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# Do innovation-intensive firms mitigate their valuation uncertainty during bad times? ☆

Ilayda Nemlioglu<sup>a,\*</sup>, Sushanta K. Mallick<sup>b</sup><sup>a</sup> Cardiff Business School, Cardiff University, 3 Colum Drive, Cardiff CF10 3EU, UK<sup>b</sup> School of Business and Management, Queen Mary University of London, Mile End Road, London E1 4NS, UK

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## ABSTRACT

In times of crisis, innovation and entrepreneurship can be considered as a path out of valuation uncertainty of firms. All types of innovation output, however, may not have a similar impact across different firm size and sectors during bad times. Specifically, financially less-constrained (high leverage) innovative firms could be valued higher or experience less uncertainty in their performance. By considering the innovation intensity and leverage in pre- and post-2008 financial crisis periods, and using firm-level quarterly data from listed firms in the UK during 2000–2014, we find that leveraged firms can achieve greater valuation and mitigate any valuation uncertainty in the post-crisis period if they are knowledge- or high-technology intensive. In terms of size effect, although leverage distorts market valuation of large UK firms, the impact is positive for SMEs that are innovation intensive. Finally, in terms of sectoral effect, firms within manufacturing and services with leverage have benefitted from R&D and patenting activities during the post-crisis period, but not in the pre-crisis period. This also gets revealed when we classify all firms into high-tech and low-tech sectors, implying that firms in the high-tech sectors with debt dependence have benefitted favorably in terms of higher valuation and lower uncertainty in the post-crisis period, not firms in the low-technology sectors, reflecting further the role of technological intensity in firm valuation.

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## 1. Introduction

Although the earlier literature has focused on the knowledge stocks such as R&D and patents in analyzing firm valuation (see for instance [Hall \(2011\)](#) and [Hall et al. \(2013, 2010, 2007\)](#)), trademarks were rarely used in evaluating the economic value of intangible assets (see studies such as [Bosworth, \(2001\)](#), [Greenhalgh and Rogers \(2006, 2007\)](#), [Sandner and Block](#)

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\* Corresponding author.

E-mail addresses: [nemlioglu@cardiff.ac.uk](mailto:nemlioglu@cardiff.ac.uk) (I. Nemlioglu), [s.k.mallick@qmul.ac.uk](mailto:s.k.mallick@qmul.ac.uk) (S.K. Mallick).

(2011)). Nevertheless, according to Block et al. (2014), patents are related to technological aspects, whereas trademarks are related to marketing services, which make both the innovation output crucial in driving firm valuation. In addition, firms build reputation and strengthen branding via investments in marketing and advertising assets, which are not officially registered as intellectual properties (IPs) but form a part of knowledge stock for a company. In that sense, advertising assets might influence market valuation, which the earlier literature has not incorporated in innovation-market valuation relationship. Moreover, patenting could be costly to some firms, and they may keep their innovations unpatented, and keep those in the firm's knowledge stock. Thus, depending on the nature of the industry, firms may accumulate different intellectual capital (IC) and hence, using patent intensity alone is not always the best proxy to symbolize a firm's total intellectual capital stock.

Even though much of the earlier literature has commonly linked the increases in market valuation of a company to its innovation activities (see Carosi (2016)), investments in those activities may get distorted by various factors including firm size, the industry in which they operate (see Mallick and Sousa (2017)) and the capital structure of a firm. In that sense, whether a firm chooses to focus on debt or equity in its capital structure, it may influence the investments channeled into those innovation activities. While the earlier literature reviews how investment decisions matter in shaping the firm-level investment behavior (Peltonen et al. (2012, 2011)), financing constraints remain critical for investment in knowledge capital. In the presence of domestic borrowing constraints (Serena and Moreno (2016), Serena and Sousa (2017), Avdjiev et al. (2017)), the literature often has contrasting views on whether financial constraints impede innovation. Some scholars argue that innovation activities are curtailed during bad times, especially when firms use borrowing to expand or sustain business activities in such periods. Banks and other lenders prefer physical assets to secure loans and are reluctant to lend for projects that involve substantial R&D investment. Therefore, as a common practice when a firm is financially constrained, the first decision a management team takes is to cut extra costs, which may reduce R&D expenses (see Hall (2010), Hall and Lerner (2010), Brown et al. (2012), Borisova and Brown (2013)). On the other hand, another stream of the literature suggests that firms prefer to maintain R&D activities in bad times because they were locked into these activities due to an initial investment (see Archibugi et al. (2013)). The question is whether innovation-intensive firms with different debt-equity structures display differences in their firm valuation; or, whether innovation-intensive firms have higher valuation even if they are financially constrained (such as SMEs). Despite the market-based equity financing system in the UK, debt finance remains the dominant form of corporate financing including short-term bank loans (see Dosi (1990)).

At a general level, ownership category, production sector, and financing type can influence investment spending and thereby firm performance. However, previous literature has not yet explored whether these differences contribute to firm performance in the post-crisis periods. Nemlioglu and Mallick (2017) analyzed the performance of the UK firms and found that in the post-crisis period, intangibles are only beneficial when combined with greater R&D activity. However, Brown et al. (2012) point out that, due to reasons such as lack of collateral and asymmetric information, R&D investments may face significant adverse selection and moral hazard problems, particularly in younger and smaller firms, who are more likely to be financed by equity than debt. Therefore, by considering the findings of Brown et al. (2012) on small firms, we believe that firm heterogeneity can matter in the innovation-leverage interaction following the crisis, which we investigate in our paper.

In this context, analyzing market valuation at the firm and industry levels is worth investigating, given the financial constraints in the aftermath of the 2008 global financial crisis. Thus, the paper investigates the temporal variation of the innovation-leverage linkage considering the sectoral and size heterogeneity. As financial constraints tend to impact the decision of innovative activities of firms including different size across sectors, the impact of such constraints is even greater during times of financial crisis.

Our research contributes to the literature in many ways. First, we incorporate both advertising and trademark intensities in addition to the traditionally used patents as innovation output, and R&D as innovation input. Second, we investigate whether the impact of innovation varies for leveraged companies who tend to utilize leverage in financing innovation activities and also whether it varies across firm size and industries. Third, the debt structure and intellectual capital intensities jointly can also help valuation during bad times. As SMEs tend to be more financially constrained, we explore whether SMEs with higher patent and trademark intensities, in the presence of leverage, perform differently from large firms during the post-crisis period. Fourth, considering the sectoral heterogeneity (see Pieri et al. (2018)), we test the role of debt and innovation on valuation uncertainty, which could be mitigated for high-technology and knowledge-intensive firms. To sum up, our main research question focuses on whether highly leveraged firms perform better during crisis times if they are innovation-intensive.

Our results can be described as follows. First, we find that different types of intellectual capital except trademarks are important in explaining valuation differences across firms. Focusing on sectoral heterogeneity, while SMEs significantly benefit from their R&D and patent intensities, large firms tend to derive positive significant benefit from trademarks and advertising intensities. Second, depending on how those firms use their leverage in creating intellectual assets, it would boost their performance. We find that SMEs, who are more financially constrained, benefit significantly by focusing jointly on R&D and patents with leverage, even in the post-crisis period. Third, when we consider valuation uncertainty, we find that the innovation-intensive debt reliant firms are able to lower any valuation uncertainty, even during the post-crisis period. Therefore, high debt firms should focus on patenting and R&D activities that help alleviate valuation uncertainty in the post-crisis period. Finally, using an alternative sectoral classification, we find that high-tech firms tend to improve their market valuation or reduce their valuation uncertainty in the post-crisis period using patents and R&D, regardless of their debt level,

whereas low tech firms may reduce their valuation uncertainty and achieve better valuation by focusing on trademarks and marketing assets.

The rest of the paper is structured as follows. Section 2 reviews the literature, dividing the literature review into subsections for each hypothesis. Section 3 presents the data, methodology, and the theoretical model. Section 4 presents empirical results and robustness checks and Section 5 concludes the paper.

## 2. Literature review and hypotheses development

### 2.1. Impact of innovation on market values

#### 2.1.1. Impact of R&D and patents on market values

Prior literature has widely focused on R&D intensity and patents to explain the changes in valuation across firms (See Bloom and Van Reenen (2002), Hall and MacGarvie (2010), O'Mahony and Vecchi (2009), Toivanen et al. (2002)). Hall et al. (2007) investigate quality-weighted patents in European firms and find that patents in software and business are considerably more valuable than others, especially if they are taken out in the US. Helmers and Rogers (2011) evaluated the effect of a firm's patenting decision on a firm's growth, using data on all high- and medium-tech start-ups and found that patentees have higher asset growth than non-patentees of between 8% and 27% per annum. On the other hand, Thomson and Webster (2013) find that small to medium-size enterprises, highly leveraged firms, and firms with less ability to patent are more likely to pursue an external R&D strategy (e.g. outsourcing), despite the risks.

On the other hand, in a cross-country setting, Kim et al. (2012) estimated the impact of intellectual property protection on firm performance and cross-country growth and found that patentable innovations matter positively and significantly for firm growth, while utility model innovations contribute to firm performance when firms are technologically lagging and those innovations can be a learning device and thus a stepping stone for developing more patentable inventions. Gao and Chou (2015) argue that patent protection plays an important role in firm valuation for globally diversified firms, especially for those with greater R&D intensity. Similarly also at an aggregate level, Nemlioglu and Mallick (2020) and Nemlioglu (2019), uncover that greater IP supported by stronger enforcement leads to higher capital stock. Consistent with evidence from the prior literature, Chen et al. (2014) also find that stronger patents stimulate R&D in countries with more frequent innovations; and, to the extent that capital-intensive industries have high fixed innovation costs, stronger patents can stimulate R&D in more capital-intensive industries. Also, high fixed innovation cost tends to require greater patent protection. Chen et al. (2014) show that when firms' innovation capability is higher, stronger patent increases innovation at industry-level. He and Wintoki (2016), and Carosi (2016) also uncovered that R&D investment explains a significant portion of the increase in the average liquidity of U.S. firms. The findings of Carosi (2016) reveal that the effect of R&D intensity on the market to book ratio is larger in firms with more patents and increases with the R&D of local firms. So, in general, the literature is in favour of the impact of patents and R&D on market values, which leads to the following hypothesis.

*Hypothesis 1: Patent and R&D have a direct positive impact on the market values of UK firms, but in the post-crisis period the impact on high-debt firms is positive only when R&D is supported by patenting.*

#### 2.1.2. Impact of trademarks on market values of the UK firms

Firms are organisations that combine a broad range of different qualities and resources to develop, manufacture, and sell their products. Besides the tangible assets such as property, plants, and equipment, firms also have intangible assets that become increasingly important. Although R&D and patents contribute to company values in financial markets, a few studies such as Bosworth (2001), Greenhalgh and Rogers (2006, 2007), Von Graevenitz (2007), Sandner and Block (2011), suggest that other IP assets, such as trademarks, might also have a significant impact on firms' market values, and they at least partially reflect their market valuation. One of the advantages of trademarks is that they can capture relevant aspects of innovation and differentiate brands from their competitors. Additionally, studying trademarks can capture small firms and start-ups that lack patenting (see Mendonça et al. (2004)). Von Graevenitz (2007) corroborates the applicability of these indicators to trademarks, which the stock market values, in addition to R&D, and patents.

Greenhalgh and Rogers (2006, 2007, 2012) link the higher stock market values with patent and trademark activities of firms. It is remarked that there are more significant differences between firms with and without trademarks for services than for manufacturing. Also, there are significant differences when a service-based firm applies for EU community trademarks, rather than just applying for UK trademarks. The most competitive sectors have the lowest market valuation of R&D. Furthermore, within the most competitive industry ('science-based' manufacturing), firms with larger market shares (an inverse indicator of competitive pressure) also have higher R&D valuations, as well as some positive return to UK patents. This evidence supports Schumpeter by finding higher returns for innovation in less than fully competitive markets. Duygun et al. (2014) find that there is a significant difference in profit efficiency of trademarking and non-trademarking UK banks, while the differences in cost efficiency are less visible for banks in the UK. Bosworth and Rogers (2001) show that trademarks have a positive impact on the performance of firms in service industries while other traditionally used intangible assets do not.

Block et al. (2015) investigated SMEs and found that trademarks are particularly important for protection, marketing, and exchange motives, whereas patents signal technological capabilities. Therefore, patents and trademarks refer to different aspects of firm innovative activities and there is complementarity between patents and trademarks (see Thoma (2015)).

Therefore, it is vital to include both patents and trademarks as IP measures in the analysis. Block et al. (2014) investigate the role of trademarks in the valuation of start-up companies by venture capitalist and found that trademarks and company valuation have an inverted U-shaped relationship, indicating that the impact of trademarks is positive up to a level, but the impact declines in later stages. This suggests that start-up firms should emphasize their brand strength by trademarks. Similarly, Helmers and Rogers (2010) also find that UK-based start-ups are more likely to apply for trademarks. A possible reason is that patents are appropriate for technology-oriented sectors while trademarks are appropriate for low tech or service firms. That explains why firms in the service industry are less R&D intensive and have fewer or no patents (see Greenhalgh and Rogers, 2006). Zhou et al. (2014) also suggest that trademarks and patents are complementary; more specifically, patents signal technological capabilities while trademarks signal marketing capabilities. Block et al. (2015) investigated the economic impact of trademark filings in SMEs and found that trademarks are particularly important for protection, marketing and exchange motives. These motives have different impacts on different clusters of SMEs. Therefore, we focus both on large and small firms. Our hypothesis is built upon this argument as follows:

*Hypothesis 2: Trademark intensity has a direct positive impact on the market valuation of large UK firms, but in the post-crisis period, the impact only becomes positive for the firms with high leverage (less credit-constrained).*

### 2.1.3. Impact of advertising assets on market values of the UK firms

Firms build reputations and strengthen their image which is embedded in a firm's knowledge stock such as trade secrets, customer relations, networks, marketing, and advertising strategies. In that sense, advertising assets, which signal the branding and position of the firm within a market should have a significant impact on market valuation. These assets are different from trademarks, which are not part of formally registered IPs. Strategic and market-related knowledge plays an important role in successful innovation as well as technical knowledge. Contrary to the majority of the earlier literature, Roper and Hewitt-Dundas (2015) found that the existing knowledge stocks (represented by patents, R&D, and patents per employee) have weak negative impacts on firms' innovation output. And they also found that the effect of existing knowledge stocks is dominated by new knowledge flows in innovation performance. The adverse effect of existing knowledge stocks might be due to the negative path-dependency, meaning that firms are locked into existing research fields due to their already accumulated knowledge in these specific areas.

Heger and Zaby (2013) analysed the observed heterogeneity of patenting propensity of firms and found that the high costs of disclosure may outweigh the merits of patenting, leading innovators to rely on alternative protection strategies, such as secrecy. Similarly, Hall et al. (2013) find that among the firms conducting R&D, only 4% of them apply for patents. De Rassenfosse et al. (2016) also find that patents are not superior to other means of enhancing disclosure. So, this implies that patents are critical, but many inventions are not disclosed via patenting. Therefore, it is essential to use other knowledge stocks in addition to patents while exploring the innovation-firm performance relation. Sandner and Block (2011), by entering trademarks into the market value equation as a ratio of marketing assets, showed that the impact on market valuation is positive. Block et al. (2014) suggest that potential future improvement would be to add advertising spending or marketing expenditures.

Therefore, we aim to address this gap in the literature and incorporate trademarks and marketing assets separately by calculating their intensity (as a ratio over total assets). Even though trademarks explain the valuation movements up to a degree, they alone do not capture all advertising and branding benefits especially in SMEs or start-ups. Therefore, our research is novel in contributing to the existing literature as we incorporate advertising and branding as well as trademarks and patents. Kim et al. (2016) use advertising intensity as a control variable in identifying the relation between patent timing and innovation performance. This is parallel to our view that firms accumulate knowledge through advertising and marketing intensity. On the other hand, Hasan and Cheung (2018) used the term organizational capital, measured it by using general and administrative (SG&A) expenses and found that firms with higher organisational capital are more likely to be in the introduction and decline stages than growth or maturity stages. Also, Kim et al. (2016) find that knowledge accumulation follows the Schumpeterian pattern of creative destruction as found in earlier studies (Agarwal and Shah, 2014; Breschi et al., 2000). Similar to Nemlioglu and Mallick (2017), we argue that firms with innovative activities perform better even in the presence of high leverage, in the post-crisis period. Following the literature, we hypothesise that firms with higher advertising intensity benefit more in terms of market valuation, even with higher debt. Above discussions lead us to the next hypothesis as shown below.

*Hypothesis 3: Advertising intensity has an indirect positive impact on high-debt firms, but in the post-crisis period, the direct impact is positive, and the indirect effect is negative for the leveraged firms.*

## 2.2. The impact of financial constraints and recent financial crisis on innovation-market value relation

In the literature, innovation activities are found to create substantial performance differences across firms. However, the question of whether financial constraints impede innovation and firm performance relation is a long-standing issue. Despite R&D's critical role in economic growth and its susceptibility to financing difficulties, the results on the studies of how financing frictions affect R&D, are mixed (Hall and Lerner (2010)). When it comes to financing R&D, stock markets are key to help explain the high R&D-intensities of young publicly-traded firms in countries such as the UK and Sweden (see Brown



et al. (2012)) and for young publicly-traded US firms (see Brown et al. (2009); and Brown and Petersen (2009)). On the other hand, an earlier study by Bond and van Reenen (2003) finds that neither German firms nor UK firms display a correlation between the level of R&D and cash flow. Besides, Hall (2010) found that the US and the UK are more sensitive to cash-flow, whereas European firms are less. So, in principle, the US and the UK firms should be more subject to financing constraints which is puzzling, as capital markets in the US are at least as developed as those in Europe. Brown et al. (2012) also find little evidence on the binding feature of financing constraints in European firms. Thus, the impact of leverage on innovation-firm performance relation has been a long-standing debate on which the literature remains inconclusive.

One strand of the literature argues that innovation activities are curtailed during bad times. As R&D activities are considered as an expense, R&D investment can be the first thing to be sacrificed. Lin et al. (2016) find that financial constraint has an adverse relation with firm performance (also see Mallick & Yang, 2011). As opposed to capital investment, R&D investment is inflexible, therefore, the risk of R&D-intensive firms increases with their financial constraints. Also, R&D spending is more sensitive to future earnings variability as compared to physical assets (see Li (2011)). Therefore, a higher risk premium is required by shareholders of innovative companies (Lin et al. (2016)). In summary, many of the early studies agree that the capital structure of R&D-intensive firms customarily exhibits less leverage than others and therefore more likely to be financed by equity (Hall (2002), Hall et al. (2009)). Considering this, Borisova and Brown (2013) show that funds from the sale of fixed assets can support a key intangible investment in firms facing binding financing constraints. Therefore, the first strand of the literature argues that financial leverage impairs innovation activities in some firms. If financing constraints are binding for these firms, the country and worldwide R&D levels will be depressed, leading to lower levels of innovation.

However, Hall (2010) suggests, there is little evidence that the intangible nature of R&D investments alone leads to lower innovative activity without any additional factor such as a period of financial crisis when the true valuation of intangibles could have little effect on firm performance unless it is combined with R&D (see Nemlioglu and Mallick (2017)). As per Guney et al., (2017), there is a positive significant relationship between used credit lines and R&D investments, and the effect of used credit lines on R&D investments is relatively stronger for financially constrained firms, i.e., small and young firms, than for financially unconstrained firms. Therefore, although the 2008 economic crisis has severely reduced the short-term willingness of firms to invest in innovation, this reduction has not occurred uniformly, and a few firms even increased their investment, despite the adverse macroeconomic environment (see studies such as Filippetti and Archibugi (2011), Archibugi and Filippetti (2011) and Archibugi et al. (2013)). Archibugi et al., (2013) argue that this is due to being locked into R&D activities as a result of previous commitments and agreements. Interestingly, the crisis has led to a concentration of innovative activities within a small group of fast-growing new firms which were already highly innovative before the crisis. So, the presence of in-house R&D activity signals a commitment to innovation, which explains increases in innovation expenditure during the crisis. Companies pursuing more explorative strategies are better able to cope with the crisis. Filippetti and Archibugi (2011) find that this persistence can be a result of several factors including firm-specific characteristics—such as strategies, managerial differences, stage of development, advertisement profits—and technological changes, scientific research, and the nature of innovation. Of course, supply-side of capital namely financial development also matters for a firm's capital structure decisions (see Antzoulatos et al. (2016)).

On the other hand, Kieschnick and Moussawi (2018) find that a public firm's capital structure choice also depends on its governance features. The more power that insiders possess, the less debt that the firm uses as it ages. Czarnitzki and Kraft (2009) find that while the market for equity capital might exert insufficient control on top managements' behavior, this weakness may be mitigated by a suitable degree of debt-financing. As argued by Younge and Tong (2018), while executives play an important role in leading firm innovation, they may economize on efforts to innovate when protected from takeover threats. The negative effect of takeover protection on innovation is weaker for larger firms, where innovation-related decision-making authority is more likely to be delegated to middle managers, with limited executive involvement. Additionally, an internal locus of control in a top manager predicts higher revenue and an increased likelihood of undertaking innovations (see Sharma and Tarp, 2018).

At an aggregate level, the governance features such as regulatory environment also matter in a firm's access to debt financing. Government assistance to SMEs in most countries usually focuses on simplifying rules for easier credit access, market support, and reducing administrative processes. Also, McNamara et al. (2017) argue that the inefficient capital regulatory environment may lead to lower debt levels and lower investments by SMEs. Interestingly, Huang and Shang (2019) find that firms surrounded by more trusting environments have less need to use financial leverage in their capital structure with less short-term debt. Moreover, larger firms use higher levels of debt, as they are likely to have lower default risks and enjoy better reputations. Aktas et al. (2015) find that firms converge to their optimal working capital level by adjusting their investment levels. Xu et al. (2013) find that Chinese firms that face under-investment problem can mitigate this issue if the firm has stronger political connections or they are more financially constrained.

In addition to R&D activities, the number of patents can signal appropriability to the market and therefore those firms are more likely to access external finance (see Guerzoni et al. (2014), Audretsch et al. (2012)). In that perspective, small firms without those assets have difficulty obtaining bank finance and thus seek finance from venture capitalists (VC) (Cosh et al., 2009). Firms with credit constraints may choose to lease instead of borrowing from a bank for buying fixed assets and therefore they will be able to allocate more resources to their projects (Cosci et al., 2013). Clausen and Hirth (2016) find that more intangible-intensive firms have lower leverage. Consistently, Cumming (2005) finds that firms at early stages are found less likely to be financed with straight debt, convertible debt, or a mixture of debt and common equity whereas high-tech firms are more likely to be financed with convertible preferred equity. Cumming et al. (2005) also find that VCs

adjust their investment decisions according to liquidity conditions on IPO exit markets. In times of high liquidity risk in exit markets, VCs invest proportionately more in new high-tech and early-stage projects with high technology risk to postpone exit requirements. When exit markets are liquid, venture capitalists rush to exit by investing more in later-stage projects. Block et al. (2014) suggest that start-up firms should emphasize their marketing aspects via trademarks as well as their research orientation via patenting to raise VC financing. Tian et al. (2017) find that the impact of openness for innovation on the access to financial leverage of Chinese firms is mainly driven by private firms or manufacturing firms.

Following this extensive review of the literature, we find that the impact of leverage on the innovative and less innovative firms may portray differences in the post-crisis period. In this paper, we aim to address that by incorporating size and sectoral classifications into our analyses. Some sectors are more innovation-oriented whereas some are less, which may direct the leverage-firm performance relation. The arguments above lead to the next hypothesis.

*Hypothesis 4: Leverage has a positive impact on financially constrained SMEs, but in the post-crisis period the impact is positive only for high-tech and knowledge-intensive firms.*

### 3. Analytical framework

#### 3.1. Specification of the theoretical model

An earlier study by Hall et al. (2007) states that the market value approach is built upon the idea that firms are bundles of assets (and capabilities) that are difficult to disentangle and to price separately on the market. These assets include plants and equipment, inventories, knowledge assets, customer networks, brand names, and reputation. The assumption is that financial markets assign a valuation to the bundle of firms' assets that is equal to the present discounted value of their future cash flows. We follow Hall et al. (2005) for approaches to patents and R&D (see Hall and Oriani (2006) for R&D, and Sandner and Block (2011) for trademarks). Adding trademarks separately and symmetrically to knowledge assets follows the approach of Hall and Oriani (2006), who include "other intangible assets" in addition to physical and knowledge assets. The complementarity between elements of intellectual capital is an important aspect. Similar to Block et al., 2014 and Thoma, 2015, Zhou et al. (2014) also suggest that trademarks and patents are complementary, meaning that patents signal technological capabilities while trademarks signal marketing capabilities. So, patent and trademark pairs lead to a higher valuation.

We mainly constructed our theoretical model based on Hall and Oriani (2006), Hausman et al. (1984), and Griliches et al. (1988). However, our approach differs as follows. In our paper, we include advertising expenditures (Hirschey (1985), Connolly and Hirschey (1988), and Block et al. (2014)) and trademarks (Bosworth (2001), Greenhalgh and Rogers (2006, 2007)) in market value equations. The theoretical model can be written as follows:  $V_{it}$  is the market value of firm  $i$  at time  $t$ , where  $A_{it}$  denotes assets,  $K_{it}$  denotes knowledge assets, and  $M_{it}$  denotes marketing and branding capital (namely, trademarks and advertising assets).

$$V_{it}(A_{it}, K_{it}, M_{it}) = q_{it}(A_{it} + \gamma_K K_{it} + \gamma_M M_{it})^\sigma \quad (1)$$

Taking logarithms on both sides of (1), we get:

$$\log V_{it} = \log q_{it} + \sigma \log A_{it} + \sigma \log \left( 1 + \gamma_K \frac{K_{it}}{A_{it}} + \gamma_M \frac{M_{it}}{A_{it}} \right) \quad (2)$$

If the value function exhibits a constant return to scale, then  $\sigma = 1$ , in that case,  $\log A_{it}$  can be moved to the left-hand side of the equation and the model is estimated with the conventional Tobin's  $Q$  as the dependent variable. The equation thus becomes:

$$\log Q_{it} = \log \frac{V_{it}}{A_{it}} = \log q_{it} + \log \left( 1 + \gamma_K \frac{K_{it}}{A_{it}} + \gamma_M \frac{M_{it}}{A_{it}} \right) + \varepsilon_{it} \quad (3)$$

The term  $\log q_{it}$  in the equation is the intercept term that varies over time and across companies.

##### 3.1.1. Estimation method of the benchmark model

The literature does not strictly specify how to enter knowledge assets into the market valuation equation. There are two common applications. The first one is to assume that the  $\log(1 + \gamma_K \frac{K_{it}}{A_{it}} + \gamma_M \frac{M_{it}}{A_{it}})$  part of the equation can be approximated with  $(\gamma_K \frac{K_{it}}{A_{it}} + \gamma_M \frac{M_{it}}{A_{it}})$  and the equation can be estimated via pooled OLS. However, the second one is noted by Hall et al. (2005, 2007), and Hall and Oriani (2006), that if the ratio of knowledge assets to physical assets is high, the approximation becomes inaccurate, therefore estimating the equation via NLLS may be valid (see (Sandner and Block, 2011)). Similarly, Belenzon and Pataconi (2013) used patent stocks in natural logarithm form to examine the relationship between firm value and patent stocks by using fixed effects estimation adding time and firm fixed effects. Therefore, we use a log-linear model

specification and estimate the model using Fixed Effects regressions including time and firm-fixed effects. Furthermore, we also use Dynamic System GMM estimation which we discuss in the sub-section below.

**3.1.1.1. Addressing Potential Endogeneity with Dynamic GMM Estimation.** Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998) devised dynamic panel estimators that are designed for situations with a dynamic process, with current realisations of the dependent variable influenced by past ones. This argues against cross-section regressions, which essentially assume away fixed effects. The idiosyncratic disturbances may have individual-specific patterns of heteroskedasticity and serial correlation. Some regressors can be predetermined but not strictly exogenous; that is, independent of current disturbances, and some regressors can be influenced by past ones. To reduce the weak correlation problem, Blundell and Bond (2000) recommend an extended version of difference GMM and a system composed of equations in first differences and equations in levels, along with the use of system GMM.

In our estimations, we draw internal instruments from variables' lags and limited maximum lagged variables to be instrumented to lag 3 as we only encounter order 1 serial-correlation. This is to prevent over-identification problem as suggested by Roodman, 2009a, 2009b. There is no specific formula to determine how many instruments are considered as “too many instruments”. However, empirically, it is reasonable that to prevent overidentification, the number of individuals or groups must be greater than the number of instruments used. Therefore, restricting the number of instruments could be necessary for some panels. For that reason, we used  $y_{i,t-1}$ ,  $y_{i,t-2}$  and  $y_{i,t-3}$  for lagged variables, and if the data are transformed by differencing, they are  $\Delta y_{i,t-1}$ ,  $\Delta y_{i,t-2}$  and  $\Delta y_{i,t-3}$ . Following diagnostic tests are conducted to ensure the validity of dynamic GMM estimations: the Sargan test, Arellano and Bond test, and the Wald Chi-Square test.

Sargan (1958) test checks for joint validity of the instruments. It investigates the existence of the overidentification of the model. Besides, as discussed in Roodman (2009b), the Sargan test is more powerful in detecting this than the Hansen test. Also, as argued by Roodman (2009a), the Sargan test is not so vulnerable to the instrument proliferation problem as in the Hansen test. Therefore, we reported Sargan test results rather than the Hansen test.

Arellano and Bond (1991) developed the AR test for the autocorrelation in the idiosyncratic disturbance term. To encounter that, we conducted the AR (1) and AR (2) tests, and the results showed only order-1 serial correlation due to the dynamic nature of our model including lagged dependent variable. Finally, the Wald Chi-square test examines the validity of the model. In all our models we reject the null at less than 1% level; therefore, the coefficients are not simultaneously equal to zero. In other words, removing the variables from the model causes harm to the fit of that model.

### 3.2. Data and descriptive analysis

We use firm-level quarterly data from nearly 2300 firms traded in the London Stock Exchange between 2000 and 2014 period. The dataset has been taken from the Amadeus database of the Bureau van Dijk. Additionally, we add firm age and employee number over total assets as control variables. We conduct our analysis using the log-linear form. Similar to Bloom and Reenen (2002, 2007, 2010), Hall et al. (2005, 2007), and Hall and Oriani (2006), we use Tobin's Q ratio as our dependent variable, as the market value of the firm should reflect the expected future return on intangible assets. By using the specification in Aktas et al. (2015), Guney et al. (2017), and Jia (2018), Tobin's Q ratio is calculated as the market value of equity plus total assets minus the book value of equity, divided by book value of total assets.

In this paper, intellectual capital elements are represented by four proxies: R&D, patent, trademark, and advertising intensity. We use patent intensity as an explanatory variable, which is calculated as total patents over total assets. The ratio shows the assets generated for each additional unit of patents granted. Here, using the variables in levels could be misleading due to different firm sizes; instead, we use this ratio, which is parallel to the studies such as Hall (2000, 2010 and 2011) and Hall et al. (2005, 2007, 2009, 2010, and 2013). Another explanatory variable is trademark intensity, which is calculated as the total number of trademarks owned cumulatively, divided by the firm's total assets. This is to see whether a higher number of trademarks brings any additional value to total assets. Instead, Sandner and Block (2011) used trademarks and marketing assets to construct TM/MA ratio and used the term “marketing assets” to refer to the difference between total assets and R&D stock. However, we use a common comparable approach for trademarks and advertising assets separately by calculating trademark intensity as TM/assets, and advertising intensity as SGA/assets (see Hasan and Cheung (2018)). The reason for choosing the SGA expenses is that these costs are outside of R&D, but still give a firm the ability to differentiate its knowledge stocks, including brands, and marketing positions. More specifically, these expenses cover salaries, advertising, and promotional materials, marketing, and sales expenses. Following Eisfeldt and Papanikolaou (2013), Lev et al.,(2009), and Hasan and Cheung (2018), we capitalized the SGA expenses using a perpetual inventory method. By creating a ratio of SGA stocks over total assets, we estimate the total assets gained for each additional unit of marketing assets. The underlying idea is similar to the one in R&D intensity. Following the earlier literature, R&D and advertising expenses, which are both expenses on a firm's balance sheet, are accumulated by using a depreciation rate of 15%. R&D stocks are denoted by Rstock, and Advertising Stocks are denoted by Mstock and are calculated as follows:

$$Rstock_t = Rflow_t + (1 - \delta_r)Rstock_{t-1} \quad \text{and,}$$

$$Mstock_t = Mflow_t + (1 - \delta_m)Mstock_{t-1}$$

The financial constraints are incorporated by using debt ratio into the models. The literature suggests numerous ways of calculating the leverage ratio. By following [Huang and Shang \(2019\)](#), [Jia \(2018\)](#), [Guney et al. \(2017\)](#), we calculate the debt ratio by dividing long-term debt to total assets. The ratio provides a general measure of the financial position of a company, including its ability to meet financial requirements for outstanding loans. An annual decrease in this ratio suggests that a company is progressively becoming less dependent on debt for its growth.

[Table 1](#) provides descriptive statistics based on firm sizes. The first panel in [Table 1](#) shows the descriptive statistics for all firms; SMEs and large firms. Panel 1 shows that SMEs are more innovation-intensive with higher TM, patent, and advertising intensities, along with higher debt ratio, whereas the large firms have higher advertising expenses, a higher number of patents, and trademarks in their portfolios, which are divided by total assets of each firm to overcome potential scaling issues. Also, SMEs need external financing to finance their operational activities and boost their performance. As we will investigate further, higher debt will help firms to become less-credit constrained and thus, help them benefit from innovation by generating innovative assets (see [Appendix A](#) for further discussions). [Fig. 1](#) presents the scatter plots of innovation variables with Tobin's Q. The graphs on the left column represent high intellectual capital-intensive firms (namely firms above the mean) whereas the right column represents low intellectual capital-intensive firms (firms below the mean). From the first set of plots, it is seen that the impact of TM on Tobin's Q is higher for high TM firms. The second set of plots represents high and low patent firms across Tobin's Q. The plots indicate that high patent-intensive firms have higher valuation than low patent-intensive firms, with a flatter trend in the latter suggesting a lower impact. From the third set of plots, it is seen that R&D intensity has a positive impact on Tobin's Q in both high and low R&D intensive firms. However, for the high R&D intensive firms, the relationship is positive up to a threshold after which it starts declining. Same inverse U-shaped pattern is also true for the fourth set containing advertising intensity. This suggests that there is an optimal level for both R&D and advertising intensity and after that firms no longer benefit. [Fig. 2](#) presents 3 scatter plots showing the Tobin's Q ratio against debt ratio. The first plot shows high leveraged firms whereas the second one shows low leveraged firms and the third one shows all sample. The figure indicates that the impact of debt on Tobin's Q is positive on all graphs. But the impact of debt on Tobin's Q is exponential, showing that at lower levels of debt the impact on Tobin's Q is higher, and with an increase in debt, the valuation starts to slow down for high debt firms. For low debt firms, the impact is positive at lower ends and then remains constant. (See [Appendices C and D](#) for further details)

## 4. Empirical results and discussions

### 4.1. Benchmark analysis: testing the existence of a structural break in the valuation of the UK firms in the pre- and post-crisis periods

The benchmark results in [Table 2](#) below show that R&D, patent and advertising intensities directly drive market valuation upwards while the impact of trademarks is found to be negative for all UK firms. So, the preliminary results demonstrate that all firms do not benefit equally from intellectual assets, which therefore needs further examination. It is expected that small firms and large firms have different levels of innovative assets. Therefore, they would benefit differently from innovation- market value relation. In [Table 2](#) (columns 7 and 8), we separate our sample into SMEs and large firms. Our findings in the 7<sup>th</sup> column are in line with [Zhou et al. \(2014\)](#), who argue that patents are essential for the performance of SMEs. So, we find that SMEs benefit from patenting. Conversely, in column 8 we find that trademarks play an important role for large firms in market valuation whereas it is negative for SMEs. Advertising stocks play a positive role in valuation both in SMEs and large firms. Overall, it is possible to see that small and large firms benefit differently from innovation output.

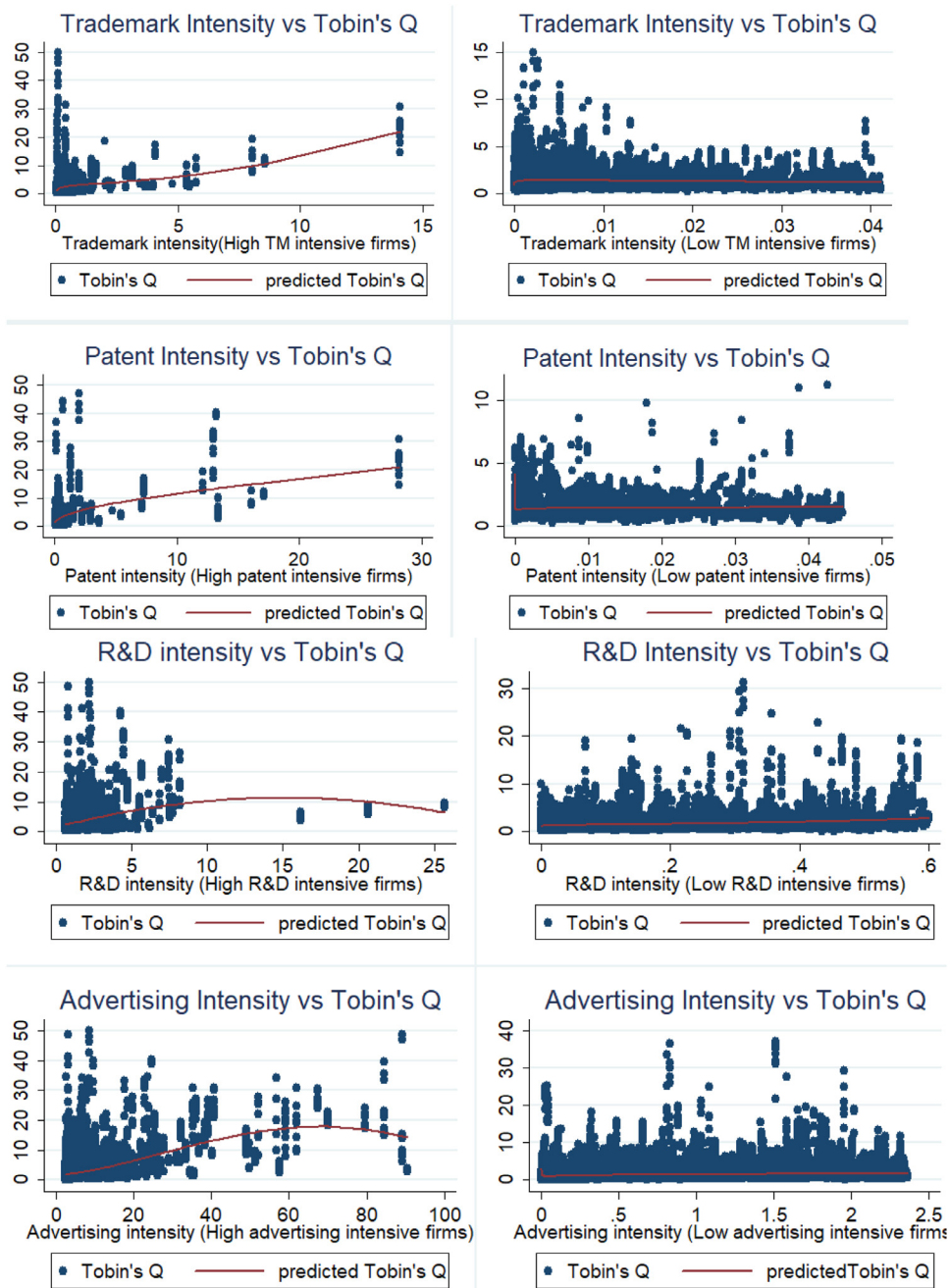
Following the recent global financial crisis, firms made substantial cuts in capital expenses to reduce their vulnerability. Therefore, it can be suggested that firms which chose to maintain their investment in innovation would benefit, or at least, would be less prone to crisis. According to [Archibugi et al. \(2013\)](#), the 2008 economic crisis has severely reduced the short-term willingness to invest in innovation. However, this reduction has not occurred uniformly, and a few firms even increased their investment, despite the adverse macroeconomic environment. When the drivers of innovation investment before and during the crisis were examined, it was found that the crisis led to a concentration of innovative activities within a small group of fast-growing new firms, and those firms were already highly innovative before the crisis. Companies pursuing more explorative strategies towards new product and market developments are better able to cope with the crisis. After an extensive review of the literature on debt and financial constraints, we find that the direct and indirect effects of leverage can be different for innovative firms during the pre- and post-crisis periods. In this paper, we aim to address this issue by looking into pre- and post-crisis and by incorporating the joint impact of debt and IC elements into our analyses. The impact of leverage on firm performance will vary if firms have better innovation capabilities.

Before investigating the impact of innovation and debt on market values across sectors, we first tested our data for the existence of a structural break. This is to empirically show whether there is a significant difference between the two periods investigated (pre-and post-financial crisis). This also helps us to show that the different results in the pre-and post-financial crisis are driven due to a structural break rather than any selection bias. We ran Zivot-Andrews unit root test for the structural break and kept maximum lags at 3, parallel to our model specifications, and the results show that indeed the year 2007 has shown a significant difference and has the minimum critical value. Therefore, this justifies the existence of a structural break in 2007. [Graph 1](#) below, presents the break drawn from the test. Critical values regarding the results of these tests can be found in [Appendix E](#).



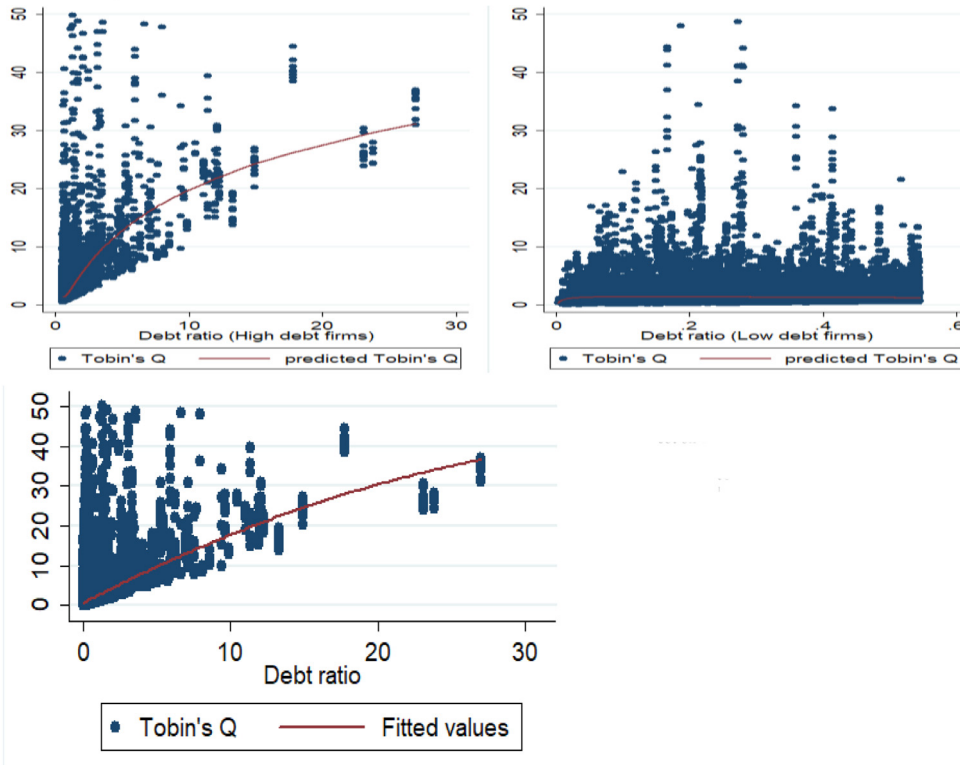
**Table 1**  
Data description and descriptive statistics

<b>Panel 1: Data Description based on firm size</b>																
Variable	Label	All Firms					SMEs (with less than 250 employees)					Large Enterprises				
		Obs	Mean	Std.Dev	Min.	Max	Obs	Mean	Std.Dev.	Min	Max	Obs	Mean	Std.Dev.	Min	Max
Tobinsq	MV/totalassets	137538	1.56	2.02	0.042	49.81	52279	1.94	2.89	0.06	49.80	84279	1.32	1.10	0.04	38.78
RnDintensity	RnDstock/totalAssets (millions in €)	52023	0.57	1.39	0	24.14	29293	0.86	1.87	0	34.84	22730	0.23	0.41	0	4.58
Advertising_intensity	stockSGA/TotalAssets (millions in €)	137538	1.99	4.96	0	95.92	58939	2.69	6.12	0	91.89	78599	1.33	3.35	0	95.92
Patent_intensity	PatentTot/TotalAssets (billions in €)	137538	0.027	0.47	0	28.17	58939	0.06	0.69	0	28.17	78599	0.005	0.13	0	12.22
TM_intensity	TMtotal/TotalAssets (billions in €)	137538	0.028	0.23	0	14.08	58939	0.041	0.37	0	14.08	78599	0.006	0.12	0	9.708
Emp_ratio	Emp/TotalAssets (billions in €)	137538	10.06	50.95	0.002	5200	58939	9.22	62.73	0.002	5200	78599	11.21	27.83	0.01	2734.9
Age	Years since company found	137538	21.80	28.36	0	157	58939	15.9	24.32	0	154	58939	23.29	29.10	0	157
Debtratio	TotalDebts/TotalAssets	137538	0.555	1.35	0.0	31.6	68464	0.58	1.05	0.004	31.07	98356	0.52	0.52	0	29.44



**Fig. 1.** Scatter Plots of Innovation and Tobin's Q

Note: The eight graphs above present the scatterplots of Tobin's Q across innovation intensities. The graphs on the left column represent high intellectual capital intensive firms (namely above the mean) whereas the right column represents low intellectual capital intensive firms (below the mean). First two plots show high and low trademark intensive firms. It is seen that high TM intensive firms have a higher valuation than low TM intensive firms. The impact of TM on Tobin's Q is higher for high TM firms. The second set of plots represents high and low patent firms across Tobin's Q. The plots indicate that high patent-intensive firms have a higher valuation than low patent-intensive firms. The patent intensity and Tobin's Q relation is positive in both low and high patent firms, however the trend is flatter in low patent firms meaning that the impact of patent intensity is lower. The third set of plots represents R&D intensity with Tobin's Q. The plots indicate that R&D intensity has a positive impact on Tobin's Q in both high and low R&D intensive firms. However, high R&D intensive firms portray a different relation with Tobin's Q showing that the relationship is positive up to a point and after the threshold it starts declining, meaning that if the firm has R&D intensity above a certain level, the impact on Tobin's Q starts declining. The same kind of inverse U shaped relation also applies to the fourth set showing Advertising intensity across Tobin's Q. Advertising intensity has a positive impact on Tobin's Q in both high and low advertising intensive firms. However, in high advertising intensive firms, the positive impact of advertising starts declining after a threshold. This suggests that there is an optimal level for both R&D and advertising intensity for firms and after that firms no longer benefit.



**Fig. 2.** Scatter Plots of Debt Ratio and Tobin's Q

Note: Figure above presents scatter plots of Tobin's Q against debt ratio. The first plot shows high leveraged firms whereas the second one shows low leveraged firms. This indicates that the impact of debt on Tobin's Q is positive on both graphs. But the impact of debt on Tobin's Q is exponential, showing that at lower levels of debt the impact increases Tobin's Q higher, and with an increase in debt the increase starts to slow down for high debt firms. The third graph represents a scatter plot of debt ratio across Tobin's Q for full sample, showing the debt-Tobin's Q relationship as positive for whole sample.

Following the structural break test, we ran our benchmark regression model for the pre and post-financial crisis periods to see whether innovation has different impact across firms in the UK (Columns 9–10). We find that in the pre-crisis period, all IC stocks have a positive impact on valuation except trademarks whereas in the post-crisis period trademark and R&D intensity harm valuation. We estimate the following equation in Table 2 as the benchmark.

$$\begin{aligned} \log Tobinsq_{i,t} = & \alpha_0 + \alpha_i + \alpha_t + \beta_1 RnDintensity_{i,t} + \beta_2 PatentInt_{i,t} + \beta_3 TMintensity_{i,t} \\ & + \beta_4 AdverInt_{i,t} + \beta_5 DebtRatio_{i,t} + \beta_6 Empratio_{i,t} + \beta_7 Age_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

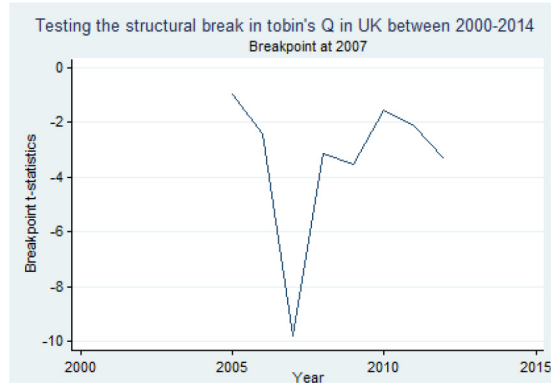
4.2. Investigating the impact of sectoral heterogeneity on the UK firms in the post-crisis

We support the view in the literature such as Hall, 2011, suggesting that the impact of debt on firm performance is inconclusive, and also not all types of leverage are bad; if it is used to generate intellectual assets, it may have a positive impact especially for SMEs and start-ups who need external financing. Firms with various forms of innovation output can access better financing than those with only one type (see Block et al., 2014; Block et al., 2015; Zhou et al., 2014). Start-up firms should emphasize their marketing aspects via trademarks as well as their research orientation via patenting to raise external financing and overcome their financial obstacles (Block et al., 2014). Therefore, creating a set of interaction terms between a firm's financial leverage and knowledge assets can signal how leverage indirectly impacts firms with higher innovation intensities. Therefore, in Table 3, from column 2 onwards we added debt interactions to investigate the joint impact of IC assets and debt on market values. In addition, firms with high R&D intensity may also have high patent intensity but, not all R&D is granted a patent. Therefore, firms focusing jointly on patenting and R&D need further investigation (see Sena et al. (2018)). We used two interaction terms to capture the firms who invest in R&D and have patents jointly and to control for the indirect effect of the firms with high debt, namely: R&D\*patent, and R&D\*patent\*debt. By considering all the above,

**Table 2**  
The impact of IC and debt on Tobin's Q in the pre-and- post crisis periods

	(1)	(2)	(3)	(4)	(5)	(6)	(7) SME	(8) Large	(9) Pre-crisis	(10) Post-crisis
RnD intensity	0.179*** [0.005]				0.0742*** [0.00819]	0.0603*** [0.00825]	0.0696*** [0.0108]	-0.0158 [0.0211]	0.0978*** [0.00980]	-0.0977*** [0.0320]
Patent intensity		0.019*** [0.004]			0.0730*** [0.0112]	0.0652*** [0.0113]	0.0700*** [0.0138]	-0.866*** [0.120]	0.0367* [0.0214]	0.209*** [0.0185]
TM intensity			0.056*** [0.008]		-0.0946*** [0.0182]	-0.0807*** [0.0187]	-0.129*** [0.024]	1.067*** [0.113]	-0.0321 [0.0371]	-0.504*** [0.0534]
Advertising intensity				0.039*** [0.0005]	0.0247*** [0.0014]	0.0190*** [0.0015]	0.0154*** [0.0021]	0.0111*** [0.00386]	0.00719*** [0.00193]	0.0713*** [0.0106]
Debt ratio						0.209*** [0.0195]	0.325*** [0.0304]	-0.0947*** [0.0246]	0.184*** [0.0219]	0.229*** [0.0620]
Empratio						0.00408*** [0.0005]	0.0112*** [0.0011]	0.0325 [0.005]	0.0729*** [0.0639]	0.0266 [0.0256]
Age						0.00199 [0.0781]	0.106 [0.133]	-0.0755 [0.0793]	-0.108 [0.0852]	0.191*** [0.0135]
Constant	0.729*** [0.0252]	0.477*** [0.0134]	0.477*** [0.0133]	0.422*** [0.0151]	0.738*** [0.0279]	0.640 [1.942]	0.151 [1.224]	3.321 [2.898]	3.428 [2.179]	-6.042*** [0.436]
Observations	37444	137371	137371	104711	31,266	31,166	13321	17,845	24,446	6720
Time-Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
F statistic	57.98	122.0	122.2	141.8	49.87	50.00	25.09	36.49	54.59	32.04
F for u <sub>i</sub> =0	94.23	124.8	124.5	107.6	87.25	84.34	60.26	119.0	77.62	99.28
R <sup>2</sup>	0.243	0.0139	0.0138	0.162	0.239	0.150	0.197	0.220	0.186	0.132
R <sup>2</sup> _adjusted	0.186	0.115	0.115	0.166	0.194	0.198	0.227	0.239	0.207	0.170

Notes: 1) Standard errors in brackets 2) \*  $p < .10$  \*\*  $p < .05$  \*\*\*  $p < .01$ . 3) The dependent variable is log Tobin's q, and models are estimated with Fixed Effects Estimation by adding time and company-fixed effects. 4) SMEs are the companies with less than or equal to 250 employees.



**Graph 1.** Testing the structural break in Tobin's Q

Notes: Above graph presents the result of the structural break test, conducted using Zivot- Andrews unit root test. As structural break tests need time-series data, we have taken average of Tobin's Q variable across firms in each year. By this, we obtained a single observation for each year and then on this new series we ran Zivot-Andrews test of a unit root. In our specification, we allowed breaks and imposed three lags.

in Table 3 (from column 2 onwards), we estimate the following equation:

$$\begin{aligned} \log Tobinsq_{i,t} = & \alpha_0 + \alpha_i + \alpha_t + \beta_1 RnDintensity_{i,t} + \beta_2 PatentInt_{i,t} + \beta_3 TMintensity_{i,t} + \beta_4 AdverInt_{i,t} \\ & + \beta_5 DebtRatio_{i,t} + \beta_6 Rnd*patent_{i,t} + \beta_7 Debt*rndint_{i,t} + \beta_8 Debt*patent_{i,t} + \beta_9 Debt*tmint_{i,t} \\ & + \beta_{10} Debt*adverint_{i,t} + \beta_{11} Rnd*patent*debt_{i,t} + \beta_{12} Empratio_{i,t} + \beta_{13} Age_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (5)$$

Column 3 of table 3 shows the estimates for SMEs and column 4 shows the estimates for large firms. The estimation using the full sample in the first column shows that the higher debt ratio only brings better firm performance for firms with higher advertising intensity, while the indirect impact of debt seems to be negative for R&D intensive, patent-intensive and trademark-intensive firms. Additionally, R&D intensity has a positive impact (Column 2) for all firms and Column 3 for SMEs, while the impact is negative and significant for large firms in column 4. Patents and R&D intensities directly influence the firm value of small firms positively in column 3. SMEs with debt indirectly benefit from joint R&D and patent activity whereas patent or R&D activities alone are not enough to boost stock market performance. Large firms differ as they indirectly tend to get a better market valuation from R&D, patent and trademarking along with debt. However, while large firms with no debt get better valuation with additional advertising and trademarking, they do not perform better with additional patenting, or through joint R&D and patenting as they already have enough knowledge stock.

Those types of differences could exist for all firms, and especially in times of financial crisis. Thus, from column 5 onwards we investigate how SMEs and large firms respond to the crisis. SMEs in the pre-crisis period (column 5) benefit from R&D and patents individually, and jointly if the firm uses debt. In addition, the patenting and marketing intensities contribute to firm performance in high-leverage firms. However, for firms with higher debt, R&D only indirectly benefits if supported by patenting. Following the crisis (column 6), this has changed. Focusing on patenting alone reduces firm performance if the firm has high leverage. R&D and patents contribute to the performance of small firms with high leverage only if they are done jointly suggesting that the impact is indirect. Large firms in general benefit from marketing and trademarks pre-crisis (column 7) and advertising and patenting in the post-crisis (column 8). Also, firms with debt can benefit from advertising, and focusing on R&D jointly with patenting could benefit firms during the post-crisis times.

According to the nature of the industry that the firm operates in, some firms, for instance, use more patenting whereas some prefer to keep inventions in the form of trade secrets. Therefore, it is arguable that the sectoral heterogeneity may cause differences in innovation-firm performance relation in general, as well as in the post-crisis periods. This leads the analysis to a sectoral level in Table 4. We used three-sector classification (Fisher, 1939) and classified them into primary, secondary and tertiary sectors. The primary sector mainly covers natural resources and raw materials, namely agriculture and mining. The secondary sector is the production sector and covers manufacturing and EGW construction industries. The tertiary sector is the services sector including knowledge-intensive ICT sectors, and it covers wholesale, retail, hotels, transportation and telecommunications, finance and real estate, professional, scientific, and technical activities, and health, education, and culture industries. The sectoral classification is kept consistent throughout the paper to prevent repetition; the terms "primary, secondary, tertiary sectors" and "raw materials, production (manufacturing), services sectors" are used interchangeably.

Thus, the sectoral results covering all periods are presented in Table 4 from columns 1-4-7. These results suggest that the primary sector in general, benefits from patenting, trademarking, and advertising activities, while firms in this category benefit indirectly from advertising and trademark activities along with debt. The secondary sector firms benefit from R&D,



**Table 3**

The impact of IC and leverage Tobin's Q for different company sizes.

All sectors ALL FIRMS	Benchmark		SIZE		SME	SME	Large	Large
	(1) ALL	(2) All Firms	(3) SME	(4) LARGE	(5) Pre-Crisis	(6) Post-Crisis	(7) Pre-Crisis	(8) Post-Crisis
RnDintensity	0.0603*** [0.00825]	0.0484*** [0.00772]	0.0459*** [0.0103]	-0.0816*** [0.0264]	0.131*** [0.0185]	0.0190 [0.0203]	0.107** [0.0426]	0.237*** [0.0513]
Patent_intensity	0.0652*** [0.0113]	0.329*** [0.0456]	0.432*** [0.0571]	-1.686*** [0.284]	1.326*** [0.130]	0.820*** [0.137]	0.266 [0.853]	0.595*** [0.693]
TM_intensity	-0.0807*** [0.0187]	-0.0355 [0.0219]	-0.123*** [0.0280]	0.806*** [0.155]	-0.0291 [0.0747]	-0.175*** [0.0663]	1.721*** [0.363]	-0.221*** [0.422]
Advertising_intensity	0.0190*** [0.00146]	0.0127*** [0.00196]	0.0153*** [0.00304]	0.0168*** [0.00505]	-0.0018 [0.0037]	0.0446*** [0.0096]	0.0179*** [0.00595]	0.0512* [0.027]
Debt ratio	0.209*** [0.0195]	0.152*** [0.0243]	0.341*** [0.0443]	-0.220*** [0.0404]	0.167** [0.065]	0.582*** [0.0989]	-0.271*** [0.0491]	-0.0366 [0.103]
Rndxpatent		-0.0540*** [0.00975]	-0.076*** [0.0121]	1.235* [0.847]	-0.33*** [0.0245]	-0.533*** [0.0514]	-0.173*** [0.356]	-0.933*** [0.126]
<b>Debt interactions</b>								
Debtxrndint		-0.0274*** [0.00344]	-0.024*** [0.00446]	0.291*** [0.0433]	0.00976 [0.0152]	-0.0151 [0.0107]	-0.0251 [0.0741]	-2.400*** [0.245]
Debtxpatent		-0.125*** [0.0376]	-0.217*** [0.0463]	1.155*** [1.453]	0.794** [0.337]	-0.496*** [0.133]	0.118** [0.521]	-0.161*** [0.251]
Debtxtmint		-0.0216 [0.0702]	0.111 [0.0853]	0.454*** [1.065]	-0.229 [0.267]	0.319 [0.291]	0.447 [0.369]	-0.516*** [0.184]
Debtxadvertint		0.0114*** [0.00160]	0.00420* [0.00235]	-0.0517*** [0.0191]	0.00576* [0.0031]	-0.003 [0.0066]	-0.000634 [0.0229]	0.152* [0.0781]
Rndxpatentxdebt		0.0412*** [0.009]	0.0615*** [0.011]	-0.590*** [1.016]	0.265*** [0.0212]	0.765*** [0.068]	0.277 [0.24]	0.326*** [0.278]
<b>Control Variables</b>								
Empratio	0.00408*** [0.000544]	0.0047*** [0.000551]	0.0116*** [0.0012]	0.00011 [0.0006]	0.020*** [0.0015]	-0.0025 [0.0021]	0.0566 [0.0064]	-0.0021 [0.001]
Age	0.00199 [0.0781]	-0.0285 [0.0782]	0.0916 [0.134]	-0.0776 [0.0789]	0.412*** [0.156]	-0.0963 [0.0196]	-0.036*** [0.0054]	0.0012 [0.009]
Constant	0.640 [1.942]	1.402 [1.940]	0.261 [1.226]	3.423 [2.887]	-3.338** [1.606]	0.238 [0.313]	1.965*** [0.222]	0.244 [0.371]
Observations	31,166	31,202	13,417	17,785	9256	4161	11,156	5206
Time Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
F statistics	50.00	48.98	24.85	36.42	31.98	23.11	40.56	29.12
F test for $\alpha_i=0$	84.34	84.69	60.32	119.0	61.20	64.09	97.14	139.1
R <sup>2</sup>	0.198	0.201	0.231	0.247	0.281	0.257	0.263	0.256
R <sup>2</sup> _adjusted	0.178	0.181	0.201	0.227	0.247	0.217	0.240	0.225

Notes: 1) Standard errors in brackets 2) \*  $p < .10$  \*\*  $p < .05$  \*\*\*  $p < .01$ . 3) The dependent variable is log Tobin's q, and models are estimated with Fixed Effects Estimation by adding time and company-fixed effects. 4) The primary sector is raw materials which cover agriculture and mining industry. The secondary sector is manufacturing sector including EGW and construction sectors. The tertiary sector is service industries including wholesale, retail, transport, telecom, finance, real estate, professional and scientific activities, education, health, and culture.

**Table 4**

The impact of debt and IC on the MV of UK firms: 3 sector model in pre- and post-crisis.

Sectors	Primary			Secondary			Tertiary			All sectors	
	(1) All	(2) Pre	(3) Post	(4) All	(5) Pre	(6) Post	(7) All	(8) Pre	(9) Post	(10) Pre	(11) Post
RnD intensity	−0.296* [0.177]	−0.320* [0.169]	−0.434 [0.668]	0.196*** [0.0308]	0.402*** [0.0398]	−0.361*** [0.0488]	0.063*** [0.0107]	0.111*** [0.0246]	0.0417* [0.0213]	0.102*** [0.0140]	−0.0290* [0.0151]
Patent intensity	1.196 [2.195]	0.579 [0.208]	0.761 [0.783]	0.290*** [0.111]	0.372** [0.161]	1.084*** [0.238]	0.196*** [0.0603]	−2.326*** [0.410]	0.737*** [0.155]	0.847*** [0.105]	0.838*** [0.105]
TM intensity	2.22*** [3.978]	0.470*** [0.099]	0.130** [0.616]	−0.0371 [0.0717]	0.871*** [0.166]	0.0102 [0.0861]	−0.0235 [0.0296]	−0.169** [0.0807]	−0.481*** [0.0817]	−0.0638 [0.0626]	−0.242*** [0.0504]
Advertising intensity	0.109*** [0.0250]	0.136*** [0.0264]	0.205 [0.193]	0.054*** [0.00627]	−0.00023 [0.008]	0.0668*** [0.0153]	−0.02*** [0.0001]	−0.0119** [0.00560]	0.0189* [0.0103]	0.00361* [0.00242]	0.0503*** [0.00707]
Debtratio	0.226* [0.134]	0.567*** [0.198]	−0.814* [0.441]	0.0128 [0.0472]	−0.122 [0.0853]	0.00125 [0.0864]	0.604*** [0.0479]	0.203*** [0.0677]	−0.377*** [0.145]	−0.110*** [0.0336]	0.219*** [0.0562]
Rndxpatent	0.707 [0.127]	0.354 [0.101]	−0.867 [0.090]	−0.496*** [0.160]	0.0781 [0.354]	−2.034*** [0.716]	−0.013 [0.013]	0.431*** [0.049]	−0.518*** [0.0522]	−0.232*** [0.0199]	−0.542*** [0.0397]
<b>Debt interactions</b>											
Debtxrndint	−0.51*** [0.042]	−0.480*** [0.452]	−0.171*** [0.355]	−0.109*** [0.0377]	−0.485*** [0.0865]	−0.113 [0.0889]	−0.02*** [0.005]	−0.00679 [0.0175]	−0.218*** [0.0530]	0.0316*** [0.0121]	−0.00280 [0.00791]
Debtxpatent	2.532 [1.444]	−0.734 [0.093]	−0.819 [0.149]	−1.579*** [0.380]	0.620 [1.355]	−0.888 [0.641]	−0.0313 [0.0490]	1.418*** [0.340]	−0.678*** [0.145]	1.728*** [0.286]	−0.560*** [0.101]
Debtxtmint	1.470** [0.073]	−0.238** [0.117]	−0.203 [0.261]	1.067* [0.595]	−0.309*** [0.109]	−1.896** [0.829]	−0.187** [0.0879]	0.189 [0.274]	0.907*** [0.300]	−0.232 [0.228]	0.537** [0.222]
Debtxadvertint	0.82*** [0.0716]	0.731*** [0.0743]	0.208*** [0.043]	−0.009* [0.0047]	0.139*** [0.0434]	0.0160 [0.0116]	0.0056* [0.003]	0.021*** [0.004]	0.146** [0.0356]	0.0166*** [0.00231]	−0.00222 [0.00489]
Rndxpatentxdebt	−0.297 [0.648]	0.257 [0.438]	0.580 [0.860]	0.205*** [0.051]	−0.311 [1.104]	0.583*** [0.0932]	0.0045 [0.0118]	−0.54*** [0.0597]	0.827*** [0.0670]	0.186*** [0.0174]	0.797*** [0.0525]
<b>Control Variables</b>											
Emp	−0.02*** [0.005]	−0.033*** [0.0104]	0.00311 [0.0107]	−0.0013** [0.0006]	0.009 [0.067]	−0.0038** [0.0015]	0.02*** [0.0015]	0.020*** [0.002]	0.019*** [0.004]	0.0065*** [0.0007]	−0.00149 [0.002]
Age	−0.0311 [0.033]	−0.0171 [0.0302]	0.0165 [0.0267]	−0.023*** [0.005]	−0.0320*** [0.0066]	0.0256** [0.0112]	−0.0443 [0.089]	0.127 [0.108]	0.0010 [0.017]	0.138 [0.0950]	0.0162 [0.010]
Constant	1.230 [1.243]	0.779 [1.258]	−0.744 [1.141]	1.305*** [0.201]	1.648*** [0.264]	−0.691 [0.460]	1.547 [1.231]	−0.861 [1.825]	0.0045 [0.336]	−2.993 [2.489]	−0.333 [0.306]
Observations	1865	1047	818	13007	8725	4282	10617	6350	4267	21,835	9367
Time Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
F statistics	6.163	4.954	12.70	27.80	25.73	48.38	22.17	28.88	14.05	57.76	47.24
F test for $u_i=0$	110.6	95.82	72.30	124.3	109.6	139.4	74.70	66.19	70.76	76.19	94.66
R <sup>2</sup>	0.362	0.366	0.504	0.254	0.245	0.410	0.252	0.339	0.169	0.227	0.236
R <sup>2</sup> _adjusted	0.293	0.278	0.450	0.235	0.222	0.384	0.225	0.309	0.129	0.205	0.207

Notes: 1) Standard errors in brackets 2) \*  $p < .10$  \*\*  $p < .05$  \*\*\*  $p < .01$ . 3) The dependent variable is log Tobin's q, and models are estimated with Fixed Effects Estimation including firm and time fixed effects. 4) The primary sector is raw materials which cover agriculture and mining industry. The secondary sector is manufacturing sector including EGW and construction sectors. The tertiary sector is service industries including wholesale, retail, transport, telecom, finance, real estate, professional and scientific activities, education, health, and culture. 5) Columns 1,4,7 represent all firms in three sectors, respectively. Columns 2-3 show primary sector before and after the crisis. Columns 5-6 for secondary and columns 7-8 for the tertiary sector. Columns 10-11 show before and after the crisis for all firms.

**Table 5**  
The impact of debt and IC on the MV of UK firms: alternative sectoral classification.

Tobin's Q	High Tech& KIS			Low Tech& KIS		
	(1) All	(2) Pre	(3) Post	(4) All	(5) Pre	(6) Post
L.logtobinsq	0.805*** [0.000203]	0.837*** [0.000721]	0.673*** [0.00221]	0.883*** [0.00665]	0.888*** [0.00642]	0.703*** [0.0141]
RnDintensity	0.0772*** [0.000806]	0.0908*** [0.00347]	0.141*** [0.00746]	-0.0101 [0.0431]	-0.00346 [0.0484]	0.697*** [0.135]
Patent_intensity	0.214*** [0.00215]	1.047*** [0.0181]	0.250*** [0.0130]	0.189 [0.348]	-2.614*** [0.330]	-0.872 [1.349]
TM_intensity	-0.149*** [0.00100]	-0.167*** [0.0149]	-0.155*** [0.0160]	0.0680 [0.165]	0.272 [0.474]	-2.042** [0.884]
Advertising_intensity	0.0227*** [0.000148]	0.0249*** [0.000577]	0.00650** [0.00264]	0.0488** [0.0205]	0.0420** [0.0191]	0.0562 [0.0444]
Debt ratio	0.232*** [0.00224]	0.162*** [0.0102]	0.0740*** [0.0219]	0.172*** [0.0643]	0.141** [0.0614]	0.0995 [0.186]
Rndxpatent	-0.0201*** [0.000451]	-0.207*** [0.00462]	-0.0240*** [0.00272]	0.203 [1.222]	1.834*** [1.594]	2.791 [2.613]
<b>Debt interactions</b>						
Debtxrndint	0.0226*** [0.000410]	0.0177*** [0.00233]	0.00745 [0.0145]	0.223 [0.310]	0.160 [0.248]	-0.124 [0.657]
Debtxpatent	-0.0812*** [0.00179]	-0.881*** [0.0199]	-0.458*** [0.0253]	2.911 [2.813]	2.552*** [1.805]	0.544 [4.683]
Debtxadvertint	-0.00893*** [0.000105]	-0.00797*** [0.000390]	-0.00924*** [0.00229]	-0.0658 [0.0609]	-0.0571 [0.0433]	0.327* [0.201]
Debtxtmint	-0.0322*** [0.00154]	0.145*** [0.0265]	0.931*** [0.0589]	-7.612 [5.126]	-1.320*** [2.699]	5.868 [6.786]
Rndxpatentxdebt	0.0749*** [0.0039]	0.164*** [0.00490]	0.0983*** [0.00564]	1.146 [1.533]	-1.075*** [7.587]	-8.596* [4.861]
<b>Control Variables</b>						
Emp	0.00322*** [0.0000321]	0.00434*** [0.000166]	0.00474*** [0.000335]	-0.000594 [0.00396]	0.0000861 [0.00246]	-0.0189*** [0.00452]
Age	-0.000699*** [0.0000201]	-0.000610*** [0.0000629]	0.00525*** [0.000183]	-0.00115 [0.00287]	-0.00170 [0.00109]	-0.00131** [0.000638]
Constant	-0.0438*** [0.000532]	-0.0768*** [0.00194]	-0.179*** [0.00629]	-0.0180 [0.113]	0.0127 [0.0407]	0.0194 [0.0213]
Observations	24721	17659	7062	5829	4249	1580
p> Wald (Chi2)	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
R <sup>2</sup> adj	0.885	0.834	0.785	0.929	0.928	0.810
Sargan	480.1	390.5	202.2	68.96	62.12	49.40
p> Sargan (Chi2)	0.9955	0.245	0.2749	0.999	0.998	0.998
AR (1)	-5.6313***	-6.011***	-2.383***	-4.591***	-4.570***	-3.049***
AR (2)	0.2348	-0.505	0.677	0.204	-0.670	-1.045
Instruments	579	387	206	439	435	122

Notes: 1) Standard errors in brackets 2) \*  $p < .10$  \*\*  $p < .05$  \*\*\*  $p < .01$ . 3) The dependent variable is the natural logarithm of Tobin's Q and the models are estimated by using Dynamic System GMM estimations. 4) The sectors are constructed using Eurostat indicators on High-Tech and Knowledge-intensive sectors based on NACE level 2 classifications. KIS represents Knowledge Intensive Service Sectors. 5) In our estimations, as we have only level 1 serial correlation, we limited our maximum lagged variables to be instrumented to lag 3. Also, the following diagnostic tests ensured the validity of the GMM estimations: Sargan test, Arellano-Bond test and Wald Chi-Square test. 6) Pre and post indicate before and after the Global Financial Crisis.

patenting, and advertising activities, while trademarking indirectly boosts the performance of the firms with high debt. Indebted firms in the secondary sector may also get higher market valuation if they jointly focus on R&D and patenting. Patents and R&D also have positive impact on market values in the tertiary sector, while advertising indirectly improves firm performance.

Moreover, in Table 4, columns 2–3 show primary sector, columns 5–6 the secondary and columns 7–8 show the tertiary sector, while Columns 10–11 look at the pre- and post-crisis at an aggregate level. All UK firms in general benefit from R&D and patents in the pre-crisis. Also, increasing the advertising intensity for high-leverage firms helps boost market values. Also, R&D only contributes to better performance in debt-intensive firms if supported by patent, in the post-crisis. Firms in the secondary sector directly benefit from R&D, patent, and trademark in the pre-crisis period, and indirectly from marketing if the firm has high debt. In the post-crisis period, firms in the secondary sector directly benefit from marketing and patenting. Focusing on R&D alone does not improve stock performance following the crisis, in the secondary sector firms. In the tertiary sector, R&D directly provides better performance whereas patenting only provides better performance in the tertiary sector if it is jointly done with R&D.

#### 4.2.1. The impact of debt and IC on valuation in pre-and post-crisis periods: an alternative sectoral classification

Initially, we used the three-sector classifications to analyze the impact of debt and IC in the market valuation of UK firms. Here, we carry out our investigations further by introducing an alternative sectoral classification. We check whether an al-

**Table 6**  
The impact of debt and IC on the valuation uncertainty of UK firms.

Dept variable: Stdev_Q	(1)	(2)	(3) Pre-crisis	(4) Post-Crisis
Stdev_Q <sub>(t-1)</sub>	0.393*** [0.00003]	0.388*** [0.00005]	0.714*** [0.00002]	0.117*** [0.00008]
RnDintensity	-0.315*** [0.0009]	-0.404*** [0.0016]	-0.247*** [0.00115]	-1.401*** [0.0318]
Patent_intensity	-0.148*** [0.0008]	-1.764*** [0.0142]	-0.679*** [0.0084]	-6.153*** [0.197]
TM_intensity	0.251*** [0.001]	0.324*** [0.0031]	-0.205*** [0.00642]	1.049*** [0.0449]
Advertising_intensity	0.0343*** [0.0003]	0.0146*** [0.0005]	0.0164*** [0.0003]	0.0339*** [0.0093]
Debratio	-0.331*** [0.0013]	0.859*** [0.007]	-0.490*** [0.006]	-2.003*** [0.086]
Rndxpatent		0.761*** [0.00317]	0.463*** [0.00189]	5.949*** [0.537]
<b>Debt Interactions</b>				
Debtxrndint		-0.0847*** [0.0117]	0.418*** [0.0101]	-0.607*** [0.137]
Debttxpatent		-2.264*** [0.128]	-0.722 [0.707]	-4.385*** [0.195]
Debtxadvertint		0.171*** [0.00283]	0.0360*** [0.00224]	0.790*** [0.0633]
Debtxtmint		1.900*** [0.0212]	-4.316*** [0.177]	2.262*** [0.361]
Rndxpatentxdebt		3.544*** [0.109]	2.530*** [3.414]	-1.833* [1.602]
<b>Control Variables</b>				
Emp	-0.00512*** [0.002]	-0.00506*** [0.005]	-0.00804*** [0.008]	-0.00302*** [0.004]
Age	-0.00652*** [0.003]	-0.00611*** [0.001]	-0.00673*** [0.007]	-0.0114*** [0.005]
Constant	0.401*** [0.0003]	0.515*** [0.0011]	0.423*** [0.0005]	1.055*** [0.008]
Observations	7357	7357	5233	1593
p > Wald (Chi <sup>2</sup> )	0.001	0.001	0.001	0.001
R <sup>2</sup> adj	0.0809	0.091	0.0748	0.11
Sargan	240.1	229.5	195.4	75.62
p>Sargan (Chi <sup>2</sup> )	1.00	1.00	1.00	1.00
AR (1)	-1.241	-1.240	-2.109***	-1.018
AR (2)	0.0636	0.0457	-1.579	0.320
Instruments	357	621	470	206

Notes: 1) Standard errors in brackets 2) \*  $p < .10$  \*\*  $p < .05$  \*\*\*  $p < .01$ . 3) The dependent variable is the natural logarithm of Tobin's Q and the models are estimated by using Dynamic System GMM estimation methodology. 4) In our estimations, as we have only order 1 serial correlation, we limited our maximum lagged variables to be instrumented to lag 3. 5) The diagnostic tests ensured the validity of the GMM estimations: Sargan test, Arellano-Bond test and Wald Chi-Square test. 6) Pre- and post-crisis indicate before and after the Global Financial Crisis.

ternative classification of sectors (see studies such as [Pieri et al. \(2018\)](#) and [Mallick and Sousa \(2017\)](#)) would yield similar results with our initial three-sector classification. For instance, [Pieri et al. \(2018\)](#) had ICT sectors and classified firms such as high-tech and low-tech, high-knowledge intensive, and low-knowledge intensive, whereas [Mallick and Sousa \(2017\)](#) had manufacturing sector and classified firms as production-intensive, supplier-dominated and science-based manufacturing. The sectors are constructed using Eurostat indicators on High-Tech and Knowledge-intensive sectors based on NACE level 2 classifications.

On the other hand, in our study, we look at the UK market at an aggregate level by including all sectors. As our measure of IC is not limited to R&D or patents, but also covers trademark and advertising assets, being in the service sector does not mean that they are less-knowledge intensive *per se*. All firms producing knowledge are embedded in IC stocks. Therefore, parallel to the classifications in [Pieri et al. \(2018\)](#) and [Mallick and Sousa \(2017\)](#), we divided our sample into two sectors. The first sector covers the companies in high tech manufacturing and high knowledge-intensive service sectors (KIS), and the second sector covers low-tech and low knowledge-intensive service sectors (KIS). [Table 5](#) below presents our two-sector results. Columns 1–3 focus on high-technology intensive manufacturing and knowledge-intensive service sectors, whereas columns 4–6 covers low-technology intensive manufacturing and knowledge-intensive service sectors. Results show that high-tech sectors benefit from R&D and patenting both directly and indirectly through their joint impact, regardless of their debt-intensity, and low-tech sectors benefit from marketing and advertising. Also, in the post-crisis period, low-tech sectors with high debt can benefit from marketing and trademarks.

**Table 7**

The impact of debt and IC on the valuation uncertainty: A sectoral classification.

Stdev_Q	High Tech& KIS			Low Tech& KIS		
	(1) All	(2) Pre	(3) Post	(4) All	(5) Pre	(6) Post
Stdev_Q <sub>(t-1)</sub>	0.291*** [0.00129]	0.383*** [0.0008]	0.168*** [0.0081]	0.279*** [0.027]	0.617*** [0.034]	0.114*** [0.042]
RnDintensity	-0.287** [0.136]	0.0320 [0.035]	-0.819*** [0.273]	-1.057* [0.575]	-0.423 [0.541]	-2.295 [1.482]
Patent_intensity	1.724* [1.008]	-5.663*** [0.660]	1.882 [5.755]	7.611*** [2.520]	4.348 [327.2]	1.887 [0.511]
TM_intensity	0.474 [0.315]	0.875* [0.451]	-0.611 [0.796]	-9.904 [9.918]	-2.891** [14.04]	-1.043 [1.800]
Advertising_intensity	0.148*** [0.036]	0.0697*** [0.0121]	0.306*** [0.097]	0.389* [0.231]	0.191 [0.201]	1.173* [0.613]
Debtratio	1.636** [0.706]	0.312** [0.132]	1.889 [1.498]	1.515 [1.132]	0.00432 [0.897]	8.074** [3.431]
Rndxpatent	-0.445** [0.217]	0.929*** [0.101]	-4.072* [12.60]	-7.054*** [2.361]	-3.1346 [4.304]	-2.7827* [4.2299]
<b>Debt interactions</b>						
Debtxrndint	0.958 [0.942]	-1.447*** [0.315]	4.325*** [0.835]	4.124* [2.162]	2.421 [1.744]	6.411 [7.821]
Debtxpatent	-3.450 [4.808]	3.750*** [0.395]	-6.987 [29.61]	-6.931 [1391.8]	-2.9140 [1.798]	3.4197 [2.9352]
Debtxadvertint	-0.671* [0.369]	0.449*** [0.111]	-1.914*** [0.383]	-1.318** [0.670]	-0.754 [0.494]	-4.754** [2.231]
Debtxtmint	-1.293*** [0.427]	-2.564*** [0.421]	-1.752 [7.147]	0.9621 [0.6438]	1.532 [2.436]	1.032 [1.037]
Rndxpatentxdebit	1.851*** [0.437]	4.675*** [0.489]	2.895 [0.444]	2.114* [1.136]	3.8127 [3.666]	2.100 [2.0743]
<b>Control Variables</b>						
Emp	0.0025* [0.0013]	-0.0081*** [0.001]	0.0049 [0.007]	-0.0111 [0.037]	0.0083 [0.0301]	-0.125 [0.137]
Age	0.00140 [0.0012]	0.0106*** [0.0004]	-0.011*** [0.003]	-0.0038 [0.003]	-0.0014 [0.003]	-0.00131 [0.008]
Constant	-2.534*** [0.0531]	-2.375*** [0.0206]	-2.434*** [0.186]	-2.585*** [0.285]	-1.248*** [0.272]	-4.165*** [0.844]
Observations	5642	4140	1118	1556	998	558
p>Wald(chi2)	0.00001	0.00001	0.0001	0.00001	0.0001	0.0194
R <sup>2</sup> adj	0.145	0.126	0.0336	0.100	0.677	0.207
Sargan	187.6	163.6	55.61	342.5	336.9	135.1
p>Sargan (Chi2)	0.9999	0.8904	0.9996	0.0798	0.0112	0.9939
AR (1)	-2.164**	-1.827*	-1.120	-1.2014	-1.185	-1.193
AR (2)	-1.392	-1.062	-0.312	-0.504	-0.669	-0.453
Instruments	475	202	110	322	295	194

Notes: 1) Standard errors in brackets 2) \*  $p < .10$  \*\*  $p < .05$  \*\*\*  $p < .01$ . 3) The dependent variable is the standard deviation of Tobin's Q and models are estimated by using Dynamic System GMM estimation methodology. The standard deviation of Tobin's Q is an indication of valuation uncertainty. 4) The sectors are constructed using Eurostat indicators on High-Tech and Knowledge-intensive sectors based on NACE level 2 classifications. KIS represents Knowledge Intensive Service Sectors. 5) In our estimations, as we have only order 1 serial correlation, we limited our maximum lagged variables to be instrumented to lag 3. Also, the following diagnostic tests ensured the validity of the GMM estimations: Sargan test, Arellano-Bond test, Wald- Chi-Square test. 6) Pre- and post-crisis periods indicate before and after the Global Financial Crisis.

#### 4.2.2. The impact of debt and IC on valuation uncertainty of the UK firms in pre- and post-crisis

According to Guerzoni et al. (2014) and Audretsch et al. (2012), firms with a greater number of patents can signal appropriability to the market and investors and are more likely to have access to external financing. Both debt and equity financing play an important role in firm performance as different firms may have different capital structures. Market prices may fluctuate during the crisis periods; therefore, the role of debt structure and intellectual capital intensities might have an important role in reducing the uncertainty created during bad times. In Table 6 we test the role of debt and intellectual capital intensities on valuation uncertainty of the UK firms. Here, the dependent variable Tobin's Q has been replaced with the standard deviation of Tobin's Q, indicated by "stdev\_Q" in this table. The standard deviation of Tobin's Q is an indication of valuation uncertainty and is calculated using a moving standard deviation over time. We started with first three observations (1 to 3), followed by observations 2 to 4, 3 to 5 etc., which helped us to have a time series, with only losing 2 observations overall.

The first column of Table 6 shows the benchmark results. Column 2 introduces the debt and intellectual capital interaction terms and suggests that R&D, patent and debt intensities reduce the price uncertainty both directly and indirectly. Column 3 shows the uncertainty equation in the pre-crisis period, whereas column 4 estimates the post-crisis period. In the pre-crisis period, R&D, patent, trademark directly reduce the valuation uncertainty while patent and trademarks have



an indirect role in reducing the valuation uncertainty of high-debt firms. In the post-crisis period, R&D, patents and debt reduce the uncertainty both directly and indirectly. As opposed to the pre-crisis period, trademarking is less effective in reducing the valuation uncertainty for high debt firms in the post-crisis period. Therefore, firms, especially high-debt ones should focus on patenting and R&D activities that help alleviate the valuation uncertainty in the post-crisis period.

Similarly, in Table 7, we carry out further investigations by checking whether sectoral classification (see studies such as (Pieri et al., 2018) and (Mallick and Sousa, 2017)) matters in reducing valuation uncertainty of the UK firms in the pre- and post-crisis periods. Parallel to Pieri et al., 2018), the first sector covers the companies in high tech manufacturing and high knowledge-intensive service sectors (KIS), and the second sector covers low-tech and low knowledge-intensive service sectors (KIS). Columns 1-3 focus on high-technology intensive manufacturing and knowledge-intensive service sectors, whereas columns 4-6 cover low-technology intensive manufacturing and knowledge-intensive service sectors. Both sectors are analyzed for the whole sample, in the pre- and the post-crisis periods, respectively. We find that focusing on patenting and R&D may help to reduce the valuation uncertainty of high-tech firms, whereas for the low-tech firms, trademark and advertising contribute to a reduction in valuation uncertainty.

4.3. Robustness checks

4.3.1. The impact of debt and IC on MV of the UK firms: 3-sector model with firm sizes

As the main empirical investigations have shown, firms with different sizes benefit differently from IC. Therefore, in our first robustness check, we carried our investigation further by separating the sample by sectors and firm size. We find that SMEs in the primary sector get better valuation by focusing on advertising activities, while larger firms in the primary

**Table 8**  
Robustness 1: The impact of debt and IC on MV of the UK firms: 3-sector model with different firm sizes

All sectors ALL FIRMS	Primary (1) SME	Secondary (2) SME	Tertiary (3) SME	Primary (4) LARGE	Secondary (5) LARGE	Tertiary (6) LARGE
RnDintensity	-0.558 [0.541]	0.489*** [0.0600]	0.036*** [0.0137]	-0.972 [0.815]	-0.26*** [0.0407]	0.512*** [0.0457]
Patent_intensity	-	1.322*** [0.183]	0.273*** [0.0682]	0.377*** [0.0134]	-1.951*** [0.302]	-2.207** [0.886]
TM_intensity	-	0.167* [0.0955]	-0.14*** [0.035]	0.163*** [0.241]	0.521* [0.273]	-0.442** [0.213]
Advertising_intensity	1.226 [0.993]	0.0290** [0.0125]	-0.0058 [0.0057]	0.0373 [0.0445]	0.038*** [0.0109]	-0.05*** [0.0076]
Debratio	0.456*** [0.106]	0.237** [0.114]	0.688*** [0.064]	-0.155 [0.130]	-0.112 [0.0702]	0.546*** [0.0862]
Rndxpatent	-	-0.250*** [0.372]	-0.029** [0.015]	-0.212** [0.0848]	0.484*** [0.114]	0.306 [0.024]
<b>Debt interactions</b>						
Debtxrndint	0.746 [0.951]	-0.435*** [0.150]	-0.0092 [0.0062]	-0.66*** [0.184]	0.791*** [0.0662]	-1.49*** [0.105]
Debtxpathent	-	-0.349*** [0.722]	-0.106* [0.0549]	-0.33*** [0.106]	0.117*** [0.017]	0.264* [0.136]
Debtxtmint	-	-0.733 [0.933]	-0.0363 [0.0976]	0.152*** [0.0447]	0.730*** [0.15]	-0.129*** [0.031]
Debtxadvertint	-0.583 [1.749]	0.0164 [0.0135]	-0.0073* [0.0038]	0.171 [0.108]	-0.263*** [0.043]	0.232*** [0.0319]
Rndxpatentxdebt	-	0.791*** [1.19]	0.0226* [0.013]	0.197*** [0.053]	-8.237*** [1.225]	-0.763 [0.537]
<b>Control Variables</b>						
Empratio	0.0371 [0.0325]	-0.008 [0.018]	0.025*** [0.002]	-0.0147 [0.042]	0.002 [0.069]	0.006** [0.0025]
Age	-0.32*** [0.0924]	0.096*** [0.013]	0.123 [0.141]	-0.013 [0.020]	-0.016*** [0.0045]	-0.124 [0.0799]
Constant	3.945** [1.742]	2.211*** [0.279]	0.423 [0.990]	0.618 [0.869]	1.28*** [0.227]	3.641* [1.937]
Observations	285	4321	6464	1580	8686	4153
Time Fixed Effects	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
F statistics	3.376	12.86	14.33	6.455	22.06	14.97
F test for u_i=0	17.99	77.01	66.24	108.5	144.4	105.0
R <sup>2</sup>	0.795	0.328	0.267	0.416	0.289	0.373
R <sup>2</sup> _adjusted	0.548	0.290	0.228	0.343	0.266	0.337

Notes: 1) Standard errors in brackets 2) \*  $p < .10$  \*\*  $p < .05$  \*\*\*  $p < .01$ . 3) The dependent variable is log Tobin's q, and models are estimated with Fixed Effects Estimation by adding time and company-fixed effects. 4) The primary sector is raw materials which cover agriculture and mining industry. The secondary sector is manufacturing sector including EGW and construction sectors. The tertiary sector is service industries including wholesale, retail, transport, telecom, finance, real estate, professional and scientific activities, education, health, and culture. 5) SMEs are companies with less than or equal to 250 employees.

Table 9

Robustness 2: The impact of debt and IC on MV of the UK firms: 3-sector model with different firm sizes in pre-and post-crisis.

	Primary Sector		Secondary Sector		Tertiary Sector		Primary Sector		Secondary Sector		Tertiary Sector	
	<i>SME</i>	<i>SME</i>	<i>SME</i>	<i>SME</i>	<i>SME</i>	<i>SME</i>	<i>Large</i>	<i>Large</i>	<i>Large</i>	<i>Large</i>	<i>Large</i>	<i>Large</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(9)	(10)	(11)	(12)	(13)	(14)
	Pre-Crisis	Post-Crisis	Pre-Crisis	Post-Crisis	Pre-Crisis	Post-Crisis	Pre-Crisis	Post-Crisis	Pre-Crisis	Post-Crisis	Pre-Crisis	Post-Crisis
R&Dintensity	.	.	0.649***	−0.814***	0.0626*	0.0530**	−0.536***	0.531	0.0291	−0.370***	0.566***	−0.268**
			[0.0798]	[0.233]	[0.0320]	[0.0264]	[0.119]	[0.366]	[0.0744]	[0.0633]	[0.0708]	[0.133]
Patent intensity	.	.	0.823***	1.297***	−0.558	0.852***	−0.705	0.189***	0.324***	0.435***	1.013***	0.571
			[0.232]	[0.278]	[0.471]	[0.188]	[0.119]	[0.425]	[0.082]	[0.119]	[0.298]	[1.501]
TM intensity	.	.	0.977***	0.211**	−0.364***	−0.658***	0.346***	0.6340**	0.271***	−0.553***	0.0348	0.130
			[0.225]	[0.102]	[0.0841]	[0.113]	[0.575]	[0.310]	[0.050]	[0.057]	[0.500]	[0.746]
Advertising intensity	−0.683	−0.128***	−0.0350**	0.127***	0.0286***	0.00844	0.441***	−0.339***	0.00409	0.118***	−0.0741***	0.155***
	[0.727]	[0.031]	[0.0167]	[0.0298]	[0.00840]	[0.0129]	[0.0722]	[0.114]	[0.012]	[0.0418]	[0.009]	[0.0518]
Debt ratio	−0.00625	.	−1.090***	0.390**	0.488***	−0.442**	0.502**	−0.942***	0.402***	0.0531	0.263**	−0.179
	[1.715]	.	[0.234]	[0.177]	[0.0883]	[0.214]	[0.206]	[0.250]	[0.0877]	[0.140]	[0.111]	[0.208]
Rndxpate	.	.	−0.396	−0.503***	2.413***	−0.548***	1.408**	−2.108***	−2.545	2.304	−0.646***	−0.111
	.	.	[0.488]	[0.902]	[0.582]	[0.0628]	[0.595]	[0.487]	[3.389]	[2.435]	[0.127]	[3.348]
<b>Debt interactions</b>												
Debtxrndint	.	.	−2.700***	0.511***	0.0157	−0.183***	0.289***	0.288	0.446***	−1.022***	−1.631***	−0.518
	.	.	[0.342]	[0.165]	[0.0208]	[0.0689]	[0.415]	[0.232]	[0.0925]	[0.371]	[0.129]	[0.548]
Debtxpate	.	.	−0.709***	0.601**	1.55***	−0.834***	−0.309	−0.314***	v0.353	−0.279***	v0.147***	0.516***
	.	.	[0.249]	[0.27]	[0.440]	[0.178]	[0.539]	[0.778]	[0.455]	[0.309]	[0.435]	[0.161]
Debtxtmint	.	.	0.415**	−0.290**	0.661**	1.278***	−0.327***	−0.147	0.670	−0.357*	−0.189***	−0.277***
	.	.	[0.194]	[1.191]	[0.280]	[0.373]	[0.715]	[0.134]	[4.205]	[0.215]	[0.542]	[0.627]
Debtxadvertint	0.499	0.211***	0.757***	−0.0537***	−0.003	0.124***	v0.559***	0.426*	−0.376***	0.322***	0.277***	−0.244*
	[0.624]	[0.442]	[0.106]	[0.0184]	[0.004]	[0.0468]	[0.174]	[0.233]	[0.0537]	[0.105]	[0.0357]	[0.147]
rndxpate debt	.	.	2.577*	−0.508	−3.184***	0.869***	−2.725	1.749***	−30.37	13.66***	0.713***	−0.160**
	.	.	[1.522]	[4.284]	[0.694]	[0.0806]	[2.594]	[0.449]	[20.78]	[4.427]	[0.182]	[0.625]
<b>Control Variables</b>												
Emp	0.564	0.265***	−0.0401	−0.0094***	0.0133***	0.0335***	−0.0235***	0.0821***	0.0986	−0.0047**	0.0123***	0.0153***
	[0.587]	[0.0474]	[0.0306]	[0.0025]	[0.0024]	[0.0667]	[0.00625]	[0.0148]	[0.068]	[0.0021]	[0.0036]	[0.00402]
Age	−0.544***	0.0522	−0.0990***	−0.0361	0.445***	0.0131	−0.0127	0.00549	−0.0380***	0.0257**	−0.171*	−0.0125
	[0.156]	[0.100]	[0.0180]	[0.0224]	[0.154]	[0.0272]	[0.0177]	[0.0153]	[0.00715]	[0.0117]	[0.104]	[0.0153]
Constant	10.78***	3.551	2.340***	0.975*	−4.212**	−0.250	0.360	−0.189	2.191***	−0.973*	5.173*	0.429
	[3.365]	[2.417]	[0.351]	[0.509]	[1.813]	[0.341]	[0.826]	[0.738]	[0.350]	[0.589]	[2.765]	[0.465]
Observations	165	120	2919	1402	3825	2639	882	698	5806	2880	2525	1628
F statistics	1.545	11.13	9.323	27.65	22.89	9.609	9.057	11.86	23.65	27.81	17.34	5.757
F test for $u_i=0$	1.77e−14	−2.9e−14	64.63	98.48	72.16	54.43	107.9	117.4	141.4	118.8	73.50	112.1
R <sup>2</sup>	0.706	0.895	0.267	0.557	0.408	0.186	0.561	0.530	0.311	0.375	0.442	0.183
R <sup>2</sup> adjusted	0.235	0.809	0.219	0.522	0.369	0.134	0.490	0.473	0.286	0.342	0.404	0.126

Notes: 1) Standard errors in brackets 2) \*  $p < .10$  \*\*  $p < .05$  \*\*\*  $p < .01$ . 3) The dependent variable is log Tobin's q, and models are estimated with Fixed Effects Estimation, company and time fixed effects are included but not reported in the table for the sake of brevity. 4) The primary sector is raw materials which cover agriculture and mining industry. The secondary sector is manufacturing sector including EWG and construction. The tertiary sector is service industries including wholesale, retail, transport, telecom, finance, real estate, professional and scientific activities, education, health, and culture. 5) Columns 1–6 shows pre- and post-crisis estimations for SMEs in primary, secondary and tertiary sectors respectively. Columns 7–8 show pre- and post-crisis estimations for all SMEs. Columns 9–14 show pre- and post-crisis estimations for large firms in primary, secondary and tertiary sectors, respectively. Columns 15–16 show pre- and post-crisis estimations for large firms.

**Table 10**

Robustness 3: The impact of debt and IC on the MV of high-debt firms in pre-and post-crisis.

High Debt Firms	Technology Intensive Firms (R&D and Patents)				Knowledge Intensive Firms (TM and Adv)			All periods (8)	Pre-Crisis (9)	Post-Crisis (10)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)			
RnD intensity	0.18*** [0.008]	0.113*** [0.009]	0.096*** [0.0132]	0.064*** [0.0139]				-0.044*** [0.0122]	0.211*** [0.0310]	0.159** [0.0699]
Patent intensity				0.0116 [0.0111]				0.146*** [0.0430]	4.302*** [1.180]	1.442*** [0.400]
TM intensity					0.08*** [0.0128]	0.09*** [0.0120]	0.08*** [0.0128]	-0.0122 [0.0351]	-0.347*** [0.0877]	0.466*** [0.167]
Advertising intensity							0.03*** [0.0009]	0.0583*** [0.00642]	0.0199*** [0.0072]	0.106*** [0.0410]
Debratio		0.36*** [0.0206]	0.33*** [0.0261]	0.345*** [0.0278]		0.57*** [0.007]	0.47*** [0.009]	0.439*** [0.0283]	0.200*** [0.0384]	-0.213 [0.144]
Rndxpatent								-0.034*** [0.00967]	-0.257 [1.463]	-1.55*** [0.306]
<b>Debt interactions</b>										
Debtxrndint			0.0189* [0.0105]	0.0308*** [0.011]				0.0181*** [0.00551]	-0.0182 [0.017]	-0.41*** [0.0719]
Debtxpatent								-0.168*** [0.0451]	-7.438*** [1.672]	-0.485** [0.239]
Debtxtmint								0.231** [0.106]	0.524*** [0.179]	-0.98*** [0.353]
Debtxadvertint								-0.0211*** [0.00340]	-0.0049 [0.0036]	0.247*** [0.047]
Rndxpatentxdebt				0.06*** [0.015]				0.0322*** [0.0103]	-0.0274 [1.818]	1.262*** [0.449]
<b>Control Variables</b>										
Emp ratio								0.0059*** [0.00145]	0.0082*** [0.0015]	-0.05*** [0.00555]
Age								-0.036*** [0.0051]	0.0021 [0.006]	-0.0159 [0.0139]
Constant	0.49*** [0.032]	0.40*** [0.0315]	0.414*** [0.0321]	0.411*** [0.032]	0.379*** [0.018]	0.169*** [0.017]	0.154*** [0.020]	1.595*** [0.201]	1.134 [0.831]	0.291 [0.594]
Observations	10213	10,213	10,213	10,213	46,873	46,873	34,840	8181	5557	2624
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
F statistics	16.67	19.14	19.03	19.27	36.85	86.53	75.85	17.86	21.79	15.18
F test for u_i=0	122.3	111.7	110.5	108.5	181.2	167.2	139.0	91.82	99.70	77.40
R <sup>2</sup>	0.197	0.221	0.221	0.226	0.104	0.216	0.247	0.262	0.307	0.267
R <sup>2</sup> _adjusted	0.163	0.187	0.188	0.192	0.0797	0.194	0.224	0.225	0.269	0.218

Notes: 1) Standard errors in brackets 2) \*  $p < .10$  \*\*  $p < .05$  \*\*\*  $p < .01$ . 3) The dependent variable is log Tobin's q, and models are estimated with Fixed Effects Estimation, company and time fixed effects are included. 4) Columns 1–4 show high debt firms that are doing R&D and patenting, in other words, "technology-intensive firms", whereas columns 5–7 show firms with Trademarking (TM) and advertising activities (Knowledge Intensive firms). Column 8 shows high debt firms for all periods whereas columns 9–10 show pre- and post-crisis estimations.

sector benefit from patenting and trademarking directly. In columns 4–6, for larger firms with leverage, the trademarking activities drive market valuation in primary and secondary sectors. Also, large firms in the secondary sector benefit from R&D and patents, along with debt. Additionally, financially unconstrained SMEs in the secondary sector benefit from all types of intellectual capital directly, and also from R&D and patenting activities. Large firms, however, only directly benefit from trademarking and marketing activities, and indirectly benefit from patenting, R&D and trademarks with higher leverage. Higher R&D activities and patents have a direct positive impact on market values of SMEs in the tertiary sector, while high debt has an indirect positive impact on R&D if jointly undertaken with patenting. However, large firms in the tertiary sector only directly benefit from higher R&D activities, and indirectly benefit from patenting and advertising with leverage.

#### 4.3.2. *The impact of debt and IC on MV of the UK firms: sectoral and size heterogeneity in pre-and post-crisis periods*

As a second robustness check, by carrying the investigation further in Table 8, we analyze the impact of innovation and debt on SME and large firms across-3 sectors both during pre- and post-crisis periods. Table 9, Columns 1–6 show the SMEs in three sectors during both periods. Columns 9–14 we investigated the large firms in three sectors in both periods separately. In the disaggregated sample (column 1–6), SMEs in the primary sector only have marketing intensities regardless of debt in both periods. SMEs in the secondary sector benefit from R&D and patents individually but not jointly during pre-crisis. However, if SMEs in the secondary sector use leverage, focusing on R&D or patents alone is not enough, as they only jointly contribute to firm performance. Additionally, high leveraged SMEs in the secondary sector could also benefit from trademarks, focusing on marketing intensity. Also, firms in the primary sector (columns 9–10) are mainly large firms who benefit from advertising and trademarks in pre-crisis, whereas in-the-post crisis high debt-dependent firms can perform better if focused on advertising. Also, following the crisis, firms can benefit from patenting alone but only jointly with R&D if they have high debt. Large firms in the secondary sector benefit from patents and trademarks pre-crisis (column 11) and advertising and patenting in the post-crisis period (column 12). Also, in the post-crisis period, large firms with leverage can focus on advertising to boost company performance. But they perform patent and R&D jointly if they are leverage-intensive. The tertiary sector, however (column 13) benefits from both R&D and patents individually pre-crisis but not jointly. Conversely, firms with high leverage can benefit from R&D and patenting if they are conducted together. On the other hand, large firms in the tertiary sector following the crisis (column 14) can benefit only from patenting if they have high leverage.

#### 4.3.3. *The impact of debt and IC on MV of high-debt firms in pre-and post-crisis periods*

As the third robustness check, we examined the impact of IC on only high-debt firms. Firms with patenting and R&D activities are labelled as technology-intensive (in Columns 1–4), whereas the firms with a greater focus on trademark and advertising are denoted as knowledge-intensive (Columns 5–7). Column 8 shows the full sample of high-debt firms whereas columns 9–10 show pre- and post-crisis estimations. Columns 1–7 of Table 10 introduce IC and debt elements individually and found that high-debt firms focusing only on one of the innovation activities could achieve higher market valuation, as well as patenting along with R&D. High debt firms also benefit from trademarks and advertising with debt. Results in Column 8 suggest that patent and advertising increase the valuation of high-debt firms. The indirect impact of patents with high debt is only positive if jointly done by R&D. Columns 9–10 reveal that, in the post-crisis period, all types of intellectual capital tend to be beneficial for high-debt firms. Also, as well as individually being beneficial for firm performance, the joint impact of patent and R&D activities also contributes to firm performance in the post-crisis period.

## 5. Conclusion

Exploring the size and sectoral heterogeneity, this paper investigates the impact of innovation on firms' valuation and its uncertainty, using quarterly data from 2000–2014 from UK firms traded in London Stock Exchange. Our preliminary analysis pointed to the existence of a structural break, making us undertake the analysis before and after the global financial crisis. Overall, we find that IC intensive firms outperform the non-IC ones in the post-crisis period.

Benchmark regression results suggest that higher R&D, patent, and advertising intensity along with debt boost market valuation while trademarks only boost the market valuation of large firms. Firms in the post-crisis period benefit from intellectual assets differently as opposed to pre-crisis. For instance, high-debt firms can boost stock market performance by focusing jointly on R&D and patents. We also found that although leverage distorts market valuation of large UK firms, the impact is positive for SMEs that are innovation intensive. Moreover, manufacturing and service sector firms benefit from R&D and patenting activities with high leverage during the post-crisis period, but not in the pre-crisis. Firms that are high IC intensive tend to have higher market valuation and less valuation uncertainty, regardless of their debt structure during bad times.

Moreover, this paper also explores the impact of sectoral heterogeneity on valuation and its uncertainty using two different sectoral classifications. The first classification is the 3-sector classification, namely primary, secondary and tertiary sectors. The primary and secondary sectors benefit from patenting, trademarking, and advertising activities. Firms in the

secondary sector get higher market valuation if they jointly focus on R&D and patenting along with debt. Patents and R&D activities also contribute to higher market values in the tertiary sector. Using the second type of sectoral classification – high-technology and high KIS sectors with low-technology and low KIS sectors –we find that high-tech manufacturing firms benefit from patenting and R&D irrespective of their debt-intensity, whereas low- KIS firms benefit from trademark and advertising in general, in the post-crisis period.

Besides, we investigated the role of debt and intellectual capital intensities on valuation uncertainty of the UK firms. In the pre-crisis period, R&D, patent, trademark directly reduce uncertainty while patent and trademarks have an indirect role in reducing the valuation uncertainty of high-debt firms. In the post-crisis period, R&D, patents and debt reduce the valuation uncertainty. Therefore, firms, especially high-debt firms should focus on patenting and R&D activities that help alleviate the valuation uncertainty in the post-crisis period. It is also found that high-tech manufacturing firms can reduce their valuation uncertainty in the post-crisis period by focusing on R&D and patenting. In the same manner, high-KIS firms can overcome the valuation uncertainty by focusing on trademarking and advertising in the post-crisis period.

Additionally, we conducted three robustness checks to ensure the credibility of our results. First, we sub-divided the sample further by separating firms in each of the three sectors as SMEs and large companies. SMEs in the primary sector get a better valuation by focusing on advertising assets, while financially less constrained (higher debt) SMEs in the secondary and tertiary sector benefit from joint R&D and patenting activities. Similarly, in the second robustness check, we again explore the SMEs and large firms at a sectoral level, but by adding the temporal variation (i.e. pre- and post-crisis periods), our results remain consistent. Furthermore, in the final robustness check, by investigating the subsample of only high-debt firms, we found that patents and R&D intensive firms benefit more than non-IC intensive firms in the post-crisis period.

In summary, we find that UK firms in general, benefit from patents during both pre- and post-crisis periods. As opposed to the previous literature, this paper finds that SMEs indeed have higher debt ratios and are more innovation-intensive than large firms, benefiting SMEs even in the post-crisis period. Finally, high-tech firms achieve better valuation and are able to reduce their valuation uncertainty by generating patents and investing in R&D irrespective of their debt level, whereas low-tech firms benefit from investing in trademarks and advertising in improving their performance.

## Declaration of Competing Interest

None.

## Appendix A-Table 1 Additional Descriptive Statistics

Panel 1 (Appendix A) reveals that high patent-intensive firms have better Tobin's Q. Panel 2 points out that the tertiary sector has the highest Tobin's Q as well as the highest debt ratio. The primary sector has the lowest IC intensive sector.

### Panel 1: Descriptive Statistics based on Patent intensities

Variable	High Patent Firms					Low Patent Firms				
	Obs	Mean	Std.Dev	Min	Max	Obs	Mean	Std.Dev	Min	Max
tobinsq	3620	2.47	3.69	0.32	46.91	133918	1.54	1.94	0.04	49.81
RnDintensity	6259	0.8401	1.136	0	8.184	46350	0.553	1.4877	0	34.836
Advertising_intensity	7696	2.785	2.938	0.085	35.184	129842	1.954	4.993	0	95.917
Patent_intensity	7696	0.8033	2.407	0.0273	28.169	129842	0.000223	0.00174	0	0.0272
TM_intensity	7696	0.259	1.033	0	14.084	129842	0.0138	0.179	0	12.195
Emp_ratio	8396	7.73	19.76	0.103	470.59	129142	10.15	51.75	0.002	5200
Age	55015	21.60	28	0	157	82523	22.08	29.37	0	154
Debt_ratio	4361	0.4742	0.55	0.018	5.26	133177	0.5460	0.79	0	31.07



## Panel 2: Descriptive statistics based on sectors

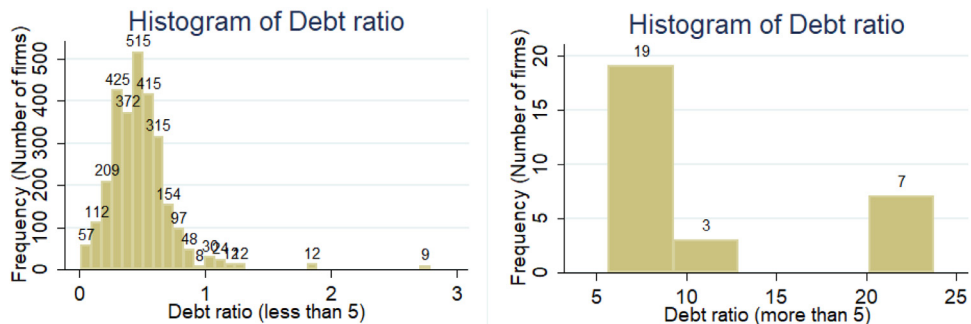
Sectors Variable	Primary					Secondary					Tertiary				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std.Dev.	Min	Max	Obs	Mean	Std.Dev.	Min	Max
Tobinsq	12254	1.39	1.27	0.094	34.18	30720	1.4	1.49	0.2	44.3	66343	1.65	2.32	0.042	49.8
RnDintensity	3300	0.13	0.46	0	6.11	18869	0.42	1.25	0	34.8	20816	0.85	1.83	0	25.7
Advertising_ Intensity	21965	1.32	3.65	0	0.83	34880	1.9	3.71	0	90.9	80693	2.1	5.21	0	95.9
Patent_ Intensity	21965	0.0003	0.01	0	0.83	34880	0.05	0.43	0	13.8	80693	0.04	0.62	0	28.2
TM_intensity	21965	0.002	0.04	0	1.36	34880	0.04	0.16	0	3.53	80693	0.03	0.34	0	14.1
Emp_ratio	25424	8.86	40.38	0.01	1491.5	44575	8.45	28.9	0.01	2734	67539	10.4	35.72	0.004	1535.2
Age	31450	15.94	27.44	0	130	38887	30.8	34.1	0	141	67201	15.7	24.10	0	157
Debtratio	14213	0.40	0.35	0.008	9.40	34195	0.51	0.46	0.007	12.27	79456	0.59	0.99	0.001	31.07

## Appendix B-Table 2 Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	RnDintensity	1						
(2)	Patent_intensity	0.235	1					
(3)	TM_intensity	0.214	0.118	1				
(4)	Advertising_intens	0.662	0.048	0.163	1			
(5)	Emp_ratio	0.200	0.086	0.043	0.226	1		
(6)	Age	0.193	0.017	0.045	0.515	0.023	1	
(7)	Debtratio	-0.178	-0.017	-0.007	-0.035	-0.025	-0.0146	1

Notes: All correlations are significant at 5% level.

## Appendix C-Figure 3 Histograms of Debt Ratio

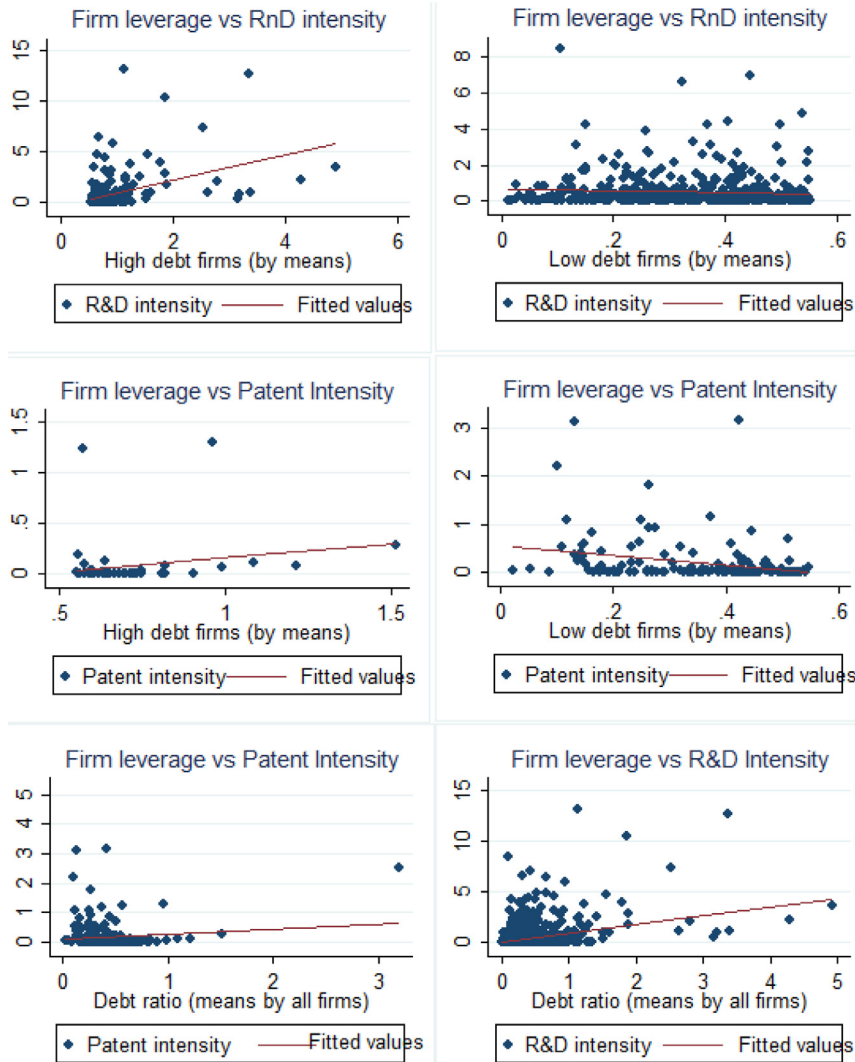


Note: Distribution of debt ratio. The first histogram presents the number of firms that have less than 5 as their debt ratio (500%). The second histogram presents the number of firms that have more than 5 as their debt ratio (500%). The third graph represents a scatter plot of debt ratio across Tobin's Q.

For the sake of visibility, Figure 3 (Appendix C) presents histograms of debt ratio in two parts. The first histogram presents the number of firms that have less than 5 as their debt ratio (500%), while the second one demonstrates the firms with more than “5” as their debt ratio (500%). It is observable from the figures that the majority of the firms in the UK have debt ratios between 0-1; however, there are extreme cases with firms' debt ratio at 30.

## Appendix D-Figure 4 scatter plots of innovation and debt ratio

We disaggregate the data further in Fig. 4 which aims to demonstrate the indirect impact of innovation variables on debt. The firms here are classified as high and low debt firms (based on mean debt) in first 4 scatter plots whereas the last two indicates all firms. When the full sample is used in the investigation (in the last two plots), the impact of debt increases with an increase in patent and R&D intensities. However, when we separate the sample as high and low debt firms, the impact of both R&D and patent intensity is positive in high debt firms, whereas the impact is less significant and declining (R&D and patent respectively) in low debt firms.



Notes: Scatter plot of innovation against the debt ratio. Above figures present scatter plots of the innovation variables and debt ratio. These plots aim to show the indirect impact of innovation variables on debt. The firms here are classified as high and low debt firms in first 4 scatter plots whereas the last two indicates all firms. If we look at all sample, in the last two tables the impact of debt increases with an increase in patent and R&D intensities. However, when we separate the sample as high and low debt firms the impact of both R&D and patent intensity is positive in high debt firms, whereas the impact is less significant and declining (R&D and patent respectively) in low debt firms. All tables indicate average firm-level R&D, patent and debt ratios. The overall impact seems also to be positive in all sample in the last two graphs.

### Appendix E- Estimating the structural break in Tobin's Q in the UK

We run four separate Dickey-Fuller unit-root tests by allowing for break-in intercept and specifying lag selection (3 lags) as per Zivot-Andrews after which the series remain stationary.

Minimum t-statistic -9.789 at 2007 (obs 8)

Critical values: 1%: -5.34 5%: -4.80 10%: -4.58

		Augmented Dickey-Fuller test for unit root		Interpolated Dickey-Fuller	
		Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Only mean	Z(t)	-1.209	-3.75	-3	-2.63
	MacKinnon approximate p-value for Z(t)	0.5349			
Mean with 3 lags	Z(t)	1.209	-3.75	-3	-2.63
	MacKinnon approximate p-value for Z(t)	0.6697			
Mean with 3 lags and drift	Z(t)	-1.209	-3.143	-1.943	-1.44
	MacKinnon approximate p-value for Z(t)	0.1361			
Mean with 3 lags and trend	Z(t)	-1.885	-4.38	-3.6	-3.24
	MacKinnon approximate p-value for Z(t)	0.6625			

## References

- Agarwal, R., Shah, S.K., 2014. Knowledge sources of entrepreneurship: Firm formation by academic, user and employee innovators. *Res. Policy* 43, 1109–1133. <https://doi.org/10.1016/j.respol.2014.04.012>.
- Aktas, N., Croci, E., Petmezas, D., 2015. Is working capital management value-enhancing? Evidence from firm performance and investments. *J. Corp. Financ.* 30, 98–113.
- Antzoulatos, A.A., Koufopoulos, K., Lambrinouidakis, C., Tsiritakis, E., 2016. Supply of capital and capital structure: the role of financial development. *J. Corp. Financ.* 38, 166–195.
- Archibugi, D., Filippetti, A., 2011. Is the economic crisis impairing convergence in innovation performance across Europe. *J. Common Mark. Stud.* 49, 1153–1182. <https://doi.org/10.1111/j.1468-5965.2011.02191.x>.
- Archibugi, D., Filippetti, A., Frenz, M., 2013. Economic crisis and innovation: is destruction prevailing over accumulation. *Res. Policy* 42, 303–314. <https://doi.org/10.1016/j.respol.2012.07.002>.
- Arellano, M., Bond, S., 1991. Some tests of specification for panel carlo application to data : evidence and an employment equations. *Rev. Econ. Stud.* 58, 277–297.
- Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. *J. Econom.* 68, 29–51.
- Audretsch, D.B., Bönte, W., Mahagaonkar, P., 2012. Financial signaling by innovative nascent ventures: the relevance of patents and prototypes. *Res. Policy* 41, 1407–1421. <https://doi.org/10.1016/j.respol.2012.02.003>.
- Avdjiev, S., Binder, S., Sousa, R., 2017. External debt composition and domestic credit cycles. BIS Work. Pap. Aoril.
- Belenzon, S., Pataconi, A., 2013. Innovation and firm value: an investigation of the changing role of patents, 1985–2007. *Res. Policy* 42, 1496–1510. <https://doi.org/10.1016/j.respol.2013.05.001>.
- Block, H.J., Fisch, C., Sandner, G.P., 2014. Trademark families: characteristics and market values. *J. Brand Manag.* 21, 150–170. <https://doi.org/10.1057/bm.2013.27>.
- Block, J.H., De Vries, G., Schumann, J.H., Sandner, P., 2014. Trademarks and venture capital valuation. *J. Bus. Ventur.* 29, 525–542. <https://doi.org/10.1016/j.jbusvent.2013.07.006>.
- Block, J.H., Fisch, C.O., Hahn, A., Sandner, P.G., 2015. Why do SMEs file trademarks? Insights from firms in innovative industries. *Res. Policy* 44, 1915–1930. <https://doi.org/10.1016/j.respol.2015.06.007>.
- Bloom, N., Van Reenen, J., 2010. Why do management practices differ across firms and countries. *J. Econ. Perspect.* 24, 203–224.
- Bloom, N., Van Reenen, J., 2007. Measuring and explaining management practices across firms and countries. *Q. J. Econ.* CXXII.
- Bloom, N., Van Reenen, J., 2002. Patents, real options and firm performance. *Econ. J.* 112, 97–116. <https://doi.org/10.1111/1468-0297.00022>.
- Blundell, R., Bond, S., 2000. GMM Estimation with persistent panel data: an application to production functions. *Econom. Rev.* 19, 321–340. <https://doi.org/10.1080/07474930008800475>.
- Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. *J. Econom.* 87, 115–143. [https://doi.org/10.1016/S0304-4076\(98\)00009-8](https://doi.org/10.1016/S0304-4076(98)00009-8).
- Bond, S., van Reenen, J., 2003. Microeconomic models of investment and employment. *ESRC Pap. Inst. Fisc 1–133 Study*.
- Borisova, G., Brown, J.R., 2013. R&D sensitivity to asset sale proceeds: new evidence on financing constraints and intangible investment. *J. Bank. Financ.* 37, 159–173. <https://doi.org/10.1016/j.jbankfin.2012.08.024>.
- Bosworth, D., Rogers, M., 2001. Market value, R&D and intellectual property: an empirical analysis of large Australian firms. *Econ. Rec.* 77, 323–337. <https://doi.org/10.1111/1475-4932.t01-1-00026>.
- Breschi, S., Malerba, F., Orsenigo, L., 2000. Technological regimes and schumpeterian patterns of innovation. *Econ. J.* 110, 388–410.
- Brown, J.R., Fazzari, S.M., Petersen, B.C., 2009. Financing innovation and growth: cash flow, external equity, and the 1990s R&D boom. *J. Financ.* 64, 151–185. <https://doi.org/10.1111/j.1540-6261.2008.01431.x>.
- Brown, J.R., Martinsson, G., Petersen, B.C., 2012. Do financing constraints matter for R&D. *Eur. Econ. Rev.* 56, 1512–1529. <https://doi.org/10.1016/j.eurocorev.2012.07.007>.
- Brown, J.R., Petersen, B.C., 2009. Why has the investment-cash flow sensitivity declined so sharply? Rising R&D and equity market developments. *J. Bank. Financ.* 33, 971–984. <https://doi.org/10.1016/j.jbankfin.2008.10.009>.
- Carosi, A., 2016. Do local causations matter? The effect of firm location on the relations of ROE, R&D, and firm SIZE with MARKET-TO-BOOK. *J. Corp. Financ.* 38, 388–409.
- Chen, Y., Pan, S., Zhang, T., 2014. (When) Do stronger patents increase continual innovation. *J. Econ. Behav. Organ.* 115–124.
- Clausen, S., Hirth, S., 2016. Measuring the value of intangibles. *J. Corp. Financ.* 110–127.
- Connolly, R.A., Hirschey, M., 1988. Market value and patents. A Bayesian approach. *Econ. Lett.* 27, 83–87. [https://doi.org/10.1016/0165-1765\(88\)90224-8](https://doi.org/10.1016/0165-1765(88)90224-8).
- Cosci, S., Guida, R., Melicani, V., 2013. Leasing decisions and credit constraints: empirical analysis on a sample of Italian firms. *Eur. Financ. Manag.* 21, n/a–n/a. <https://doi.org/10.1111/j.1468-036X.2013.12019.x>.
- Cosh, A., Cumming, D., Hughes, A., 2009. Outside entrepreneurial capital. *Econ. J.* 119, 1494–1533.
- Cumming, D., 2005. Capital structure in venture finance. *Journal of Corporate Finance* 11, 550–585.
- Cumming, D., Fleming, G., Schwienbacher, A., 2005. Liquidity risk and venture capital finance. *Financ. Manag.* 77–105.
- Czarnitzki, D., Kraft, K., 2009. Capital control, debt financing and innovative activity. *J. Econ. Behav. Organ.* 372–383.
- DeRassenfosse, G., Palangkaraya, A., Webster, E., 2016. Why do patents facilitate trade in technology? Testing the disclosure and appropriation effects. *Res. Policy*. <https://doi.org/10.1016/j.respol.2016.03.017>.
- Dosi, G., 1990. Finance, innovation and industrial change. *J. Econ. Behav. Organ.* 299–319.
- Duygun, M., Sena, V., Shaban, M., 2014. Trademarking status and economic efficiency among commercial banks: Some evidence for the UK. *J. Bank. Financ.* 49, 506–514. <https://doi.org/10.1016/j.jbankfin.2014.06.009>.

- Eisfeldt, A.L., Papanikolaou, D., 2013. Organization capital and the cross-section of expected returns. *J. Financ.* 68, 1365–1406.
- Filippetti, A., Archibugi, D., 2011. Innovation in times of crisis: national systems of innovation, structure, and demand. *Res. Policy* 40, 179–192. <https://doi.org/10.1016/j.respol.2010.09.001>.
- Fisher, A.G.B., 1939. Production, primary, secondary and tertiary. *Econ. Rec.* 15, 24–38.
- Gao, W., Chou, J., 2015. Innovation efficiency, global diversification, and firm value. *J. Corp. Financ.* 30, 278–298.
- Greenhalgh, C., Rogers, M., 2012. Trade marks and performance in UK firms: evidence of Schumpeterian competition through innovation. *Aust. Econ. Rev.* 45, 50–76.
- Greenhalgh, C., Rogers, M., 2007. Trade marks and performance in UK firms: evidence of schumpeterian competition through innovation. *Oxford Intellectual Prop. Res. Cent.* 1–38.
- Greenhalgh, C., Rogers, M., 2006. The value of innovation: the interaction of competition, R&D and IP. *Res. Policy* 35, 562–580. <https://doi.org/10.1016/j.respol.2006.02.002>.
- Griliches, Z., Hall, B.H., Pakes, A., 1988. R&D, Patents, and Market Value Revisited: Is There A Second (Technological Opportunity) Factor. NBER Work. Pap.
- Guerzoni, M., Aldridge, T.T., Audretsch, D.B., Desai, S., 2014. A new industry creation and originality: insight from the funding sources of university patents. *Res. Policy* 43, 1697–1706. <https://doi.org/10.1016/j.respol.2014.07.009>.
- Guney, Y., Karpuz, A., Ozkan, N., 2017. R&D investments and credit lines. *J. Corp. Financ.* 261–283.
- Hall, B.H., 2011. Innovation and Productivity. NBER Work. Pap. Ser. 17178.
- Hall, B.H., 2010. The financing of innovative firms. *Rev. Econ. Inst.* 3880, 1–30. <https://doi.org/10.5202/rei.v1i1.4>.
- Hall, B.H., 2002. The financing of research and development. *Oxford Rev. Econ. Policy*.
- Hall, B.H., 2000. Innovation and market value. *Product. Innov. Econ. Perform.* 177–198. <https://doi.org/10.2139/ssrn.151912>.
- Hall, B.H., Helmers, C., Rogers, M., Sena, V., 2013. The importance (or not) of patents to UK firms. *Oxf. Econ. Pap.* 65, 603–629. <https://doi.org/10.1093/oepl/gpt012>.
- Hall, B.H., Jaffe, A., Trajtenberg, M., 2005. Market value and patent citations. *RAND J. Econ.* 36, 16–38. <https://doi.org/10.1007/s00216-009-2643-x>.
- Hall, B.H., Lotti, F., Mairesse, J., 2009. Innovation and productivity in SMEs: empirical evidence for Italy. *Small Bus. Econ.* 33, 13–33. <https://doi.org/10.1007/s11187-009-9184-8>.
- Hall, B.H., Lerner, J., 2010. The Financing of R & D and Innovation. In: Hall, B., Rosenberg, N. (Eds.), *Handbook of the Economics of Innovation 2010*.
- Hall, B.H., MacGarvie, M., 2010. The private value of software patents. *Res. Policy* 39, 994–1009. <https://doi.org/10.1016/j.respol.2010.04.007>.
- Hall, B.H., Mairesse, J., Mohnen, P., 2010. Measuring Returns to R&D UNU-MERIT Work. Pap.
- Hall, B.H., Oriani, R., 2006. Does the market value R&D investment by European firms? Evidence from a panel of manufacturing firms in France, Germany, and Italy. *Int. J. Ind. Organ.* 24, 971–993. <https://doi.org/10.1016/j.ijindorg.2005.12.001>.
- Hall, B.H., Thoma, G., Torrisi, S., 2007. The Market Value of Patents and R&D: Evidence From European Firms. In: NBER Work. Pap. No. 13426, pp. 1–6 <https://doi.org/10.3386/w13426>.
- Hasan, M.M., Cheung, A., 2018. Organization capital and firm life cycle. *J. Corp. Financ.* 556–578.
- Hausman, J., Hall, B.H., Griliches, Z., 1984. Econometric models for count data with an application to the patents-R&D relationship. *Econometrica* 52, 909–938.
- He, Z., Wintoki, M.B., 2016. The cost of innovation: R&D and high cash holdings in U.S. firms. *J. Corp. Financ.* 280–303.
- Heger, D., Zaby, A.K., 2013. The heterogeneous costs of disclosure and the propensity to patent. *Oxf. Econ. Pap.* 65, 630–652. <https://doi.org/10.1093/oepl/gpt018>.
- Helmers, C., Rogers, M., 2011. Does patenting help high-tech start-ups. *Res. Policy* 40, 1016–1027. <https://doi.org/10.1016/j.respol.2011.05.003>.
- Helmers, C., Rogers, M., 2010. Innovation and the survival of new firms in the UK. *Rev. Ind. Organ.* 36, 227–248. <https://doi.org/10.1007/s11151-010-9247-7>.
- Huang, K., Shang, C., 2019. Leverage, debt maturity, and social capital. *J. Corp. Financ.* 26–46.
- Jia, N., 2018. Corporate innovation strategy and stock price crash risk. *J. Corp. Financ.* 155–173.
- Kieschnick, R., Moussawi, R., 2018. Firm age, corporate governance, and capital structure choices. *J. Corp. Financ.* 597–614.
- Kim, B., Kim, E., Miller, D.J., Mahoney, J.T., 2016. The impact of the timing of patents on innovation performance. *Res. Policy* 45, 914–928. <https://doi.org/10.1016/j.respol.2016.01.017>.
- Kim, Y.K., Lee, K., Park, W.G., Choo, K., 2012. Appropriate intellectual property protection and economic growth in countries at different levels of development. *Res. Policy* 41, 358–375. <https://doi.org/10.1016/j.respol.2011.09.003>.
- Lev, B., Radhakrishnan, S., Zhang, W., 2009. Organization Capital Abacus 45.
- Li, D., 2011. Financial constraints, R&D investment, and stock returns. *Rev. Financ. Stud.* 24, 2974–3007. <https://doi.org/10.1093/rfs/hhr043>.
- Lin, H., Chien, C., Chiu, S., 2016. The impact of value-relevant accounting rules on innovative activities. *R&D Manag.* 46, 1–15. <https://doi.org/10.1111/radm.12143>.
- Mallick, S., Yang, Y., 2011. Sources of financing, profitability and productivity: First evidence from matched firms. *Financial Markets, Institutions and Instruments* 20 (5), 221–252. <https://doi.org/10.1111/j.1468-0416.2011.00170.x>.
- Mallick, S.K., Sousa, R.M., 2017. The skill premium effect of technological change: new evidence from United States manufacturing. *Int. Labour Rev.* 156, 114–130.
- Mark Hirschey, J.J.W., 1985. Amortization policy for advertising and research and development expenditures. *J. Account. Res.* 23, 326–335.
- Mc Namara, A., Murro, P., O'Donohoe, S., 2017. Countries lending infrastructure and capital structure determination: the case of European SMEs. *J. Corp. Financ.* 122–138.
- Mendonça, S., Pereira, T.S., Godinho, M.M., 2004. Trademarks as an indicator of innovation and industrial change. *Res. Policy* 33, 1385–1404. <https://doi.org/10.1016/j.respol.2004.09.005>.
- Nemlioglu, I., 2019. A comparative analysis of intellectual property rights: a case of developed versus developing countries. *Procedia Comput. Sci.*
- Nemlioglu, I., Mallick, S.K., 2020. Does multilateral lending aid capital accumulation? Role of intellectual capital and institutional quality. *J. Int. Money Financ.*
- Nemlioglu, I., Mallick, S.K., 2017. Do managerial practices matter in innovation and firm performance relations? New evidence from the UK. *Eur. Financ. Manag.* 23, 1016–1061. <https://doi.org/10.1111/eufm.12123>.
- O'Mahony, M., Vecchi, M., 2009. R&D, knowledge spillovers and company productivity performance. *Res. Policy* 38, 35–44. <https://doi.org/10.1016/j.respol.2008.09.003>.
- Peltonen, T.A., Sousa, R.M., Vansteenkiste, I.S., 2012. Investment in emerging market economies. *Empir. Econ.* 43, 97–119.
- Peltonen, T.A., Sousa, R.M., Vansteenkiste, I.S., 2011. Fundamentals, financial factors, and the dynamics of investment in emerging markets. *Emerg. Mark. Financ. Trade.* <https://doi.org/10.2753/REE1540-496x4703S205>.
- Pieri, F., Vecchi, M., Venturini, F., 2018. Modelling the joint impact of R&D and ICT on productivity: a frontier analysis approach. *Res. Policy* 1842–1852.
- Roodman, D., 2009a. How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata J* 9, 88–136 <https://doi.org/The Stata Journal>.
- Roodman, D., 2009b. A note on the theme of too many instruments. *Oxf. Bull. Econ. Stat.* 71, 135–158.
- Roper, S., Hewitt-Dundas, N., 2015. Knowledge stocks, knowledge flows and innovation: evidence from matched patents and innovation panel data. *Res. Policy* 44, 1327–1340. <https://doi.org/10.1016/j.respol.2015.03.003>.
- Sandner, P.G., Block, J., 2011. The market value of R&D, patents, and trademarks. *Res. Policy* 40, 969–985. <https://doi.org/10.1016/j.respol.2011.04.004>.
- Sena, V., Duygun, M., Lubrano, G., Marra, M., Shaban, M., 2018. Board independence, corruption and innovation. Some evidence on UK subsidiaries. *J. Corp. Financ.* 22–43.
- Serena, J.M., Moreno, R., 2016. Domestic financial markets and offshore bond. *BIS Q. Rev.*
- Serena, J.M., Sousa, R., 2017. Does exchange rate depreciation have contractionary effects on firm-level investment BIS Work. Pap. April.

- Sharma, S., Tarp, F., 2018. Does managerial personality matter? Evidence from firms in Vietnam. *J. Econ. Behav. Organ.* 432–445.
- Thoma, G., 2015. Trademarks and the patent premium value: Evidence from medical and cosmetic products. *World Pat. Inf.* 41, 23–30. <https://doi.org/10.1016/j.wpi.2015.02.003>.
- Thomson, R., Webster, E., 2013. Risk and vertical separation: the case of developing new technology. *Oxf. Econ. Pap.* 65, 653–674. <https://doi.org/10.1093/oeq/gpt014>.
- Tian, X., Ruan, W., Xiang, E., 2017. Open for innovation or bribery to secure bank finance in an emerging economy: a model and some evidence. *J. Econ. Behav. Organ.* 226–240.
- Toivanen, O., Stoneman, P., Bosworth, D., 2002. Innovation and the Market Value of UK Firms , 1989–1995 \*. *Oxf. Bull. Econ. Stat.* 39, 1989–1995.
- Von Graevenitz, G., 2007. Which reputations does a brand owner need ? Evidence from trade mark opposition. *Gov. Effic. Econ. Syst. Discuss. Pap.* 49.
- Xu, N., Xu, X., Yuan, Q., 2013. Political connections, financing friction, and corporate investment: evidence from Chinese listed family firms. *Eur. Financ. Manag.* 19, 675–702. <https://doi.org/10.1111/j.1468-036X.2011.00591.x>.
- Younge, K.A., Tong, T.W., 2018. Competitive pressure on the rate and scope of innovation. *J. Econ. Behav. Organ.* 162–181.
- Zhou, H., Sandner, P.G., Martinelli, S.L., Block, J.H., 2014. Patents, trademarks, and their complementarity in venture capital funding. *Technovation* 47, 14–22.