Introduction

Innovation as the key engine of economic growth and as a potential source of firm level heterogeneity in competitiveness is well established in the academic literature (Agarwal and Bayus 2002; Rothaerml and Hess 2007). With overwhelming evidence of information technologies (IT) fueling increases in tangible firm-level output and productivity (cf. Brynjolfsson and Hitt 1996; Hitt and Brynjolfsson 1996 ), attention has turned to the role of IT as a key input variable to intangible innovation processes and outcomes thereof. At a conceptual level, emergent research has documented the significant changes in innovation resulting from advances in information and communication technologies (ICT). For example, ICT in the form of databases and knowledge sharing tools have enabled greater and more effective sharing of knowledge distributed across heterogeneous, dispersed business units of a firm (Thomke 2006). Similarly, IT-based methods for product design, test and simulation have yielded greater precision and reduction of costs in the production of innovations (Nightingale 2000). Internet based networks and open source innovation platforms have fostered collaborations with and access to ideas and other innovation components from individuals and groups outside the firm (Krogh and Hippel 2006). All of these IT-enabled changes to innovation processes help boost R&D output; indeed, Kleis et al. (2012) document a 1.7% increase in the number of quality adjusted patents filed by a firm for every 10% increase in IT capital. Using a knowledge production framework that includes IT capital input, the authors conclude that both IT and R&D capital play a positive and significant role in innovation production as measured by patent counts, which remains a key metric of overall firm level innovation.

In this study, we focus on another important shift in the R&D function that is enabled through ICT – the systematic reallocation of innovation efforts in IT consuming firms towards more digital-centric innovations. Significant anecdotal evidence of this shift already exists. For example, in a popular article titled “Why Software is Eating the World,” Andreessen (2011) observes that over the past decade, nearly all industries, and not just the IT producing industries, have been fundamentally transformed through ICT with products and traditional services increasingly being delivered as software or online services. For example, cars today incorporate a variety of software to run engines, control safety features, identify current coordinates of drivers and guide them to their destinations, and integrate with satellite, mobile and GPS networks. More recently, driverless cars further emphasize this shift. Similar examples abound for a variety of industries ranging from aircrafts to oil and gas exploration to financial services. What this implies is that IT is not merely serving up tools to improve and boost traditional R&D productivity and innovation outcomes, but is fundamentally changing the nature of innovation by making innovation more digitally centered. While the argument of a more digitally-biased shift in the trajectory of innovation is supported by ample anecdotal evidence, to the best of our knowledge, large scale empirical evidence of this shift has been lacking.

In this paper, we empirically examine this important shift to more digital-centric innovations by US firms. By digital centricity, we refer to the increasing proportion of ICT patents in the overall patent portfolio of a firm. Using data from U.S public firms between 1980 and 2012, we document the growing digital centricity of firm innovations and test the subsequent impact of this shift on innovation performance and firm valuation. We show that firms that increase digital-centricity of their innovation portfolio (measured as the proportion of ICT patents in the overall patent portfolio) are able to achieve higher innovation efficiency (measured as the number of patents per innovator) and higher innovation effectiveness (measured as the number of new products per dollar of R&D capital introduced by the firm in a given year). In addition, we also show that both these measures of innovation performance are salient to market valuation. While innovation effectiveness or the value of new product introductions is completely incorporated in current market valuation, innovation efficiency is not fully priced in current market value, but is more fully reflected in the long-run abnormal returns for the firm.
The rest of this paper is organized as follows. In the next section we review the relevant prior literature and present the key hypotheses. Next we describe the data and the empirical specifications followed by the results and conclude with a brief discussion of the key implications and contributions of our work.

**Digital-Centric Innovation: Theoretical Framework**

We organize our theoretical framework around a discussion of digital centric innovations and how they impact innovation efficiency and effectiveness and their subsequent linkages to a firm’s market valuation.

**Digital-Centric Innovations**

Information and communication technologies (ICT) have had far-reaching impacts in reshaping the innovation processes and outcomes of nearly every industry. The term digital-centric innovations broadly describe innovations in products, processes and business models that are fundamentally ‘embodied-in’ or ‘enabled by’ ICT (Fichman et al. 2014). The increasing digitization opportunities unleashed by forces such as Moore’s law and network effects are being leveraged not only by IT-producing industries but also by IT-consuming industries to redesign their products, processes and business models. This in turn has led to an increase in the ‘digital content’ of many products and services regardless of whether they are finally embodied in pure virtual (e.g. e-books) or physical forms (e.g. driverless cars). Businesses that have taken advantage of these transformations by creating new digitally enabled products, services and business models have sought to patent these digital artifacts through filings that reflect the underlying ICT content in the patent descriptions. By examining the patent activity at the firm level, we can therefore measure the extent to which the firm’s innovation portfolio has been transformed by digital forces and therefore we use the proportion of ICT patents to the total patent portfolio as a measure of this important transformation. At a conceptual level, digital-centric innovation is different from other measures of firm level IT intensity and IT-capability which tend to focus on measures of IT-based inputs to the firm. In contrast, digital-centricity is a measure of the firms innovation output that is reflected in the degree to which the firm has embodied ICT in its patenting activity.

**Innovation Efficiency**

Innovation is the successful exploitation of new ideas and innovation efficiency is a reflection of the firm’s ability to convert its innovation inputs into valuable outputs (Wheelwright and Clark 1992). The product innovation literature has focused on the patents owned by a firm as the most objective and unbiased measure of the overall innovation output of a firm (Griliches 1990). There are arguably at least two potential impacts of the shift toward a more digital-centric innovation portfolio on innovation efficiency. First, as firms increase the proportion of their digital-centric patents, they create unique internal design and production capabilities through effective use of technologies such as CAD/CAM, 3-D printing, robotic manufacturing, and use of digital sensors and other network devices. These in turn allow product team members to integrate design efforts, whether co-located or dispersed, from product conception through final assembly. CAD based designs also allows for virtual prototypes. Scientists and engineers can use digital prototypes and computer simulations to test component compatibility, overall workability and failure analysis (Kleis et al. 2012).

Second, digitization of innovation components helps create a digital infrastructure for capturing and sharing knowledge at speed and scale that were previously unimaginable. Knowledge gaps within the firms are more easily and effectively filled through improved knowledge search processes and via interconnected pools of distributed expertise and problem-solving skills (Malhotra et al. 2001). Even knowledge sources external to the firm are frequently accessed thereby broadening and deepening the available pool of expertise that a firm can tap into. Open innovation networks and innovation contests on online platforms have allowed for the rapid internalization of externally accessed knowledge and the fruits of these efforts have accrued to firms that have been able to exploit these digitally enabled capabilities. As a case in point, consider the changes that have occurred in pharmaceutical and biotech R&D. To quote Nightingale and Mahdi (2006), “While biologists in the late 1980s may have focused primarily on
empirical “wet” biology, today they may spend much of their time in front of computers engaging in more theoretical in-silico science, experimental design, quality control, or trawling through large data sets.” The shift toward a more digital centric process of science has not only made pharmaceutical R&D more interdisciplinary with biologists working with medical clinicians, but has also made the process much more efficient. The digitization of “wet” science has been complemented by the analysis of stored and simulated data and has greatly helped to reduce experimentation costs and waste while increasing the speed and accuracy of doing R&D. Therefore we expect, 

**H1: Firms with higher digital-centric innovation will have higher levels of overall innovation efficiency.**

**Innovation Effectiveness**

As firms become more digital-centric in their innovation efforts, they look for more opportunities to render their physical products in digital forms (as in the case of Amazon’s Kindle that rendered books in digital formats), convert physical processes to digital processes (as in online shopping which moved from being a physical process to a digital process), embed digital services within their core physical products (as in auto manufacturers embedding software enabled services in cars) and even render entire business models on digital platforms (as in services like Airbnb and Uber).

Scholars have argued that opportunities through digitization arise primarily from three unique characteristics of digital technologies, namely, reprogrammability of digital devices, the homogenization of data, and the self-referential nature of digital technology (Yoo et al. 2010). Device reprogrammability enables the separable of the functional logic of a device from its physical embodiment, thereby allowing it to perform a wide array of functions that previously required separate and distinct functional devices. One only needs to consider today’s multifunctional mobile phone to fully appreciate what this separation of form and functionality has meant and how this has helped fuel further innovations. This has also led to the homogenization of all data accessible by digital devices, be they audio, video, text or image. As long as data are in digital form, they can come from heterogeneous sources and yet can be combined easily with other digital data forms to deliver a wide array of innovative services. By separating the content from the medium, entirely new sets of digital product and services have been created that have blurred traditional product and industry boundaries. Finally, the self-referential aspect of digitization has meant that as digital innovation has relied on the use of digital technologies (e.g. computer and communication technologies) the diffusion of digital innovations have set in motion virtuous cycles of positive network externalities that have further accelerated the creation and spread of digital innovations (Yoo et al. 2010). Since such products are also relatively easier to create and distribute, an increase in the digital-centricity of a firm’s innovation portfolio should also increase the pace at which firms introduce new products. Therefore we expect, 

**H2: Firms with higher digital-centric innovation will have greater innovation effectiveness in the form of more new products and services.**

**Innovation efficiency, effectiveness and market valuation**

Prior research (Mani et al. 2013; Daniel and Titman 2006) finds that the private signals of investors in interpreting intangible, complex information on future cash flows may be imprecise in the case of certain investments. In such cases, long-term abnormal returns may be a more appropriate measure of market value. Thus, we examine the effects of innovation outcomes on both short- and long-term stock returns.

Innovation is a primary engine of firm growth and performance and can lead to higher financial market valuations for firms (Chandy and Tellis 1998; Sorescu and Spanjol 2008). Prior research suggests that innovation effectiveness, especially in the form of new product introductions is more easily discernible by the external investment community and can therefore lead to higher short- and long-term market returns (e.g., Blundell et al. 1999), and that the more innovative these products are the greater the returns. Investors can value a new product on the basis of how successful they expect the firm to be in commercializing and marketing it and can price in the likelihood of the product’s success into the firm’s current stock prices (Sorescu et al. 2003). These gains when sustained are also likely to impact the long run abnormal returns to the firm. Therefore, we posit:
H3: Firms with higher innovation effectiveness will have higher current and long term market returns.

Research examining market returns to innovation efficiency has been more limited. Past studies have shown that when patent counts or citations are included in market value equations, they have not had much explanatory power (Hall, Jaffe, and Trajtenberg 2000). A potential reason for this might be due to the fact that any patent based measure of innovation is a very noisy signal to the market as the underlying economic value of the innovation is far from clear (Griliches, Hall, and Pakes 1991). The distribution of the value of the patented innovations can also be extremely slow as it may take many years to commercialize and extract value from the underlying patents. Therefore, we expect the value of higher innovation efficiency to be reflected in the long term abnormal market returns but will not be priced into the firm’s current market value. Therefore, we posit:

H4: Firms with higher innovation efficiency will have higher long term market returns.

Empirical Analyses

Data

Our sample comprises U.S. public firms at the intersection of four databases – Compustat Industrial Annual and Segment files, the National Bureau of Economic Research (NBER) patent data, United States Patent Office (USPTO) data, and Center for Research in Security Prices (CRSP). We obtain firm-specific accounting variables, including R&D and marketing expenditures, sales, industry concentration, total assets, net income and book equity from Compustat Industrial Annual files. We use the segment-level Product Database from the Compustat Segment File to compute new product introductions for each firm-year. The Compustat Segment file records a unique product number for each new product that persists through time (e.g., iPod is product number 10 for Apple, starting in 2004). We use the change in the total number of products listed in a given year to estimate the new product introductions for that year. These data on new products are available from 1994.

We use NBER and USPTO data to estimate the patent portfolio of the firm as well as patent level information, including classification, citations and inventors. Patents are indexed in both databases by their application date as well as grant date. To prevent any potential look-ahead bias, we choose the grant date as the effective date of each patent. The NBER database contains information on all patents granted by the U.S. Patent and Trademark Office (USPTO) between January 1976 and December 2006. Therefore, for patents granted during this time period, we use the NBER data to estimate the patent portfolio and other patent level information. For patents granted after 2006, we directly use the USPTO data to estimate patent level measures. We draw monthly stock returns, shares outstanding and other stock price data from CRSP. Finally, we use the Bureau of Economic Analysis’ (BEA) Input-Output Use Tables to estimate the average annual industry spend on IT.

Following prior research (e.g. Hirshleifer et al. 2013; Cohen et al. 2013), our sample period starts in 1980. This is because although patent data is available in NBER from 1976, the accounting treatment of R&D expenses reporting was standardized in 1975 (Financial Accounting Standards Board Statement no. 2). Therefore, to ensure the quality of data on R&D expenditure, we start our estimation of R&D capital in 1980 to allow for a full 5-year period with reliable R&D expenditure data. Therefore, 1980 is the first year for our sample data.

Measures

Our analyses test the impact of digitization on innovation efficiency and effectiveness and subsequently, the market’s valuation of these innovation outcomes. The operationalization of these key constructs and other controls in our analyses is described below:

Table 1: Measures of Variables

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Construct</th>
<th>Measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market Valuation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$Tobin_{Q,t}$</td>
<td>Tobin’s Q (as a measure of current market value)</td>
<td>Tobin’s Q of firm $i$ in year $t$, estimated as the book value of assets plus the market value of common stock less the sum of the book value of common stock and balance sheet deferred taxes divided by the book value of assets.</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>$Ret_{t}$</td>
<td>Long-term abnormal stock returns</td>
<td>12-month stock return of firm $i$ in year $t$ adjusted by the risk-free rate.</td>
</tr>
</tbody>
</table>

### Innovation Outcome Metrics

<table>
<thead>
<tr>
<th>$RnD_{Prod_{i,t}}$</th>
<th>Innovation Efficiency</th>
<th>The innovative efficiency of firm $i$ in year $t$ is operationalized as patents per inventor or the ratio of the number of patents granted to the firm in Year $t$ to the total number of inventors involved in their creation that year.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta RnD_{Prod_{i,t}}$</td>
<td>Growth in innovation efficiency of firm $i$ in year $t$.</td>
<td>$RnD_{Prod_{i,t}} - RnD_{Prod_{i,t-1}}$</td>
</tr>
<tr>
<td>$RnD_{NPD_{i,t}}$</td>
<td>Innovation Effectiveness - New Product Introductions</td>
<td>The innovative effectiveness of firm $i$ in year $t$ is operationalized as the number of new products reported by the firm $i$ in year $t$ scaled by its R&amp;D capital. The products that are reported by a firm in Year $t$ but not in $(t - 1)$ are considered to be new. R&amp;D capital is defined as the five-year cumulative R&amp;D expense, depreciated at an annual rate of 20%, beginning in year $t$.</td>
</tr>
<tr>
<td>$\Delta RnD_{NPD_{i,t}}$</td>
<td>Growth in new product introductions of firm $i$ in year $t$.</td>
<td>$RnD_{NPD_{i,t}} - RnD_{NPD_{i,t-1}}$</td>
</tr>
</tbody>
</table>

### Digital Centricity of Innovations

<table>
<thead>
<tr>
<th>$PropICTPat_{i,t}$</th>
<th>Digital centricity of innovations</th>
<th>We use the IPC classes identified in Corrocher et al. (2007) to classify patents as information and communication technology (ICT) patents. Corrocher et al. (2007) use patent abstracts to detect important applications in the ICT field by selecting the most frequent sequential triples of words that identify technological applications in the field. Their method yields a set of IPC classes related to these applications that are broader than those usually considered. We then use these ICT patent classes to estimate the percent of ICT patents in the portfolio of patents granted to firm $i$ in year $t$. This measure estimates IT-centricity of the firm’s innovations.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Ind_{IT}_{i,t}$</td>
<td>Industry Spend on IT</td>
<td>The BEA Input-Output Use tables are a matrix representation of the expenditures of each industry $i$ on intermediate inputs purchased from industry $j$. BEA provides these data that span 55 NAICS codes in five-year periods between 1967 and 1996 and annually after 1996. Following Jorgenson et al. (2011), we identify the list of IT producing industries as software and IT services industries – information and data processing services and computer systems design – and hardware</td>
</tr>
</tbody>
</table>
Methodology

In order to test our hypotheses on the impact of digital-centricity on innovation performance, we run separate regressions of innovation efficiency and new product introductions on the proportion of IT patents in the focal firm’s patent portfolio after controlling for the industry- and firm-level time variant controls described in Table 1. In addition, we also control for unobserved time-invariant firm and industry controls by including firm fixed effects, two-digit industry fixed effects and year fixed effects. The specifications that we use are as follows:

\[
RnD_{Prodc_{i,t+2}} = \beta_0 + \beta_1 PropICTPat_{i,t} + \beta_2 \Delta RnD_{Prodc_{i,t}} + \beta_3 \Delta RnD_{NPD_{i,t}} + \beta_4 SalesHHI_{j,t} + \beta_5 PatHHI_{i,t} + \beta_6 RDI\_Intens\_i_{,t} + \beta_7 Mkt\_Intens\_i_{,t} + \beta_8 ROA_{i,t} + \beta_9 BTM_{i,t} + \beta_{10} MVE_{i,t} + \beta_{11} FSize_{i,t} + \beta_{12} \log\_Patents_{i,t} + X_t + Y_t + T_t + \epsilon_{i,t}
\]  (1)
\[ RnD\text{ }_{\text{NPD}_{i,j,t+2}} = \gamma_0 + \gamma_1 \text{PropICTPat}_{i,t} + \gamma_2 \Delta RnD\text{ }_{\text{Prod}_{i,t}} + \gamma_3 \Delta RnD\text{ }_{\text{NPD}_{i,t}} + \gamma_4 \text{SalesHHI}_{i,t} \]  
\[ + \gamma_5 \text{PatHHI}_{i,t} + \gamma_6 \text{R&DIntesity}_{i,t} + \gamma_7 \text{MktIntesity}_{i,t} + \gamma_8 \text{ROA}_{i,t} + \gamma_9 \text{BTM}_{i,t} \]
\[ + \gamma_{10} \text{MVE}_{i,t} + \gamma_{11} \text{FSIZE}_{i,t} + \gamma_{12} \text{Log_Patents}_{i,t} + X_i + Y_j + T_t + \epsilon_{i,j,t} \]

In the case of innovation efficiency (Model 1), the two-year lag between the measure of innovation performance and proportion of IT patents reflects the time taken by firms to systematically reallocate their R&D resources to produce more digital-centric innovations. In the case of new product introductions (Model 2), the lag reflects the time taken by the firm to translate its digital-centric innovations into products and put in place complementary practices that are required to appropriate value from these products.

It may be argued that firms, in anticipation of improvements in R&D performance, invest in greater digitization or IT patents. In general, unobservable factors that drive firms’ choice of IT patents may also drive their R&D performance. In order to address this endogeneity of IT patent stock, we include firm fixed effects to control for any time invariant, unobserved heterogeneity that impacts stock of IT patents and R&D outcomes. In order to control for time variant heterogeneity, we run a two stage least squares estimation that includes industry IT spend as an instrument for proportion of IT patents in the firm’s patent portfolio. As instrument diagnostic tests, we use statistics from the first stage estimations, notably, the partial F-statistic, and Cragg–Donald weak instrument test. We obtain large and significant F-statistics in the first-stage regressions. Further, the Cragg–Donald statistics for our estimation are far higher than the Stock and Yogo critical values, indicating the absence of the weak instruments problem. For reasons of brevity, we only report results of the second-stage regressions of the digital centricity of the firm’s patent portfolio on innovation efficiency and effectiveness outcomes.

In order to test our hypotheses on the market valuation of the innovation outcomes, we regress Tobin’s Q and one-year abnormal stock returns on patents per inventor and new product introductions. Together, the regressions tell us whether the whether the stock market accords higher valuation to firms with higher innovative performance and whether current period valuations fully reflect the information contained in the innovative performance measures. The specifications for the valuation regressions are as follows:

\[ \text{Tobin}_Q_{i,t} = \alpha_0 + \alpha_1 \text{RnD}_\text{NPD}_{i,t} + \alpha_2 \text{RnD}_\text{Prod}_{i,t} + \alpha_3 \text{SalesHHI}_{i,t} + \alpha_4 \text{PatHHI}_{i,t} \]  
\[ + \alpha_5 \text{R&DIntesity}_{i,t} + \alpha_6 \text{MktIntesity}_{i,t} + \alpha_7 \text{ROA}_{i,t} + \alpha_8 \text{FSIZE}_{i,t} \]
\[ + \alpha_9 \text{Log_Patents}_{i,t} + X_i + Y_j + T_t + \epsilon_{i,j,t} \]

\[ \text{Ret}_{i,j,t} = \delta_0 + \delta_1 \text{RnD}_\text{NPD}_{i,t} + \delta_2 \text{RnD}_\text{Prod}_{i,t} + \delta_3 \text{SalesHHI}_{i,t} + \delta_4 \text{PatHHI}_{i,t} + \delta_5 \text{R&DIntesity}_{i,t} \]
\[ + \delta_6 \text{MktIntesity}_{i,t} + \delta_7 \text{ROA}_{i,t} + \delta_8 \text{FSIZE}_{i,t} + \delta_9 \text{Log_Patents}_{i,t} + X_i + Y_j + T_t \]
\[ + \epsilon_{i,j,t} \]

We check the robustness of our results for the valuation of innovation performance to an accounting-based asset valuation model developed in Ohlson (1995) and used by Sougiannis (1994). This specification involves running Fama-MacBeth (1973) cross-sectional regressions of the natural log of firm i’s equity market-to-book ratio in year t on innovation performance measures for that year. We also check the robustness of the results for long-term abnormal returns to other time horizons. Our results are robust to alternative model specifications and time horizons of up to 24 months.

**Results**

**Summary Statistics**

Figures 1 - 2 provide preliminary evidence of our thesis on increased digitization and its impacts on R&D. Prior research (e.g. McAfee and Brynjolfsson 2008) has documented the significant growth in corporate consumption of IT beginning the mid-nineties. Our data suggests that this increase in IT capital coincides with a significant increase in the digital centricity of products, as reflected in the proportion of IT patents in the firm’s patent portfolio. Figure 2 provides model-free evidence of the positive impact of digitization on innovation outcomes – firms in the highest tercile of proportion of IT patents have significantly higher innovation productivity relative to firms in the lowest tercile of proportion of IT
patents. We examine these results more closely in the regressions below.

**Figure 1:** Digital centricity of patent portfolios of firms over time

![Figure 1](image1.png)

**Figure 2:** Innovative efficiency across low and high quartiles of digital centricity of innovations

![Figure 2](image2.png)

**Digital-centricity of Innovation and Performance**

Table 2 presents the outcome of the 2SLS model detailed in Equations (1) and (2). Model I presents the results for the impact of digital centricity of innovations on R&D productivity corresponding to Hypothesis 1 while Model II presents the results for the equivalent impact on new product introductions corresponding to Hypothesis 2. The coefficient of PropICTPat_{i,t}, representing the proportion of ICT patents in the overall patent portfolio of the firm, is positive and significant in both models, providing strong support for Hypotheses 1 and 2 respectively.
Table 2: Digitization and Innovation Performance

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Model I $RnD_{Prod_{i,t+2}}$</th>
<th>Model II $RnD_{NPD_{i,t+2}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PropICTPat$_{i,t}$</td>
<td>19.896** (9.357)</td>
<td>0.113* (0.0619)</td>
</tr>
<tr>
<td>$\Delta RnD_{Prod_{i,t}}$</td>
<td>1.088** (0.426)</td>
<td></td>
</tr>
<tr>
<td>$\Delta RnD_{NPD_{i,t}}$</td>
<td></td>
<td>0.067*** (0.112)</td>
</tr>
<tr>
<td>SalesHHI$_{j,t}$</td>
<td>-18.299* (10.41)</td>
<td>-0.120 (1.34)</td>
</tr>
<tr>
<td>PathHHI$_{j,t}$</td>
<td>-1.574 (2.865)</td>
<td>0.165** (0.0689)</td>
</tr>
<tr>
<td>R&amp;DIntensity$_{i,t}$</td>
<td>0.000 (0.001)</td>
<td>0.000 (0.000)</td>
</tr>
<tr>
<td>MktIntensity$_{i,t}$</td>
<td>0.004 (0.016)</td>
<td>0.000 (0.000)</td>
</tr>
<tr>
<td>ROA$_{i,t}$</td>
<td>-0.006 (0.418)</td>
<td>0.007 (0.005)</td>
</tr>
<tr>
<td>BTM$_{i,t}$</td>
<td>-0.004* (0.002)</td>
<td>0.000* (0.000)</td>
</tr>
<tr>
<td>MVE$_{i,t}$</td>
<td>-0.000 (0.000)</td>
<td>0.000** (0.000)</td>
</tr>
<tr>
<td>FSize$_{i,t}$</td>
<td>1.491** (0.648)</td>
<td>-0.018*** (0.006)</td>
</tr>
<tr>
<td>Log_Patents$_{i,t}$</td>
<td>9.900* (5.435)</td>
<td>-0.058 (0.072)</td>
</tr>
<tr>
<td>Observations</td>
<td>9,006</td>
<td>6,730</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.237</td>
<td>0.112</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Market Valuation of Innovation Performance

Table 3 presents the results of regressions of market performance on innovation outcome measures. Specifically, Model I presents the results for the impact of innovation performance on Tobin's Q while Model II presents the results for the equivalent impact on long-term abnormal returns. We find that while the value of new product introductions is incorporated in current market prices, innovation efficiency (measured as patents per inventor) is not fully priced in current market value but reflected more accurately in the long-run model, resulting in a significant association between R&D productivity and long-term abnormal returns. The results are consistent with prior research (e.g. Hirshleifer et al. 2013, Cohen et al. 2013), which finds that investors underreact to the information content in innovative efficiency because of the difficulty evaluating the economic implications of the output patents and patent citations. As a result, firms that are more efficient in generating innovations are likely to remain undervalued by the market. In contrast, the uncertainty around the value of new product introductions is
lower than that around new patents, since elements of the industrial organizational structure such as capital budget constraints, competition and market demand have been addressed in the development of new products. Therefore, the market response to new product introductions is likely to be more accurate and complete relative to the response to patent productivity.

**Table 3: Market Valuation of Innovation Performance**

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Model I Tobin_Q&lt;sub&gt;it&lt;/sub&gt;</th>
<th>Model II Ret&lt;sub&gt;it&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>( RnD_{NPD} )</td>
<td>0.000** (0.000)</td>
<td>-0.000 (0.000)</td>
</tr>
<tr>
<td>( RnD_{Prod} )</td>
<td>0.001* (0.000)</td>
<td>0.009* (0.005)</td>
</tr>
<tr>
<td>( SalesHHI_{ij,t} )</td>
<td>0.210 (0.362)</td>
<td>0.358 (0.348)</td>
</tr>
<tr>
<td>( PathHHI_{ij,t} )</td>
<td>0.117 (0.077)</td>
<td>0.063 (0.127)</td>
</tr>
<tr>
<td>( R&amp;DIntensity_{ij,t} )</td>
<td>-0.000 (0.000)</td>
<td>0.000 (0.000)</td>
</tr>
<tr>
<td>( MktIntensity_{ij,t} )</td>
<td>0.001 (0.002)</td>
<td>-0.010** (0.005)</td>
</tr>
<tr>
<td>( ROA_{ij,t} )</td>
<td>0.001 (0.044)</td>
<td>-0.060*** (0.012)</td>
</tr>
<tr>
<td>( FSize_{ij,t} )</td>
<td>-0.156*** (0.017)</td>
<td>-0.263*** (0.038)</td>
</tr>
<tr>
<td>( Log_Patents_{ij,t} )</td>
<td>0.314* (0.182)</td>
<td>0.132 (0.263)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>2.470*** (0.190)</td>
<td>1.132*** (0.321)</td>
</tr>
</tbody>
</table>

**Observations** 12,546 8,467

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Conclusion**

This study sought to test the widespread assertion of a growing digitally-biased shift in innovation. Across a wide spectrum of industries and businesses, the rules of competition are being rewritten due to the effects of digitization. While this is certainly true for industries such as music and media that are closer in the spectrum of being pure digital, the shift is being felt as well in industries of the old economy. Even in an industry as old as mining, the potential to achieve breakthrough innovation is coming within the industry’s reach through digital innovations that could transform key aspects of mining operations (Durant-Whyte et al. 2015). Similar patterns have been observed even in other industries with heavy real-world components such as oil and gas.

The dramatic growth in the digital-centricity of firm-level patent portfolios (see Figure 1) documents this shift, but more importantly its relationship to other firm level innovation outcomes has not been examined previously. Our results speak to the important benefits that have accrued to firms that have successfully shifted
their patent portfolio to exploit the opportunities and affordances of digitization. The results obtained here have significant theoretical and practical implications.

Our finding that the digital centricity of innovations increases the overall innovation productivity of firms suggests that the scale and scope benefits of digitization extend far beyond the tangible productivity gains that have been extensively documented in past studies, to the more intangible and knowledge-based gains due to innovation performance. In industries such as biotechnology and pharmaceuticals, this shift has been documented as a shift toward “in-silico” science, where R&D has moved from a craft-based sequential process of experimentation to a more industrial scale of parallel experimentation augmented by computer simulations and computer-aided molecular discoveries (Nightingale 2000). From a practical point of view, the findings confirm that digital technologies are profoundly changing the nature of innovation and thereby the structure of competition and ultimately, performance across industries. Firms, especially large incumbent businesses that fail to leverage digital-centric innovations in their patent portfolio will see an ever widening gap relative to their more digitally agile peers.

Our study also explores the likely performance gap in innovative efficiency and effectiveness across low and high digital centricity by analyzing the corresponding market based returns. Our results show high market efficiency in pricing out the value of new product introductions as reflected in both current and long-term abnormal returns, which are both greater for firms with higher innovation effectiveness. In the case of innovation productivity, our measure using patent counts per inventor as the underlying metric indicates that the value of patents to the patenting firm might remain private and not get fully reflected in market prices. It would be worthwhile to also verify this result using alternate measures of patent citation counts that might better capture the true value of the underlying patents. These findings are consistent with prior results but more in-depth investigation of how a digital-shift in the patent portfolio is linked to market valuation outcomes is warranted. For example, it would be interesting to examine if digital-centricity has led to more incremental or radical innovations and the corresponding market-based valuation outcomes.
References


