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The impact of organization capital on firm innovation☆

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ABSTRACT

We show that firms' organization capital has a positive and economically important impact on innovation. Specifically, we find that firms with more organization capital have greater number of patents and receive more citations on their patents. The results are robust to alternative measures of organization capital and innovation, and endogeneity concerns. We also find that the ability to handle inherent difficulties associated with the innovation process and the reduction in managerial career concern threats are possible mechanisms through which organization capital affects firm innovation positively. These results provide strong evidence of the importance of a firm's organization capital in their innovation process.

1. Introduction

Innovation is widely regarded as one of the key mechanisms for corporations to sustain and drive business growth (e.g., Solow, 1957; Bloom and Van Reenen, 2002; Hall et al., 2005; Hasan et al., 2020; Wen and Zheng, 2020). A recent survey conducted by PricewaterhouseCoopers shows that almost 83% of executives consider innovation to be vital for the success of their companies (Percival and Shelton, 2013). Given its importance, there is a growing literature that examines the economic determinants of innovation. For example, a number of studies have looked at how the legal environment, financial market characteristics, and institutional settings affect innovation.[1] The primary focus of these studies is the relationship between a firm's external environment and its innovation activities. In this paper, we add to innovation literature by examining to what extent a firm's internal environment, such as corporate culture and the talent and skill of executives, impacts innovation. Specifically, we examine how organization capital, one of the most important types of firm's intangible capital (Corrado et al., 2009; Eisfeldt and Papanikolaou, 2014), affects innovation.

Organization capital, as defined by Evenson and Westphal (1995, p. 2237), is the organization's "knowledge used to combine human skills and physical capital into systems for producing and delivering want-satisfying products." Organization capital represents the firms' accumulated stock of knowledge and capabilities about the firms, and it can be interpreted as intangible capital of firms which is embodied in its employees' talents such as managers, executives, and research employees (Eisfeldt and Papanikolaou, 2013, 2014). However, it is very different from general human capital because

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[1] Studies have shown that legal systems protecting corporate failures or personal failures such as creditor-friendly bankruptcy codes (Acharya and Subramanian, 2009), enactment of state antitakeover laws (Atanassov, 2013) and laws protecting employees against unjust dismissal impact innovation (Acharya et al., 2014). Another stream of literature has shown that financial market characteristics such as extent of banking deregulation (Amore et al., 2013; Chava et al., 2013) and the development of equity and credit markets (Hsu et al., 2014) affect innovation. Other studies have provided empirical evidence that institutional settings such as institutional investors (Aghion et al., 2013) and shareholders' tolerance for failure (Tian and Wang, 2014) influence innovation.

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it also includes elements specific to firms such as corporate culture, the unique business processes firms develop, the recruiting and training of employees along with the accompanying incentive programs. Prior studies have shown that organization capital is an important input in the production process and helps firms improve the match between human capital and physical capital. This results in increased operational efficiency and firm value (e.g., Lev and Radhakrishnan, 2005; Lev et al., 2009).

The motivation to explain innovation using organization capital is consistent with the view of Porter (1992, p. 65) that "Innovation and upgrading come from sustained investment in physical as well as intangible assets – things like employee skills and supplier relationships." Anecdotal evidence suggests that factors that constitute a firm's organization capital such as its corporate culture, key talents employees, and recruiting and training programs, could enhance innovation. For example, *Coca Cola Co*. in the 10-K statement filed in 1999 states that:

> "*Our continued success depends on recruiting, training and retaining people who can quickly identify and act on profitable business opportunities. This means maintaining and refining a corporate culture that encourages learning, innovation and value creation on a daily basis. The Coco-Cola Learning Consortium works with the management of our entire system to foster learning as a core capability. This group helps build the culture, systems and processes our people need to develop the knowledge and skills to take advantage of new opportunities.*" [2]

We contend that organization capital could enhance innovation. First, organization capital interacts with intellectual and social capital to improve innovative capability of the firm and it creates a greater exchange of ideas, including the social trust that is particularly useful since innovation is a collective activity (Subramaniam and Youndt, 2005; Nahapiet and Ghoshal, 1998). Second, firms with more organization capital have higher managerial quality (Eisfeldt and Papanikolaou, 2013; Li et al., 2014) and make higher amounts of investment in information technology (IT) (Eisfeldt and Papanikolaou, 2013). Firms with more quality managers and more investments in IT should be able to innovate more, and hence, organization capital should enhance innovation. Further, Carlin, Chowdhry, and Garmaise (2012) argue that firms with more organization capital have lower employee turnover. Therefore, managers of firms with more organization capital are less likely to face career concern threats. Hence, firms with more organization capital are more likely to participate in long-term oriented activities such as innovation that improves future firm value (Stein, 1989; Acharya et al., 2014).

On the other hand, organization capital could reduce innovation. Lustig et al. (2011) argue that for successful firms, when there is an increase in the accumulation of organization capital, there is an increase in the outside options of managers. And, voluntary turnover is associated with replacement costs and loss of human and social capital and is otherwise associated with diminished organizational performance (Dess and Shaw, 2001). Hence, the departure of personnel in firms in general and especially in those firms with high organization capital could affect innovation negatively either directly or indirectly by affecting the productivity of incumbent employees.

The impact of the interplay between organization capital and managerial talent on innovation is also obfuscated by compensation incentives in place. As it turns out firms with higher organization capital also tend to reward managers with high pay for performance contracts because as managers outside options increase, greater pay for performance sensitivity is required to bind the manager with the firm and prevent him/her from exercising those options (Lustig et al., 2011). And, a higher pay-for-performance sensitivity in firms with more organization capital could induce managerial risk aversion and discourage involvement in long-term activities like innovation (Holmstrom, 1989; Manso, 2011; Chang et al., 2015; Francis et al., 2019).

We empirically investigate these competing arguments in examining the overall effect of a firm's organization capital on innovation. Lev and Radhakrishnan (2005) argue that selling, general, and administrative (SG&A) expenditures contain items that include most of the expenditures that generate organization capital including labor costs such as wages, salaries, compensation paid to its employees, recruiting and employee training costs and IT expenditures. Following Eisfeldt and Papanikolaou (2013), we accumulate the deflated value of firms' SG&A expenditures using a perpetual inventory method scaled by the book value of total assets to measure organization capital. We use the most recent information on patents and citations of U.S. firms provided by Kogan et al. (2012) to construct innovation measures.

We find that over the 1980–2008 period, there is a positive and significant relation between a firm's organization capital and innovation. Specifically, we find that firms with more organization capital are associated with a greater number of patents granted and citations received after controlling for various characteristics that have been shown in the literature to affect innovation. The relationship is also economically meaningful. For example, a one standard deviation increase in a firm's organization capital is associated with a 5.56% increase in the log of the number of patents granted and a 6.27% increase in the log of the number of citations received in the following year. To account for the possibility that organization capital may have a lagged effect on innovation, we look at two-year ahead patents granted, and citations received, and the results remain statistically and economically significant. Our results are robust to alternative measures of organization capital and innovation, when we control for executive pay, performance-sensitive compensation, and corporate governance characteristics.

One potential caveat in the interpretation of the results is the issue of endogeneity. It is possible that there are omitted variables that affect both organization capital and innovation. In addition, there is also a concern that more innovative firms could have more organization capital, instead of more organization capital of firms making them innovate better (i.e., reverse causality concern). We address this issue of endogeneity using several econometric techniques.

First, we include firm fixed effects in the regressions to control for any firm-specific time-invariant omitted variables that could affect the relation between organization capital and innovation. The main results are robust to the inclusion of firm fixed effects. We also focus on the change in organization capital and find that changes in organization capital within a firm lead to a higher amount and better quality of innovation.

Second, we employ an instrumental variable (IV) approach to alleviate the concern that omitted variables that are time-variant could be driving the relation between organization capital and innovation. Motivated by Carlin, Chowdhry, and Garmaise (2012) and Li, Qui and Shen (2014), we use the growth in uncertainty of the industry to which the firm belongs as an instrument for firm's

[2] As another example, *Google Inc.* in the 10-K statement filed in 2006 states that "*We compete aggressively for talent, and our people drive our innovation, technology development and operations. We strive to hire the best computer scientists and engineers to help us solve very significant challenges across systems design, artificial intelligence, machine learning, data mining, networking, software engineering, testing, distributed systems, cluster design and other areas. We work hard to provide an environment where these talented people can have fulfilling jobs and produce technological innovations that have a positive effect on the world through daily use by millions of people. We employ technology whenever possible to increase the efficiency of our business and to improve the experience we offer our users.*"

organization capital. Jones and Tuzel (2013) find that firms belonging to industries that experience rapid technological changes are, in general, more innovative than the less dynamic ones. Therefore, to mitigate the potential concern that the instrument could be correlated with the innovativeness of industries, we regress industry growth uncertainty on industry-level innovation measured by the number of patents granted and citations received on all patents of firms in the industry and use the residual from this time-series regression as an instrument for organization capital. We find that the relation between organization capital and innovation is robust when estimated using a two-stage least squares IV methodology.

Third, we use a propensity score matching methodology and match firms with more organization capital to firms with less organization capital in the same industry along with the various firm characteristics used as control variables in the baseline regressions. This methodology ensures that firms, except for their organization capital, are similar in terms of their observable characteristics. Consistent with the baseline results, we find that firms with more organization capital are more innovative than the matching firms with less organization capital.

We explore possible channels through which organization capital enhances innovation. We find that firms with more organization capital have better capabilities to deal with inherent difficulties associated with the innovation process. Specifically, we find that the impact of organization capital on innovation is stronger for firms in high-tech industries than those in low-tech industries. We also find that the effect is stronger for firms with lower managerial ability than firms with higher managerial ability.To the extent that innovation is more complex in high-tech industries (Tian and Wang, 2014) and more difficult in firms with lower ability managers (Chen et al., 2015), our finding shows that firms with more organization capital, and hence, higher quality managers and superior processes in place, cope more ably with the inherent complexities associated with innovation process and thereby, increase innovation output.

In addition, we find that organization capital enhances innovation by reducing career concern threats. In particular, the effect of organization capital on innovation is stronger for firms with higher profitability growth. Because previous literature shows a lower likelihood of CEO turnover when profitability growth is higher (Aghion et al., 2013), this finding is consistent with the view that organization capital, by mitigating career concern threats, helps managers to focus on risky and long-term focused activities like innovation.

Finally, we examine the impact of Inevitable Disclosure Doctrine (IDD) on innovation. IDD was adopted by US courts to enhance legal protection for trade secrets, and pevious studies show that the passage of the act can be associated with lower likelihood of "job hopping" within a state (Warner et al., 1988; Weisbach, 1988; Fee and Hadlock, 2004). We find that the effect of organzation capital on innovation becomes less positive after the passage of IDD, confirming that mitigating career concern threats is a plausiable channel through which organzation capital affects innovation positively.

This paper makes contributions to three major streams of literature. First, it extends a growing literature examining the economic determinants of innovation. Existing studies mainly focus on the relation between a firm's external environment and innovation. More recently, a new stream of studies starts to investigate how a firm's internal environment affects innovation (e.g., Sugheir et al., 2011; Fang et al., 2014; Chang et al., 2015; Bradley et al., 2017; Francis et al., 2019). Our study adds to this line of research by showing that intangible assets in general, and organization capital in particular, are important for innovation.

Second, our study adds to the growing, but still sparse, the literature on the impact of organization capital on corporate decisions. The impact organization capital has on the production process and on firm value has been documented in the extant literature (e.g., Prescott and Visscher, 1980; Atkeson and Kehoe, 2005; Lev et al., 2009). However, evidence on the effect of organization capital on corporate policies and the mechanisms through which it affects firm value is rather limited. Recent studies have shown that firms with more organization capital make better mergers and acquisitions (M&As) decisions (Li et al., 2014), and have lower investment cash-flow sensitivity (Attig and Cleary, 2014). Our work adds to this growing literature by showing that organization capital enhances corporate innovation activities and that innovation is a plausible channel through which organization capital improves firm value.

Finally, our work contributes to an emerging literature examining the importance of firm intangibles on firm performance and corporate policy making (Berk et al., 2010; Edmans, 2011; Falato et al., 2013). Our study demonstrates that firms' intangibles such as organization capital can have a significant influence on corporate policies such as firms' innovation policy that are vital to economic growth.

2. Hypothesis development

2.1. Organization capital increases innovation

Firms with more organization capital differ in many aspects from those with less organization capital and these differences have important implications for firms' innovation process. First, firms with more organization capital have higher production efficiency compared to firms with less organization capital because of their highly skilled employees and a collection of unique business processes (Lev et al., 2009; Eisfeldt and Papanikolaou, 2013). Further, Eisfeldt and Papanikolaou (2013), Li, Qui, and Shen (2014), and others, show that firms with more organization capital are associated with higher managerial quality and make greater investment in information technology (Eisfeldt and Papanikolaou, 2013) relative to firms with less organization capital firms. Because executive talent and skills (Bernstein, 2012; Custodio et al., 2013) and advances in information technology (Bresnahan and Trajtenberg, 1995) enhance the innovation process, organization capital should improve innovation.[3] In addition to higher level of intellectual or human capital, higher organization capital is also associated with greater levels of social capital that is further associated with exchange of knowledge and creation of new ideas (Nahapiet and Ghoshal, 1998). Subramaniam and Youndt (2005) examine the interactions of organizational, human and social capital and find that organization capital is positively associated with innovative capability and human capital combined with social capital was associated with radical innovative capability. Hasan, Hoi, Wu, and Zhang (2020) find a positive relation between social capital and innovation.

Organization capital indirectly affects innovation through its impact on manager's outside options. Carlin, Chowdhry, and Garmaise (2012) show that firms with more organization capital have lower employee turnover than firms with less organization capital. They argue that firms with more organization capital are less likely to replace their employees with outsiders because

[3] Bernstein (2012) shows the importance of firms to retain skilled inventors in order to continue the pre-initial public offering (IPO) innovation growth in the post-IPO period. Custodio, Ferreira and Matos (2013) show that general management skills of CEOs spur corporate innovation activities. Bresnahan and Trajtenberg (1995) show that advances in information technology (IT) have greatly enhanced the product and process innovations of firms in most industries.

incumbents can be more effective in utilizing firms' existing systems to share ideas with others thereby, improving productivity. This has implications for the corporate innovation process. Manso (2011) in a theoretical setting shows that firms with a high tolerance for failure are more successful in getting managers to participate in activities that are associated with uncertainties such as innovation. However, if managers of firms with low tolerance of failure have career and reputational concerns they are more likely to pursue less innovative short term projects rather than riskier more innovative long term projects. For example, Graham, Harvey and Rajgopal (2005), in their survey of Chief Financial Officers, show that most of the managers when faced with career and external reputation concerns are willing to forgo some long-term activities to fulfill short-term goals. Stein (1989) argues that managers facing career concerns and takeover threats are likely to invest less in activities such as innovation and rather focus more on routine and short-term activities. And Acharya et al. (2014) show that laws that protect employees against unjust dismissal encourage innovation. Therefore, to the extent that firms with more organization capital have lower employee turnover suggesting that managers of such firms are less likely to face career concern threats, more organization capital could enhance innovation. There is also lower incidence of voluntary turnover in firms with high organization capital (Dess and Shaw, 2001; Manchester, 2010). In sum, firms with more organization capital are likely to be more innovative than those with less organization capital.

2.2. Organization capital decreases innovation

There is a potential for organization capital to decrease innovation through market for talent. For example, Eisfeldt and Papanikolaou (2013) show that firms with more organization capital are highly reliant upon employees to produce superior performance and that shareholders demand a higher risk premium for investing in such firms due to the impact that high turnover could have on future firm performance. Bernstein (2012) shows that the exit of skilled inventors has a negative impact on the productivity of the remaining inventors which leads to a decline in the quality of innovation. Hence, turnover in firms with more organization capital could have a negative impact of firm innovation either directly or indirectly by reducing the productivity of incumbent workers. Voluntary turnover is itself associated with depletion of organization capital and can consequently reduce innovation.

Additional negative feedback effect of organization capital on innovation comes from the incentive contracts in place. Pay-for-performance sensitivity of executive incentive contracts is higher for firms with more organization capital than for firms with less organization capital ones (Lustig et al., 2011). Lustig, Syverson and Van Nieuwerburgh (2011) contend that when firms are successful, there is an increase in the accumulation of organization capital and an accompanying increase in managerial compensation. However, traditional compensation contracts with higher pay-for-performance sensitivity could discourage involvement in long-term activities like innovation. Holmstrom (1989) and Manso (2011) argue that because innovation activities are characterized by high levels of risk and uncertainty, firms should design compensation contracts that are less sensitive to performance in order to motivate managers to actively pursue innovation. This suggests that if more organization capital increases the pay-for-performance sensitivity of compensation contracts, it could discourage firms from pursuing innovation opportunities. Consequently, features such as increased pay-for-performance sensitivity and the potential decline in productivity of incumbent workers through managerial turnover, suggest that organization capital could have a negative impact on innovation.

3. Sample, variable construction and descriptive statistics

3.1. Data sources and sample

We use several data sources to construct the dataset we use in our empirical investigation. The data on patents granted to firms and the information on citations are from the most recent version of the United States Patent and Trademark Office (USPTO) patent database made available by Kogan, Papanikolaou, Seru and Stoffman (2012). This patent database contains detailed information on all patents issued by the USPTO between 1926 and 2010 to publicly traded U.S. firms. We use this patent database over the commonly used National Bureau of Economics Research (NBER) patent database created by Hall, Jaffe and Trajtenberg (2001) because it provides patent information for a much longer time period than the NBER database. In addition, this database is created using the entire history of U.S. patent documents obtained from Google Patents, and hence is more comprehensive (Kogan et al., 2012). Although this database provides detailed patent information, it does not have information on the patent technology classes and subclasses. The patent classification information is obtained from Google's website and matched to the new patent database using patent numbers available as a common identifier in these two datasets.[4]

We collect financial data from the Compustat and Center for Research in Security Prices (CRSP) databases to construct organization capital measures and control variables required for multivariate analyses. We obtain institutional shareholdings data from the Thomson Reuters Institutional (13F) Holdings. Although the patents data are available from 1926, the SG&A expenditures required to construct our organization capital measures are available in Compustat only from 1950 and the institutional holdings data required to control for institutional ownership in our analyses are available only from 1980. We drop the years 2009 and 2010 from our sample because the information on patents for these years is likely to be adversely affected by the truncation bias that we discuss in detail in Section 3.2 below. As a result, the sample period for this study is from 1980 to 2008. We exclude all financial firms from the sample (SIC codes between 6000 and 6999). We further exclude observations missing control variables required to conduct multivariate analyses. The final sample consists of 87,873 firm-year observations.

3.2. Innovation measures

We use patent-based metrics to measure a firm's innovation activities. Patent-based measures are not perfect measures of firm innovation; however, Griliches (1990) and Trajtenberg (1990) show that they are better proxies for firms innovativeness than research and development (R&D) investments. Patents also indicate the success of R&D investments made by firms. In addition, these measures have been widely accepted in the finance literature as innovation measures (e.g., Aghion et al., 2013; Acharya et al., 2014; Sayili et al., 2017; Cheng et al., 2020; Hasan et al., 2020).[5]

We employ two types of patent-based metrics to measure innovation. The first is a count of a firm's patent applications filed in a year and eventually granted. Patent application year is used as the relevant year to count the number of patents because it is more closely related to the actual time of innovation. Although this

[4] Retrieved from Google's website: http://www.google.com/googlebooks/uspto-patents-class.html

[5] Using patent-based metrics has one limitation. Not all firms and industries have the same propensity to patent their innovations and cite other patents. The amount of patenting depends on the patentability criteria and also on the extent to which inventors choose to rely on patents to protect their inventions. To alleviate this concern, we control for industry trends by using industry fixed effects.

patent count variable provides a way to measure the amount of innovation, it doesn't necessarily distinguish between incremental and breakthrough innovation and hence, is not very informative with regard to the quality of innovation. Studies have shown that citations received by patents is a good measure of the influence of patents (see, for example, Trajtenberg, 1990; Hall et al., 2005). Hence, to assess innovation quality, we construct a second patent-based measure by counting the number of citations received in subsequent years on all the patents a firm generates in a given year.

The patent-based measures suffer from truncation bias towards the end of the sample. Specifically, it takes an average of about two years for a patent to be granted by the USPTO from the time of its application. As a consequence, many patents applied for by firms towards the end of our sample would not have been granted, and hence patent count is likely to be underestimated. Similarly, we do not account for citations received by patents after the end of our sample period, and this introduces a truncation bias, as patents continue to receive citations, several years after they are granted. We follow Hall, Jaffe and Trajtenberg (2001) and correct for these biases in two ways. First, we divide each patent (patent's citations received) by the average number of patents (citations received on all patents) of all the applications made by firms in the same year and technology class to which the firm's patent belongs. We refer to this truncation adjustment as *Time-Tech* adjustment henceforth. The adjusted variables $Patents^{Time-Tech}$ and $Citations^{Time-Tech}$ is the sum of adjusted number of patents (citations received on all patents) applied for by the firm during the year. Second, we divide each patent (patent's citations received) by the average number of patents (citations received of all patents) of all the applications made by firms in the same year to which the firm's patent belongs. This truncation adjustment procedure is referred to as *Time* adjustment hereafter. The adjusted variables are constructed analogously to the first set of variables defined earlier and are referred to as $Patents^{Time}$ and $Citations^{Time}$.

Table 1 reports the summary statistics on innovation related variables of the 87,873 firm-year observations in the sample. The average number of $Patents^{Time-Tech}$ and $Patents^{Time}$ in the sample is 1.392 and 0.160 per year, respectively. On average, the total number of $Citations^{Time-Tech}$ and $Citations^{Time}$ is about 5 per year. The distributions of all the patent-based innovation measures are non-normal. Hence we take the natural logarithm (ln) of (one plus) the adjusted patent count and patent citations received to correct for the skewness in the data. The innovation measures we use in the analyses are defined as $LnPat^{Time-Tech} = \ln(1+Patents^{Time-Tech})$, $LnCit^{Time-Tech} = \ln(1+Citations^{Time-Tech})$, $LnPat^{Time} = \ln(1+Patents^{Time})$ and $LnCit^{Time} = \ln(1+Citations^{Time})$.

3.3. Organization capital measures

Recent studies have shown that SG&A expenditures contain items that generate firm's organization capital including labor costs such as wages, salaries, and compensation paid to its employees, recruiting and employee training costs and IT outlays (Lev and Radhakrishnan, 2005; Lev et al., 2009; Eisfeldt and Papanikolaou, 2013; Danielovaa et al., 2020). Because SG&A expenditures do not result in any particular output, it is likely to include any spending by the firm to increase its organization capital. We follow Eisfeldt and Papanikolaou (2013) and construct organization capital (OC) as a stock variable by accumulating the inflation adjusted value of SG&A expenditures using the perpetual inventory method. The initial stock of organization capital for each firm is computed using the following formula:

$$OC_{i,0} = \frac{SG\&A_{i,1}}{g + \delta_{OC}}. \tag{1}$$

Where, $SG\&A_{i,1}$ is the first non-missing SG&A expenditures available in Compustat for each of our sample firms; g is the growth rate for investment in organization capital and is assumed to be 10%, which is the average growth rate of SG&A expenditures in real terms for firms in Compustat database; δ_{OC} denotes the depreciation rate of organization capital and, following Eisfeldt and Papanikolaou (2013), we assume a 15% depreciation rate for organization capital, the rate used by Bureau of Economic Analysis for the estimation of R&D capital stock.

The subsequent stock of organization capital is estimated recursively using the following formula:

$$OC_{i,t} = \left(1 - \delta_{OC}\right) OC_{i,t-1} + \frac{SG\&A_{i,t}}{CPI_t}. \tag{2}$$

Where, CPI_t represents the consumer price index. Missing values of SG&A expenditures subsequent to the first non-missing value are treated as zero when constructing the stock of organization capital using Eq. (2). In addition, we subtract the R&D expenditures from SG&A expenditures and use this adjusted SG&A expenditures to construct the stock of organization capital. We do this to alleviate the concern that SG&A expenditures may include R&D expenditures and hence, the organization capital measure could be mechanically related to innovation variables. Finally, we scale the stock of organization capital by the book value of the firm's total assets. The scaled organization capital variable, denoted as *OC/Assets* henceforth, is used as our main measure of organization capital.

Eisfeldt and Papanikolaou (2013) argue that their method of measuring organization capital by cumulating firms' SG&A expenditures is a superior measure of organization capital than that obtained by using structural models, which is likely to be sensitive to model specifications. Table 1 shows that the mean and median of *OC/Assets* for the sample are 1.064 and 0.776, respectively. In addition, the standard deviation of *OC/Assets* is relatively high (1.011), suggesting that there is significant amount of variation in the amount of organization capital across our sample of firms.

3.4. Control variables

We follow the innovation literature and control for a number of characteristics while examining the relation between organization capital and innovation. We control for firm size, *LnAssets*, defined as the natural logarithm of book value of total assets in 2010 dollars to account for the possibility that larger firms may innovate more. We include *Market-to-book*, measured as the ratio of the market value of assets to book value of total assets, to control for growth opportunities. We control for firm performance using return on assets (*ROA*) and annual stock returns (*Stock Returns*) over the year. We control for leverage (*Leverage*, defined as the ratio of book value of total debt to book value of total assets), asset tangibility (*Tangibility*, defined as the ratio of net property, plant and equipment to book value of total assets), capital expenditures (*CAPEX*, defined as the ratio of capital expenditures to book value of total assets), research and development spending (*R&D/Assets*, defined as the ration of R&D expenditures to book value of total assets), firm age (*LnAge*, defined as the natural of the number of years that a firm has been listed in the Compustat database) and financial constraints (*KZ Index*, measured as per Kaplan and Zingales (1997)).[6] Aghion, Bloom, Blundell, Griffith, and Howitt (2005) show that there is a non-linear relationship between innovation and industry competition. Therefore, we control for competition using the Herfindahl Index based on sales (*H Index*) and Herfindahl Index squared (*H*

[6] We assume that firms with missing values for R&D expenses in the COMPUSTAT database to have zero R&D expenses.

Table 1
Descriptive Statistics of Innovation Measures, Organization Capital, and other Variables.

Variable	N	Mean	Median	Std Dev
Innovation Variables				
$Patents_t^{Time-Tech}$	87,873	1.392	0.000	5.419
$Patents_t^{Time}$	87,873	0.160	0.000	0.661
$Citations_t^{Time-Tech}$	87,873	5.087	0.000	20.732
$Citations_t^{Time}$	87,873	4.951	0.000	20.559
$Patents_t$ (unadjusted)	87,873	4.681	0.000	19.166
$Citations_t$ (unadjusted)	87,873	57.827	0.000	248.110
Firm Characteristics				
$OC/Assets_t$	87,873	1.064	0.776	1.011
$Assets_t$ ($B)	87,873	1.349	0.173	4.055
$Market\text{-}to\text{-}book_t$	87,873	1.592	1.093	1.501
ROA_t (%)	87,873	7.160	11.443	19.840
Stock $Returns_t$ (%)	87,873	13.324	2.513	66.337
$Leverage_t$ (%)	87,873	21.066	18.509	18.377
$Tangibility_t$ (%)	87,873	28.993	23.650	21.881
$CAPEX_t$ (%)	87,873	6.760	4.708	6.733
$R\&D/Assets_t$ (%)	87,873	4.491	0.000	8.600
Age_t	87,873	16.773	13.000	12.207
H $Index_t$	87,873	0.268	0.214	0.191
H Index sq_t	87,873	0.108	0.046	0.163
KZ $Index_t$	87,873	0.575	0.599	1.278
IO_t (%)	87,873	33.991	27.631	28.179

This table reports the descriptive statistics of various innovation characteristics, organization capital variable, and other firm characteristics for the 87,873 firm-year observations in our sample of U.S. firms between 1980 and 2008. Please refer to the Appendix for detailed definitions of these variables.

Index sq). Finally, we include percentage of common shares held by institutional investors (*IO*) because Aghion, Van Reenen and Zingales (2013) show that institutional holdings affect innovation activities. All the continuous variables are winsorized at the 1% and the 99% level to minimize the effect of outliers.

Table 1 presents the statistics of these firm characteristics. The average firm in the sample has $1.349 billion in total assets, market-to-book ratio of 1.592, return on operating assets of 7.16%, and leverage of 21.1%. In addition, on average, about 29% of firm's assets are in the form of plant, property, and equipment and the fraction of capital expenditures and R&D expenditures over total assets are 6.8% and 4.5%, respectively. Finally, about 34% of the firm's common shares outstanding are held by institutional investors.

4. Empirical results

This section presents empirical results of the relation between organization capital and innovation. We discuss the main research design and the baseline regression results in Section 4.1. We present a discussion on the results exploring potential alternative explanations and a battery of robustness checks in Section 4.2.

4.1. Organization capital and innovation

To examine the relationship between organization capital and innovation we estimate the following ordinary least squares (OLS) regression model:

$$LnPat_{i,t+n}\left(LnCit_{i,t+n}\right) = \alpha + \beta OC/Assets_{i,t} + \gamma Z_{i,t} + Year_t + Industry_i + \varepsilon_{i,t} \quad (3)$$

Where, *i* refers to firm, *t* indexes time and *n* is the number of years after time period *t* and equals to one and two. The dependent variable is either *LnPat* (*LnCit*), which is the natural logarithm of (one plus) the sum of adjusted number of patents (citations received on all patents) applied for by the firm during the year. We measure innovation both one and two years ahead, to mitigate potential endogeneity issues and also to allow for the possibility that organization capital could have a delayed impact on innovation. The key independent variable *OC/Assets* is the stock of organization capital scaled by the book value of total assets for firm *i* over its fiscal year *t*. *Z* is a vector of control variables described in Section 3.4 that could affect the innovation activities of firms. We also include year and industry (at the two-digit SIC level) fixed effects to account for time and industry trends. Standard errors are heteroskedasticity-robust in all the specifications and are clustered at the firm level.

4.1.1. Organization capital and patent count

We first examine the relation between organization capital and the number of patents. Panel A of Table 2 reports the baseline regression results. Columns (1) and (2) contain results for the dependent variable, $LnPat^{Time-Tech}$ measured one ($t+1$) and two years ($t+2$) forward. Similarly, Columns (3) and (4) contain results for the dependent variable, $LnPat^{Time}$ measured one ($t+1$) and two years ($t+2$) ahead. Irrespective of the patent count measure that we use, the coefficient on organization capital (*OC/Assets*) is positive and statistically significant at the 1% level. This indicates that firms with more organization capital are associated with greater amount of innovation in the subsequent two years. The results are economically significant as well. In particular, Columns (1) and (2) show that a one standard deviation increase in firm's organization capital is associated with a 5.56% (= 0.055*1.011*100) increase in its log number of patent counts ($LnPat^{Time-Tech}$) in the following year and 5.26% (= 0.052*1.011*100) increase in its log number of patent counts two years later. Our result indicates that one-unit increase in organization capital is associated with a 5.7% (=exp(0.055)) increase of patent counts.[7]

In general, the control variables have coefficients consistent with the extant literature (see, for example, Hirshleifer et al., 2012; Fang et al., 2014). Larger firms, firms with better growth opportunities, higher research and development expenditures, and lower leverage produce more patents. Industry concentration and asset tangibility do not significantly affect innovation. Financially constrained firms are associated with a lower number of patent count. Firm performance and institutional ownership are nega-

[7] Given the mean value of patent is 4.68, a one-unit increase in organization capital is associated with a 0.27 (=0.057x4.68) increase in the number of patent counts.

Table 2
Organization Capital and Innovation.

Panel A. Patent Count

	$LnPat_{t+1}^{Time-Tech}$ (1)	$LnPat_{t+2}^{Time-Tech}$ (2)	$LnPat_{t+1}^{Time}$ (3)	$LnPat_{t+2}^{Time}$ (4)
$OC/Assets_t$	0.055***	0.052***	0.022***	0.021***
	(8.75)	(8.52)	(8.59)	(8.35)
$LnAssets_t$	0.223***	0.210***	0.086***	0.080***
	(23.97)	(23.29)	(18.29)	(17.89)
Market-to-book$_t$	0.042***	0.042***	0.015***	0.015***
	(10.01)	(10.16)	(8.03)	(8.03)
ROA_t	−0.082***	−0.068***	−0.027***	−0.022**
	(−3.27)	(−2.80)	(−2.70)	(−2.26)
Stock Returns$_t$	−0.032***	−0.029***	−0.013***	−0.011***
	(−7.52)	(−6.85)	(−6.87)	(−6.29)
$Leverage_t$	−0.179***	−0.184***	−0.077***	−0.078***
	(−4.38)	(−4.64)	(−4.47)	(−4.71)
$Tangibility_t$	0.049	0.059	0.013	0.016
	(1.22)	(1.54)	(0.83)	(1.07)
$CAPEX_t$	0.320***	0.329***	0.142***	0.146***
	(5.28)	(5.55)	(5.41)	(5.68)
R&D/Assets$_t$	0.699***	0.637***	0.258***	0.240***
	(10.05)	(9.41)	(8.72)	(8.36)
$LnAge_t$	0.078***	0.072***	0.026***	0.024***
	(8.56)	(8.20)	(7.39)	(7.08)
H Index$_t$	−0.091	−0.087	−0.057	−0.053
	(−0.77)	(−0.75)	(−1.04)	(−1.00)
H Index sq$_t$	0.239*	0.234*	0.116*	0.109*
	(1.78)	(1.79)	(1.80)	(1.75)
KZ Index$_t$	−0.020***	−0.021***	−0.007***	−0.007***
	(−3.23)	(−3.42)	(−2.67)	(−2.68)
IO_t	−0.195***	−0.179***	−0.119***	−0.108***
	(−5.73)	(−5.49)	(−7.51)	(−7.16)
Constant	−1.474***	−1.465***	−0.518***	−0.518***
	(−23.13)	(−22.46)	(−17.40)	(−17.23)
Year and SIC2 FE	Yes	Yes	Yes	Yes
N	87,873	87,873	87,873	87,873
adj. R^2	0.382	0.361	0.321	0.304

Panel B. Patent Citations

	$LnCit_{t+1}^{Time-Tech}$ (1)	$LnCit_{t+2}^{Time-Tech}$ (2)	$LnCit_{t+1}^{Time}$ (3)	$LnCit_{t+2}^{Time}$ (4)
$OC/Assets_t$	0.062***	0.059***	0.061***	0.058***
	(7.08)	(6.86)	(7.06)	(6.91)
$LnAssets_t$	0.316***	0.296***	0.308***	0.287***
	(25.40)	(24.51)	(24.84)	(23.90)
Market-to-book$_t$	0.074***	0.074***	0.076***	0.075***
	(11.44)	(11.51)	(11.79)	(11.79)
ROA_t	−0.045	−0.026	−0.011	0.010
	(−1.15)	(−0.69)	(−0.28)	(0.28)
Stock Returns$_t$	−0.046***	−0.040***	−0.046***	−0.041***
	(−7.10)	(−6.29)	(−7.22)	(−6.49)
$Leverage_t$	−0.288***	−0.302***	−0.316***	−0.327***
	(−.91)	(−5.34)	(−5.56)	(−6.00)
$Tangibility_t$	−0.002	0.024	−0.035	−0.006
	(−0.03)	(0.45)	(−0.63)	(−0.11)
$CAPEX_t$	0.608***	0.613***	0.669***	0.662***
	(6.76)	(6.92)	(7.43)	(7.48)
R&D/Assets$_t$	1.485***	1.318***	1.491***	1.315***
	(13.08)	(12.01)	(13.14)	(12.03)
$LnAge_t$	0.075***	0.072***	0.061***	0.058***
	(5.58)	(5.55)	(4.67)	(4.61)
H Index$_t$	−0.291*	−0.269	−0.363**	−0.332**
	(−1.71)	(−1.62)	(−2.16)	(−2.04)
H Index sq$_t$	0.453**	0.436**	0.511***	0.485***
	(2.39)	(2.37)	(2.72)	(2.66)
KZ Index$_t$	−0.026***	−0.025***	−0.021**	−0.020**
	(−2.99)	(−3.00)	(−2.49)	(−2.44)
IO_t	−0.200***	−0.181***	−0.199***	−0.179***
	(−4.10)	(−3.86)	(−4.10)	(−3.83)
Constant	−2.067***	−2.021***	−1.959***	−1.915***
	(−24.00)	(−23.26)	(−23.13)	(−22.44)
Year and SIC2 FE	Yes	Yes	Yes	Yes
N	87,873	87,873	87,873	87,873
adj. R^2	0.365	0.344	0.354	0.334

This table reports the pooled Ordinary Least Squares (OLS) regression results examining the relation between organization capital and innovation. The sample period is from 1980 to 2008. The dependent variable in Panel A (Panel B) *LnPat* (*LnCit*) is the sum of the natural logarithm of one plus the number of patents granted (citations received on granted patents) in a given year *t* for firms adjusted for truncation bias. Columns (1) and (2) in each panel adjust for truncation bias using *Time-Tech* adjustment procedure. Columns (3) and (4) in each panel adjust for truncation bias using *Time* adjustment procedure. The key independent variable *OC/Assets* is the ratio of firm's organization capital to book value of total assets in year *t*. Please refer to the Appendix for detailed definitions of the control variables. All variables are winsorized at the 1st and 99th percentiles. T-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

tively related to the number of patents produced.[8] Overall, the results show that firms with more organization capital are associated with a significantly higher amount of innovation.

4.1.2. Organization capital and patent citations

In this subsection, we examine whether organization capital affects the quality of innovation by examining the relation between organization capital and the number of citations received on patents. Panel B of Table 2 presents the results. For Columns (1) and (2), we use $LnCit^{Time-Tech}$ measured one ($t+1$) and two years ($t+2$) forward. For Columns (3) and (4), we use $LnCit^{Time}$ measured one ($t+1$) and two years ($t+2$) ahead. The coefficient on organization capital (*OC/Assets*) is positive and statistically significant at the 1% level in all the specifications, suggesting that firms with more organization capital are associated with greater number of citations on the patents produced by the firms. In terms of economic significance, Column (1) shows that, on average, a one standard deviation increase in a firm's organization capital is associated with a 6.27% (=0.062*1.011*100) increase in the log of the number of patent citations ($Cit^{Time-Tech}$) in the following year. Our result indicates that one-unit increase in organization capital is associated with a 6.4% (=exp(0.062)) increase of citations.[9] Again, the control variables largely have coefficients consistent with the extant literature. In sum, the results show that firms with more organization capital are associated with a significantly higher quality of innovation.

4.2. Robustness checks

In this subsection, we conduct a series of robustness checks including alternative measures of innovation and organization capital, exploring potential alternative explanations, controlling for incentive schemes and governance characteristics, conducting subsample analyses and using alternative model specifications.[10]

4.2.1. Alternative measures of innovation and organization capital

First, we examine whether the results are robust to alternative measures of innovation and organization capital. The first set of tests involves using different measures aimed at addressing potential concerns about the measure of organization capital. Eisfeldt and Papanikolaou (2013) argue that there are differences in accounting procedures related to the constituents of SG&A expenditures across industries that could potentially result in a situation that some elements of SG&A expenditures may not reflect investment in organization capital. We mitigate this concern using three different measures of organization capital. First, we sort Compustat firms within each two-digit SIC industry annually into quintiles based on their organization capital and use the resulting rank as a measure of organization capital in Eq. (3). The rank variable is likely to be free of any measurement error in organization capital variable resulting from the composition of firms' SG&A expenditures of firms within an industry. Panel A (Panel B) of Table 3 presents the regression results for patent count (patent citations) using this alternative measure of organization capital. The results are consistent with our baseline results. Second, we follow Li et al. (2014) and use SIC2-median adjusted ratio of organization capital to total assets as another alternative measure of organization capital and the results are also consistent with our baseline findings.

Further, we use the residual from the regression of *OC/Assets* constructed using SG&A expenditures unadjusted for R&D expenditures on *OC_R&D/Assets*, where *OC_R&D/Assets* is the stock of R&D expenditures measured in a similar manner as discussed in Section 3.3. To the extent that SG&A expenditures may also include R&D expenditures, the residual from this regression will be orthogonal to organization capital resulting from R&D expenditures and will also capture organization capital that is directly attributable to firms' key talents and other business processes. We re-estimate Eq. (3) by replacing *OC/Assets* with the residual and find that the estimated coefficients are positive and significant, both statistically and economically. For brevity, the results are not tabulated.

The third set of tests examines the relation between organization capital and innovation using alternative measures of organization capital that is not based on selling and general expenses. To that end we obtain the organization capital measure from Evans et al. (2020). The authors argue that the lack of capitalization of SG&A expense reduces the information content of off-balance sheet items. The authors propose an alternative measure of intangible capital that more accurately captures market prices of intangible assets. In Panel C of Table 3 we reproduce our main results using the organization capital measure, *OC_EPW/Assets*, computed by Evans, Peters and Wang (2020). The results show that *OC_EPW/Assets* has a positive relationship with patents and citations. The coefficient on the *OC_EPW/Assets* is however smaller than our original measure. This is to be expected because Evans et al. (2020) claim that their measure of intangible capital is 10% smaller than previous measures. However, we still find a robust association between organization capital and innovation after using multiple alternative specifications of organizational capital.

Finally, we examine the relation between organization capital and innovation using alternative measures of innovation. The larger number of firms' patent citations could be due to two reasons. First, firms could be generating more patents or receiving more citations per patent. Second, larger number of citations could be due to self-citations where firms cite their own previous patents for the new patents they generate. In order to better assess the quality of innovation, we use citations per patent and number of non-self-citations received as alternative measures for innovation and find that the results are qualitatively similar. For brevity, the results are not tabulated.

4.2.2. Alternative explanations and additional controls

In this subsection, we explore potential alternative explanations and also control for additional characteristics that could impact the relation between organization capital and innovation. First, executive compensation could confound the results. Eisfeldt and Papanikolaou (2013) show that firms with more organization capital pay higher compensation to their executives. This poses a potential alternative explanation for our results, which is that they could be due to the relatively higher executive compensation that is paid to firms with more organization capital, rather than a firm's organization capital. To address this concern, we add two additional CEO compensation related variables to our baseline specification (Eq. (3)): the natural logarithm of CEO total compensation (*LnPay*); and the CEO's equity-based compensation as a percentage of total compensation (*Equity Pay Percent*). These two variables help to control for the possible confounding compensation effect that the observed relationship between organization capital and innovation might be driven by the underlying CEO compensation. This conjecture, however, is not supported by the empirical results in Panels A and B of Table 4 for patent counts and patent citations.

[8] The negative relation between institutional holdings and innovation is not consistent with Aghion, Van Reenen and Zingales (2013). However, Hirshleifer, Low and Teoh (2012) find a negative relation between insitutional ownership and innovation.

[9] Given the mean value of citation is 57.8, a one-unit increase in organization capital is associated with a 3.7 (=57.8x0.064) increase in the number of citations.

[10] For brevity, only a few results are tabulated, with the remaining available upon request.

Table 3
Organization Capital and Innovation: Robustness Checks.

Panel A. Alternative Measure of Organization Capital and Patent Count

	$LnPat_{t+1}^{Time-Tech}$ (1)	$LnPat_{t+2}^{Time-Tech}$ (2)	$LnPat_{t+1}^{Time}$ (3)	$LnPat_{t+2}^{Time}$ (4)
OC/Assets Quintile $Rank_t$	0.050***	0.047***	0.019***	0.017***
	(9.36)	(9.05)	(7.94)	(7.67)
Controls	Yes	Yes	Yes	Yes
Year and SIC2 FE	Yes	Yes	Yes	Yes
N	87,873	87,873	87,873	87,873
adj. R^2	0.385	0.364	0.323	0.305

Panel B. Alternative Measure of Organization Capital and Patent Citations

	$LnCit_{t+1}^{Time-Tech}$ (1)	$LnCit_{t+2}^{Time-Tech}$ (2)	$LnCit_{t+1}^{Time}$ (3)	$LnCit_{t+2}^{Time}$ (4)
OC/Assets Quintile $Rank_t$	0.056***	0.053***	0.053***	0.051***
	(7.34)	(7.18)	(7.07)	(6.96)
Controls	Yes	Yes	Yes	Yes
Year and SIC2 FE	Yes	Yes	Yes	Yes
N	87,873	87,873	87,873	87,873
adj. R^2	0.367	0.346	0.356	0.335

Panel C. Alternative measure based on Ewan, Peters, and Wang (2020)

	$LnPat_{t+1}^{Time-Tech}$(1)	$LnCit_{t+1}^{Time-Tech}$(2)	$LnPat_{t+2}^{Time}$(3)	$LnCit_{t+2}^{Time-Tech}$(4)
OC_EPW/$Assets_t$	0.023***	0.021***	0.025***	0.023***
	(12.067)	(11.455)	(11.780)	(11.219)
$LnAssets_t$	0.037***	0.034***	0.039***	0.035***
	(17.832)	(16.809)	(17.518)	(16.462)
Market-to-$book_t$	0.001***	0.001***	0.001***	0.001***
	(7.154)	(6.888)	(6.884)	(6.527)
ROA_t	−0.009***	−0.008***	−0.009***	−0.008***
	(−7.558)	(−7.368)	(−6.640)	(−6.475)
Stock $Returns_t$	0.001***	0.001***	0.001***	0.001***
	(4.015)	(3.215)	(3.811)	(3.249)
$Leverage_t$	−0.008***	−0.008***	−0.012***	−0.011***
	(−3.428)	(−3.122)	(−4.129)	(−3.890)
$Tangibility_t$	−0.031***	−0.030***	−0.035***	−0.034***
	(−3.774)	(−3.651)	(−3.905)	(−3.759)
$CAPEX_t$	0.099***	0.097***	0.117***	0.112***
	(7.372)	(7.280)	(7.699)	(7.367)
R&D/$Assets_t$	0.015*	0.013	0.018**	0.017*
	(1.834)	(1.630)	(2.049)	(1.944)
$LnAge_t$	−0.155***	−0.141***	−0.153***	−0.139***
	(−41.692)	(−36.956)	(−39.471)	(−34.944)
H $Index_t$	0.079**	0.117***	0.071*	0.112***
	(2.055)	(3.007)	(1.704)	(2.665)
H Index sq_t	−0.043	−0.077*	−0.035	−0.071
	(−1.065)	(−1.872)	(−0.791]	(−1.596]
KZ $Index_t$	0.000***	0.001***	0.001***	0.001***
	(3.642)	(3.907)	(3.766)	(3.809)
IO_t	−0.001***	−0.001***	−0.001***	−0.001***
	(−7.657)	(−7.815)	(−6.751)	(−6.916)
Constant	0.490***	0.439***	0.473***	0.422***
	(33.012)	(28.637)	(30.298)	(26.205)
Year and SIC2 FE	Yes	Yes	Yes	Yes
Observations	136,739	136,515	122,036	121,819
R-squared	0.323	0.262	0.322	0.262

This table reports the pooled Ordinary Least Squares (OLS) regression results examining the relation between organization capital and innovation using alternative measure of organization capital (Panel A and Panel B) and examining alternative explanations (Panel C and Panel D). The sample period is from 1980 to 2008. In Panel A and C (Panel B and D) dependent variable *LnPat* (*LnCit*) is the sum of natural logarithm of one plus the number of patents granted (citations received on granted patents) in a given year *t* for firms adjusted for truncation bias. Columns (1) and (2) in each panel adjust for truncation bias using *Time-Tech* adjustment procedure. Columns (3) and (4) in each panel adjust for truncation bias using *Time* adjustment procedure. *OC/Assets* is the ratio of firm's organization capital to book value of total assets in year *t*. *OC/Assets Quintile Rank* is the quintile rank of firm's *OC/Assets* among the universe of two-digit SIC Compustat firms. *LnPay* is the natural logarithm of CEO total direct compensation (TDC1 in Execucomp). *Equity Pay Percent* is the equity-based compensation of CEO as a percentage of total compensation Please refer to the Appendix for detailed definitions of the control variables. All variables are winsorized at the 1st and 99th percentiles. T-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4
Organization Capital and Innovation.

Panel A. Controlling for Executive Compensation: Patent Count

	$LnPat_{t+1}^{Time-Tech}$ (1)	$LnPat_{t+2}^{Time-Tech}$ (2)	$LnPat_{t+1}^{Time}$ (3)	$LnPat_{t+2}^{Time}$ (4)
$OC/Assets_t$	0.131***	0.119***	0.053***	0.047***
	(5.59)	(5.36)	(5.57)	(5.34)
$LnPay_t$	0.008	0.012	0.001	0.003
	(0.43)	(0.65)	(0.09)	(0.33)
Equity Pay $Percent_t$	0.012	−0.011	−0.000	−0.008
	(0.27)	(−0.28)	(−0.02)	(−0.43)
Other Controls	Yes	Yes	Yes	Yes
Year and SIC2 FE	Yes	Yes	Yes	Yes
N	17,350	17,350	17,350	17,350
adj. R^2	0.505	0.471	0.450	0.418

Panel B. Controlling for Executive Compensation: Patent Citations

	$LnCit_{t+1}^{Time-Tech}$ (1)	$LnCit_{t+2}^{Time-Tech}$ (2)	$LnCit_{t+1}^{Time}$ (3)	$LnCit_{t+2}^{Time}$ (4)
$OC/Assets_t$	0.163***	0.146***	0.154***	0.138***
	(4.85)	(4.54)	(4.73)	(4.45)
$LnPay_t$	0.022	0.025	0.020	0.025
	(0.79)	(0.96)	(0.74)	(0.96)
Equity Pay $Percent_t$	0.036	−0.010	0.037	−0.012
	(0.57)	(−0.16)	(0.61)	(−0.20)
Other Controls	Yes	Yes	Yes	Yes
Year and SIC2 FE	Yes	Yes	Yes	Yes
N	17,350	17,350	17,350	17,350
adj. R^2	0.490	0.456	0.482	0.448

This table reports the pooled Ordinary Least Squares (OLS) regression results examining the relation between organization capital and innovation. The sample period is from 1980 to 2008. The dependent variable in Panel A (Panel B) *LnPat* (*LnCit*) is the sum of the natural logarithm of one plus the number of patents granted (citations received on granted patents) in a given year *t* for firms adjusted for truncation bias. Columns (1) and (2) in each panel adjust for truncation bias using *Time-Tech* adjustment procedure. Columns (3) and (4) in each panel adjust for truncation bias using *Time* adjustment procedure. The key independent variable *OC/Assets* is the ratio of firm's organization capital to book value of total assets in year *t*. Please refer to the Appendix for detailed definitions of the control variables. All variables are winsorized at the 1st and 99th percentiles. T-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

After including these pay related variables, we find that the impact of organization capital on innovation remains positive and significant.

Prior literature has shown that corporate governance (Becker-Blease, 2011; O'Connor and Rafferty, 2012) and performance-sensitive compensation schemes (Holmstrom, 1989; Manso, 2011) affect innovation. We therefore, examine the relation between organization capital and innovation adding control variables to our baseline specification, such as G-Index (Gompers et al., 2003),[11] E-Index (Bebchuk et al., 2009),[12] and performance sensitivity of compensation contracts using Edmans, Gabaix and Landier's (2009) "scaled-wealth-performance sensitivity" measure as proxies for corporate governance.[13] The sample sizes for these robustness tests are smaller and vary due to the limited availability of information on these additional variables, nevertheless the results remain consistent with our baseline findings.

4.2.3. Subsample analysis and alternative model specification

In this subsection, we discuss the final set of robustness checks that includes subsample analyses and alternative model specifications. We conduct three subsample analyses. First, because a large fraction of firm-year observations in our sample have zero patent count (about 77.8% of the sample). We repeat the baseline analysis (Eq. (3)) for a subsample of firms that has non-zero firm-year 'observations on patent count. The motivation to conduct this analysis is to examine the extent to which the variation of organization capital among the patenting firms impacts innovation output. This also alleviates the concern that the observed relationship is driven by firms with and without patents. In un-tabulated results, we find that the coefficient on organization capital is positive and statistically significant. Second, we drop the first five firm-year observations for each firm in our full sample to minimize the impact of the initialization scheme (Eq. (1)) that we use in the construction of the organization capital variable. We then re-run our baseline regressions and find that the results are qualitatively unchanged. Third, the results are robust to excluding utility firms from the sample. Finally, we use a Tobit model to examine the relation between organization capital and innovation to account for the fact that patent count and patent citations variables take the value of zero for a large portion of the sample. Once again, the results are robust to this specification. Collectively, the results for both the amount and quality of innovation indicate that organization capital is positively related to innovation.

5. Addressing endogeneity concerns

Endogeneity is a concern in most empirical studies, as such, in this section we present a discussion about the various econometric techniques we use to mitigate the endogeneity concerns surrounding the relation between organization capital and innovation.

[11] The data are available online for a subsample of firms for the period 1990 – 2006 from the website of Prof. Andrew Metrick: http://faculty.som.yale.edu/andrewmetrick/data.html.

[12] The data are available online for a subsample of firms for the period 1990 – 2006 from the website of Prof. Lucian Bebchuk: http://www.law.harvard.edu/faculty/bebchuk/data.shtml.

[13] Scaled-wealth-performance sensitivity is the ratio of change in CEO wealth in dollar terms for a 100 percentage point change in firm value to CEO annual flow compensation. The data are mainly for SP1500 firms and are available online from the website of Prof. Alex Edmans: http://faculty.london.edu/aedmans/data.html.

5.1. Firm fixed effects approach

One of the main endogeneity concerns arises from the possibility that the relation between organization capital and innovation could be influenced by omitted variables. While we explicitly control for several characteristics that the literature shows affect innovation, there still could be unobservable factors that affect both organization capital and innovation. Such a possibility could potentially result in biased estimates making it difficult to draw inferences from our findings. In order to address the issue of unobservable firm heterogeneity in the error term, we re-estimate our baseline specification by replacing industry fixed effects with firm fixed effects to remove time-invariant firm characteristics that could bias our estimated coefficients.

Table 5 reports the results including firm fixed effects. Panel A presents the results for patent count. We find that the coefficient on organization capital continues to remain positive and statistically significant at the 1% level in all the specifications after the inclusion of firm fixed effects. Panel B reports the results for patent citations. Similar to the results on the amount of patents, we find that the organization capital coefficient, with patent citations as the dependent variable, is positive and significant with the inclusion of firm fixed effects.[14] Overall, the results are robust to the potential omitted variable problem and confirm the positive relation between organization capital and innovation.

5.2. Change regression approach

We further use the change regression method to address the endogeneity issue related to time-invariant omitted variables. This method enables us to identify the relation between organization capital and innovation by examining the incremental effects of organization capital on innovation by focusing on the year-to-year changes in organization capital and the number of patent count and patent citations. As a consequence, this change specification is a more powerful approach to explain incremental effects of organization capital on innovation than the levels specification with firm fixed effects.

We estimate the following regression model using OLS:

$$\Delta LnPat_{i,t+n}\left(\Delta LnCit_{i,t+n}\right) = \alpha + \beta\Delta OC/Assets_{i,t} + \gamma\Delta Z_{i,t} + Year_t + \varepsilon_{i,t}. \quad (4)$$

Where, i refers to firm, t indexes time and n is the number of years after time period t and takes the value of 1 and 2. The dependent variable is $\Delta LnPat$ or $\Delta LnCit$, which is the change in *LnPat* and *LnCit*, as defined previously for firm i in fiscal year $t+n$ from fiscal year t. The key independent variable $\Delta OC/Assets$ is the change in organization capital for firm i in fiscal year t from the previous fiscal year $t-1$and ΔZ is the vector of control variables defined in Section 3.4; all the variables are measured as first differences between fiscal years t and $t-1$.

Table 6 presents the change regression results. Panel A presents the results for the change in patent count and Panel B the change in patent citations. We find that the coefficients on the changes in organization capital for both changes in patent count and patent citations are positive and significant. These results provide additional support to the view that organization capital has a positive impact on firm innovation.

[14] The one exception is when $LnCit_{t+2}^{Time}$ is used as a measure of innovation. The coefficient on organization capital is positive, however, it is not statistically significant.

5.3. Instrumental variables approach

In this subsection, we use IV two-stage least squares (2SLS) approach to address another type of endogeneity (e.g., Hasan et al., 2017). The inclusion of firm fixed effects can effectively mitigate the endogeneity due to potential omitted variables that are time-invariant. However, the IV method can alleviate this problem even if the unobservable is not constant over time. Hence, we perform the 2SLS analysis to efhpstablish a causal relationship between organization capital and innovation and to address endogeneity concerns that cannot be effectively mitigated using fixed firm effects.

The instrumental variable that provides plausibly exogenous variation required to identify the impact of organization capital on innovation is motivated by Carlin, Chowdhry and Garmaise (2012). They argue that firms belonging to industries that are rapidly evolving and changing are less likely to invest in organization capital because there is a higher rate in technology obsolescence that characterize these industries and hence, it is less value enhancing to invest in organization capital under such conditions. They further point out that it is usually the case that firms with more organization capital are averse to replacing incumbent managers with outsiders because incumbents tend to produce more efficiently. However, when future profits are relatively uncertain, firms are less likely to retain incumbents, especially the less efficient ones, to retain their organization capital and are more willing to accept inferior performance today in exchange for possible improvements in the future. Hence, firms belonging to rapidly changing industries, whose future profits are less likely to be realized, are likely to invest less in organization capital.

Following Li, Qui and Shen (2014), we use the uncertainty of the industry-level growth to which the firm belongs as an instrument for organization capital. They argue that industry-level growth uncertainty captures the demand side consideration for firms to invest in organization capital and provides the plausibly exogenous variation required to implement the IV methodology. For each firm in the CRSP–Compustat universe, we first define quarterly asset growth rate as the change in total book value of assets in a given quarter q from the previous quarter $q-1$ as a fraction of firm's total book value of assets in quarter $q-1$. For each of the four quarters in a given year, we estimate for each firm the seasonally adjusted quarterly asset growth rate as the difference between quarterly asset growth rate and the average asset growth rate in the respective quarters over the past three years. Next, for each firm in the CRSP-Compustat universe, we calculate the standard deviation of the seasonally adjusted quarterly asset growth rate over the years t and $t-1$. Finally, we compute industry-level growth uncertainty (*SIC_AGU) as* the median value of the standard deviation of the seasonally adjusted quarterly asset growth rate for the CRSP-Compustat universe of firms in the same two-digit SIC industry of firm i in year t.

Although the above mentioned variable, *SIC2_AGU,* satisfies the relevance condition, there is a potential concern that it may not satisfy the exclusion restriction required for an instrumental variable. That is, firms belonging to industries that experience rapid technological change, could be more innovative than the less dynamic ones (Jones and Tuzel, 2013). Hence, this instrument could be correlated with the innovativeness of industries. We alleviate this potential concern by removing the industry innovativeness component from the industry-level growth uncertainty variable. Specifically, we first compute the sum of the adjusted number of patent count and patent citations of all the firms at the two-digit SIC industry level for each year. We then estimate a time-series regression of the following specification for every two-digit SIC industry:

$$SIC2\_AGU_{j,t} = \alpha + LnPat_{j,t} + LnCit_{j,t} + \varepsilon_{j,t}. \quad (5)$$

Table 5
Organization Capital and Innovation: Firm Fixed Effects.

Panel A. Patent Count

	$LnPat^{Time-Tech}_{t+1}$ (1)	$LnPat^{Time-Tech}_{t+2}$ (2)	$LnPat^{Time}_{t+1}$ (3)	$LnPat^{Time}_{t+2}$ (4)
$OC/Assets_t$	0.022***	0.016***	0.013***	0.009***
	(4.04)	(3.10)	(5.17)	(4.14)
$LnAssets_t$	0.108***	0.090***	0.043***	0.035***
	(11.38)	(10.29)	(9.45)	(8.58)
Market-to-book$_t$	0.015***	0.017***	0.005***	0.006***
	(6.01)	(6.86)	(5.12)	(5.41)
ROA_t	−0.021	−0.027*	−0.013**	−0.011*
	(−1.33)	(−1.82)	(−2.15)	(−1.92)
Stock Returns$_t$	−0.008***	−0.007***	−0.002**	−0.002*
	(−3.37)	(−3.13)	(−2.39)	(−1.79)
$Leverage_t$	−0.094***	−0.110***	−0.047***	−0.052***
	(−4.22)	(−4.64)	(−5.49)	(−5.66)
$Tangibility_t$	0.068**	0.093***	0.027**	0.037***
	(2.44)	(3.40)	(2.35)	(3.38)
$CAPEX_t$	0.005	0.038	−0.005	0.010
	(0.17)	(1.38)	(−0.46)	(0.94)
$RD/Assets_t$	0.304***	0.248***	0.083***	0.068***
	(5.93)	(4.74)	(4.09)	(3.32)
$LnAge_t$	0.095***	0.134***	0.044***	0.058***
	(6.00)	(8.19)	(6.05)	(7.81)
H Index$_t$	0.040	0.066	0.034	0.042
	(0.43)	(0.71)	(0.79)	(1.06)
H Index sq$_t$	0.004	−0.010	−0.006	−0.013
	(0.04)	(−0.11)	(−0.13)	(−0.31)
KZ Index$_t$	−0.005*	−0.006**	−0.001	−0.001
	(−1.80)	(−2.07)	(−1.10)	(−0.81)
IO_t	−0.032*	−0.020	−0.016*	−0.005
	(−1.65)	(−1.02)	(−1.93)	(−0.65)
Constant	−0.958***	−1.110***	−0.395***	−0.445***
	(−11.04)	(−12.48)	(−9.54)	(−10.63)
Year and Firm FE	Yes	Yes	Yes	Yes
N	87,873	87,873	87,873	87,873
adj. R^2	0.827	0.789	0.837	0.803

Panel B. Patent Citations

	$LnCit^{Time-Tech}_{t+1}$ (1)	$LnCit^{Time-Tech}_{t+2}$ (2)	$LnCit^{Time}_{t+1}$ (3)	$LnCit^{Time}_{t+2}$ (4)
$OC/Assets_t$	0.027***	0.014*	0.022***	0.010
	(3.30)	(1.76)	(2.69)	(1.26)
$LnAssets_t$	0.162***	0.130***	0.152***	0.120***
	(11.96)	(10.34)	(11.33)	(9.57)
Market-to-book$_t$	0.030***	0.034***	0.028***	0.032***
	(7.34)	(7.95)	(7.03)	(7.54)
ROA_t	−0.027	−0.039	−0.035	−0.039
	(−0.98)	(−1.46)	(−1.24)	(−1.45)
Stock Returns$_t$	−0.015***	−0.014***	−0.013***	−0.013***
	(−3.89)	(−3.48)	(−3.38)	(−3.22)
$Leverage_t$	−0.138***	−0.175***	−0.146***	−0.176***
	(−3.70)	(−4.51)	(−3.89)	(−4.56)
$Tangibility_t$	0.074*	0.114***	0.055	0.101**
	(1.74)	(2.72)	(1.32)	(2.47)
$CAPEX_t$	0.049	0.103**	0.063	0.107**
	(1.00)	(2.16)	(1.31)	(2.26)
$R\&D/Assets_t$	0.610***	0.478***	0.591***	0.446***
	(5.78)	(4.54)	(5.69)	(4.33)
$LnAge_t$	0.119***	0.160***	0.119***	0.148***
	(5.11)	(6.67)	(5.09)	(6.21)
H Index$_t$	0.025	0.092	−0.030	0.030
	(0.18)	(0.68)	(−0.21)	(0.22)
H Index sq$_t$	0.045	−0.005	0.115	0.063
	(0.31)	(−0.04)	(0.81)	(0.45)
KZ Index$_t$	−0.008*	−0.008*	−0.007	−0.006
	(−1.84)	(−1.79)	(−1.52)	(−1.36)
IO_t	−0.017	−0.006	−0.006	0.003
	(−0.57)	(−0.20)	(−0.21)	(0.10)
Constant	−1.462***	−1.547***	−1.387***	−1.430***
	(−11.85)	(−12.32)	(−=−11.31)	(−11.55)
Year and Firm FE	Yes	Yes	Yes	Yes
N	87,873	87,873	87,873	87,873
adj. R^2	0.780	0.740	0.777	0.736

This table reports the regression results examining the relation between organization capital and innovation with firm fixed effects. The sample period is from 1980 to 2008. The dependent variable in Panel A (Panel B) is *LnPat* (*LnCit*) and is the sum of natural logarithm of one plus the number of patents granted (citations received on granted patents) in a given year *t* for firms adjusted for truncation bias. Columns (1) and (2) in each panel adjust for truncation bias using *Time-Tech* adjustment procedure. Columns (3) and (4) in each panel adjust for truncation bias using *Time* adjustment procedure. The key independent variable *OC/Assets* is the ratio of firm's organization capital to book value of total assets in year *t*. Please refer to the Appendix for detailed definitions of the control variables. All variables are winsorized at the 1st and 99th percentiles. T-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Organization Capital and Innovation: Change Regression.

Panel A. Patent Count

	$\Delta LnPat^{Time-Tech}_{t+1}$ (1)	$\Delta LnPat^{Time-Tech}_{t+2}$ (2)	$\Delta LnPat^{Time}_{t+1}$ (3)	$\Delta LnPat^{Time}_{t+2}$ (4)
$\Delta OC/Assets_t$	0.017***	0.016***	0.005***	0.005***
	(6.06)	(6.44)	(6.48)	(7.05)
$\Delta LnAssets_t$	0.039***	0.021***	0.012***	0.008***
	(9.31)	(5.41)	(9.40)	(5.89)
$\Delta Market\text{-}to\text{-}book_t$	0.002	0.003**	0.001***	0.001***
	(1.62)	(2.50)	(2.87)	(3.04)
ΔROA_t	0.018**	−0.016**	0.002	−0.001
	(2.38)	(−2.00)	(0.93)	(−0.53)
$\Delta Stock\ Returns_t$	0.000	−0.001	0.000	−0.001*
	(0.24)	(−1.15)	(0.15)	(−1.94)
$\Delta Leverage_t$	−0.022**	−0.013	−0.006*	−0.007**
	(−2.02)	(−1.24)	(−1.94)	(−2.28)
$\Delta Tangibility_t$	0.030**	0.015	0.008**	0.009**
	(2.38)	(1.14)	(2.35)	(2.43)
$\Delta CAPEX_t$	0.001	−0.018	0.002	−0.003
	(0.08)	(−1.19)	(0.53)	(−0.81)
$\Delta R\&D/Assets_t$	0.060**	−0.023	0.013	−0.001
	(2.24)	(−0.87)	(1.63)	(−0.17)
$\Delta H\ Index_t$	−0.059	−0.079*	−0.014	−0.019
	(−1.39)	(−1.82)	(−1.33)	(−1.56)
$\Delta H\ Index\ sq_t$	0.051	0.087**	0.022**	0.018
	(1.20)	(2.06)	(2.15)	(1.51)
$\Delta KZ\ Index_t$	0.001	−0.002	−0.000	−0.000
	(1.00)	(−1.63)	(−0.26)	(−0.16)
ΔIO_t	0.009	0.026**	0.004	0.008**
	(1.00)	(2.46)	(1.33)	(2.25)
Constant	−0.056***	0.004	−0.006***	0.002
	(−7.90)	(0.69)	(−2.69)	(1.07)
Year FE	Yes	Yes	Yes	Yes
N	74,227	74,227	74,227	74,227
adj. R^2	0.006	0.007	0.005	0.008

Panel B. Patent Citations

	$\Delta LnCit^{Time-Tech}_{t+1}$ (1)	$\Delta LnCit^{Time-Tech}_{t+2}$ (2)	$\Delta LnCit^{Time}_{t+1}$ (3)	$\Delta LnCit^{Time}_{t+2}$ (4)
$\Delta OC/Assets_t$	0.018***	0.019***	0.013**	0.014***
	(2.94)	(3.95)	(2.17)	(2.95)
$\Delta LnAssets_t$	0.046***	0.033***	0.040***	0.025***
	(5.40)	(4.18)	(4.73)	(3.26)
$\Delta Market\text{-}to\text{-}book_t$	0.006**	0.007***	0.006**	0.007***
	(2.44)	(2.66)	(2.47)	(2.71)
ΔROA_t	0.023	−0.028	0.018	−0.022
	(1.25)	(−1.60)	(0.98)	(−1.27)
$\Delta Stock\ Returns_t$	−0.005*	−0.003	−0.004	−0.004
	(−1.80)	(−1.13)	(−1.45)	(−1.47)
$\Delta Leverage_t$	−0.025	−0.017	−0.017	−0.009
	(−1.05)	(−0.78)	(−0.73)	(−0.43)
$\Delta Tangibility_t$	0.051**	0.012	0.043*	0.019
	(1.99)	(0.50)	(1.68)	(0.79)
$\Delta CAPEX_t$	0.029	−0.004	0.036	−0.021
	(0.97)	(−0.12)	(1.15)	(−0.67)
$\Delta R\&D/Assets_t$	0.021	−0.073	0.011	−0.062
	(0.32)	(−1.05)	(0.16)	(−0.91)
$\Delta H\ Index_t$	−0.095	−0.179**	−0.062	−0.215***
	(−1.08)	(−2.14)	(−0.73)	(−2.62)
$\Delta H\ Index\ sq_t$	0.057	0.175**	0.055	0.196**
	(0.69)	(2.15)	(0.67)	(2.47)
$\Delta KZ\ Index_t$	0.001	−0.002	0.001	−0.003
	(0.28)	(−1.04)	(0.31)	(−1.18)
ΔIO_t	−0.017	0.026	−0.010	0.025
	(−0.91)	(1.26)	(−0.57)	(1.26)
Constant	−0.087***	0.020*	−0.089***	0.018*
	(−8.08)	(1.93)	(−8.22)	(1.82)
Year FE	Yes	Yes	Yes	Yes
N	74,227	74,227	74,227	74,227
adj. R^2	0.006	0.008	0.006	0.007

This table reports the pooled OLS change regression results between organization capital and innovation in terms of patent count (Panel A) and patent citations (Panel B). The sample period is from 1980 to 2008. All dependent and independent variables are first differences. The dependent variable in Panel A (Panel B) is $\Delta LnPat$ ($\Delta LnCit$) and is the change in the sum of the natural logarithm of one plus the number of patents granted (citations received on granted patents). Columns (1) and (2) in each panel adjust for truncation bias using *Time-Tech* adjustment procedure. Columns (3) and (4) in each panel adjust for truncation bias using *Time* adjustment procedure. The key independent variable $\Delta OC/Assets$ is the change in firm's ratio of organization capital to book value of total assets between year *t* and *t-1*. All the other independent variables are also in first differences between year *t* and *t-1*. Please refer to the Appendix for detailed definitions of the control variables. All variables are winsorized at the 1st and 99th percentiles. T-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Where, j indexes the two-digit SIC industry and t indexes time. The dependent variable, *SIC2_AGU,* is the industry median value of the seasonally adjusted standard deviation of quarterly asset growth rates of all firms in the two-digit SIC industry j of firm i during time t. The independent variables are *LnPat and LnCit,* which are the natural logarithm of (one plus) the sum of adjusted number of patents and citations received on all patents applied for by all firms in two-digit SIC industry j of firm i during the year t, respectively. The residual resulting from this regression *SIC2_AGU_Res*, the industry-level growth uncertainty unexplained by innovation, is used as the instrument for organization capital.[15]

Table 7 presents the 2SLS estimation results. Panel A reports the results for patent count. Column (1) presents the first-stage regression results using *SIC2_AGU_Res1,* the residual from the regression of industry-level growth uncertainty on industry-level patent count ($LnPat^{Time-Tech}$) and patent citations ($LnCit^{Time-Tech}$) as the instrument for firm's organization capital. Similarly, Column (4) presents the first-stage regression using *SIC2_AGU_Res2,* the residual from the regression of industry-level growth uncertainty on industry-level $LnPat^{Time}$ and $LnCit^{Time}$, as the instrument for firm's organization capital. The first stage regressions show that the instrument is negatively correlated with *OC/Assets* and statistically significant at the 1% level. This finding is consistent with the argument that firms in industries with high growth uncertainty are likely to invest less in organization capital. The second-stage results with one and two year ahead $LnPat^{Time-Tech}$ as the dependent variable are reported in Columns (2) and (3). Results with $LnPat^{Time}$ as the dependent variable are reported in Columns (5) and (6). We find that the coefficient on the fitted value of *OC/Assets* is positive and statistically significant. These results are consistent with the baseline regression results that organization capital has a positive and significant impact on innovation.[16]

We conduct several formal tests to examine whether the instrument used for organization capital meets the relevance and validity condition and report the results in Table 7. Column (2) shows that the Durbin χ^2 test statistic is 73.570 (p-value = 0.000) and the Wu-Hausman F-statistic is 73.544 (p-value = 0.000). These two test statistics reject the null hypothesis that *OC/Assets* is exogenous to $LnPat_{t+1}^{Time-Tech}$. We next test the instrument relevance condition by examining the first-stage F-statistic. The F-statistic reported in Column (1) is 26.292 (p-value = 0.000) and shows that the instrument satisfies the relevance condition.

Table 7, Panel B contains the second stage regression results for the quality of innovation (patent citations) as the dependent variable. The results are similar to our baseline patent citations results and hence, for the purpose of brevity, we do not discuss them in detail. Overall, the results show the positive relation between organization capital and innovation is causal and is robust to the potential endogeneity issue of time-variant omitted variables.

5.4. Propensity score matching approach

Lastly, we employ a propensity score matching procedure to address another specific endogeneity concern, which is that of reverse causality (e.g., Hoi et al., 2019). Specifically, there is the concern that more innovative firms could have more organization capital, instead of more organization capital making firms more innovate. Under this scenario, another possible interpretation of the main results is that firms with more organization capital are simply better innovators, rather than more organization capital of firms helping them to innovate better. We address this concern by using propensity score matching approach. Rosenbaum and Rubin (1983), in their seminal work, show that such biases can be reduced by employing a propensity score matching approach. Specifically, this procedure can be used to identify a control group of firms that have less organization capital but very similar other observable firm characteristics relative to firms with more organization capital (treatment firms). Because control firms, except for their organization capital, are similar in other observables to treatment firms, ceteris paribus, one may expect the treatment firms to have greater innovation than the control group of firms.

We start by identifying a group of treatment and control firms to conduct a propensity score matching analysis. First, we sort the sample firms into deciles every year based on their organization capital among the Compustat universe of firms. We define the top (bottom) three deciles of firms that have the most (least) organization capital as *High OC* (*Low OC*) firms. We retain only *High OC* and *Low OC* firms for this analysis. Columns (1) – (3) in Panel A of Table 8 report the differences in observable characteristics between these two sets of firms. We find that firms with more organization capital are relatively smaller, have superior growth opportunities, higher R&D expenditures, and lower asset tangibility, capital expenditures, and firm performance.

Because there are significant differences in observable characteristics between *High OC* and *Low OC* firms, we match firms with more organization capital (treatment) to firms with less organization capital (control) in the same industry along with various firm characteristics used as control variables in the baseline regression. We conduct a propensity score matching to identify a control firm for each treatment firm. Specifically, we estimate a probit model of the following form:

$$Treatment_{i,t} = \alpha + \gamma Z_{i,t} + Year_t + Industry_j + \varepsilon_{i,t}, \quad (6)$$

where, the dependent variable *Treatment* equals one if the firm is a *High OC* firm and zero otherwise and Z is the vector of control variables used in the baseline regressions. Column (1) in Panel B of Table 8 reports the probit estimation for the predicted probability of the firm being a treatment firm. The results of the probit regressions are largely consistent with the univariate comparisons shown in Panel A. In addition, a Pseudo R^2 of 51.6% shows that there is large amount of variation in the model and a p-value of almost 0.00 from the χ^2 test which indicates superior goodness of fit.

Using these predicted probabilities, we perform a nearest-neighbor propensity score matching procedure and match each treatment firm in a given year to a control firm with the closest propensity score in the same two-digit SIC industry. If a control firm is matched to more than one treatment firm, the pair with the smallest difference in propensity scores between the treatment and control firm is retained. We further impose a restriction that the difference in propensity scores between the treatment and control firms cannot exceed 0.10 to ensure accurate matching.[17] This procedure produces 3,991 unique pairs of matched firms.

We investigate the accuracy of our propensity score matching in two ways. First, we make univariate comparisons of observable characteristics between treatment firms and their matched counterparts and the results are presented in Columns (4) – (6) in Panel A of Table 8. We find that treatment firms have significantly more organization capital than control firms. However, none of the other observable firm characteristics of treatment firms are statistically

[15] Equation 5 focuses only on the time-series relation between industry growth uncertainty and innovation and do not pick up any cross-sectional relation.

[16] The results are qualitatively similar when industry-level growth uncertainty unadjusted for industry innovativeness is used as the instrument for organization capital.

[17] The results are robust to even smaller differences in propensity scores of 0.01 and 0.05 between treatment and control firms.

Table 7
Organization Capital and Innovation: IV 2SLS Regressions.

Panel A. Patent Count

	$OC/Assets_t$ (1)	$LnPat^{Time-Tech}_{t+1}$ (2)	$LnPat^{Time-Tech}_{t+2}$ (3)	$OC/Assets_t$ (4)	$LnPat^{Time}_{t+1}$ (5)	$LnPat^{Time}_{t+2}$ (6)
$SIC2\_AGU\_Res1_t$	−1.474***					
	(−5.13)					
$SIC2\_AGU\_Res2_t$				−1.091***		
				(−4.46)		
Fitted $OC/Assets_t$		0.646***	0.703***		0.260***	0.291***
		(3.59)	(3.74)		(3.04)	(3.23)
$LnAssets_t$	−0.201***	0.343***	0.341***	−0.201***	0.133***	0.135***
	(−30.52)	(9.09)	(8.72)	(−30.51)	(7.36)	(7.10)
$Market\text{-}to\text{-}book_t$	−0.042***	0.067***	0.070***	−0.042***	0.025***	0.026***
	(−7.31)	(7.42)	(7.40)	(−7.32)	(6.00)	(5.99)
ROA_t	−0.410***	0.155*	0.193**	−0.408***	0.068*	0.086**
	(−8.97)	(1.88)	(2.24)	(−8.93)	(1.84)	(2.20)
Stock $Returns_t$	0.014**	−0.040***	−0.037***	0.014**	−0.016***	−0.015***
	(2.41)	(−6.84)	(−6.18)	(2.38)	(−6.36)	(−5.76)
$Leverage_t$	−0.499***	0.119	0.145	−0.502***	0.043	0.059
	(−9.50)	(1.14)	(1.33)	(−9.55)	(0.89)	(1.16)
$Tangibility_t$	−0.478***	0.327***	0.365***	−0.476***	0.125***	0.144***
	(−9.44)	(3.42)	(3.67)	(−9.40)	(2.82)	(3.09)
$CAPEX_t$	−0.249***	0.474***	0.499***	−0.250***	0.204***	0.217***
	(−3.07)	(4.98)	(5.12)	(−3.09)	(4.93)	(5.05)
$R\&D/Assets_t$	0.362***	0.495***	0.413***	0.352***	0.176***	0.147***
	(2.79)	(3.92)	(3.11)	(2.70)	(3.31)	(2.61)
$LnAge_t$	0.341***	−0.124**	−0.150**	0.341***	−0.055*	−0.068**
	(27.91)	(−2.01)	(−2.34)	(27.92)	(−1.90)	(−2.24)
H $Index_t$	0.111	−0.174	−0.177	0.123	−0.091	−0.091
	(0.83)	(−1.23)	(−1.24)	(0.92)	(−1.45)	(−1.44)
H Index sq_t	−0.083	0.301*	0.302*	−0.090	0.141**	0.137*
	(−0.54)	(1.89)	(1.87)	(−0.59)	(1.96)	(1.90)
KZ $Index_t$	0.063***	−0.058***	−0.062***	0.063***	−0.022***	−0.024***
	(6.80)	(−4.04)	(−4.17)	(6.82)	(−3.40)	(−3.53)
IO_t	0.109***	−0.262***	−0.253***	0.110***	−0.146***	−0.138***
	(3.31)	(−6.11)	(−5.88)	(3.34)	(−7.43)	(−7.05)
Constant	1.867***	−2.130***	−2.186***	1.858***	−0.765***	−0.802***
	(15.32)	(−9.45)	(−9.27)	(15.39)	(−7.24)	(−7.21)
Year and SIC2 FE	Yes	Yes	Yes	Yes	Yes	Yes
N	87,833	87,833	87,833	87,833	87,833	87,833
Tests of endogeneity						
Durbin χ^2		73.570***	90.784***		43.885***	58.571***
Wu-HausmanF-statistic		73.544***	90.769***		43.854***	58.540***

	$OC/Assets_t$ (1)	$LnPat^{Time-Tech}_{t+1}$ (2)	$LnPat^{Time-Tech}_{t+2}$ (3)	$OC/Assets_t$ (4)	$LnPat^{Time}_{t+1}$ (5)	$LnPat^{Time}_{t+2}$ (6)
Weak identification statistics						
F-statistic	26.292***			19.904***		

Panel B. Patent Citations

	$LnCit^{Time-Tech}_{t+1}$ (1)	$LnCit^{Time-Tech}_{t+2}$ (2)	$LnCit^{Time}_{t+1}$ (3)	$LnCit^{Time}_{t+2}$ (4)
Fitted $OC/Assets_t$	0.941***	1.060***	0.481**	0.739***
	(3.70)	(3.91)	(2.11)	(2.90)
$LnAssets_t$	0.493***	0.497***	0.393***	0.425***
	(9.28)	(8.83)	(8.13)	(7.98)
$Market\text{-}to\text{-}book_t$	0.111***	0.116***	0.093***	0.103***
	(8.40)	(8.27)	(7.99)	(8.04)
ROA_t	0.307***	0.375***	0.157	0.283**
	(2.62)	(3.00)	(1.56)	(2.51)
Stock $Returns_t$	−0.058***	−0.054***	−0.052***	−0.050***
	(−6.57)	(−5.79)	(−6.91)	(−6.15)
$Leverage_t$	0.156	0.204	−0.103	0.017
	(1.04)	(1.29)	(−0.79)	(0.12)
$Tangibility_t$	0.412***	0.495***	0.162	0.314**
	(3.04)	(3.43)	(1.35)	(2.35)
$CAPEX_t$	0.837***	0.874***	0.778***	0.840***
	(6.01)	(6.01)	(6.54)	(6.50)

Table 7 (*Continued*)

Panel A. Patent Count						
	$OC/Assets_t$ (1)	$LnPat_{t+1}^{Time\text{-}Tech}$ (2)	$LnPat_{t+2}^{Time\text{-}Tech}$ (3)	$OC/Assets_t$ (4)	$LnPat_{t+1}^{Time}$ (5)	$LnPat_{t+2}^{Time}$ (6)
$R\&D/Assets_t$	1.182***	0.973***	1.346***	1.081***		
	(6.19)	(4.78)	(8.90)	(6.34)		
$LnAge_t$	−0.225***	−0.270***	−0.082	−0.174**		
	(−2.59)	(−2.91)	(−1.06)	(−2.01)		
H $Index_t$	−0.414**	−0.408*	−0.424**	−0.428**		
	(−2.01)	(−1.93)	(−2.39)	(−2.31)		
H Index sq_t	0.544**	0.540**	0.558***	0.557***		
	(2.38)	(2.28)	(2.83)	(2.70)		
KZ $Index_t$	−0.082***	−0.089***	−0.048***	−0.063***		
	(−4.03)	(−4.13)	(−2.71)	(−3.25)		
IO_t	−0.299***	−0.294***	−0.247***	−0.256***		
	(−4.81)	(−4.65)	(−4.36)	(−4.40)		
Constant	−3.062***	−3.149***	−2.441***	−2.683***		
	(−9.61)	(−9.26)	(−8.68)	(−8.58)		
Year and SIC2 FE	Yes	Yes	Yes	Yes		
N	87,833	87,833	87,833	87,833		
Tests of endogeneity						
Durbin χ^2	69.225***	92.223***	9.482***	25.736***		
Wu-Hausman F-statistic	69.167***	92.209***	9.472***	25.713***		

This table reports the 2SLS regression results examining the relation between organization capital and patent count (Panel A) and patent citations (Panel B). The sample period is from 1980 to 2008. The dependent variable for each specification is at the top of each column. The first stage regression results are reported in Columns (1) and (4) of Panel A. Column (1) ((4)) uses industry-level growth uncertainty adjusted for industry innovativeness using innovation variables adjusted for truncation using *Time-Tech (Time)* adjustment procedure as the instrument for organization capital. Please refer to the Appendix for the detailed definitions of the control and instrumental variables. All variables are winsorized at the 1st and 99th percentiles. T-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

different from the control firms.[18] Second, we re-estimate Eq. (6) restricting the regression to the matched sample of firms. Column (2) in Table 8, Panel B reports the probit estimation results. All the coefficients are statistically insignificant and economically small. Furthermore, the Pseudo R^2 is only 0.1% which is substantially lower than the corresponding value of 51.6% shown in Column (1) for the full sample of treatment and control firms prior to matching. Finally, the p-value of close to 1.00 for the χ^2 test indicates that collectively the coefficients on the variables in the model are not statistically different from zero.

We first examine the differences in innovation output for the matched pairs in a univariate setting. Specifically, we pool the treatment firms and their matching control firms together and compute the differences in the average number of patent count and citations received one and two years forward for these two groups of firms. Panel C of Table 8 presents the results. We find that treatment firms that have more organization capital produce more patents and receive more citations on their patents than the control firms with less organization capital.

Next, we examine the difference in innovation output for the matched pairs of firms in a multivariate setting using the following regression:

$$LnPat_{i,t+n}\left(LnCit_{i,t+n}\right) = \alpha + \beta Treatment_{i,t} + \gamma Z_{i,t} + Year_t + Industry_i + \varepsilon_{i,t}. \quad (7)$$

Where, *Treatment* is as defined earlier and is a dummy variable that equals one if firm i at time period t is a treatment firm, and zero otherwise and Z is a vector of control variables used in the baseline regressions. The coefficient of interest is that of the variable *Treatment* which captures the impact of organization capital on innovation. Panel D (Panel E) of Table 8 reports the results for patent count (patent citations). The coefficient on *Treatment* is positive and statistically significant in all the specifications. Collectively, these results suggest that the relation between organization capital and innovation is not due to observed differences in firm characteristics; further, they provide additional support for our main finding that firms' organization capital has a statistically significant positive and economically important impact on innovation.

6. Mechanisms through which organization capital impact innovation

The results thus far show that firms' organization capital has a positive and causal impact on innovation. In this section, we examine possible mechanisms through which organization capital impacts innovation. Section 6.1 examines whether organization capital helps firms to better cope with the inherent difficulties associated with the innovation process. Section 6.2 explores reduction in career concern threats as another potential channel.

6.1. Difficulty in innovation process

Innovation is a lengthier and more difficult process in certain industries compared to others. For example, Tian and Wang (2014) argue that innovation in high technology industries is more challenging than in low technology industries. They contend that high-tech industries, such as the pharmaceutical industry, have a particularly complex innovation process because developing a new drug, for example, typically involves a large number of steps with different intensities of experimentation. To the extent that firms with relatively more organization capital have managers that are of higher quality and more talented, then these firms should be better able to cope with the inherent complexities associated with the innovation process. This suggests that the ability of firms to deal with innovation complexities could be a channel through which organization capital affects innovation.

To provide evidence on this mechanism, we estimate our baseline specification separately for subsamples of firms belonging to high- and low-tech firms. We expect that the relation between organization capital and innovation to be stronger for firms in high-tech industries than for those in low-tech industries if a firm's ability to deal with innovation complexities is a channel. We use

[18] Two exceptions are stock returns and leverage, which are significant but only weakly.

Table 8
Organization Capital and Innovation: Propensity Score Matching.

Panel A. Difference in Observables

Variable	Pre-match High OC (1)	Pre-match Low OC (2)	Pre-match High – Low (3)	Post-match High OC (4)	Post-match Low OC (5)	Post-match High – Low (6)
$OC/Assets_t$	2.240	0.201	2.039***	2.054	0.223	1.831***
$LnAssets_t$	4.504	6.131	−1.627***	5.155	5.101	0.054
$Market\text{-}to\text{-}book_t$	1.582	1.556	0.025*	1.920	1.951	−0.031
ROA_t	0.027	0.085	−0.058***	0.031	0.033	−0.003
Stock $Returns_t$	0.106	0.157	−0.051***	0.132	0.158	−0.026*
$Leverage_t$	0.175	0.270	−0.094***	0.194	0.186	0.008**
$LnAge_t$	2.617	2.449	0.168***	2.449	2.448	0.001
$Tangibility_t$	0.221	0.440	−0.219***	0.262	0.259	0.003
$CAPEX_t$	0.053	0.100	−0.047***	0.065	0.064	0.001
$R\&D/Assets_t$	0.057	0.031	0.026***	0.063	0.062	0.001
H $Index_t$	0.282	0.235	0.046***	0.267	0.269	−0.002
H Index sq_t	0.115	0.091	0.024***	0.110	0.112	−0.002
KZ $Index_t$	0.519	0.738	−0.219***	0.447	0.412	0.034
IO_t	0.273	0.380	−0.107***	0.322	0.318	0.004

Panel B. Probit Regressions

	$Treatment_t$ Pre-Match (1)	$Treatment_t$ Post-Match (2)
$LnAssets_t$	−0.496***	0.023
	(−22.38)	(0.83)
$Market\text{-}to\text{-}book_t$	−0.072***	0.001
	(−5.31)	(0.05)
ROA_t	0.513***	−0.058
	(5.72)	(−0.46)
Stock $Returns_t$	−0.079***	−0.032
	(−4.82)	(−1.24)
$Leverage_t$	−1.207***	0.167
	(−8.19)	(0.88)
$Tangibility_t$	0.825***	−0.022
	(21.41)	(−0.47)
$CAPEX_t$	−1.555***	0.022
	(−10.40)	(0.12)
$R\&D/Assets_t$	−0.585**	0.120
	(−2.32)	(0.33)
$LnAge_t$	0.051	0.083
	(0.20)	(0.28)
H $Index_t$	1.278***	−0.042
	(3.27)	(−0.09)
H Index sq_t	−1.156***	−0.016
	(−2.61)	(−0.03)
KZ $Index_t$	0.141***	−0.005
	(6.70)	(−0.21)
IO_t	0.244**	−0.034
	(2.18)	(−0.23)
Year and SIC2 FE	Yes	Yes
Observations	43,134	7982
Pseudo R^2	0.516	0.001
P-value of χ^2	0.000	1.000

Panel C. Univariate Results

Variable	N	Treatment Mean	Control Mean	Mean Diff.	T-statistics
$LnPat_{t+1}^{Time-Tech}$	3,991	0.401	0.217	0.184	11.50***
$LnPat_{t+2}^{Time-Tech}$	3,991	0.368	0.208	0.160	10.20***
$LnPat_{t+1}^{Time}$	3,991	0.116	0.055	0.060	10.27***
$LnPat_{t+2}^{Time}$	3,991	0.107	0.053	0.054	9.50***
$LnCit_{t+1}^{Time-Tech}$	3,991	0.612	0.391	0.221	8.99***
$LnCit_{t+2}^{Time-Tech}$	3,991	0.556	0.376	0.180	7.49***
$LnCit_{t+1}^{Time}$	3,991	0.590	0.375	0.216	8.98***
$LnCit_{t+2}^{Time}$	3,991	0.530	0.357	0.173	7.40***

Table 8 (*Continued*)

Panel A. Difference in Observables

	Pre-match			Post-match		
Variable	High OC (1)	Low OC (2)	High – Low (3)	High OC (4)	Low OC (5)	High – Low (6)

Panel D. Multivariate Results: Patent Count

	$LnPat^{Time-Tech}_{t+1}$ (1)	$LnPat^{Time-Tech}_{t+2}$ (2)	$LnPat^{Time}_{t+1}$ (3)	$LnPat^{Time}_{t+2}$ (4)
$Treatment_t$	0.170***	0.147***	0.055***	0.050***
	(6.34)	(5.59)	(5.04)	(4.69)
$LnAssets_t$	0.259***	0.246***	0.098***	0.091***
	(12.93)	(12.44)	(9.47)	(9.09)
$Market\text{-}to\text{-}book_t$	0.048***	0.050***	0.016***	0.016***
	(6.16)	(6.48)	(5.15)	(5.07)
ROA_t	−0.113**	−0.126**	−0.059***	−0.059***
	(−2.24)	(−2.55)	(−3.11)	(−3.16)
Stock $Returns_t$	−0.033***	−0.033***	−0.012***	−0.011***
	(−3.15)	(−3.15)	(−3.09)	(−2.71)
$Leverage_t$	0.093	0.105	0.033	0.034
	(1.10)	(1.28)	(1.01)	(1.09)
$Tangibility_t$	0.313***	0.294***	0.130***	0.123***
	(3.84)	(3.68)	(3.99)	(3.89)
$CAPEX_t$	0.321**	0.393***	0.126**	0.158***
	(2.36)	(2.91)	(2.45)	(3.08)
R&D/$Assets_t$	0.831***	0.697***	0.255***	0.221***
	(7.57)	(6.65)	(6.38)	(5.78)
$LnAge_t$	0.009	0.008	−0.002	−0.002
	(0.46)	(0.41)	(−0.30)	(−0.27)
H $Index_t$	−0.326	−0.298	−0.214*	−0.192*
	(−1.37)	(−1.27)	(−1.94)	(−1.79)
H Index sq_t	0.393	0.378	0.243**	0.218*
	(1.48)	(1.47)	(2.03)	(1.90)
KZ $Index_t$	−0.047***	−0.051***	−0.019***	−0.020***
	(−3.61)	(−3.92)	(−3.26)	(−3.44)
IO_t	−0.212***	−0.189***	−0.117***	−0.101***
	(−3.09)	(−2.80)	(−4.03)	(−3.60)
Constant	−1.596***	−1.562***	−0.545***	−0.532***
	(−13.23)	(−12.97)	(−9.84)	(−9.77)
Year and SIC2 FE	Yes	Yes	Yes	Yes
N	7,982	7,982	7,982	7,982
adj. R^2	0.412	0.390	0.354	0.336

Panel E. Multivariate Results: Patent Citations

	$LnCit^{Time-Tech}_{t+1}$ (1)	$LnCit^{Time-Tech}_{t+2}$ (2)	$LnCit^{Time}_{t+1}$ (3)	$LnCit^{Time}_{t+2}$ (4)
$Treatment_t$	0.201***	0.161***	0.197***	0.155***
	(5.09)	(4.16)	(5.08)	(4.10)
$LnAssets_t$	0.376***	0.359***	0.366***	0.349***
	(13.91)	(13.57)	(13.52)	(13.14)
$Market\text{-}to\text{-}book_t$	0.075***	0.075***	0.070***	0.071***
	(6.24)	(6.37)	(6.22)	(6.40)
ROA_t	−0.107	−0.119	−0.106	−0.103
	(−1.25)	(−1.40)	(−1.23)	(−1.26)
Stock $Returns_t$	−0.055***	−0.049***	−0.049***	−0.047***
	(−3.09)	(−2.77)	(−2.88)	(−2.80)
$Leverage_t$	−0.040	0.035	−0.080	0.001
	(−0.33)	(0.30)	(−0.70)	(0.01)
$Tangibility_t$	0.417***	0.362***	0.375***	0.327***
	(3.60)	(3.18)	(3.28)	(2.94)
$CAPEX_t$	0.507**	0.690***	0.616***	0.767***
	(2.37)	(3.24)	(2.85)	(3.54)
R&D/$Assets_t$	1.684***	1.477***	1.626***	1.404***
	(8.60)	(7.99)	(8.34)	(7.68)
$LnAge_t$	−0.034	−0.036	−0.050	−0.053*
	(−1.02)	(−1.12)	(−1.55)	(−1.72)
H $Index_t$	−0.356	−0.436	−0.457	−0.526
	(−1.01)	(−1.26)	(−1.32)	(−1.56)
H Index sq_t	0.455	0.567	0.552	0.649*
	(1.19)	(1.52)	(1.46)	(1.78)
KZ $Index_t$	−0.055***	−0.063***	−0.049***	−0.058***
	(−3.10)	(−3.63)	(−2.98)	(−3.58)
IO_t	−0.236**	−0.218**	−0.231**	−0.214**
	(−2.32)	(−2.22)	(−2.33)	(−2.24)

Table 8 (*Continued*)

Panel A. Difference in Observables						
	Pre-match			Post-match		
Variable	High OC (1)	Low OC (2)	High – Low (3)	High OC (4)	Low OC (5)	High – Low (6)
Constant	−2.267***	−2.193***	−2.120***	−2.048***		
	(−13.46)	(−13.53)	(−12.87)	(−13.00)		
Year and SIC2 FE	Yes	Yes	Yes	Yes		
N	7,982	7,982	7,982	7,982		
adj. R^2	0.373	0.357	0.360	0.345		

This table reports the differences in innovation output based on a sample where firms with more organization capital are matched to firms with less organization capital using a propensity score matching procedure. The initial sample includes all sample firms that belong to the top and bottom three deciles based on their organization capital among the Compustat universe of firms. *High OC* (*Low OC*) firms are firms with the most (least) organization capital that belong to the top (bottom) three deciles. Panel A reports the differences in observables between *High OC* and *Low OC* firms. Panel B presents the parameter estimates from the probit model used in estimating the propensity scores for *High OC* and *Low OC* firms. The dependent variable for Panel B, *Treatment*, is a dummy variable that equals one if the firm is a *High OC* firm and zero otherwise. The *Pre-Match* column contains all *High* OC and *Low OC* firms. The *Post-Match* column contains a subsample of matched *High OC*–*Low OC* pairs after propensity score matching. If a *Low OC* firm is matched with more than one *High OC* firm, we retain the pair for which the difference in propensity scores between the *High OC* and *Low OC* firm is the smallest. Panel C reports the differences in mean number of adjusted patent count and patent citations between the propensity score matched *High OC*–*Low OC* pairs of firms. Panel D and Panel E reports the multivariate results for a subsample of propensity score matched *High OC*–*Low OC* pairs of firms examining the relation between organization capital and innovation estimated using pooled OLS regression. Panel D (Panel E) dependent variable *LnPat* (*LnCit*) is the sum of natural logarithm of one plus the number of patents granted (citations received on granted patents) in a given year *t* for firms adjusted for truncation bias. Columns (1) and (2) in Panel D and Panel E adjust for truncation bias in innovation variables using *Time-Tech* adjustment procedure. Columns (3) and (4) in Panel D and Panel E adjust for truncation bias in innovation variables using *Time* adjustment procedure. Please refer to the Appendix for detailed definitions of the control variables. All variables are winsorized at the 1st and 99th percentiles. T-statistics or Z-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

the Fama and French (1997) 12 industry classification and classify industries into *High-tech* and *Low-tech* categories. Firms that belong to healthcare, medical equipment, drugs, chemicals, computers, electronic equipment and telecommunications industries are classified as *High-tech*. Firms belonging to all the other industries which includes software programming, nondurables, durables, manufacturing and utilities are defined *Low-tech*.

Table 9, Panels A and B contain the subsample regression results. Columns (1) and (2) of Panel A report the results for the relation between organization capital and $LnPat_{t+1}^{Time-Tech}$ for *High-tech* and *Low-tech* industries, respectively. For both *High-tech* and *Low-tech* industries, the coefficient on organization capital is positive and statistically significant, which is consistent with the baseline results. However, the coefficient on organization capital is economically larger for *High-tech* industries (0.070) than for *Low-tech* industries (0.036). Performing a Chow test which enables us to test for a difference in organization capital coefficients between *High-tech* and *Low-tech* industries we obtain an F-statistic of 6.20 (p-value = 0.000), indicating that there is a significant difference in coefficients across the two subsamples. The results are similar for $LnPat_{t+2}^{Time-Tech}$, $LnPat_{t+1}^{Time}$, and $LnPat_{t+2}^{Time}$ as dependent variables. We report patent citations results in Panel A and find similar results to those reported for patent count.

Demerjian, Lev and McVay (2012) develop a firm specific measure of managerial ability. The authors estimate a measure of managerial ability using frontier analysis, wherein they are able to distinguish managerial specific component of efficiency from firm specific component and focus particularly on a multitude of revenue generating expenses such as inventory, selling and general expenses, fixed costs, operating leases and R&D. The authors argue that managers with better understanding of economic trends will be better able to utilize firm resources. Chen, Podolski, and Veeraraghavan (2015) link managerial ability to higher innovative output. Consequently, we examine the role of organization capital in firms with high versus low managerial ability. We obtain managerial ability data provided by Professor Peter Demerjian at University of Illinois Chicago. [19] We present these results in Panel B of Table 9. Similar to the results for High-tech, we find that the coefficient on organization capital is significantly larger for firms with lower managerial ability compared to those with higher managerial ability. This suggests that organization capital plays an important role in enhancing innovation and compensates for lower managerial specific ability. Thus, managerial ability and organization capital are complementary in terms of a firm's innovative capacity.

6.2. Reduction in career concern threats

Graham, Harvey, and Rajgopal (2005) and Stein (1989), among others, contend that managers facing career concern threats are less likely to participate actively in long-term oriented activities such as innovation. Instead, they are more likely to focus on short-term projects that produce quick returns but possibly could destroy firms' long-term value. Because firms with more organization capital have lower employee turnover, managers of these firms are less concerned with career threats, and hence, are more likely promote firm innovation. This suggests that a possible channel through which organization capital impacts innovation is the reduction in career concern threats.

We investigate this possibility by estimating Eq. (3) for subsamples of firms with high and low profitability growth. The career concerns literature suggests that the likelihood of managerial turnover is less pronounced for firms with high profitability growth (Fisman et al., 2005; Aghion et al., 2013). Therefore, to the extent that reduction in career concern threats is a channel through which organization capital impacts innovation, then the impact should be stronger for firms with higher profitability growth.

We divide our sample firms into terciles and focus on those firms whose ΔROA (the change in firms' returns on assets from the previous year) relative to its two-digit SIC industry peers is in the top and bottom terciles. Firms that belong to the top (bottom) tercile are classified as *High* ΔROA (*Low* ΔROA) firms. We repeat our baseline estimation for each subsample and report the results in Panel A (Panel B) of Table 10 for patent count (patent citations). Table 10, Panel A, Columns (1) and (2) report the results for the relation between organization capital and $LnPat_{t+1}^{Time-Tech}$ for *High* ΔROA and *Low* ΔROA subsamples. The coefficient on organization capital is larger for *High* ΔROA firms (0.041) than for *Low* ΔROA firms (0.036). A Chow test F-statistic of 9.22 (p-value = 0.003) indicates that the difference in organization capital coefficients between *High* ΔROA and *Low* ΔROA firms is statistically significant. The results

[19] Data are available at: http://https://peterdemerjian.weebly.com/managerialability.html

Table 9
Organization Capital and Innovation: Difficulty in Innovation.

Panel A. Hi-Tech

	$LnPat_{t+1}^{Time-Tech}$		$LnPat_{t+2}^{Time-Tech}$		$LnCit_{t+1}^{Time-Tech}$		$LnCit_{t+2}^{Time-Tech}$	
	High -tech (1)	Low-tech (2)	High-tech (3)	Low-tech (4)	High -tech (5)	Low-tech (6)	High-tech (7)	Low-tech (8)
$OC/Assets_t$	0.070***	0.036***	0.067***	0.035***	0.073***	0.043***	0.070***	0.040***
	(6.00)	(5.70)	(5.82)	(5.54)	(4.42)	(4.83)	(4.31)	(4.64)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and SIC2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	34,887	52,986	34,887	52,986	34,887	52,986	34,887	52,986
adj. R^2	0.444	0.342	0.421	0.322	0.412	0.324	0.389	0.305

Panel B. Managerial Ability

	$LnPat_{t+1}^{Time-Tech}$		$LnPat_{t+2}^{Time-Tech}$		$LnCit_{t+1}^{Time\_Tech}$		$LnCit_{t+2}^{Time-Tech}$	
	High -MA (1)	Low-MA (2)	High-MA (3)	Low-MA (4)	High-MA (5)	Low-MA (6)	High-MA (7)	Low-MA (8)
$OC/Assets_t$	0.017***	0.025***	0.019***	0.025***	0.016***	0.022***	0.018***	0.022***
	(10.26)	(8.43)	(10.28)	(7.92)	(9.72)	(7.67)	(9.98)	(7.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and SIC2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	50,823	43,949	46,164	40,008	50,737	43,868	46,080	39,939
adj. R^2	0.339	0.354	0.339	0.352	0.278	0.297	0.278	0.297

This table reports the pooled Ordinary Least Squares (OLS) regression results examining the relation between organization capital and innovation. The sample period is from 1980 to 2008. The dependent variable in Panel A (Panel B) *LnPat* (*LnCit*) and is the sum of the natural logarithm of one plus the number of patents granted (citations received on granted patents) in a given year *t* for firms adjusted for truncation bias. The key independent variable *OC/Assets* is the ratio of firm's organization capital to book value of total assets in year *t*. *High-tech* refers to subsample of firms that belong to healthcare, medical equipment, drugs, chemicals, computers, electronic equipment, and telecommunications industries as per Fama and French (1997) 12 industry classification. *Low-tech* refers to all firms that are not *High-tech* firms. Please refer to the Appendix for detailed definitions of the control variables. All variables are winsorized at the 1st and 99th percentiles. T-statistics are in parentheses and are computed using the robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 10
Organization Capital and Innovation: Career Concern Threats.

Panel A. Patent Count

	$LnPat_{t+1}^{Time\text{-}Tech}$		$LnPat_{t+2}^{Time\text{-}Tech}$	
	High *ΔROA* (1)	Low *ΔROA* (2)	High *ΔROA* (3)	Low *ΔROA* (4)
$OC/Assets_t$	0.041***	0.036***	0.040***	0.034***
	(7.52)	(7.54)	(7.36)	(7.26)
Controls	Yes	Yes	Yes	Yes
Year andSIC2 FE	Yes	Yes	Yes	Yes
N	29,249	28,629	29,249	28,629
adj. R^2	0.359	0.315	0.337	0.298

Panel B. Patent Citations

	$LnCit_{t+1}^{Time-Tech}$		$LnCit_{t+2}^{Time-Tech}$	
	High *ΔROA* (1)	Low *ΔROA* (2)	High *ΔROA* (3)	Low *ΔROA* (4)
$OC/Assets_t$	0.044***	0.038***	0.042***	0.035***
	(5.38)	(5.06)	(5.19)	(4.74)
Controls	Yes	Yes	Yes	Yes
Year andSIC2 FE	Yes	Yes	Yes	Yes
N	29,249	28,629	29,249	28,629
adj. R^2	0.345	0.302	0.323	0.283

This table reports the pooled Ordinary Least Squares (OLS) regression results examining the relation between organization capital and innovation. The sample period is from 1980 to 2008. The dependent variable is Panel A (Panel B) *LnPat* (*LnCit*) and is the sum of the natural logarithm of one plus the number of patents granted (citations received on granted patents) in a given year *t* for firms adjusted for truncation bias. The key independent variable *OC/Assets* is the ratio of firm's organization capital to book value of total assets in year *t*. *ΔROA* is the change in firm's ROA during the year *t* from the previous year *t*-1. *High ΔROA* (*Low ΔROA*) refers to subsample of firms that belong to top (bottom) tercile based on *ΔROA* among its two-digit industry peers. Please refer to the Appendix for detailed definitions of the control variables. All variables are winsorized at the 1st and 99th percentiles. T-statistics are in parentheses and are computed using the robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 11
The effect of Inevitable Disclosure Doctrine.

	$LnPat_{t+1}^{Time-Tech}$(1)	$LnCit_{t+1}^{Time-Tech}$(2)	$LnPat_{t+2}^{Time-Tech}$(3)	$LnCit_{t+2}^{Time-Tech}$(4)
IDD * High OC	−0.010***	−0.011***	−0.012***	−0.014***
	(−3.331)	(−3.630)	(−3.794)	(−4.225)
IDD	0.012***	0.011***	0.015***	0.015***
	(5.702)	(5.098)	(6.500)	(6.235)
High OC	0.024***	0.024***	0.028***	0.029***
	(13.015)	(12.418)	(14.285)	(13.892)
$LnAssets_t$	0.022***	0.020***	0.024***	0.022***
	(44.916)	(40.015)	(43.920)	(39.012)
$Market\text{-}to\text{-}book_t$	0.000***	0.000***	0.000***	0.000***
	(4.678)	(4.397)	(4.163)	(3.460)
ROA_t	−0.011***	−0.011***	−0.012***	−0.012***
	(−24.752)	(−22.476)	(−23.114)	(−20.823)
Stock $Returns_t$	0.001***	0.001***	0.001***	0.001**
	(4.186)	(2.800)	(3.260)	(2.546)
$Leverage_t$	0.003***	0.003***	0.001	0.002
	(2.981)	(3.086)	(1.401)	(1.451)
$Tangibility_t$	−0.015***	−0.014***	−0.018***	−0.016***
	(−4.841)	(−4.237)	(−5.191)	(−4.493)
$CAPEX_t$	0.059***	0.060***	0.077***	0.072***
	(8.645)	(7.922)	(9.630)	(8.289)
$R\&D/Assets_t$	0.008**	0.008**	0.009**	0.011***
	(2.483)	(2.327)	(2.478)	(2.604)
$LnAge_t$	−0.134***	−0.121***	−0.133***	−0.120***
	(−76.643)	(−64.997)	(−72.504)	(−61.697)
H $Index_t$	0.065***	0.083***	0.056***	0.081***
	(4.811)	(5.766)	(3.725)	(5.089)
H Index sq_t	−0.024	−0.037**	−0.011	−0.032*
	(−1.480)	(−2.201)	(−0.608)	(−1.672)
KZ $Index_t$	0.000***	0.000***	0.000***	0.000***
	(4.303)	(4.591)	(4.574)	(4.240)
IO_t	−0.000***	−0.000***	−0.000***	−0.000***
	(−10.443)	(−10.790)	(−9.428)	(−10.036)
Constant	0.445***	0.395***	0.431***	0.380***
	(56.130)	(46.578)	(51.921)	(43.235)
Observations	88,490	88,414	78,609	78,537
R-squared	0.315	0.247	0.315	0.249

This table reports the pooled Pre-post IDD regression results examining the relation between organization capital and innovation. The sample period is from 1980 to 2008. The dependent variable *LnPat* (*LnCit*) is the sum of the natural logarithm of one plus the number of patents granted (citations received on granted patents) in a given year *t* for firms adjusted for truncation bias. The key independent variable *OC/Assets* is the ratio of firm's organization capital to book value of total assets in year *t*. IDD is a dummy variable that equals 1 for IDD law passed in a state and 0 otherwise.Please refer to the Appendix for detailed definitions of the control variables. All variables are winsorized at the 1st and 99th percentiles. T-statistics are in parentheses and are computed using robust standard errors clustered by firm. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

are similar when we use $LnPat_{t+2}^{Time-Tech}$, $LnPat_{t+1}^{Time}$, and $LnPat_{t+2}^{Time}$ as dependent variables. We obtain similar results for patent citations which are displayed in Panel B.[20]

For our final check, we examine the impact of Inevitable Disclosure Doctrine (IDD) on innovation. Inevitable Disclosure Doctrine (IDD) was adopted by US courts to enhance legal protection for trade secrets. Trade secrets include things like softwares, business plans, details about certain processes or techniques and are valued at two thirds of the value of intangible assets of US Firms (US Chamber of Commerce, 2014). Under the IDD, employees can be prohibited from working for a competitor especially if the employee through access to trade secrets can cause considerable harm to the firm. Therefore the passage of the act can be associated with lower likelihood of "job hopping" within a state. IDD laws were adopted within 20 U.S. states at different periods in time and provide us with an opportunity to investigate the imapct of labor market on innovation for high versus low organization capital firms. As such, the passage of IDD within a state should be associated with a "thin" labor market. We create a dummy variable, *IDD*, that equals 1 after the law was passed in a state and 0 otherwise. We interact our IDD measure with the dummy which is 1 for firms with high organization capital and 0 for firms with low organizational capital. High organization capital firms are those whose organizationl capital is greater than the median social capital.

Column 1 of Table 11 shows results for patents. While both *High OC* and *IDD* have a positive relationship with patents, the coefficient on the interaction between *High OC* and *IDD* is negative, suggesting the effect of organzation capital on innovation becomes weaker after the passage of IDD. We find similar results for citations. These findings suggest that when managers are restricted from "job hopping", organization capital's effect on innovation is deminished. Conversly, when labor markets are thick, high organzational capital is associated with higher innovation, consistent with our previous result. These findings are also consistent with Chen, Gao and Ma (2020) who find that IDD is positively associated with retention of key talent in a merger and acquistion event.

Previous work by Warner, Watts, and Wruck (1988); Weisbach (1988), and Fee and Hadlock (2004), among others, shows that there is a lower likelihood of CEO turnover when firm performance is relatively higher than that of their industry peers. Given this existing literature, our finding provides additional support for the argument that organization capital, by mitigating career concern threats, helps managers to focus on more risky, long-term activities like innovation. In sum, our results provide strong support for the

[20] As a robustness check, we examine the impact of organization capital on innovation for subsamples of firms with stronger and weaker performance relative to their industry peers. In untabulated analysis we find that the effect of organization capital on innovation is stronger for firms with superior performance relative to their industry peers.

notion that reduction in career concern threats is a viable channel through which organization capital affects innovation.

7. Conclusion

In this study, we examine the impact of firms' internal environment on innovation by examining whether firms' organization capital affects innovation. Using a comprehensive sample of patents granted to U.S. firms between 1980 and 2008, we find robust evidence that firms with more organization capital are relatively more innovative than their counterparts with less organization capital. Specifically, we find that firms with more organization capital produce more patents and receive more citations on their patents compared to firms with less organization capital. The relation is not sensitive to endogeneity issues and is robust to alternative measures of organization capital and innovation. Further, these results remain unaffected after we control for variables that proxy for various firm characteristics, corporate governance, and performance-sensitive compensation.

In addition to examining the impact of organization capital on innovation, we identify potential channels through which organization capital enhances innovation. We find that a firm's ability to deal with the inherent difficulties associated with the innovation process is one of the channels through which organization capital impacts innovation. We also find that that the reduction of career concern threats of managers is another channel through which organization capital positively impacts firm innovation.

In sum, our paper contributes to the innovation literature by highlighting the importance of firm intangibles for innovation. It also adds to an emerging body of literature demonstrating the importance of firm intangibles on corporate policies and decision making. We believe our paper has important implications for firms, investors, and policymakers.

Appendix A

Variable Definitions

Variable	Definition
Innovation Variables	
$LnPat_{i,t}^{Time-Tech}$	Natural logarithm of one plus $Patents^{Time-Tech}$, where $Patents^{Time-Tech}$ is the sum of patent count in application year *t* by firm *i* with each patent adjusted for truncation bias using *Time-Tech* adjustment procedure. That is, we divide each patent by the mean patent counts per firm of all patents applied in the same year *t* and technology class to which the patent belongs to
$LnPat_{i,t}^{Time}$	Natural logarithm of one plus $Patents^{Time}$, where $Patents^{Time}$ is the sum of patent count in application year *t* by firm *i* with each patent adjusted for truncation bias using *Time* adjustment procedure. That is, we divide each patent by the mean patent counts per firm of all patents applied in the same year *t* to which the patent belongs to
$LnCit_{i,t}^{Time-Tech}$	Natural logarithm of one plus $Citations^{Time-Tech}$, where $Citations^{Time-Tech}$ is the sum of patent citations received across all patents applied in year *t* by firm *i* with each patent's citations adjusted for truncation bias using *Time-Tech* adjustment procedure. That is, we divide each patent's number of citations by the mean citation counts of all patents applied in the same year *t* and technology class to which the patent belongs to
$LnCit_{i,t}^{Time}$	Natural logarithm of one plus $Citations^{Time}$, where $Citations^{Time}$ is the sum of patent citations received across all patents applied in year *t* by firm *i* with each patent's citations adjusted for truncation bias using *Time* adjustment procedure. That is, we divide each patent's number of citations by the mean citation counts of all patents applied in the same year *t* to which the patent belongs to
Organization Capital Variables	
$OC_{i,t}$	Stock of organization capital in year *t* constructed by cumulating firms *i*'s CPI-deflated selling, general and administrative (SG&A) expenditures using a perpetual inventory method (Eisfeldt and Papanikolaou, 2013). A 15% depreciation rate in organization capital and 10% growth rate in organization capital 10% is assumed.
$OC/Assets_{i,t}$	Ratio of stock of organization capital computed using SG&A expenditures (OC) to book value of total assets of firm *i* in year *t*
OC/Assets Quintile $Rank_{i,t}$	Quintile Rank of *OC/Assets* of firm *i* among Compustat universe of two-digit SIC industry firms in year *t*
Other Variables	
$Assets_{i,t}$	Book value of total assets in 2010 dollars of firm *i* in year *t*
$Market\text{-}to\text{-}book_{i,t}$	Ratio of (book value of assets – book value of equity + market value of equity) to book value of total assets of firm *i* in year *t*
$ROA_{i,t}$	Ratio of operating income before depreciation to book value of total assets of firm *i* in year *t*
Stock $Returns_{i,t}$	Annual stock returns measured by cumulating monthly stock returns over the 12 months of firm *i* in year *t*
$Leverage_{i,t}$	Ratio of sum of short and long term debt to book value of total assets of firm *i* in year *t*
$Tangibility_{i,t}$	Ratio of net property, plant and equipment (PPE) to book value of total assets of firm *i* in year *t*
$CAPEX_{i,t}$	Ratio of capital expenditures to book value of total assets of firm *i* in year *t*
$RD/Assets_{i,t}$	Ratio of research and development expenditures to book value of total assets of firm *i* in year *t*
$Age_{i,t}$	Number of years that firm *i* has been listed in the Compustat database at the end of year t
H $Index_{i,t}$	Herfindahl index of firm *i*'s industry in year *t* constructed based on sales at the four-digit SIC industry level.
H Index $sq_{i,t}$	Squared term of Herfindahl index of firm *i*'s industry in year *t* constructed based on sales at the four-digit SIC industry level.
KZ $Index_{i,t}$	Kaplan and Zingales (1997) financial constraints index of firm *i* in year *t*. It is calculated as -1.002*(cash flows/lagged book value of total assets)-39.368*(Dividends/ lagged book value of total assets)-1.315*(cash holding/ lagged book value of total assets)+3.139*(sum of short and long term debt /sum of short and long term debt and common equity)+0.238*Tobin's Q
$IO_{i,t}$	Percentage of firm *i*'s common shares outstanding held by the institutional investors for the year *t*
$\Delta ROA_{i,t}$	Change in ratio of operating income before depreciation to book value of total assets of firm *i* in year *t* from previous year *t-1*
$LnPay_{i,t}$	Natural logarithm of CEO total direct compensation (TDC1 in Execucomp) of firm *i* in year *t*
Equity Pay $Percent_{i,t}$	Equity-based compensation of CEO as a percentage of total compensation of firm *i* in year *t*
G $Index_{i,t}$	Gompers et al. (2003) governance index based on 24 anti-takeover provisions of firm *i* in year *t*
E $Index_{i,t}$	Bebchuk et al. (2009) entrenchment index based on staggered boards, limits to shareholder bylaw amendments, poison pills, golden parachutes, and super majority requirements for mergers and charter amendments provisions of firm *i* in year *t*
$WPS_{i,t}$	Scaled wealth-performance sensitivity defined as the ratio of change in CEO wealth in dollar terms for a 100 percentage point change in firm value to CEO annual flow compensation of firm *i* in year *t*
Instrumental Variables	

Variable	Definition
$SIC2\_AGU_{i,t}$	Industry uncertainty of firm *i*'s industry in year *t* constructed based on the asset growth rate at the two-digit SIC industry level. For each firm in the CRSP-Compustat universe, we compute the standard deviation of its seasonally adjusted quarterly asset growth rate over the years *t* and *t-1*. $SIC2\_AGU_{i,t}$ is calculated as the median value of the standard deviation of the seasonally adjusted quarterly asset growth rate for the CRSP-Compustat universe of firms in the same two-digit SIC industry of firm *i* in year *t*
$SIC2\ \_AGU\_Res1_{i,t}$	For each two-digit industry, we compute the sum of the adjusted number of patent count and patent citations of the all firms in the industry every year. $SIC2\_AGU\_Res1_{i,t}$ is the residual of a time-series regression of $SIC2\_AGU_{i,t}$ on the natural logarithm of one plus the sum of adjusted number of patent count and natural logarithm of one plus the sum of adjusted number citations received across all patents applied for by all firms in the same two-digit SIC industry of firm *i* in year *t*. Truncation bias in innovation variables are adjusted for using *Time-Tech* adjustment procedure.
$SIC2\_AGU\_Res2_{i,t}$	For each two-digit industry, we compute the sum of the adjusted number of patent counts and patent citations of the all firms in the industry every year. $SIC2\_AGU\_Res2_{i,t}$ is the residual of a time-series regression of $SIC2\_AGU_{-i,t}$ on the natural logarithm of one plus the sum of adjusted number of patent count and natural logarithm of one plus the sum of adjusted number citations received across all patents applied for by all firms in the same two-digit SIC industry of firm *i* in year *t*. Truncation bias in innovation variables are adjusted for using *Time* adjustment procedure.

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