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General Purpose and Focused Invention, Market Value, and Productivity

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Abstract

We study returns to general purpose and focused invention at the firm level for a panel of manufacturing firms in the U.S. for the period 1976-1995, by studying their relationships with market value and Total Factor Productivity. We construct stocks of patents that lie at the two relevant tails of the distribution of the generality index (Trajtenberg et al., 1997; Henderson et al, 1998) to measure general purpose and focused invention at the firm level. In line with expectations, there is a market value premium to focused invention, and a productivity premium to general purpose invention. Estimates for the value of focus indicate that moving a single patent from the upper tail of the generality distribution to the lower tail would increase market value by $.24 \times q$ million 1992 dollars on average, where q is Tobin's q. The firm with the average general patent stock would gain $6.7 \times q$ million in market value if all its patents at the highest quartile of the generality distribution were moved to the lowest. In terms of the value of general purposeness, moving all its focused patents to the general category increases Total Factor Productivity by 2.3% to 2.8%, and five-year productivity growth by 3.9% to 5.2%, for the average firm. A potential implication is that corporate basic research is associated with significant long-term benefits in terms of productivity growth.

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1. INTRODUCTION

This paper examines returns to *general purpose* and *focused* invention at the firm level. We use valuation and productivity analysis to examine the relationship of each type of invention to the traded market value and Total Factor Productivity (TFP) at the firm level. No previous study, to our knowledge, has considered the valuation of patents across this important dimension of heterogeneity in the nature of invention.

For the purpose of identifying inventions that are more general purpose or focused than others, we use the measure of patent generality proposed by Trajtenberg et al. (1997) and Henderson et al. (1998). The generality index is originally proposed as a measure of the "basicness" of invention, i.e., the closeness of the knowledge embedded in the patent to basic science. A patent with a larger generality score is one that finds future applications and antecedents in a larger variety of technological classes. In this sense, the generality index is a proxy for the general purpose nature of the technology embedded in the patent. A patent with a small index value is one whose technological antecedents belong in a more concentrated set of technological classifications. These latter patents are deemed more "focused" in their inventive content and the opportunities they generate. Generality has been extensively used to identify and study General Purpose Technologies (GPTs) in patent data (Hall & Trajtenberg, 2004; Moser & Nicholas, 2004; Youtie et al., 2008; Raiteri, 2018; Martinelli et al., 2021; among others.).

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We identify the general purpose (*resp.* focused) inventions of a given firm using its patents that have generality scores above (*resp.* below) a given threshold. Hence, we study the association with market value and productivity of a firm's patents that are located at the two tails of the distribution of the generality index. Market value and productivity approaches are not substitutes with one another, nor they are alternative measures of firm performance: market value of a firm quantifies the valuation of the firm by investors, while factor productivity is a measure of the firm's productive efficiency. It is then interesting to see whether different portions of a firm's patent portfolio are associated more or less strongly with these two measures, whether some patents are highly valued by investors, while others contribute more to productivity.

A large literature in Economics deals with the valuation of R&D expenditures and patents at the firm level (Griliches, 1981; Hall et al., 2005; Hall & Oriani, 2005; among others). The approach holds that the excess market value of the firm relative to the value of its physical assets (a quantity known as Tobin's q) can be explained by the intangible assets of the firm, including its "knowledge assets." Hence, the market's valuation of the various knowledge assets of the firm can be estimated, which are proxied by the stock of its R&D expenditures, its patent stock, and related and derivative properties of its knowledge base (Cockburn & Griliches, 1987; Blundell et al., 1999). However, the literature has overlooked the heterogeneity of patents in various dimensions. The main premise of the current study is that the heterogeneity of patented inventions with respect to generality matters in interesting and important ways.

Another key interest in Economics has been the productivity effects of R&D, invention and innovation at various levels of aggregation (Hall, 2011). This literature uses a production function framework that can incorporate knowledge assets, to study the association between total factor productivity and the said knowledge assets. The approach attempts to estimate the private (and also social) rate of return to R&D and patent holdings of a company (and also, industry, region, ...etc.). Authors mostly focused on R&D stocks ("R&D capital"), but the relationship between productivity and patenting, and various other properties of the firm's knowledge base have also been studied (Crépon et al., 1998; Harhoff, 1998; Greenhalgh & Longland, 2005; Griffith et al., 2006; Crass & Peters, 2014).

We begin with the simple idea that patents that are highly general and those that are focused are indicators of different kinds of research activities. One therefore expects the generality distribution of a firm's patent stock to be reflected in observable economic outcomes in predictable ways. Main hypotheses of the paper are that (i) more focused patents are primarily associated with the market value of the firm, but (ii) highly general patents are primarily associated with firm-level productivity. We test these hypotheses by estimating hedonic Tobin's q equations on the one hand, and production function estimates on the other, in conjunction with measurements of general purpose and focused patent stocks described above.

Results of the paper indeed show that different tails of the generality distribution are associated with different measures in predicted ways. The market places a larger premium on focused invention than general purpose invention. This is in line with the interpretation of generality, in that more general invention may not find immediate applicability, hence short-term returns for the firm, leading to relatively small increases in market value. Productivity analyses show that this delimitation matters for productivity estimates as well: productivity at the firm level is associated more strongly with general purpose invention rather than focused invention. [1] According to estimates, moving a single patent from the upper tail of the generality distribution to the lower tail results in a $.24 \times q$ million dollars increase in market value, where q denotes Tobin's q.[2] The firm with mean general patent stock would gain an additional $6.7 \times q$ million dollars in market value if all its general patents were moved to the lower tail of the generality distribution On the other hand, the firm would gain approximately 0.23% to 0.28% increase in productivity, and 0.39% to 0.52% in five-year productivity growth if 10% of its patents at the lower tail of the generality scale were instead at the upper tail, indicating that the

[1] To be more specific, both general and focused invention are positively associated with market value and productivity. However, the effect of general patents is greatly diminished, and loses significance in some specifications, when we control its stock of highly focused patents. Productivity results mirror this, in that the effect of focused patents is reduced or loses significance when the firm's general patent stock is controlled for.

[2] Tobin's q is a measure of the traded value of the firm above the value of its physical assets. For specific calculations, note that Tobin's q takes values between.08 and 14.77 with mean value 1.76 across all firms in the sample.

productivity effect of moving all focused patents to the general category would amount to 2.3% to 2.8%, with the associated gain in five-year productivity growth ranging from 3.9% to 5.3%. Such valuations are relevant for Technology Management and Engineering Management in helping strategic planning and capital budgeting decisions within the firm, and for Economics in their potential guidance for policy making.

Overall, our results confirm that there is a large productivity premium to general purpose invention. We also show that this premium is associated with an opportunity cost in terms of foregone market value, which would have been realized with a more focused strategy. These results, along with recent results that study the strategic choice of basic and applied research (Guo et al., 2022; Arora et al., 2021), send to the idea of balancing focused and general purpose inventive activity at the firm level. Our results provide valuations in terms of market values and productivity that can guide formalizations and decision making in this context.

2. RELATED LITERATURE

The current study relies on Trajtenberg et al. (1997) and Henderson et al. (1998) by attempting a direct application of their measure of generality. Trajtenberg et al. (1997) find that university patents in their sample have higher generality scores than non-academic patents, from which they discern that generality is associated with basic science. Henderson et al. (1998) and Schmid and Fajebe (2019) report similar results. Generality is also positively related to usual indicators of patent value, such as forward citations, the likelihood of renewal, and the likelihood to be traded (Serrano, 2010).

The generality measure has been used in empirical studies of invention for a variety of purposes. Hall and Trajtenberg (2004) identified and studied General Purpose Technologies (GPTs) using various formulations of generality. Mowery and Ziedonis (2002) reported a decline in the importance and generality of academic patents in the US during 1980s, in the wake of the Bayh-Dole act. This finding is disputed by Sampat et al. (2003). Moser and Nicholas (2004) used the measure to show that electricity inventions in the 1920s, as a group, did not accord with the commonly used definitions of a GPT. Gómez-Baquero (2009) and Youtie et al. (2008) used generality to argue that nanotechnologies were becoming GPTs. The former also identified transitions from focused to general technologies. Raiteri (2018) uses the generality index to show that government procurement encouraged and led developments in GPTs. Filippova (2019) shows that the generality of blockchain technology rose consistently between 2013 and 2017 and was of comparable magnitude to that of ICT technologies by 2017. Martinelli et al. (2021) study generality (and originality) to argue that Big Data and AI showed characteristics of distinct GPTs, while other enablers of Industry 4.0 (IoT, cloud, robotics, additive manufacturing) did not. Industry 4.0 fields in general exhibited less general (more focused) character than the average invention. Barirani et al. (2015) study the relationship between a measure of recombination depth (including more distinct domains in its knowledge sources) and generality for a sample of Canadian nanotechnology patents, showing that corporate invention generality is more sensitive to recombination depth than public invention.[3]

A large literature in Economics studies the valuation of various knowledge-related assets at the firm level by using the variation in the market values of firms in relation to R&D, invention and innovation. The premise of the literature is that the excess market value of a firm relative to the value of its physical assets (a quantity known as Tobin's q) is due to its intangible holdings, which must include its knowledge assets. The literature has shown that both the amount and various attributes of a firm's R&D inputs and invention activity are indeed valued by market actors, allowing a market-based valuation strategy for corporate knowledge assets. Griliches (1981) reported a positive association between market value, R&D and patent stocks. Cockburn and Griliches (1987) include survey-based measures of appropriability at the firm level in the market value equation, showing the latter are not valued by the market. Megna and Klock (1993) provide industry-specific estimates from the semiconductor industry, also including rival firms' patents. Blundell et al. (1999) and Hall and Vopel

[3] A critique to the measure has been posed by Petralia (2020), who criticizes the index by demonstrating its inability to differentiate fields at the highest level of generalization (Chemical, Mechanical, Electrical) in terms of generality. However, each of these aggregate technologies have their own citation habits and patterns, and it is known that unnormalized citation-based metrics should not be used to make comparisons *between* and *across* different disciplines. For this reason, we use a classification method that makes comparisons only *within*, and not *between*, the six large technology classes (Section 3.1.3).

(1997) report that the market's valuation of knowledge assets is higher if the firm has higher market share. Hall and Oriani (2007) provide estimates for European firms, while Toivanen et al. (2002) restrict attention to the value of knowledge assets in the UK. Hall et al. (2005) use the market value framework to study the valuation of the company's citation stock, finding that the market values citations of the firm over and above its R&D expenditures and patents. Belenzon (2012) finds that not all citations have a uniform effect on market value: citations on which the firm can capitalize in later periods affect market value positively, while those the firm does not build on in later invention are associated negatively with market value. Bessen (2009) extends the theoretical framework in order to obtain direct measures of patent rents. Sandner and Block (2011) extended the analysis to the valuation of trademarks. Hsu et al. (2021) show that academic publications by Chinese firms are associated with higher market value. A related literature extends the analysis to the valuation (hence measurement) of spillover effects (Jaffe, 1986; Bloom et al., 2013; Lychagin et al., 2016; Dindaroglu, 2014; among others).

Another key line of inquiry in Economics has been the measurement of the productivity effects of patenting and R&D, usually in a production function framework.[4] The interest was initially on finding explanations for the productivity increase during the 1960s (Griliches, 1963) and fall during the 1970s (Griliches, 1979, 1986, 1998) with the premise that changes in the rate of technological progress may be an underlying factor (Griliches, 1988). Crépon et al. (1998) show that productivity is positively associated with the share of sales due to new products, a common measure of innovation. They introduce a structural model that corrects for selection and simultaneity biases specific to patent and R&D data. Griffith et al. (2006) extend the same framework to four European countries and provide interesting differences with respect to product and process invention. Variants of the production function framework have been estimated for the Netherlands (Bartelsman et al., 1996), Germany (Harhoff, 1998), Spain (Dorazelski & Jaumandreu, 2008), China (Jefferson et al., 2006), among many others. A survey of the earlier literature is provided by Mairesse and Sassenou (1991). Hall et al. (2009) offer a survey with an econometric focus, while Hall (2011) surveys the general findings and accumulated evidence till then.

The current study contributes to these two lines of research traditions by directly studying the significance of heterogeneity in an important technological characteristic. Studies that have looked at patenting and other innovation indicators in their relationship to productivity have found little relation between patents and productivity (Crass and Peters, 2014), or found that positive effects are short-lived (Greenhalgh and Longland, 2005). This supports one of the main insights of the current paper: market value is most immediately linked to aspects of innovation and other intangibles that are of quick or immediate commercial use, but such activity exhibits a weaker relationship with productivity. The current paper shows that patent generality may be an important confounder in these previous studies, since it is able to demonstrate a large productivity premium to general invention.

The generality index is proposed as a measure of the "basicness" of the underlying invention. The evidence that links patent generality to the "basic" character for underlying research (Trajtenberg et al., 1997; Henderson et al., 1998; Schmid and Fajebe, 2019) also relates the current work to the literature examining the productivity effects of basic and applied research activity at the firm level. Lichtenberg and Siegel (1991) found that the productivity effect of R&D comes mostly from basic research, and many others reported a productivity premium to corporate basic research activity (Lichtenberg, 1992; Link, 1981; Griliches, 1986; Czarnitzki & Thorwarth, 2012; among others). Ernst (1998) finds that firms that spend a larger share of their overall R&D expenditures on research hold higher quality patents. Bolívar-Ramos (2023) show that corporate science expenditures lead to innovation in Environmental Technologies, while Zhao et al. (2023a, 2023b) show that scientific publishing and corporate scientific labs are associated with higher invention counts and impact in China. Krieger et al. (2022) show that patents that build on a scientific publication are, on average, 26% more valuable than otherwise. Hsu et al. (2021) show that academic publications by Chinese firms are associated

[4] The literature on the estimation of links between R&D, invention and productivity is vast. We focus here on firm-level analysis using micro data, rather than industry and country-level analysis, and only discuss a representative set of papers that are most relevant for the current study.

with higher market value and exhibit synergetic effects with firm-level patenting. Chen et al. (2024) report that corporations that produce and cite scientific literature produce more inventions overall.

Trends in basic research in relation to applied research has been the focus of Arora et al. (2021), who show that returns to corporate basic research depend on the balance between in-house potential and spillovers to rivals and report a trend towards less "R" and more "D" in corporate R&D in recent decades. In previous work, Arora et al. (2018) document a shift away from basic science in most industries -except, and notably, biotechnology- between 1980 and 2006. Coad et al. (2020) and Leten et al. (2022) note the same trend, the former in Spanish manufacturing and the latter in global pharmaceuticals. Camerani and Rotolo (2023) argue that the fall is in proportional terms while corporate basic research expenditures had been on the rise, studying the first half of 2010s. Krieger et al. (2021) show that the number and share of publishing firms have declined and publications became more concentrated in Germany between 2008 and 2016, while Yang et al. (2023) report fewer management science publications and fewer citations to existing publications over time between 2000-2019.

More recent research has also demonstrated and measured the social and private value of corporate basic research. Leten et al. (2022) propose and demonstrate an absorptive capacity motive to corporate basic science that is stronger than a direct innovation sourcing effect. Rotolo et al. (2020) review the literature on the scientific publications of corporations and argue that corporations publish to increase absorptive capacity, to attract and retain better researchers, to support their IP strategies, to build reputation, and to support commercialization. Shvadron (2023) adds and empirically studies a leadership motive to corporate basic research, i.e., that basic research influences the direction of external research in ways that benefit the focal firm. In line with these observations, Wen (2023) discusses policy measures to boost basic research at corporations. Choi et al. (2022) and Ceccagnoli et al. (2024) both show that the relationship between basic research and productivity is positively mediated by technological diversity. Arora et al. (2023) show that innovation that is science-based tend to be socially and privately more valuable, where the latter also exhibits a strong first-mover advantage. Dean et al. (2023) discuss and demonstrate the effect of organizational and product complexity on a firm's ability to translate basic research into market success. Guo et al. (2022) examine the strategic balance between basic research and applied development, finding that corporate basic research increases the productivity of the firm up to a saturation point (about 65% research intensity of R&D) and plateaus afterwards. They also report an inverted-U type relationship between applied development intensity and productivity, peaking at 28% intensity. These recent results, as well as of the current paper, point towards benefits of balancing focused and general purpose inventive activity at the firm level.

3. MATERIAL AND METHOD

3.1 Measurement of General Purpose and Focused Invention Stocks

3.1.1. Generality

Trajtenberg et al. (1997) construct an index of patent generality based on information on citations made to the original patent by its antecedents, i.e., its forward citations. The measure is based on the spread of citing patents among existing technological classes. If patent i receives N_i citations, N_{ik} coming from patents classified in technology class $k \in \{1, \dots, \bar{k}\}$, then its generality is defined as

$$G_i = 1 - \sum_{k=1}^{\bar{k}} \left(\frac{N_{ik}}{N_i}\right)^2 \tag{1}$$

Notice that G_i will be relatively low if i's citations are from few distinct technological classes, and will be larger, the larger the spread of citations across different technological fields. The idea is that patent i is more general if it spawns antecedents in a larger number of different technology fields, which coincides with the definition of general purpose technologies, as well as the definition of fundamental (basic) science.

3.1.2. Classification of Patents and Construction of Stock Variables

A firm's general and focused invention stocks for a given year are constructed as follows. For two thresholds f and g such that $0 < f \leq g < 1$, let $\{p_{it}^{g}\}_{t=0}^{T_i}$ denote the sequence of the number of it (firm i, year t) patents that have a generality score above g, and $\{p_{it}^{f}\}_{t=0}^{T_i}$ the sequence of the number of it patents that have a generality score below f (g is chosen as shorthand for general, and f as shorthand for focused). Also let P_{it}^{g} be the depreciated stock of $\{p_{it}^{g}\}_{t=0}^{T_i}$, P_{it}^{f} the depreciated stock of $\{p_{it}^{f}\}_{t=0}^{T_i}$, and P_{it}^{fg} the depreciated stock of remaining patents, all calculated as perpetual inventories. That is,

$$P_{it}^{g} = \sum_{\tau=0}^{T_i-1} (1-d)^{\tau}\, p_{it-\tau}^{g} + (1-d)^{T_i} P_{i0}^{g}, \text{ and } P_{it}^{f} = \sum_{\tau=0}^{T_i-1} (1-d)^{\tau}\, p_{it-\tau}^{f} + (1-d)^{T_i} P_{i0}^{f} \qquad (2)$$

where T_i is the number of years firm i is observed in the panel, and d is the depreciation rate for patent stocks. Following convention, a depreciation rate of 15% is assumed.[5] The (unobserved) initial values P_{i0}^{g} and P_{i0}^{f} are approximated by extrapolating the relevant series to minus infinity using the aggregate growth rate of respective sequences, i.e., $P_{i0}^{l} = P_{i1}^{l}/\left(d + r^{l}\right), l \in \{f, g\}$ where r^{l} represents the aggregate growth rate of p_{it}^{l} in the sample.

The classification into general and focused categories is made only for patents that have at least three overall citations. An additional stock variable $\left(P_{it}^{lc}\right)$ is computed for the remaining low-cite (cites < 3) patents. This variable is included in most regressions, except where its inclusion leads to multicollinearity (see Section 3.3.1). Finally, we use P_{it} to represent the firm's total patent stock, i.e., $P_{it} = P_{it}^{f} + P_{it}^{fg} + P_{it}^{g} + P_{it}^{lc}$.

3.1.3. Thresholds

We use a different pair of thresholds for each of the six aggregate technology categories (Chemicals, Computers and Communication, Drugs and Medical, Electric and Electronics, Mechanical, and Others). For each of the six aggregate technologies, we first choose thresholds such that a patent is deemed as general (resp. focused) if its generality score lies in the lowest (resp. highest) quartile of the generality distribution in its aggregate technological category. That is, we set the thresholds for category $k \in \{1, \ldots, 6\}$ to be $f_k = F_{G_k}^{-1}(0.25)$ and $g(k) = F_{G_k}^{-1}(0.75)$, where F_{G_k} is the cumulative distribution of generality in category k. General inventions $\left(P_{it}^{g}\right)$, then, are those who have generality scores at the highest quartile of the respective generality distribution, while patents at the lowest quartile of the distribution in their aggregate categories are deemed as focused $\left(P_{it}^{f}\right)$. Remaining patents $\left(P_{it}^{fg}\right)$ are those that are in the interquartile range. As a robustness check, we also construct patent stocks by decomposing the overall distribution of generality into its *thirds*, i.e., by choosing $f_k = F_{G_k}^{-1}(1/3)$ and $g_k = F_{G_k}^{-1}(2/3)$. Main results are robust to the choice between the two sets of thresholds.

3.2. Econometric Specification

3.2.1. Market Value

We begin with the standard market value specification, which expresses firm i's stock market value at the end of year t (V_{it}) as

$$V_{it} = q_{it}(A_{it} + \gamma K_{it})^{\sigma} \qquad (3)$$

[5] It is reasonable to expect more general patents to depreciate more slowly than specific ones. Incorporating these differences is outside the scope of the study.

where A_{it} represents ordinary physical assets, K_{it} denotes intangible knowledge capital, γ is the shadow value of knowledge capital with respect to physical assets, and q_{it} is a constant that is parametrized with firm and year effects, and other variables. Some algebraic manipulation, imposing constant returns to scale ($\sigma = 1$), and the approximation $\log(1 + x) \approx x$ yields the equation,

$$\log\left(\frac{V_{it}}{A_{it}}\right) = \tilde{q}_{it} + \gamma \frac{K_{it}}{A_{it}} \tag{4}$$

where $V_{it}/A_{it} \equiv Q_{it}$ is called Tobin's q, which is defined as the market value of the firm relative to its total asset value. Equation (4) naturally leads to a linear multivariate regression specification for Tobin's q, regressed on measures of normalized knowledge capital. Knowledge capital (K_{it}) is usually proxied with stocks of R&D expenditures, patents, and/or citation-weighted patents of the firm. Using R&D and various patent stocks as proxies for intangible knowledge capital, distinguishing general purpose and focused invention capital, and following Hall et al. (2005), the market value equation to be estimated becomes,

$$\log Q_{it} = \gamma_F \tilde{P}_{it}^{f} + \gamma_{FG} \tilde{P}_{it}^{fg} + \gamma_G \tilde{P}_{it}^{g} + \gamma_R \tilde{R}_{it} + \gamma_{FG} \tilde{P}_{it}^{fg} + \lambda_t + \eta_i + v_{it} \tag{5}$$

where $\tilde{P}_{it}^{j} = P_{it}^{j}/A_{it}$ for $j \in \{f, fg, g\}$ represent general (g) and focused (f) patent stocks and the patent stock in the interquartile range (fg), all divided by the value of physical assets. $\tilde{R}_{it} = R_{it}/A_{it}$ is R&D stock of the firm divided by physical assets and $\tilde{C}_{it} = C_{it}/P_{it}$ is citation stock divided by patent stock. λ_t, η_i and v_{it} represent year effects, permanent firm effects, and the usual error term, respectively. All stock variables in equation (5) are calculated as perpetual inventories with 15% yearly depreciation as described by equation (2). We estimate the coefficients in equation (5) using Least Squares (henceforth LS) and panel data regression methods that control for fixed effects, i.e., account for unobserved permanent heterogeneity among firms.

3.2.2. Total Factor Productivity

In order to obtain an estimate for Total Factor Productivity (TFP) and study its determinants, we begin with the standard Cobb-Douglas production function in logs,

$$y_{it} = \alpha_0 + \alpha_K \cdot a_{it} + \alpha_L \cdot l_{it} + \xi_t + \mu_i + u_{it} \tag{6}$$

where y_{it} is the logarithm of firm i's output level (measured by total sales) at year t, a_{it} denotes the logarithm of physical capital, l_{it} denotes the logarithm of labor inputs (employment). We use the usual two-way error component specification, where ξ_t, μ_i and u_{it} are year effects, permanent firm effects and the usual error term, respectively.

Consistent estimation of the parameters in equation (6) is not straightforward since productivity shocks in the current period (which are part of u_{it}) are at least partially observed by the firm prior to making its input decisions. Hence, all variable inputs in the production function are endogenous, and usual least squares or panel data methods will yield biased and inconsistent estimates. Additionally, standard estimates of the production function suffer from selection bias since productivity shocks observed by the firm are correlated with subsequent exit decisions. Since labor inputs can be adjusted in the short-run, endogeneity will result in a positive bias in the coefficient of labor. Selection bias, on the other hand, is likely to cause a negative bias in the coefficient of capital.

Due to these empirical issues, we rely on an estimation procedure developed by Olley and Pakes (1996) to obtain consistent estimates of production function coefficients. This method relies on the three assumptions that (i) productivity evolves as a first order Markov process, (ii) firms decide whether to stay in the market or exit in the current period based on realizations of productivity and other relevant state variables (usually assumed to be the capital stock, but a richer set of state variables can be used as well) at the beginning of the period, and (iii) if the firm decides to keep it operations, it determines current investments based on observed productivity and state variables. The procedure estimates equation (6) in three steps. Assuming that the firm's investment function is an increasing function of productivity, current productivity level can be inverted and expressed as a function of investment and state variables. In the first step, this function is approximated by a polynomial function and replaces the part of u_{it} in equation (6) that is observed by the firm. Least squares estimation of this transformed equation identifies the labor coefficient, $\hat{\alpha}_L$. The second step estimates exit probabilities for each firm by using a regression model for observed exit decisions. Fitted probabilities from this specification are then used to control for selection bias in a third stage regression that identifies the capital coefficient, $\hat{\alpha}_K$. The procedure requires that current investments, as well as exit decisions to be observed by the econometrician. In the current case, we use capital as the sole relevant state variable and define firm exit as the occurrence of bankruptcy or liquidation. Parameter estimates are robust to conditioning productivity (stage 1) on additional state variables, such as firm age.[6]

Productivity is calculated as Total Factor Productivity, which is given by

$$TFP_{it} = \exp(y_{it} - \hat{\alpha}_K \cdot a_{it} - \hat{\alpha}_L \cdot l_{it}) \qquad (7)$$

where $\hat{\alpha}_K$ and $\hat{\alpha}_L$ are estimates of production function coefficients obtained using the Olley and Pakes procedure. The estimate for the constant term is excluded from (7) since it cannot be consistently estimated, and it is just a multiplier common for all observations. The logarithm of expression (7) and its 5-year compounded growth rate ($\log TFP_{it} - \log TFP_{it-5}$) are used as dependent variables in second stage regressions, which are estimated using Fixed-Effects LS (for TFP) and LS (for TFP growth) methods. Sample statistics for all variables are given in Table 1.

3.3. Data Sources and Variables

Data from patent records are taken from the NBER US Patent Citations Data File initiated by Hall et al. (2001) and the following literature. The latest update used for this paper contained information on all patents granted in the U.S. between 1976 and 2006, and all citations made to these patents till 2006. Generality for each patent in the sample is computed using all citations made to the patent till 2006. Data on market value, physical capital, employment, current investments, and firm status are from the Compustat database. We matched the NBER assignee codes to Compustat GVKEY and CUSIP identifiers using the NBER PDP Project match file constructed by Bessen (2009). We focus on a 20 year window between 1976 and 1995 (inclusive). Year 1995 is chosen as the final year to minimize the bias in citations and the generality measure due to the truncation in the citation distribution (Hall et al., 2001). Removing observations outside the sample period, firms with a single year of observations between 1975 and 1990, cleaning key variables and deleting large outliers ($|\ln(x_{it}/x_{it-1})| \geq 1.5$), result in an unbalanced panel of 10469 total observations for the estimation of the market value equation, and 8472 observations for the estimation of the production function and the productivity equations. The two samples differ due to missing variables and cleaning procedures for different variables used. All values in current U.S. dollars are deflated using the GNP deflator with base year 1992. Table 2 includes correlations among variables for both specifications as well as Variance Inflation Factors (VIFs) for addressing potential collinearity among key variables.

3.3.1. Multicollinearity

A potential problem with this set of variables is the presence of multicollinearity among key variables. Table 2 reports simple correlations between key variables, as well as variance inflation factors (VIF) for a number of specifications. In Table 2, correlations and VIF calculations for the two specifications are reported separately in Panel A (market value) and Panel B (productivity). In Panel A, it is observed that the correlation between the interquartile-range patent stock (divided by assets) and remaining patent stock variables are quite high (between .79 and .88). The column VIF/UR contains variance inflation factors for each variable in the *unrestricted* specification in which the interquartile-range patent stock is included as a regressor. The VIF corresponding to this variable (6.93) is above commonly used thresholds (usually, 5) to detect problematic regressors. VIF/R reports variance inflation factors for each variable in the *restricted* case that excludes this

[6] Olley & Pakes method is implemented using the Stata command opreg provided by Yasar et al (2008).

variable. When the patent stock in the interquartile-range of the generality distribution is excluded, VIF levels for all variables fall to acceptable ranges. Hence, the market value equation is estimated after excluding this variable. Note that including this variable in the market value specification remains key conclusions of the study unchanged. Panel B in Table 2 performs a similar exercise for variables in the productivity equation, where two controls were excluded to obtain low VIF values for all specifications. Finally, note that citation stock is not included productivity regressions due to its high correlation with patent stock(s). This is not the case in market value regressions where citation stock is used after being divided by patent stock.

Table 1. *Sample Statistics*

		Mean	Median	Standard Deviation	Minimum	Maximum
Market Value*		2031.92	330.18	5889.40	0.10	120756.5
Tobin's *q**		1.76	1.20	1.78	0.08	14.77
Sales		2532.12	671.15	5691.08	0.04	84231
Employment		17.33	5.36	33.26	0.02	480
Capital		1882.07	380.42	4647.53	0.72	51652.4
R&D Stock		428.90	65.81	1474.95	0.00	30245.1
Patent Stock		141.40	27.90	369.49	1.65	8353.1
Citation Stock		2084.18	375.25	7305.35	9.36	233246.6
R&D Stock/Assets*		0.38	0.19	0.68	0.00	14.46
Patent Stock/Assets*		0.24	0.09	0.91	0.00	20.58
Citation Stock/Patent Stock*		14.71	11.44	12.51	0.00	154.97
Low-Cite Patent Stock/Assets*		0.03	0.01	0.16	0.00	4.41
General Patent Stock	*Upper quartile*	27.92	5.46	86.65	0.05	2477.84
Interquartile P. Stock		47.54	9.54	133.72	0.09	3340.99
Focused Patent Stock	*Lower quartile*	37.49	7.62	99.78	0.12	2007.16
General Patent Stock	*Upper third*	34.95	6.88	107.47	0.10	3057.38
Middle Third P. Stock		31.78	6.51	92.77	0.00	2446.80
Focused Patent Stock	*Lower third*	46.21	9.23	120.89	0.20	2321.81
Low-Cite Patent Stock		26.04	3.91	73.52	0.00	1371.41

Notes: Sample size: 10755 (max) for starred variables (market value sample) and 8472 (max) for remaining variables (production function sample). The two samples differ due to missing variables and cleaning procedures for different variables involved. All monetary values are in millions of 1992 U.S. dollars. Sample statistics for general, focused, and intermediate patent stock variables per physical asset are avoided to preserve space. Sample period: 1976-1995.

Table 2. *Correlations and Variance Inflation Factors*

Panel A: Variables in Market Value Regressions

Variable Name	Abbr.	GPA	FPA	IPA	LCPA	RA	CP		VIF/UR	VIF/R
General Patent Stock/Assets	GPA	1							2,99	2,55
Focused Patent Stock/Assets	FPA	.618	1						3,18	2,53
Interquartile P. Stock/Assets	IPA	.790	.817	1					6,93	-
Low-Cite Patent Stock/Assets	LCPA	.745	.763	.877	1				5,03	3,61
R&D Stock/Assets	RA	.398	.300	.339	.255	1			1,62	1,30
Citation Stock/Patent Stock	CP	.121	.100	.094	-.032	.299	1		1,17	1,15

Panel B: Variables in Productivity Regressions

Variable Name	Abbr.	GPS	FPS	IPS	LCPS	RS		VIF/UR	VIF/R1	VIF/R2
log (General Patent Stock)	GPS	1						5,59	3,79	3,79
log (Focused Patent Stock)	FPS	.810	1					6,67	4,90	3,22
log (Interquartile P. Stock)	IPS	.894	.903	1				11,24	-	-
log (Low-Cite Patent Stock)	LCPS	.808	.863	.873	1			4,81	4,52	-
log (R&D Stock)	RS	.733	. 716	.747	.697	1		2,50	2,89	2,79

Notes: Patents are classified according to quartiles of the generality distribution. Correlations and VIFs for the classification with respect to lower and upper thirds of the generality distribution are similar and are not reported. VIF is calculated as 1/(1-R^2_{Aux}), where R^2_{Aux} is the R^2 from an OLS regression where the row variable is regressed on a constant and all remaining independent variables. VIF/UR (Unrestricted) is the variance inflation factor when patent stock in the interquartile range of the generality distribution (IPA) is included and VIF/R (Restricted) is the VIF from the specification that excludes this variable. In Panel B, VIF/R1 excludes the interquartile range patent stock (IPS), and VIF/R2 excludes the low-cite patent stock (LCPS) as well. Based on correlations and variance inflation factors, including IPA in the market value equation significantly increases collinearity among independent variables. A similar situation is observed in the productivity equation (Panel B) for IPS and LCPS. These variables are excluded from their respective baseline specifications to avoid multicollinearity.

4. RESULTS AND DISCUSSION

4.1. Market Value

Estimates of the market value specification in equation (5) are reported in Table 3[7]. Panel A reports coefficient estimates for the case in which general and focused invention stocks are computed using the upper and lower quartiles of generality. We begin by reporting least squares estimates (columns 1 and 2), and then move on to a fixed effects panel specification (column 3). For comparison, the specification in column 1 includes the overall patent stock, while remaining columns introduce general and focused invention stocks separately. All specifications include year and industry dummies[8] except column 3, where industry dummies are differenced out in the fixed effects specification.

Coefficients in column 1 indicate that market value is positively associated with the firm's R&D stock, total patent stock and citation stock. All of these invention indicators have positive associations with market value above and beyond each other. Column 2 replaces the aggregate patent stock with general and focused patent

[7] Likelihood Ratio (LR) tests for the presence of time and individual effects all reject the null hypothesis with $p < 0.0001$.

[8] Industry classification used is due to Hall and Vopel (1997) and it follows the 2-digit SIC classification with some modification.

stocks, as well as the firm's low-cite patent stock. It is observed that both general and focused patents are associated positively with market value with effects that are statistically significant, while the coefficient of focused patent stock (.249) is much larger than that of the general patent stock (.154).

Low-cite patent stock of the firm has a large and negative coefficient (-.320) that is statistically significant, indicating the cost of technological efforts that end up being unimpactful. R&D and citation stock coefficients have comparable magnitudes to their counterparts in column 1. An interesting finding is that the magnitudes of general, focused, and low-cite patent stocks, while in different directions, are of much greater magnitude than the coefficient of the aggregate patent stock term in column 1. This has been common in the literature, i.e., the additional explanatory power of patents above and beyond R&D has been found to be low, which is often interpreted to mean that patenting choices do not contribute to value over and above R&D inputs. However, current analysis show that these studies may be suffering from aggregation bias. Patent heterogeneity matters greatly, and different portions of a firm's patent stock have different roles in creating value for the firm. These distinct effects are lost when one does not pay attention to patent heterogeneity (column 1).

In column 3, we estimate the market value equation (Eq. 5) using fixed-effects least squares. A Hausman test rejects the null hypothesis that individual effects are random (χ^2_{26} = 225.7, $p < 0.0001$). Most importantly, after controlling for permanent firm effects, the coefficient of the firm's focused patent stock remains high and statistically significant, while the sign of the firm's general patent stock becomes negative and insignificant. This indicate that investors reward inventions with more focused and narrow content that will bear short-term gains. Reported estimates in Table 4 allow measuring the value of a focus strategy, by hypothetically changing the nature of an existing patent or a group of patents. According to the difference between the coefficients of focused and general invention stocks (reported as Δ(Focused-General), moving a single patent from the upper tail of the generality distribution to the lower tail results in a $.24 \times q$ million dollars increase in market value (note that q takes values between .08 and 14.77 in the sampke with a mean value of 1.76). The firm with mean general patent stock, then, would gain an additional $6.7 \times q$ million dollars in market value if all its general patents were instead focused in nature, while this number is $27.5 \times q$ million dollars for a firm with a general patent stock that is one standard deviation above the sample average. As expected, accounting for permanent firm effects reduces the coefficient of knowledge assets, and especially that of the R&D stock variable, which is also common in the larger literature.

Column 4 reports between-firm estimates of the market value specification. While these coefficients are inconsistent estimates of the true coefficients in (5), it is useful to see what we can learn by examining the variation *between* firms in addition to the variation *within* firms. Between-firm estimates suggest that the relationship between focused invention stock and market value remains positive and is much stronger in the between dimension. R&D stock has a coefficient comparable to its counterpart from LS regressions (columns 1 and 2), which is expected since most of the variation in R&D is observed between (rather than within) firms.

Panel B in Table 3 estimates the market value equation with general and focused stock variables that are classified using the upper and lower thirds of the relevant generality distribution. Each column in Panel B replicates the results in the column directly above it using this new set of variables. Due to the new partition, the magnitudes of coefficients change, but the basic result remains unaltered. Focused invention stock is positively and strongly associated with market value, with coefficients somewhat smaller than their counterparts in Panel A.[9]

[9] Recall that patents that are at the intermediate range of the generality distribution are excluded from all regressions in Table 2 due to a concern for multicollinearity. Results in Table 3 are robust to including a stock variable for these intermediate range patents. These additional estimates are available from the author upon request.

Table 3. *Market Value Regressions. Dependent variable is the logarithm of Tobin's q*

Panel A: Patents are classified according to the upper and lower quartiles of the generality distribution				
	(1)	**(2)**	**(3)**	**(4)**
	LS	**LS**	**Fixed Effects LS (Within)**	**Fixed Effects LS (Between)**
Patent Stock/Assets	0.0128**			
	(2.03)			
General Patent Stock/Assets *Upper quartile*		0.154***	-0.072	0.105
		(3.99)	(-1.46)	(1.05)
Focused Patent Stock/Assets *Lower quartile*		0.249***	0.167***	0.562***
		(5.42)	(3.31)	(4.43)
Low-Cite Patent Stock/Assets		-0.320***	-0.022	-0.334*
		(-4.90)	(-0.25)	(-1.79)
R&D Stock/Assets	0.118***	0.102***	0.038***	0.116***
	(12.01)	(10.07)	(2.76)	(4.86)
Citation Stock/Patent Stock	0.012***	0.012***	0.002***	0.001***
	(23.65)	(22.51)	(3.23)	(7.17)
Δ (Focused - General)		0.104	0.239	0.457
R-squared	0.406	0.409	0.192	0.655
N	10469	10469	10469	10469
Panel B: Patents are classified according to the upper and lower thirds of the generality distribution				
		(5)	**(6)**	**(7)**
		LS	**Fixed Effects LS (Within)**	**Fixed Effects LS (Between)**
General Patent Stock/Assets *Upper third*		0.058*	-0.116***	-0.088
		(1.73)	(-2.83)	(-0.97)
Focused Patent Stock/Assets *Lower third*		0.175***	0.121**	0.478***
		(4.24)	(2.55)	(4.31)
Low-Cite Patent Stock/Assets		-0.237***	0.067	-0.168
		(-3.28)	(0.71)	(-0.81)
R&D Stock/Assets		0.110***	0.043***	0.219***
		(10.92)	(3.19)	(9.70)
Citation Stock/Patent Stock		0.012***	0.003***	0.013***
		(22.62)	(3.40)	(9.48)
Δ (Focused - General)		0.117	0.237	0.566
R-squared		0.408	0.191	0.585
N		10469	10469	10469

Notes: Constant terms are not reported. Δ (Focused - General) is the difference in the coefficients of focused and general patent stock terms. LS and between-firm Fixed Effects LS specifications include year and industry dummies (three-digit SIC), and within-firm specifications include year dummies. All logarithms are natural logs. t-statistics are reported in parentheses. Significance indicators: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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Table 4. *Production Function Estimates. Dependent variable is the natural logarithm of sales*

	(1)	(2)	(3)	(4)
	Olley and Pakes	LS	Fixed Effects LS (Within)	Blundell and Bond System GMM
log (Employment)	0.524***	0.549***	0.558***	0.567***
	(20.92)	(51.75)	(20.62)	(15.85)
log (Capital)	0.451***	0.437***	0.367***	0.234***
	(16.99)	(48.17)	(16.44)	(7.68)
R-squared		0.967	0.827	
N	8472	8472	8472	7696
Sargan				452.5 (186) [p = 0.00]
Arellano and Bond m1				-9.403 [p=0.000]
Arellano and Bond m2				.0047 [p=0.996]

Notes: Columns 1, 2 and 4 include year and industry dummies (three-digit SIC), and column 3 includes year dummies. All logarithms are natural logs. *t*-statistics are reported in parentheses. Constant terms are not reported.

Column 1: The proxy for unobserved productivity shock is the natural logarithm of current investments. Firm exit is defined as bankruptcy or liquidation.

Column 4: Lags 3 through 5 are used as instruments for both the level and first-differenced equations. Standard errors are from a two-step GMM procedure. Sargan is a test of overidentifying restrictions, i.e., tests the hypothesis that the instrument set is valid conditional on the validity of at least one instrument in the set. Sargan degree of freedom is given in parentheses and p-values are reported in brackets. Arellano and Bond (1991) m1 and m2 are tests for the lack (null hypothesis) of first-order and second-order serial correlation in first-differenced residuals, respectively. These jointly indicate that residuals are not serially correlated after accounting for permanent firm effects. The coefficients and standard errors for lagged sales, employment and capital are not reported in the table. These are 0.647 (28.55) for lagged sales, -0.348 (-9.32) for lagged employment and -0.099 (-3.45) for lagged capital.

Significance indicators: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

4.2. Total Factor Productivity

We now turn to studying the association between invention indicators of interest and firm-level productivity. To repeat, the effects of general and focused invention on productivity are estimated in two steps. First, we obtain consistent estimates of a standard firm-level Cobb-Douglas production function using the Olley and Pakes (1996) methodology. We then calculate Total Factor Productivity (TFP) for each firm-year as the natural logarithm of (7), and the compounded TFP growth rate in 5-year intervals. We then study the determinants of TFP and its growth rate using standard panel data (for TFP) and least squares (for TFP growth) regressions.

We begin by reporting and discussing estimates of the production function model (6), which are reported in Table 4. Column 1 of the table reports estimates obtained by the preferred Olley and Pakes (1996) methodology. For comparison, we also report coefficient estimates using methods that are commonly employed in production function estimation. Column 2 reports LS estimates of production function coefficients, column 3 uses fixed-effects LS, and column 4 uses the system-GMM methodology due to Arellano and Bond (1991) and Blundell and Bond (2000).

The estimated coefficients of capital and labor in Table 4 are in line with expectations. Endogeneity and selection biases that remain unchecked are expected to create a downward bias in the coefficient of capital, and an upward bias in the coefficient of labor. Compared to column 1, columns 2, 3 and 4 exhibit lower coefficients for capital and higher coefficients for labor. Assuming that estimates reported in column 1 are consistent, the difference between an estimate and the coefficient estimate in this column is a measure of bias in estimated effects. We can thus see that the bias in both coefficients increase as one moves (i) from LS to fixed-effects, and (ii) from fixed-effects to system-GMM. The former point (i) suggests that productivity shocks are not time-invariant and cannot be accounted for by employing differencing. The latter (ii) is expected if lagged levels and differences of endogenous variables are not valid instruments. In the current exercise, finding instruments that are irrefutably valid in system-GMM estimation proves to be infeasible according to the Sargan test of overidentifying restrictions ($\chi^2_{(186)} = 452.2$ with $p = 0.00$ for the set of instruments reported in column 4). The coefficient of capital is particularly low in column 4, which indicates that lagged capital adjustments are not valid instruments for the current level of capital. This is usual for persistent variables such as capital or R&D stocks, and the system-GMM methodology does not resolve the problem in the current case.

Total Factor Productivity is calculated according to equation (7) using the preferred Olley and Pakes (1996) estimates reported in column 1 of Table 4. Figure 1 gives the histogram of estimated Total Factor Productivity and its logarithm for the sample used in productivity analysis. The logarithm of TFP gives a distribution that is slightly asymmetric and clearly non-normal, as indicated by the Jacque-Bera test for normality ($p < 0.0001$). Note that normality of (log) TFP is not required for the following analysis. We expect this variable to be skew, due to survival bias, i.e., that we are less likely to see firms with bad realizations for productivity in the sample.

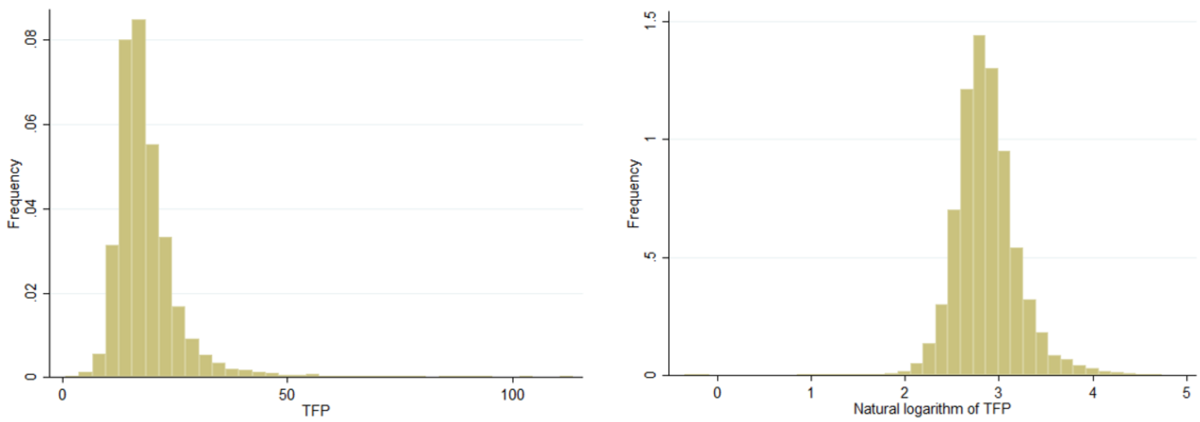

Figure 1. *The distribution of estimated Total Factor Productivity (left panel) and its logarithm (right panel)*

Table 5 turns to the analysis of the determinants of firm-level productivity. The distinction between results in Panel A and Panel B is similar to that in Table 3, and each column in Panel B is comparable the one directly above it. Before estimation, observations with *annual* log TFP growth outside $[-1,1]$ are deleted, as these may represent outliers. The sample used in Table 5 is also smaller than previously used samples due to missing variables for R&D and patent stock variables.[10]

When one is dealing with the *level* of Total Factor Productivity (columns 1,2 and 6), a fixed effects specification that removes the permanent component of TFP is preferred, since the productivity level can easily be linked to unobserved and permanent differences among firms which need to be accounted for. The Hausman test also strongly rejects the null hypothesis that individual effects are random (χ^2_{19} = 490.71, $p < 0.0001$). The fixed-effects estimation links the deviation of productivity from its average to the deviation of knowledge assets from their own averages. This is also preferred to studying a first-differenced specification (i.e., examining the annual compounded growth rate of TFP) since it is difficult to link annual changes in productivity to its correlates, i.e., one year is likely too short to large productivity effects. Simple LS regression

[10] Similar to Market Value regressions, Likelihood Ratio (LR) tests for the nested models indicate that both individual fixed effects and time effects are present in the *level* of TFP, with $p < 0.0001$.

is preferred for the analysis of TFP growth, since the fixed effects specification is too demanding, as well as unnecessary, for a variable that is already constructed as a growth rate, i.e., is already in differenced form.

We begin with estimating a specification that takes the logarithm of TFP as the dependent variable, and invention indicators as independent variables. These estimates are reported in columns 1 and 2 of Table 5. Column 1 includes the firm's total R&D and patent stocks, as well as year dummies as independent variables, while column 2 replaces the total patent stock with its general and focused components. Not surprisingly, both the R&D and aggregate patent stock of the firm are positively associated with productivity. Column 2 replaces the patent stock variable with its general and focused components. According to these estimates, the firm's general patent stock has a positive effect on productivity that is statistically significant. On the other hand, focused patent stock does not have a statistically significant coefficient. It is also interesting to note that almost all of the explanatory power provided by the patent stock variable (column 1) is in fact explained by patents at the upper tail of generality (column 2).

It is useful to compare these findings with those from market value regressions (Table 3). It is seen that different portions of a firm's patent stock have different effects on market value and productivity. The market mechanism places value on the focused portion of the firm's patent portfolio more strongly, while the general patent stock is more strongly associated with productivity. The difference in coefficient estimates of general and focused patent stocks (Δ(General - Focused)) in column 2 indicates that the average firm would gain an approximately 0.23% increase in productivity if 10% of its patents at the lower tail of the generality scale were moved to the upper tail. The same figure implied by estimates in Panel A (column 6) is a bit higher, at 0.28%. These estimates imply that the productivity effect of moving all focused patents of the average firm to the general category would have a productivity effect that ranges between 2.3% and 2.8%.

Columns 3 through 5 in Table 5 use the five-year compounded TFP growth rate as dependent variable. The sample consists of the four non-overlapping five-year intervals between 1976 and 1995. Figure 2 gives the distribution of five-year TFP growth. Mean productivity growth in the sample over five-year intervals is 0.0874 (8.74%). This variable is expected, and indeed observed to be skewed as well, due to the same survival bias with respect to productivity. To analyze the correlates of this variable, and avoid endogeneity issues, all independent variables are measured at the beginning of the relevant five-year window. In column 3, it is observed that R&D stock is positively related to TFP growth. However, patent stock has no additional effect above and beyond that of R&D. Similar to the market value estimates in Table 3, a low productivity estimate for the overall patent stock term (column 3) is observed to hide the separate and significant effects of its components (columns 4 and 5). In column 4 we replace the aggregate patent stock with general and focused patent stocks and find that the two types of patents have different relationships with productivity. General patent stock at the beginning of a period has a positive effect on productivity growth during the ensuing five years (coefficient is .197 and statistically significant). On the other hand, focused patent stock at the beginning of the period obtains a negative coefficient. When the R&D term is excluded and only patent-related measures are included (column 5), the negative effect of the focus patent stock disappears, and the coefficient of general patent stock increases. These set of results support and complement those found in TFP regressions reported in column 2.

Finally, we replicate the analyses in Panel A with the classification that uses thirds (instead of quartiles) of the relevant generality distribution. All columns in Panel B replicate the model directly above using these new set of invention indicators. Coefficient estimates are larger in magnitude to their counterparts in Panel A, but main results remain unchanged. Estimates reported in Table 5 indicate that moving 10% of a firm's focused patents to the upper tail of the generality distribution would lead to 0.39% (column 4) to 0.52% (column 8) increase in productivity growth during the following five years, on average. In terms of the productivity effect of the average firm's entire patent cohort, moving all of the average firm's focused patents to the general category would increase five-year productivity growth by 3.9% to 5.2%.

Table 5. *Total Factor Productivity Regressions*

Panel A: Patents are classified according to the upper and lower quartiles of the generality distribution					
	Natural logarithm of TFP (From Table 4, Column 1)		5-year compounded TFP growth (Independent variables are lagged 5 years)		
	(1)	(2)	(3)	(4)	(5)
	Fixed Effects LS	Fixed Effects LS	LS	LS	LS
log (Patent Stock)	0.0191***		-0.0080		
	(3.49)		(-1.03)		
log (General Patent Stock) *Upper quartile*		0.0181***		0.0197**	0.0243***
		(4.12)		(2.29)	(3.11)
log (Focused Patent Stock) *Lower quartile*		-0.0051		-0.0191**	-0.0153
		(-1.08)		(-2.26)	(-1.92)
log (R&D Stock)	0.0350***	0.0367***	0.0138**	0.0080	
	(6.70)	(7.17)	(2.25)	(1.29)	
Δ (General - Focused)		0.0232		0.0388	0.0396
R-squared	0.312	0.313	0.007	0.0122	0.0106
N	7258	7258	972	972	1027
Panel B: Patents are classified according to the upper and lower thirds of the generality distribution					
		(6)		(7)	(8)
		Fixed Effects LS		LS	LS
log (General Patent Stock) *Upper third*		0.0208***		0.0251***	0.0307***
		(4.24)		(2.66)	(3.60)
log (Focused Patent Stock) *Lower third*		-0.0075		-0.0239***	-0.0214**
		(-1.49)		(-2.68)	(-2.50)
log (R&D Stock)		0.0366***		0.0075	
		(7.11)		(1.21)	
Δ (General - Focused)		0.0283		0.0490	.0521
R-squared		0.313		0.0143	0.0136
N		7258		972	1027

Notes: Constant terms are not reported. Total Factor Productivity is calculated using production function coefficients given in Table 4, column 1 (Olley and Pakes methodology). Δ (General - Focused) is the difference in the coefficients of general and focused patent stock terms. All Fixed Effects LS specifications (1, 2 and 6) include year dummies. 5-year TFP growth regressions (3, 4, 5, 7 and 8) use 5-year lagged values of all independent variables, and the sample consists of the years 1995, 1990, 1985 and 1980. All logarithms are natural logs. *t*-statistics are reported in parentheses. Significance indicators: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

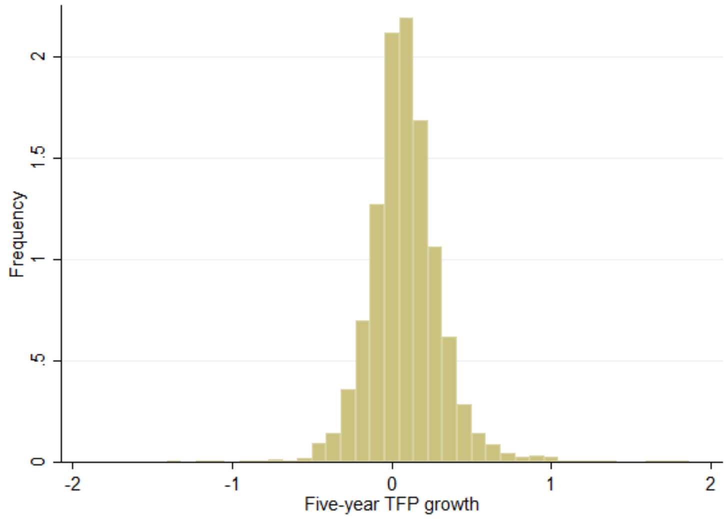

Figure 2. *The distribution of five-year Total Factor Productivity growth*

5. CONCLUSION

This paper has studied the association of general purpose and focused invention at the firm level, with firm market value, productivity, and productivity growth. Valuation and productivity estimation frameworks have been employed at the firm level in relation to the traded market value and the Total Factor Productivity of the firm, by also distinguishing the two types of invention among the firm's patents. Examining corporate patenting with respect to its heterogeneity in generality is shown to be empirically valuable and informative. In line with expectations, there is a market value premium to a firm's focused, and a productivity premium to its general purpose invention activity. That is, market value is most immediately linked to aspects of innovation that signal short-term commercial potential, but such activity exhibits a weaker relationship with productivity. On the other hand, invention in general purpose technologies as part of corporate R&D is associated with longer-term benefits in terms of productivity growth. This is intuitive since general-purpose technologies offer wider varieties of commercialization opportunities, which are reflected in firm-level productivity, even though such benefits are expected to come later and are not priced by the market quickly. The valuations and estimates produced by the analysis are important for decision making as they shed light on the nature of the trade-off between research efforts that are geared towards general vs. more specific and focused areas.

While we do not directly observe basic research expenditures at the firm level, there is extensive evidence showing that patent generality is correlated with the closeness of the embedded knowledge to basic science (Trajtenberg et al., 1997; Henderson et al., 1998; Schmid & Fajebe, 2019). In this sense, results of the paper speak indirectly of corporate basic science and point to the existence of large long-term benefits to corporate basic science in terms of productivity growth, potentially compensating for deferring immediate gains of a more focused strategy.

Recall that all estimates that are presented in the paper are of *private*, and not *social* returns to inventive activity. Estimates of social returns would require measurements of the relevant spillover effects, which differ for general purpose and focused technologies (Akcigit et al., 2021). Further studies of such differences in the spillover potential, as well as in the social returns to different types of inventive activity are promising areas for future work.

While the study period is a bit dated, it is a period that has witnessed significant technological change as well as the creation of new technological fields and industries. Estimates and valuations produced for this period, while calling for more recent analysis, are useful for understanding returns to inventive activity, which can further guide management decisions at the firm level as well as the policy choices of governing bodies.

CONFLICT OF INTEREST

The author declares no conflict of interest.

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