2), pp.429-465.

Bovha Padilla, S., Damijan, J.P. and Konings, J., 2009. Financial Constraints and the Cyclicality of R&D investment: Evidence from Slovenia.

Breschi, S., Lissoni, F. and Malerba, F., 2003. Knowledge-relatedness in firm technological diversification. *Research Policy*, *32*(1), pp.69-87.

Bryce, D.J. and Winter, S.G., 2009. A general interindustry relatedness index. *Management Science*, *55*(9), pp.1570-1585.

Campello, M., Graham, J.R. and Harvey, C.R., 2010. The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics*, *97*(3), pp.470-487.

Cincera, M., Cozza, C., Tübke, A. and Voigt, P., 2010. *Doing R&D or not, that is the question (in a crisis…)* (No. 2010-12). Joint Research Centre (Seville site).

Cohen, W.M., Nelson, R.R. and Walsh, J.P., 2000. *Protecting their intellectual assets: Appropriability conditions and why US manufacturing firms patent (or not)* (No. w7552). National Bureau of Economic Research.

Cyert, R.M. and March, J.G., 1963. A behavioral theory of the firm. *Englewood Cliffs, NJ*, *2*, pp.169-187.

Danneels, E., 2008. Organizational antecedents of second-order competences. *Strategic Management Journal*, *29*(5), pp.519-543.

Della Malva, A. and Riccaboni, M., 2015. *(Un) conventional combinations: At the origins of breakthrough inventions* (No. 497108). KU Leuven, Faculty of Economics and Business, Department of Managerial Economics, Strategy and Innovation (MSI).

Devinney, T.M., 1990. New products over the business cycle. *Journal of Product Innovation Management*, *7*(4), pp.261-273.

Dosi, G., 1982. Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. *Research Policy*, *11*(3), pp.147-162.

Fabrizio, K.R. and Tsolmon, U., 2014. An empirical examination of the procyclicality of R&D investment and innovation. *Review of Economics and Statistics*, *96*(4), pp.662-675.

Filippetti, A. and Archibugi, D., 2011. Innovation in times of crisis: National Systems of Innovation, structure, and demand. *Research Policy*, *40*(2), pp.179-192.

Fleming, L., 2001. Recombinant uncertainty in technological search. *Management Science*, *47*(1), pp.117-132.

Garicano, L. & Steinwender, C. 2016. Survive another day: does uncertain financing affect the composition of investment?. *Review of Economics and Statistics*, 98(5), pp. 913-924.

Geroski, P.A. and Walters, C.F., 1995. Innovative activity over the business cycle. *The Economic Journal*, pp.916-928.

Hadlock, C.J. and Pierce, J.R., 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies*, *23*(5), pp.1909-1940.

Hall, B.H., Jaffe, A.B. and Trajtenberg, M., 2001. *The NBER patent citation data file: Lessons, insights and methodological tools* (No. w8498). National Bureau of Economic Research.

Hall, B.H. and Lerner, J., 2010. The financing of R&D and innovation. In *Handbook of the Economics of Innovation* (Vol. 1, pp. 609-639). North-Holland.

Hill, C.W. and Rothaermel, F.T., 2003. The performance of incumbent firms in the face of radical technological innovation. *Academy of Management Review*, *28*(2), pp.257-274.

Himmelberg, C.P. and Petersen, B.C., 1994. R & D and internal finance: A panel study of small firms in high-tech industries. *The Review of Economics and Statistics*, pp.38-51.

Hombert, J. and Matray, A., 2016. The real effects of lending relationships on innovative firms and inventor mobility. *The Review of Financial Studies*, *30*(7), pp.2413-2445.

Kahneman, D. and Lovallo, D., 1993. Timid choices and bold forecasts: A cognitive perspective on risk taking. *Management Science*, *39*(1), pp.17-31.

Kaplan, S.N. and Zingales, L., 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints?. *The Quarterly Journal of Economics*, *112*(1), pp.169-215.

Katila, R. and Chen, E.L., 2008. Effects of search timing on innovation: The value of not being in sync with rivals. *Administrative Science Quarterly*, *53*(4), pp.593-625.

Katila, R. and Ahuja, G., 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal*, *45*(6), pp.1183-1194.

Koh, P.S. and Reeb, D.M., 2015. Missing r&d. *Journal of Accounting and Economics*, *60*(1), pp.73-94.

Leonard-Barton, D., 1992. Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal*, *13*(S1), pp.111-125.

Leten, B., Belderbos, R. and Van Looy, B., 2007. Technological diversification, coherence, and performance of firms. *Journal of Product Innovation Management*, *24*(6), pp.567-579.

Levinthal, D. and March, J.G., 1981. A model of adaptive organizational search. *Journal of Economic Behavior & Organization*, *2*(4), pp.307-333.

Levinthal, D.A. and March, J.G., 1993. The myopia of learning. *Strategic Management Journal*, *14*(S2), pp.95-112.

Li, G.C., Lai, R., D'Amour, A., Doolin, D.M., Sun, Y., Torvik, V.I., Amy, Z.Y. and Fleming, L., 2014. Disambiguation and co-authorship networks of the US patent inventor database (1975–2010). *Research Policy*, *43*(6), pp.941-955.

Manso, G., Balsmeier, B. and Fleming, L., 2017. *Heterogeneous Innovation over the Business Cycle*. Working paper, University of California at Berkeley.

March, J.G., 1991. Exploration and exploitation in organizational learning. *Organization science*, *2*(1), pp.71-87.

Nesta, L. and Saviotti, P.P., 2005. Coherence of the knowledge base and the firm's innovative performance: evidence from the US pharmaceutical industry. *The Journal of Industrial Economics*, *53*(1), pp.123-142.

Nohria, N. and Gulati, R., 1996. Is slack good or bad for innovation?. *Academy of Management Journal*, *39*(5), pp.1245-1264.

OECD publishing 2012. Innovation in the crisis and beyond. Ch. 1 in OECD Science, Technology and Industry Outlook, OECD, Paris.

Ouyang, M., 2011. On the Cyclicality of R&D. *Review of Economics and Statistics*, *93*(2), pp.542-553.

Paunov, C., 2012. The global crisis and firms' investments in innovation. *Research Policy*, *41*(1), pp.24-35.

Peia, O., 2016. Banking crises, R&D investments and slow recoveries *(April 8, 2016)*.

Perkins, D. N., 1995. Insight in minds and genes. R.J. Sternberg and J.E. Davidson, eds. The nature of insight. MIT Press, Cambridge, MA, 495-534.

Saint-Paul, G., 1997. Business cycles and long-run growth. *Oxford Review of Economic Policy*, *13*(3), pp.145-153.

Schilling, M.A., 2005. A" small-world" network model of cognitive insight. *Creativity Research Journal*, *17*(2-3), pp.131-154.

Shleifer, A., 1986. Implementation cycles. *Journal of Political Economy*, *94*(6), pp.1163-1190.

Schumpeter, J. A. (1911). 1934. *The theory of economic development*.

Schumpeter, J. (1939). *Business Cycles: A Theoretical, Historical and Statistical Analysis of the Capitalist Process* (New York: McGrawHill).

Schumpeter, J., 1942. Creative destruction. *Capitalism, socialism and democracy*, *825*.

Simon, H.A., 1978. Rationality as process and as product of thought. *The American Economic Review*, *68*(2), pp.1-16.

Simonton, D.K., 1999. Creativity as blind variation and selective retention: Is the creative process Darwinian?. *Psychological Inquiry*, pp.309-328.

Singh, J. and Fleming, L., 2010. Lone inventors as sources of breakthroughs: Myth or reality?. *Management Science*, *56*(1), pp.41-56.

Steenkamp, J.B.E. and Fang, E., 2011. The impact of economic contractions on the effectiveness of R&D and advertising: evidence from US companies spanning three decades. *Marketing Science*, *30*(4), pp.628-645.

Teece, D.J., Rumelt, R., Dosi, G. and Winter, S., 1994. Understanding corporate coherence: Theory and evidence. *Journal of economic behavior & organization*, *23*(1), pp.1-30.

Trajtenberg, M., 1990. A penny for your quotes: patent citations and the value of innovations. *The Rand Journal of Economics*, pp.172-187.

Trajtenberg, M., Henderson, R. and Jaffe, A., 1997. University versus corporate patents: A window on the basicness of invention. *Economics of Innovation and new technology*, *5*(1), pp.19-50.

Troilo, G., De Luca, L.M. and Atuahene-Gima, K., 2014. More innovation with less? A strategic contingency view of slack resources, information search, and radical innovation. *Journal of Product Innovation Management*, *31*(2), pp.259-277.

Verhoeven, D., Bakker, J. and Veugelers, R., 2016. Measuring technological novelty with patent-based indicators. *Research Policy*, *45*(3), pp.707-723.

Appendix A: Analytical derivation of the measure for the degree of Unconventionality

Teece et al. (1994) introduce the relatedness measure to assess the extent of diversification among firms' activities. In the present study this measure is adapted to describe the diversification patterns of recombination of knowledge over the knowledge space (Breschi et al., 2003; Nesta and Saviotti, 2005; Piscitello, 2005). Following Teece et al. (1994), let $C_{ik} = 1$ if invention k has membership in patent class i, and 0 otherwise. The number of inventions with membership in class i is $n_i = \sum_k C_{ik}$.

It follows that the joint occurrence of each possible combination of subclasses within the same patent over the whole universe of USPTO patents granted in the previous five years is:

$$J_{ijt} = \sum_k C_{ik} C_{jk} \tag{A1}$$

where J_{ijt} provides the number of inventions having simultaneously membership in class i and class j. Raw counts of the number of inventions having membership in each couple of patent classes, however, cannot be taken directly as a measure of relatedness. Classes must be present at a rate greater than what would be expected if combinations were made at random.

We computed the conditional probability that a patent belongs to class i given that it also belongs to class j, $P(i|j)=J_{ij}/n_j$ where n_j represents the number of patents citing class j only. The main issue is that $P(i|j)$ and $P(j|i)$ are not equal as n_i is different from n_j. The fact that $n_i \neq n_j$ implies that J_{ij} increases with the relatedness of i and j, but also with n_i and n_j, the number of inventions having membership in each class of the couple determining potential overestimations of the actual co-occurrence of the couple of classes in the same patent. Thus, we benchmarked the observed number of co-occurrences against their expected number, had the combinatorial process followed a random process. We adjusted J_{ij} for the number of inventions that would appear in the couple ij under the null hypothesis that inventors combine patent classes at random. To operationalize the null hypothesis, the distribution of J_{ij} must be derived by assuming that inventions are assigned to classes at random, call this random variable x_{ij}. Teece et al. (1994) identify the distribution of the random variable, but they do not derive it in their paper. For the sake of exposition, we derive the distribution in order to clarify the construction of the measure. This brief exposition is based on Bryce and Winter (2009). Draw a sample of size n_i from the population of K multi-class inventions. Now draw another sample of size n_j and observe x_{ij}, or the number of inventions that were also in the n_i sample. The number of ways of selecting x inventions to fill x positions in sample n_j is equivalent to the number of ways of selecting x from a total of n_i inventors, or $\binom{n_i}{x}$.

The number of ways of selecting inventions not receiving assignment to class i for the remaining ($n_j - x$) positions in the n_j sample is equivalent to the number of ways of selecting ($n_j - x$) from a possible ($K - n_i$) inventions, or $\binom{K-n_i}{n_j-x}$.

Then the number of possible permutations of the n_j sample is the number of ways of combining a set of x inventions assigned to class i (n_i) multiplied by ($n_j - x$) inventions not assigned to class i[19], or:

$$\binom{n_i}{x}\binom{K-n_i}{n_j-x} \tag{A2}$$

The number of different samples of size n_j that can be drawn from K is $\binom{K}{n_j}$. The number of possible permutations of the n_j sample divided by the number of ways of choosing a sample of size n_j is the probability that x inventions from population K are assigned to both class i and class j. Thus, the number x_{ij} of inventions having membership in both class I and class j is a hypergeometric random variable with probability given by:

$$P\left[X_{ij} = x\right] = \frac{\binom{n_i}{x}\binom{K-n_i}{n_j-x}}{\binom{K}{n_j}} \tag{A3}$$

whit mean[20]:

[19] Since sample n_j was fixed as the number of inventions in class j, inventions assigned to class i in this quantity are *de facto* also assigned to class j.

[20] Since sample n_j was fixed as the number of inventions in class j, inventions assigned to class i in this quantity are *de facto* also assigned to class j. For intuition of the mean, assume that *nj* inventions in K have been assigned to class j. Now randomly assign inventions in K to class i. The probability that any one invention receives a class i assignment is $\frac{n_i}{K}$. Since there are *nj* inventions in K, each with probability $\frac{n_i}{K}$ of being assigned to class i, the expected number of inventions assigned to both class i and class j is $n_j\left(\frac{n_i}{K}\right)$.

$$\mu_{ij} = E(X_{ij}) = \frac{n_i n_j}{K} \tag{A4}$$

and variance:

$$\sigma^2{}_{ij} = \mu_{ij}\left(1 - \frac{n_i}{K}\right)\left(\frac{K - n_j}{K - 1}\right) \tag{A5}$$

The difference between J_{ij} and the expected value of the random variable provides the basis for the final measure of conventionality in combinations:

$$\tau_{ij} = \frac{J_{ij} - \mu_{ij}}{\sigma_{ij}} \tag{A6}$$

where the difference between the observed and the expected occurrence of the couple of classes (J_{ij}-μ_{ij}) is divided by the standard deviation of the observed incidence. From (A.6), we can derive the degree of unconventionality of the patent *z*, as the median of τ_{ij} of all combinations of technologies (i,j) in which the patent has membership.

For instance, if a patent has four subclasses, then *m* is equal to six, since this is the number of subclass combinations (4(4-1)/2). Hence, *m*=1, …, 6.

Higher value of the unconventionality measure indicates that inventions have successfully combined subclasses in an unconventional way, suggesting that the combination(s) thereof is not systematic and points to search strategies that connect more distant pieces of knowledge. Conversely, smaller values flag inventions that are based on systematic, typical or conventional combination(s) thus relying on local search strategies.

Appendix B: Description of variables and data sources

[Table B1 about here]

[Table B2 about here]

Appendix C: Robustness checks

In addition to the robustness checks discussed in the main text, we also perform additional tests to validate our results to alternative specifications of the model. Robustness checks for the patent level analysis are summarized in table C1 whereas those relative to the firm level analysis are reported in tables C2-C6.

We check the robustness of our results using a two year lag on our main independent variable, namely output. Row 1 of table C1 shows that output, lagged by two years, remains positively associated with unconventionality with effects that are similar in magnitude compared to table 3. Row 2 reports the results relative of the coefficient of output when standard errors are clustered by sector while row 3 shows the estimation coefficient of output when standard errors are clustered by sic and year. This approach is useful to account for possible change of the business cycle among sectors and years, although in our main models we always included time and firm dummies. Results are also robust to this different cluster of standard errors.

We then control for possible entry/exit bias (row 4) by limiting our analysis to the set of patents of firms observed over the entire time window of our analysis (1980-2000). In total only 60 firms are observed every year between 1980 to 2000 for a total of 100,413 patents observations. The coefficient of output slightly decrease but remains highly significant.

To check the robustness of the results to an alternative measure of financial constraints, row 5 reports the coefficient of the financial constraint variable using the Size and Age Index (SA)[21]. Contrary to our expectation, although the procyclical relationship between unconventionality and business cycle is confirmed, the SA index suggests that financially constrained firm produce more unconventional inventions, an effect that was not significant in our main results reported in table 3 where we relied on the Kaplan Zingales Index.

[21] The Size-Age Index is based on Hadlock and Pierce (2010) and it is calculated as (-0.737*Size)+(0.043*Size^2)-(0.040*Age), where Size equals the log of inflation-adjusted book assets, and Age is the number of years the firm is listed with a non-missing stock price on Compustat. Size and Age are winsorized at the 95% percentile of the distribution; specifically they are capped at 9,9 million of total Assets and 62 years. We use the median value of the index to construct the dummy for low and high financially constrains firms.

[Table C1 about here]

We performed the same robustness checks also for the firm level analysis focusing on the estimations model for patent production, unconventionality (weighted), technological as well as market value and Tobin's Q (tables C2-C6). Overall, the robustness checks at the firm level confirm the results described in section 4.2. The procyclical trend is confirmed in all the estimations model of the firm level analysis without a substantial variation in the magnitude of the coefficient of output. The restriction of the analysis to firms observed in all years, controlling in this way for potential entry/exit bias, confirms our results showing for the technological impact and the Tobin's Q even stronger effects. The use of SA as an alternative measure of dependence on financial resources confirms the negative effect of financial constraints with coefficients that are slightly higher as compared to our main findings. However, we don't find a significant impact of financial constraints on the unconventionality weighted estimation model showed in row 4 of table C3 and on the market value of the firm as reported in row 4 of table C5 and C6.

[Table C2-C6 about here]

Table

Table 1

Descriptive statistics of patent unconventionality			
Distribution of unconventionality over time			
Year	**Mean**	**S.D.**	**Observations**
1980 -1985	-3.747	0.559	20,003
1986-1990	-3.677	0.559	24,292
1991-1995	-3.574	0.577	43,196
1996-2000	-3.433	0.649	78,677
Unconventionality by firm size			
Firm Size			
Small	-3.612	0.636	14,508
Medium	-3.597	0.614	70,920
Large	-3.484	0.614	80,741
Unconventionality by technological categories			
Most unconventional technological categories			
Information Storage	-3.299	0.587	8,020
Semiconductors	-3.411	0.545	17,641
Drugs	-3.484	0.620	14,616
Electrical devices	-3.572	0.592	8,122
Power systems	-3.616	0.589	5,550
Least unconventional technological categories			
Materials Processing & Handling	-3.757	0.587	5,041
Miscellaneous-Mechanical	-3.847	0.622	3,323
Motors, Engines & Parts	-3.893	0.577	3,514
Agriculture, Husbandry, Food	-4.049	0.728	854
Transportation	-4.065	0.609	2,679
Unconventionality in the most representative sectors			
SIC, 3 digit level			
Semiconductors and related devices	-3.368	0.594	43,681
Plastic material, synthetic resins and non-vulcanizable elastomers	-3.504	0.553	7,530
Pharmaceutical preparations	-3.519	0.599	14,042
Radio and television broadcasting and communications equipment	-3.521	0.588	15,400
Photographic equipment and supplies	-3.633	0.609	12,871

Note that the summary statistics of unconventionality refer to the primary sector of operation of the firms included in our sample.

Table 2

Summary statistics and correlation table of the variables used in the patent level analysis

	Variable	Obs	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11
1	Unconventionality$_{(t)}$	166,168	-3.543	0.619	1.0000										
2	Ln Output$_{(t-1)}$	166,168	10.422	1.545	0.1827*	1.0000									
3	Citations	166,168	2.418	0.896	0.0410*	-0.0197*	1.0000								
4	No prior cits	166,168	0.008	0.093	0.0042	0.0052*	-0.2547*	1.0000							
5	Num. tech. components	166,168	1.441	0.561	0.2155*	0.0323*	0.1204*	0.0052*	1.0000						
6	Team	166,168	2.371	1.565	0.0323*	-0.0204*	0.1544*	0.0067*	0.0926*	1.0000					
7	Experience	166,168	15.965	29.05	0.0802*	0.2151*	0.1046*	0.0120*	0.1110*	0.1526*	1.0000				
8	Concentration	166,168	0.120	0.114	0.0263*	-0.0778*	0.1842*	0.0073*	0.0356*	0.0692*	0.1276*	1.0000			
9	Assignee Size	166,168	5.769	1.749	0.1024*	0.4312*	-0.0658*	-0.1139*	0.0314*	0.0326*	0.1856*	-0.4452*	1.0000		
10	Financial Constraints$_{(t-1)}$	145,652	0.288	0.453	0.0790*	0.3041*	-0.0030	-0.0014	0.0130*	-0.0387*	0.1659*	0.0941*	0.0886*	1.0000	
11	Multiple Segments	166,168	0.596	0.490	-0.0782*	-0.1277*	-0.1269*	0.0046	0.0135*	-0.0660*	-0.0781*	-0.3652*	0.1470*	-0.0557*	1.0000

Table 3

Patent level estimations for the degree of patent unconventionality

	Model 1	Model 2	Model 3	Model 4
Ln $Output_{(t-1)}$	0.0855***	0.0848***	0.0805***	0.0794***
	(0.0077)	(0.0086)	(0.0085)	(0.0096)
Citations	-0.0103**	-0.0103**	-0.0102*	-0.0102*
	(0.0049)	(0.0049)	(0.0053)	(0.0053)
No prior Citations	-0.0171	-0.0171	-0.0010	-0.0011
	(0.0205)	(0.0205)	(0.0225)	(0.0225)
Num. Tech. Comp	0.2182***	0.2182***	0.2211***	0.2210***
	(0.0082)	(0.0082)	(0.0091)	(0.0091)
Team	-0.0031*	-0.0031*	-0.0028	-0.0028
	(0.0017)	(0.0017)	(0.0018)	(0.0018)
Experience	0.0000	0.0000	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Concentration	-0.1675**	-0.1639**	-0.1573*	-0.1508*
	(0.0806)	(0.0792)	(0.0911)	(0.0882)
Assignee Size	0.0007	0.0007	0.0047	0.0046
	(0.0052)	(0.0052)	(0.0055)	(0.0055)
Multiple Segment		0.0053		0.0077
		(0.0132)		(0.0154)
Financial $Constraints_{(t-1)}$			0.0228	0.0225
			(0.0197)	(0.0194)
Firm dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Tech dummies	yes	yes	yes	yes
Constant	-4.8803***	-4.8766***	-4.8398***	-4.8347***
	(0.0929)	(0.0951)	(0.1019)	(0.1045)
N	166,168	166,168	145,652	145,652
R^2	0.1728	0.1728	0.1740	0.1740

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The models report the results of the Ordinary Least Square on unconventionality resulting from the median value of the degree of unconventionality of all combinations of classes in the focal patent. Models include 20 year, 36 technology and firm dummies. Models also include controls (dummies) for missing information about backward citations. Standard errors are clustered by firm. Models 3 and 4 have a reduced number of observations due to missing data in the computation of the KZ index.

Table 4

Summary statistics of firm level variables

Variables	Obs	Mean	Std. Dev.	Min	Max
Patent Production$_{(t)}$	10,653	1.099	1.388	0	7.471
Conventionality weighted Patent$_{(t)}$	10,653	0.637	0.989	0	6.339
Technological Impact$_{(t)}$	10,653	2.372	2.509	0	10.224
Market to Book Value$_{(t)}$	10,653	3.470	1.810	-16.098	13.315
Tobin's Q$_{(t)}$	10,653	0.677	0.838	-1.398	6.317
Unconventionality$_{(t)}$	10,653	-2.047	1.818	-6.679	0
Ln Output$_{(t-1)}$	10,653	9.373	1.307	5.250	13.61
Ln Assets$_{(t-1)}$	10,653	4.418	2.271	-3.817	12.52
Ln R&D Stock$_{(t-1)}$	10,653	2.699	2.279	-4.564	11.13
Ln Patent Stok$_{(t-1)}$	10,653	1.573	1.865	-3.087	8.688
Ln Sales$_{(t)}$	10,653	4.427	2.588	-6.907	12.236
R&D Intensity$_{(t-1)}$	10,653	1.415	43.149	0	2701.82
Profitability$_{(t-1)}$	10,653	4.477	131.39	0	5957.80
Patent Intensity$_{(t-1)}$	10,653	0.710	3.053	0	163.136
Financial constraints$_{(t-1)}$	9,471	0.395	0.489	0	1
Multiple Segments	10,653	0.433	0.495	0	1
No R&D Stock	10,653	0.111	0.315	0	1
No Patent Stock	10,653	0.200	0.400	0	1
No Patents	10,653	0.442	0.495	0	1

Table 5

Correlation table of firm level variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Patent Production$_{(t)}$	1.0000																			
2	Conventionality weighted patent$_{(t)}$	0.9818*	1.0000																		
3	Technological Impact$_{(t)}$	0.9239*	0.8602*	1.0000																	
4	Market to Book value$_{(t)}$	0.5045*	0.5153*	0.4426*	1.0000																
5	Tobin's Q$_{(t)}$	0.1494*	0.1466*	0.1743*	0.6724*	1.0000															
6	Unconventionality$_{(t)}$	-0.6739*	-0.5405*	-0.8047*	-0.2685*	-0.1015*	1.0000														
7	Ln Output$_{(t-1)}$	0.1857*	0.2020*	0.1406*	0.3590*	0.3203*	-0.0627*	1.0000													
8	Unconventionality*Output$_{(t-1)}$	-0.6957*	-0.5717*	-0.8094*	-0.3291*	-0.1679*	0.9774*	-0.2266*	1.0000												
9	Ln Assets$_{(t-1)}$	0.5669*	0.5743*	0.4640*	0.4432*	-0.1659*	-0.3155*	0.2277*	-0.3403*	1.0000											
10	Ln R&D Stock$_{(t-1)}$	0.7077*	0.7044*	0.6290*	0.5818*	0.1513*	-0.4386*	0.2801*	-0.4766*	0.7095*	1.0000										
11	Ln Patent Stock$_{(t-1)}$	0.8532*	0.8438*	0.7660*	0.4911*	0.1005*	-0.5404*	0.1626*	-0.5594*	0.6041*	0.7388*	1.0000									
12	Ln Sales$_{(t)}$	0.4896*	0.4995*	0.3983*	0.3541*	-0.1936*	-0.2613*	0.2174*	-0.2865*	0.9210*	0.6150*	0.5219*	1.0000								
13	R&D Intensity$_{(t-1)}$	0.0388*	0.0400*	0.0356*	0.0274*	0.0080	-0.0169	-0.0193*	-0.0110	-0.0485*	0.0457*	0.0455*	0.0250*	1.0000							
14	Profitability$_{(t-1)}$	0.0358*	0.0336*	0.0314*	0.0161	-0.0149	-0.0225*	-0.0036	-0.0212*	-0.0493*	0.0451*	0.0454*	0.0431*	0.7539*	1.0000						
15	Patent Intensity$_{(t-1)}$	-0.0618*	-0.0558*	-0.0646*	-0.0771*	-0.0168	0.0599*	-0.0352*	0.0589*	-0.1255*	-0.2967*	-0.0742*	-0.0972*	-0.0062	-0.0053	1.0000					
16	Financial constraints$_{(t-1)}$	-0.1581*	-0.1494*	-0.1627*	-0.1083*	-0.0894*	0.1308*	0.0415*	0.1231*	-0.1174*	-0.1745*	-0.1435*	-0.0745*	0.0379*	0.0639*	0.0326*	1.0000				
17	Multiple Segments	0.0576*	0.0720*	0.0160	-0.0502*	-0.1612*	0.0108	-0.0844*	0.0208*	0.1646*	0.0310*	0.0699*	0.1789*	0.0206*	0.0294*	0.0103	0.0510*	1.0000			
18	No R&D Stock	-0.2050*	-0.1817*	-0.2291*	-0.1211*	-0.1471*	0.2028*	-0.0133	0.2021*	0.0477*	-0.4203*	-0.2252*	0.0811*	-0.0106	-0.0082	0.1364*	0.1010*	0.0883*	1.0000		
19	No Patent Stock	-0.3275*	-0.2839*	-0.3501*	-0.1704*	-0.0250*	0.3535*	-0.0912*	0.3530*	-0.2359*	-0.3250*	-0.4222*	-0.1928*	-0.0097	-0.0123	0.0355*	0.0632*	0.0363*	0.1625*	1.0000	
20	No Patents	-0.6908*	-0.5626*	-0.8245*	-0.2981*	-0.1363*	0.9817*	-0.0835*	0.9647*	-0.3039*	-0.4547*	-0.5557*	-0.2403*	-0.0185	-0.0215*	0.0630*	0.1413*	0.0302*	0.2193*	0.3616*	1.0000

Table 6

Estimations for patent production

	Model 1	Model 2	Model 3	Model 4
Ln Output$_{(t-1)}$	0.0981***	0.1006***	0.0850***	0.0869***
	(0.0220)	(0.0220)	(0.0231)	(0.0231)
Ln Assets$_{(t-1)}$	0.1270***	0.1259***	0.1630***	0.1610***
	(0.0145)	(0.0144)	(0.0162)	(0.0162)
Ln R&D Stock$_{(t-1)}$	0.2311***	0.2321***	0.2376***	0.2396***
	(0.0160)	(0.0159)	(0.0173)	(0.0172)
Ln Sales$_{(t)}$	0.0715***	0.0708***	0.0477***	0.0469***
	(0.0118)	(0.0117)	(0.0131)	(0.0131)
Multiple Sectors		0.0715***		0.0690***
		(0.0246)		(0.0264)
Financial Constraints$_{(t-1)}$			-0.0386**	-0.0384**
			(0.0173)	(0.0173)
Firm dummies	Yes	yes	yes	yes
Year dummies	Yes	yes	yes	yes
Constant	-3.3219***	-3.3823***	-3.2932***	-3.3495***
	(0.3065)	(0.3087)	(0.3218)	(0.3239)
N	10,653	10,653	9,471	9,471
R^2	0.8358	0.8360	0.8406	0.8408

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The models report the results of the Ordinary Least Square on patent production. Models include firm and 20 years dummies. Models also include controls (dummies) for missing information about R&D stock and assets. All models include firm and year fixed effects with robust standard errors.

Table 7

Estimations for the unconventionality (weighted by patent)

	Model 1	Model 2	Model 3	Model 4
Ln Output$_{(t-1)}$	0.1189***	0.1204***	0.1105***	0.1117***
	(0.0169)	(0.0169)	(0.0178)	(0.0178)
Ln Assets$_{(t-1)}$	0.0838***	0.0831***	0.1113***	0.1100***
	(0.0090)	(0.0090)	(0.0101)	(0.0101)
Ln R&D stock$_{(t-1)}$	0.1720***	0.1726***	0.1788***	0.1801***
	(0.0109)	(0.0108)	(0.0117)	(0.0117)
Ln Sales$_{(t)}$	0.0454***	0.0450***	0.0336***	0.0331***
	(0.0072)	(0.0072)	(0.0080)	(0.0080)
Multiple Segments		0.0443***		0.0434**
		(0.0166)		(0.0179)
Financial Constraints$_{(t-1)}$			-0.0198*	-0.0197*
			(0.0111)	(0.0111)
Firm dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Constant	-2.9969***	-3.0343***	-3.0592***	-3.0947***
	(0.2146)	(0.2169)	(0.2291)	(0.2315)
N	10,653	10,653	9,471	9,471
R^2	0.8613	0.8615	0.8675	0.8676

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The models report the results of the Ordinary Least Square on unconventionality (the measure is weighted by patent). Models include firm and 20 years dummies. Models also include controls (dummies) for missing information about R&D stock and assets. All models include firm and year fixed effects with robust standard errors.

Table 8

Estimations for the technological impact of inventions (forward citations)

	Model 1	Model 2	Model 3	Model 4
Unconventionality$_{(t)}$	0.1996***	0.1994***	0.1503**	0.1501**
	(0.0587)	(0.0587)	(0.0628)	(0.0628)
Ln Output$_{(t-1)}$	0.2576***	0.2586***	0.2366***	0.2378***
	(0.0289)	(0.0290)	(0.0314)	(0.0315)
Unconv.*Ln Output$_{(t-1)}$	-0.0152***	-0.0151***	-0.0097*	-0.0097*
	(0.0053)	(0.0053)	(0.0057)	(0.0057)
R&D Intensity$_{(t-1)}$	-0.0004	-0.0004	0.0510**	0.0511**
	(0.0004)	(0.0004)	(0.0211)	(0.0211)
Profitability	0.0006***	0.0006***	0.0666**	0.0662**
	(0.0002)	(0.0002)	(0.0283)	(0.0283)
Patents intensity	0.0121**	0.0120**	0.0129*	0.0129*
	(0.0058)	(0.0058)	(0.0072)	(0.0071)
Ln Assets$_{(t-1)}$	0.2003***	0.2000***	0.2596***	0.2590***
	(0.0159)	(0.0159)	(0.0214)	(0.0215)
Multiple Segments		0.0195		0.0226
		(0.0329)		(0.0350)
Financial Constraints$_{(t-1)}$			-0.0007	-0.0006
			(0.0237)	(0.0237)
Firm dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Constant	-0.7733**	-0.7913**	-0.9817**	-1.0025**
	(0.3772)	(0.3783)	(0.4023)	(0.4041)
N	10,653	10,653	9,471	9,471
R^2	0.9080	0.9080	0.9105	0.9105

Standard errors in parentheses   * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The models report the results of the Ordinary Least Square on the technological impact of inventions measured through the forward citations. Models include firm and 20 years dummies. Models also include controls (dummies) for missing information on R&D stock, assets and patents. All models include firm and year fixed effects with robust standard errors.

Table 9

Estimations for the market to book value of firms

	Model 1	Model 2	Model 3	Model 4
Unconventionality$_{(t)}$	0.3511***	0.3517***	0.3323***	0.3330***
	(0.0563)	(0.0564)	(0.0579)	(0.0580)
Ln Output$_{(t-1)}$	0.5035***	0.5023***	0.5067***	0.5055***
	(0.0367)	(0.0369)	(0.0397)	(0.0399)
Unconv.*Ln Output$_{(t-1)}$	-0.0389***	-0.0389***	-0.0372***	-0.0373***
	(0.0061)	(0.0061)	(0.0062)	(0.0063)
Ln Assets$_{(t-1)}$	-0.0838***	-0.0834***	-0.0841***	-0.0830***
	(0.0238)	(0.0239)	(0.0318)	(0.0318)
Ln R&D Stock$_{(t-1)}$	0.1431***	0.1426***	0.1367***	0.1355***
	(0.0236)	(0.0236)	(0.0280)	(0.0281)
Ln Patent Stock$_{(t-1)}$	0.1512***	0.1514***	0.1508***	0.1511***
	(0.0157)	(0.0157)	(0.0170)	(0.0170)
Ln Sales$_{(t)}$	0.1840***	0.1842***	0.1993***	0.1997***
	(0.0250)	(0.0250)	(0.0300)	(0.0300)
Multiple Segments		-0.0303		-0.0367
		(0.0405)		(0.0422)
Financial Constraints$_{(t-1)}$			-0.0196	-0.0197
			(0.0274)	(0.0274)
Firm dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Constant	-1.0962**	-1.0675**	-1.3690***	-1.3357***
	(0.4706)	(0.4757)	(0.4987)	(0.5049)
N	10,653	10,653	9,471	9,471
R^2	0.8024	0.8024	0.8085	0.8085

Standard errors in parentheses   * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The models report the results of the Ordinary Least Square on the technological impact of inventions measured through the forward citations. Models include firm and 20 dummies. Models also include controls (dummies) for missing information about R&D stock, patent stock and assets. All models include firm and year fixed effects with robust standard errors.

Table 10

Estimations for firms' Tobin's Q

	Model 1	Model 2	Model 3	Model 4
Unconventionality$_{(t)}$	0.1841***	0.1840***	0.1852***	0.1850***
	(0.0299)	(0.0299)	(0.0300)	(0.0300)
Ln Output$_{(t-1)}$	0.5438***	0.5440***	0.5315***	0.5318***
	(0.0232)	(0.0232)	(0.0246)	(0.0247)
Unconv.*Ln Output$_{(t-1)}$	-0.0208***	-0.0208***	-0.0211***	-0.0211***
	(0.0033)	(0.0033)	(0.0033)	(0.0033)
Ln Assets$_{(t-1)}$	-0.1916***	-0.1916***	-0.2469***	-0.2472***
	(0.0143)	(0.0143)	(0.0174)	(0.0174)
Ln R&D Stock$_{(t-1)}$	0.0094	0.0095	0.0223	0.0227
	(0.0133)	(0.0133)	(0.0153)	(0.0154)
Ln Patent Stock$_{(t-1)}$	0.0374***	0.0373***	0.0366***	0.0366***
	(0.0081)	(0.0081)	(0.0087)	(0.0087)
Ln Sales$_{(t)}$	0.0581***	0.0580***	0.0800***	0.0799***
	(0.0148)	(0.0148)	(0.0177)	(0.0177)
Multiple Segments		0.0036		0.0096
		(0.0205)		(0.0216)
Financial Constraints$_{(t-1)}$			-0.0470***	-0.0470***
			(0.0149)	(0.0149)
Firm dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Constant	-3.6321***	-3.6355***	-3.4675***	-3.4762***
	(0.2579)	(0.2598)	(0.2714)	(0.2735)
N	10,653	10,653	9,471	9,471
R^2	0.7137	0.7137	0.7162	0.7162

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The models report the results of the Ordinary Least Square on the firms' Tobin's Q. Models include firm and 20 years dummies. Models also include controls (dummies) for missing information about R&D stock, patent stock and assets. All models include firm and year fixed effects with robust standard errors.

Table 11

Patent level estimations for the degree of patent novelty

	Model 1	Model 2	Model 3	Model 4
ln $Output_{(t-1)}$	0.0028^{*}	0.0024	0.0026^{*}	0.0025
	(0.0015)	(0.0016)	(0.0015)	(0.0017)
Citations	0.0056^{***}	0.0056^{***}	0.0056^{***}	0.0056^{***}
	(0.0010)	(0.0010)	(0.0011)	(0.0011)
No prior Citations	0.0062	0.0062	0.0091	0.0091
	(0.0056)	(0.0057)	(0.0062)	(0.0062)
Num. Tech. Comp	0.0116^{***}	0.0116^{***}	0.0113^{***}	0.0113^{***}
	(0.0019)	(0.0019)	(0.0021)	(0.0021)
Team	0.0022^{***}	0.0022^{***}	0.0025^{***}	0.0025^{***}
	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Experience	-0.0000	-0.0000	-0.0000^{**}	-0.0000^{**}
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Concentration	-0.0324^{**}	-0.0306^{*}	-0.0319^{*}	-0.0310
	(0.0162)	(0.0163)	(0.0187)	(0.0188)
Assignee size	-0.0015^{*}	-0.0016^{*}	-0.0009	-0.0009
	(0.0009)	(0.0009)	(0.0010)	(0.0010)
Multiple segment		0.0026		0.0011
		(0.0026)		(0.0026)
Financial $Constraints_{(t-1)}$			-0.0010	-0.0010
			(0.0016)	(0.0017)
Firm dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Tech dummies	yes	yes	yes	yes
Constant	0.0214	0.0232	0.0248	0.0256
	(0.0181)	(0.0188)	(0.0191)	(0.0197)
N	166,168	166,168	145,652	145,652
R^2	0.0270	0.0270	0.0258	0.0258

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The models report the results of the Ordinary Least Square on the degree of novelty used as an alternative measure of unconventionality. Models include 20 years, 36 technology and firm dummies. Models also include controls (dummies) for missing information about backward citations. Standard errors are clustered by firm.

Table 12

Firm level estimations for the degree of patent novelty

	Model 1	Model 2	Model 3	Model 4
Ln Output$_{(t-1)}$	0.0276**	0.0296**	0.0343**	0.0356**
	(0.0133)	(0.0133)	(0.0141)	(0.0141)
ln Assets$_{(t-1)}$	0.0260***	0.0250***	0.0427***	0.0412***
	(0.0083)	(0.0083)	(0.0092)	(0.0092)
ln R&D stock$_{(t-1)}$	0.0418***	0.0427***	0.0385***	0.0400***
	(0.0077)	(0.0077)	(0.0085)	(0.0085)
ln Sales$_{(t)}$	0.0154***	0.0148**	0.0087	0.0081
	(0.0059)	(0.0059)	(0.0062)	(0.0063)
Multiple segments		0.0600***		0.0498***
		(0.0165)		(0.0173)
Financial Constraints$_{(t-1)}$			-0.0033	-0.0032
			(0.0096)	(0.0096)
Firm dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
Constant	-0.7798***	-0.8304***	-0.8918***	-0.9325***
	(0.1561)	(0.1561)	(0.1686)	(0.1692)
N	10,653	10,653	9,471	9,471
R^2	0.6364	0.6370	0.6411	0.6415

Standard errors in parentheses* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The models report the results of the Ordinary Least Square on the novelty measure. Models include firm and 20 year dummies. Models also include controls (dummies) for missing information about R&D stock and assets. All models include firm and year fixed effects with robust standard errors.

Appendix B

Table B1

Patent Level Variables

Label	Description	Source
Dependent Variable		
Unconventionality	Ln of the yearly frequency of the joint occurrence of each possible combination of classes within the same patent compared to the outcome of a purely random process (derivation based on Teece et al., 1994).	USPTO
Independent Variable		
Ln Output $_{(t-1)}$	Ln of industry real output computed as industry value added plus material cost corrected for the industry shipment deflator and then lagged by 1 year	NBER-CES Manufacturing Industry database
Controls at the level of the invention		
Citations	Ln of the backward citations + 1 of patent *i*	USPTO
Num. Tech. Components	Ln of the number of technological components (patent classes) recombined in patent *i*	USPTO
Controls at the team level		
Team	Ln of the number of inventors in patent *i*	USPTO
Experience	Ln of the number of patents of the most prolific inventor in patent *i*	USPTO
Controls at the firm level		
Size	Ln of the tot number of patents of firm *j*	USPTO
Concentration	Herfindahl Index of the firm *j*	USPTO
Firm Financial Constraints (KZ Index)	$KZ_{it} = -1.002\frac{CF_{it}}{PPENT_{it-1}} - 39.368\frac{Div_{it}}{PPENT_{it-1}} - 1.315\frac{CHE_{it}}{PPENT_{it-1}} + 3.139LEV_{it} + 0.283Q$ Dummy equal 1 for financially constrained firms.	Compustat
Multi Segment Firms	Dummy equal 1 if focal firm operates in different sectors	Compustat Segment Data

Table B2

Firm level variables

Label	Description	Source
Dependent Variable		
Market to Book Value	Ln of the ratio of market to book value of the firm, computed on Compustat items as ((csho*prcc) / bkvlps)	Compustat
Tobin's Q	Ln of the Tobin's Q of the firm, computed on Compustat items as (at + (csho*prrcc_f)-ceq)/at)	Compustat
Technological Impact	Ln of the number of forward citation +1 of firm *j* in year *t*	USPTO
Patent Production	Ln of the num of patents of firm *j* in year *t*	USPTO
Unconventionality (weighted)	Ln of patent weighted by conventionality	USPTO
Independent Variable		
Ln Output ($_{(t-1)}$)	Industry real output computed as industry value added plus material cost corrected for the industry shipment deflator	NBER-CES Manufacturing Industry database
Unconventionality	Ln of the yearly frequency of the joint occurrence of each possible combination of classes within the same patent compared to the outcome of a purely random process (derivation based on Teece et al., 1994).	USPTO
Controls		
Ln R&D Stock $_{(t-1)}$	Ln of R&D stock of firm j at *t-1*	Compustat
Ln Assets $_{(t-1)}$	Ln of asset of firm *j* at time *t-1*	Compustat
Ln Patent Stock $_{(t-1)}$	Ln of patent stock of firm *j* at time *t-1*	
Ln Sales	Ln of sales of firm *j* at time *t-1*	Compustat
Firm Financial Constraints(KZ Index)	$KZ_{it} = -1.002\frac{CF_{it}}{PPENT_{it-1}} - 39.368\frac{Div_{it}}{PPENT_{it-1}} - 1.315\frac{CHE_{it}}{PPENT_{it-1}} + 3.139LEV_{it} + 0.283Q$	Compustat
	Dummy equal 1 for financially constrained firms	
Multi Segment	Dummy equal 1 if focal firm operates in different sectors	Compustat Segment Data

Appendix C

Table C1

Robustness checks of the patent level analysis: unconventionality			
	Unconventionality (t)	Standard errors (SEs)	Observations
1. Ln Output $_{(t-2)}$	0.0866***	(0.0106)	145,652
2. SEs clustered by sector	0.0794***	(0.0093)	145,652
3. SEs clustered by industry x year	0.0794***	(0.0063)	145,652
4. Controlling for industry exit/entry	0.0754***	(0.0113)	100,413
5. Coefficient for alternative financial constraints	0.0507**	(0.0197)	160,855

All rows report the value relative to the output coefficient for the full model, except for row 5 which reports eventual changes in the coefficient of the financial constraints variable.

Table C2 Robustness checks of the firm level analysis: patent production			
	Dep. Var	Standard errors (SEs)	Observations
1. Ln Output $_{(t-2)}$	0.0767***	(0.0244)	9,240
2. SEs clustered by firm	0.0869*	(0.0510)	9,471
3. SEs clustered by sector	0.0869***	(0.0329)	9,471
4. Controlling for industry exit/entry	0.0913***	(0.0296)	4,931
5. Alternative measure of financial constraints	-0.0642**	(0.0272)	10,520
Table C3 Robustness checks of the firm level analysis: unconventionality			
1. Ln Output $_{(t-2)}$	0.1032***	(0.0184)	9,240
2. SEs clustered by firm	0.1117**	(0.0455)	9,471
3. SEs clustered by sector	0.1117***	(0.0285)	9,471
4. Controlling for industry exit/entry	0.1094***	(0.0237)	4,931
5. Alternative measure of financial constraints	-0.0144	(0.0180)	10,520
Table C4 Robustness checks of the firm level analysis: technological impact			
1. Ln Output $_{(t-2)}$	0.2418***	(0.0337)	9,240
2. SEs clustered by firm	0.2378***	(0.0589)	9,471
3. SEs clustered by sector	0.2378***	(0.0376)	9,471
4. Controlling for industry exit/entry	0.2296***	(0.0393)	4,931
5. Alternative measure of financial constraints	-0.1156***	(0.0362)	10,520
Table C5 Robustness checks of the firm level analysis: market to book value			
1. Ln Output $_{(t-2)}$	0.4985***	(0.0421)	9,240
2. SEs clustered by firm	0.5055***	(0.0797)	9,471
3. SEs clustered by sector	0.5055***	(0.1858)	9,471
4. Controlling for industry exit/entry	0.3262***	(0.0525)	4,931
5. Alternative measure of financial constraints	-0.0408	(0.0399)	10,520
Table C6 Robustness checks of the firm level analysis: Tobin's Q			
1. Ln Output $_{(t-2)}$	0.5461***	(0.0264)	9,240
2. SEs clustered by firm	0.5318***	(0.0503)	9,471
3. SEs clustered by sector	0.5318***	(0.1506)	9,471
4. Controlling for industry exit/entry	0.3743***	(0.0322)	4,931
5. Alternative measure of financial constraints	-0.0283	(0.2678)	10,520

All rows report the value of the coefficient of output (our main variable of interest) except for row 5 which reports eventual changes in the coefficient of financial constraints using the SA index. The number of observations decreases when the model is estimated on a subsample, firms observed over the entire period in row 4, and when we use a two year lagged value of Output. In row 5 the number of observation increases due to a lower number of missing values in computing the SA index.