Introduction of innovations during the 2007-8 financial crisis: US companies compared with universities

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ABSTRACT

Financing innovation presents informational and control problems for the financier, and different solutions are used for funding of US companies and universities. In this paper we examine how funding characteristics influenced the change in innovation during the 2007-8 financial crisis for both. We extend prior theories of external financing's effect on company performance during crises, firstly to university performance, and secondly to show the influence of time variation in aggregate funding. Empirical results are consistent with our theory: external dependence and asset intangibility had a limited effect on company innovation on entering the crisis, but increased university innovation. Overall, however, company patenting was more robust than university patenting, despite the out-performance being masked by respective portfolio characteristics.

Keywords: Innovation, patenting, economic crisis, financing constraint

1 Introduction

The 2007-8 financial crisis marked a period of financial decline and disruption unusual since 1945 (Reinhart and Reinhart (2010), figure 1). Defaults on loans in the US subprime mortgage market resulted directly and indirectly in losses to lenders and their resulting bankruptcies (Acharya et al, 2009; Brunnermeier, 2009). The cost of

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lending rose across many debt instruments (Acharya et al, 2009), and the crisis spread to international financial markets through losses and reduced availability of external finance (Claessens et al, 2010).

The resulting real economic disruption affected industrial innovation. Paunov (2012) finds that many Latin American companies stopped innovation projects, while Archibugi et al (2013b) and Filippetti and Archibugi (2011) determine broad innovation expenditure reductions for European companies. Laperche et al's (2011) examination of French businesses finds them streamlining and prioritising R&D during the crisis. Makonnen (2013) looks at European government R&D expenditures by innovation type, and shows that governments tended to reduce their budgets during the crisis.

If funding sources suffered losses in the crisis, or if their means of transferring funds to recipients were interrupted, the cost of finance would have risen and institutions dependent on it would have found their operations curtailed (Campello et al, 2010; Dell'Ariccia et al, 2008; Kroszner et al, 2007). Research on the 2007-8 crisis' effect on innovation has examined the role of dependence on external finance in passing. Paunov's (2012) investigation of Latin American companies uses indicator variables for corporate access to public funding (which significantly reduces the chance of discontinuing an innovation project) and private external funding (which has no significant effect). Archibugi et al's (2013a) European study uses an indicator variable for whether companies considered availability to be an innovation obstacle prior to the crisis. It has a negative insignificant effect on innovation expenditure growth before the crisis, and positive insignificant effect during it. Filippetti and Archibugi (2011) examine behaviour of an ordinal variable indicating whether European firms moved from decreasing innovation investment to maintaining or increasing it during the crisis (or other permutations of this movement). They find that in countries with large national private credit markets there was a tendency to move from declining investment to increasing investment during the crisis, and interpret the result as showing that the financial system depth counteracts the effect of the financial crisis.

In this paper we address more fully questions about whether necessity and ability to attract funding had a major effect on innovation during the crisis. How did US company innovation respond to external funding requirements during the crisis? What was the response of US university innovation? How did their innovation respond to asset intangibility, a measure of the ability to attract external funding?

To answer these questions, we examine the funding relations that financiers have with companies and universities, and how they are affected by the crisis. We find that the change during the crisis in aggregate R&D funding to companies and universities can be used to predict how their innovation responds to external funding dependence. We also determine the relation between asset intangibility and innovation for both types of innovator. The results are used to predict that when US companies are undertaking innovation, the dependence of a class of project on external finance does not significantly change output from that class during the crisis. By contrast, when universities are innovating, more externally dependent classes have increased output during the crisis. A further prediction is that if a project class has a higher ratio of intangible to total assets, then its innovative output will increase during the crisis for university innovators.

We test our hypotheses by examining how predicted patent counts change during the crisis for each innovator type. A database is constructed by joining US patent data with Compustat data, in which the unit of analysis is patent counts in each patent class. The construction allows us to associate measures of external funding dependence, R&D intensity, and other financial quantities to specific innovation classes and their statistics. The empirical results are broadly consistent with the theoretical predictions. We use our parameter estimates to investigate the effect of US company innovation responding to the crisis in the same way as US university innovation, but acting on the same portfolio of US company innovation projects, and vice versa. US company responses are associated with more patenting than US university responses, acting both through financial and non-financial effects.

Section 2 looks at aggregate innovation funding to US companies and universities, section 3 gives our theoretical framework, section 4 describes our data, section 5 gives our empirical method, section 6 presents our results, section 7 looks at counterfactuals, and section 8 concludes.

2 Aggregate innovation funding before and during the crisis

2.1 Funding sources

In 2008, total R&D expenditures in the US were $404 billion, or 2.8 percent of GDP (National Science Board (2012), appendix tables 4-1 and 4-44). US business R&D alone accounted for 1.7 percent of GDP, with government accounting for a further 0.8 percent of GDP. Universities and colleges invested 0.1 percent of GDP from their own funds, with smaller investments from non-profit and foreign sources making up the balance.

Industrial R&D is mainly self-funded by industry, with industrial self-funding accounting for around 90 percent of total expenditure throughout the 2000s (National Science Board (2012), appendix table 4-3). Government funding rose slightly to 13 percent in 2008 and 14 percent in 2009, but remained at historically low levels having exceeded 50 percent throughout most of the 1960s.

By comparison, around two thirds of funding for university R&D came from government in the 2000s, and industry only provided around six percent (National Science Board (2012), appendix table 4-3). Internal university and college monies accounted for about a fifth of the total, with non-profit funding outstripping industrial funding in the final years of the decade. The funding shares were quite stable.

2.2 The effect of the financial crisis

Many US banks and financial institutions faced large declines in their capital reserves during the 2007-8 financial crisis. Debt defaults were common, credit lines were quickly used up by borrowers, and short-term creditors to banks withdrew their lending (Ivashina and Scharfstein, 2010). As a consequence, a number became bankrupt, and others were severely financially compromised. Regaining sufficient reserves became important for maintaining an acceptable level of bankruptcy risk and to meet regulatory requirements. The opportunity cost of loaning new money therefore increased sharply. The increased difficulty in raising finance is manifested in aggregate data: bank loans to the corporate sector fell sharply from the middle of

2007 (Ivashina and Scharfstein, 2010), and a precipitous decline was also observed in venture capital funding (OECD, 2009).

Government finances were also severely impacted by the financial crisis. Nevertheless, despite large deficits developed country governments generally provided substantial fiscal stimuli over the crisis period (OECD (2009), figure 5). In the US, the total fiscal package between 2008 and 2010 exceeded five percent of 2008 GDP. Specific funds for innovative investment were made available through the American Recovery and Reinvestment Act (ARRA, 2009) which was passed in February 2009. The occurrence of an increase in government support for industrial R&D at the same time as a substantial downturn in industry's own funding was unique in the period since 1953 (National Science Board (2012), appendix table 4-3).

Industry self-funding for industrial R&D underwent a large decline in 2009 at an annual rate of 5.5 percent, marking the second largest percentage decline since the 1950s (National Science Board (2012), appendix table 4-3). The absolute level remained near historically record levels. Government expenditure in 2008 and 2009 rose with fiscal measures including the American Recovery and Reinvestment Act, but was still far less than industrial funding. The extra government spending was not sufficient to offset the decline in industrial expenditure in 2009. Nevertheless, total R&D funding to industry in 2009 was at its second highest level ever.

3 Theoretical framework

3.1 Corporate innovation during the crisis

Innovation can be expensive (DiMasi et al, 2003; Adams and Brantner, 2006; DiMasi and Grabowski, 2007), time-consuming (Griffin, 1997), and risky (Cooper and Kleinschmidt, 1995). It may require substantial financing over extended periods in the presence of high risk. Some companies may be able to use internal funds to finance their R&D, but many will not have sufficient available assets and will have to seek external financing for innovation. There are a number of difficulties for a commercial external funding source that are liable to restrict the availability of external finance, or at least make it more expensive than internal finance (Hall, 2002). One problem is information asymmetry between investors and innovators. Because innovation is usually technically demanding, and because innovators often want to preserve secrecy to protect their ideas from rivals, investors generally know less about the projects than the innovators. Thus, a lemons market (Akerlof, 1970) can emerge where investors make higher charges than the better innovators will accept, and the market shrinks.

Financial markets connect investors with fund recipients and can mitigate these informational problems (Rajan and Zingales, 1998). Expert intermediaries operate in financial markets, and they can monitor agent behaviour more closely and enforce better corporate governance. Financial markets often require companies operating on them to follow accounting and disclosure rules, and adopt behavioural standards. These requirements may improve investor knowledge about the companies.

A financial crisis can affect the ability of companies to finance themselves on a commercial basis. In the 2007-8 crisis, funds available from commercial sources were reduced by large scale defaults experienced against their portfolios particularly from US sub-prime mortgages (Calomiris, 2008), which resulted in reduction of revenue streams either directly or through counterparty exposure. The inability to use these assets as collateral reduced the sources' borrowing ability and so the cost of funds available for investment (Acharya et al, 2009; Brunnermeier, 2009; Gorton, 2009). In addition to contraction in the available stock of funding, potential innovators may be less attractive as recipients of funding due to a concurrent recession. The value of monitoring to information intermediaries may be reduced in a depressed market and the credibility of their monitoring may fall for potential investors (Holmström and Tirole, 1997), so increasing the uncertainty associated with investment.

To elaborate on the consequences of these considerations, it is helpful to consider the problems solved by investors and managers considering investment in a project. A private investor deciding on whether to invest in the project during the crisis expects to receive an immediate utility (net of investment cost) of

$$\mu - \Sigma + \varepsilon$$

where μ is the net income from investment, Σ is a measure of the risk from investment due to the crisis interrupting normal market information provision and so leading to ignorance about managerial quality, and ε is an error term with distribution function $f(\varepsilon)$. The crisis risk Σ declines with a rise in T, the level of tangible assets available as collateral to protect against the consequences of imperfect information, so $d\Sigma / dT < 0$. Investment occurs if

$$\mu - \Sigma + \varepsilon > 0$$

or

$$\varepsilon > \Sigma - \mu .$$

The manager who has perfect information about their own managerial quality would act on behalf of the investor and invest if

$$\varepsilon > -\mu .$$

Thus, the excess in investment by managers over external investors during the crisis occurs in the region given by

$$\Sigma - \mu \geq \varepsilon > -\mu \qquad (1)$$

This is the region in which a project that had to be entirely externally financed would not be given approval, while the same project that was entirely internally financed would result in investment.

Prior to the crisis, the market informational provision functions normally, and so the investor faces no crisis risk and $\Sigma = 0$. They receive an immediate net utility from investment of

$$\mu_b + \varepsilon$$

where μ_b is the net income from investment before the crisis. Since there is a recession at the same time as the financial crisis, $\mu_b > \mu$. Investment occurs if

$$\varepsilon > -\mu_b.$$

Investment occurs before the crisis but not during it if

$$\Sigma - \mu \geq \varepsilon > -\mu_b,$$

which happens with probability $\int_{-\mu_b}^{\Sigma-\mu} f(\varepsilon)d\varepsilon$. As we saw in section 2, there was a small change in observed company investment during the crisis relative to investment before it, so this probability is small.

From equation (1), the probability that a manager invests but an investor does not invest is $\int_{-\mu}^{\Sigma-\mu} f(\varepsilon)d\varepsilon$. Since $\mu_b > \mu$, it follows that

$$\int_{-\mu_b}^{\Sigma-\mu} f(\varepsilon)d\varepsilon > \int_{-\mu}^{\Sigma-\mu} f(\varepsilon)d\varepsilon > 0$$

and so there is a very small probability that a project would be financed if internal finance is available but not financed if external finance is necessary. It follows that there is a very small negative change in expected investment when the project moves from being entirely internally dependent to entirely externally dependent. Assuming innovative outputs are positively related to investment, we then have the following hypothesis:

H1: For US companies during the financial crisis, dependence on external finance will not change significantly the innovative output from project classes.

We next investigate the effect of asset intangibility on innovation during the crisis. Intangible assets *N* are assumed to rise with the level of investment, other things being equal, so $dN/dI > 0$. We also assume that innovative outputs *P*, being a subset of intangible assets, increase when they do, so $dP/dN > 0$.

From equation (1), we have the lower and upper limits on the region over which non-investment occurs. Since $d\Sigma/dT < 0$, the upper limit $\Sigma - \mu$ reduces with tangible assets *T*, while the lower limit $-\mu$ is unchanged and so the probability of investment rises. Hence the expected investment rises as well and $dI/dT > 0$.

The intangibility ratio of a company is the value of intangible assets divided by the value of total assets, or $N/(T+N)$. It can measure how much protection an investor has in the event of a company being wound up, and has been as a performance determinant in financial crises (Kroszner et al, 2007). The response of innovative outputs to changes in the intangibility ratio is given by $\dfrac{dP}{d(N/(T+N))}$. We analyse the properties of this quantity. When the derivative is non-zero, the inverse function theorem says that $\dfrac{dP}{d(N/(T+N))} = \left(\dfrac{d(N/(T+N))}{dP}\right)^{-1}$. The derivative in the bracket can be expanded using the chain rule to give

$$\frac{dP}{d(N/(T+N))} = \left(\frac{dN}{dP}\frac{dI}{dN}\frac{d(N/(T+N))}{dI}\right)^{-1}$$

or, using the inverse function theorem again and the product rule,

$$\frac{dP}{d(N/(T+N))} = \left(\left(\frac{dP}{dN}\right)^{-1}\left(\frac{dN}{dI}\right)^{-1}\left(\frac{dN/dI}{T+N} - (dT/dI + dN/dI)\frac{N}{(T+N)^2}\right)\right)^{-1}$$

or

$$\frac{dP}{d(N/(T+N))} = \frac{dP}{dN}\frac{dN}{dI}\left((dN/dI)\left(\frac{1}{T+N} - \frac{N}{(T+N)^2}\right) - (dT/dI)\frac{N}{(T+N)^2}\right)^{-1}$$

or

$$\frac{dP}{d(N/(T+N))} = \frac{dP}{dN}\frac{dN}{dI}(T+N)\left(\frac{dN}{dI}\left(1 - \frac{N}{T+N}\right) - \left(\frac{dI}{dT}\right)^{-1}\frac{N}{T+N}\right)^{-1}$$

The terms $\frac{dP}{dN}$, $\frac{dN}{dI}$, $T+N$, $\left(1-\frac{N}{T+N}\right)$, $\frac{dI}{dT}$, and $\frac{N}{T+N}$ are all positive, so $\frac{dP}{d(N/(T+N))} > 0$ if and only

$$\frac{dN}{dI}\left(1 - \frac{N}{T+N}\right) - \left(\frac{dI}{dT}\right)^{-1}\frac{N}{T+N} > 0$$

or

$$\frac{dN}{dI}\frac{dI}{dT} > \frac{N}{T}.$$

Thus, innovative outputs grow as the intangibility ratio increases if and only if the product of growth of intangible assets as investment increases and the growth of investment as tangible assets increase is sufficiently large. In other words, growth in intangible assets is induced by tangible asset growth through investment, and for innovative output growth to be associated with a rising intangibility ratio, the intangible asset growth has to be large enough to outpace the tangible asset growth. Hence, we cannot state certainly how the intangibility ratio will affect company innovative outputs.

3.2 University innovation during the crisis

Many US university laboratories consider basic research as their primary objective, with much of their time spent on publishing academic research (Bozeman, 2000).

Nevertheless, their work often has an applied character (Mowery et al, 2001), and some of that work gives rise to commercial innovations. The funding for such innovations may come from, among other sources, industry or government. The latter source has become more important through a series of government policy initiatives including the Bayh-Dole Act of 1980 allowing universities to commercialise federally funded innovations, the National Cooperative Research Act of 1984 and its amendment in 1993 facilitating research collaborations, and the Advanced Technology Program from 1990 and the Technology Innovation Program from 2007 providing funding for research projects that often resulted in university-private sector partnerships (Bozeman, 2000; Hall et al, 2003).

A source providing funding to a university faces information problems similar to those faced by a funder of a company. It typically has less information than the university or the funded academic about their ability to implement a project, or about the project's progress. However, commercial sources funding universities usually extract information from the recipients directly rather than through the information intermediaries commonly used in financing companies, reflecting the frequent utility to the funding source of the university knowledge generated. The direct information extraction can take the form of technical queries, consultancy, direct employment, co-authoring papers, and hiring graduates and post-doctoral researchers (Boardman and Ponomariov, 2009; Bozeman and Gaughan, 2007). The US federal and state governments generally limit the information gap by competitive tender of grants, with applications having to give detailed information on their planned technological and financial aspects (see for example, Department of Health and Human Services (2007) or National Science Foundation (2013)). The applications are subject to monitoring during their progress and the possibility of non-renewal for ongoing projects. Expert evaluation of applications is maintained by use of peer review.

The provision of funding for US university innovation is not necessarily as badly disrupted by a financial crisis as provision for company innovation. The largest university funding source is the US government which is less financially constrained than US companies during crises. It could run deficits and make available extra funds to universities, which it did in 2007-8. Available funds from commercial sources may be subject to acute pressure due to the financial crisis and recession, as described above. Given the non-market form of the informational ties between universities and capital providers, the collapse of the information provision function of the market does not affect information passing directly between them.

These observations can be given a formal mathematical form in order to theorise on how university innovation responded to the financial crisis. We analyse investment by a government investor who values the income from a project (whether it accrues to the government or the university), and also other consequences from investment. During the crisis, a government investor in a project expects to receive an immediate utility (net of investment cost) of

$$\mu + P + \varepsilon$$

where μ is the net income from investment, P is a measure of the political value of other consequences of investment in excess of any benefits before the crisis, and ε is an error term with distribution function $f(\varepsilon)$.

Investment occurs if

$$\mu + P + \varepsilon > 0$$

or

$$\varepsilon > -P - \mu .$$

A commercially motivated university manager will invest if

$$\varepsilon > -\mu .$$

Thus, the excess in investment by investors over managers during the crisis occurs in the region given by

$$-\mu \geq \varepsilon > -P - \mu \qquad (2)$$

This is the region in which a project that was did not have access to external finance would not be given approval, while the same project that was externally financed would result in investment.

Prior to the crisis, the additional political benefits of investment in the crisis are not present, so $P = 0$. They receive an immediate net utility from investment of

$$\mu_b + \varepsilon$$

where μ_b is the net income from investment before the crisis. Since there is a recession at the same time as the financial crisis, $\mu_b > \mu$. Investment occurs if

$$\varepsilon > -\mu_b.$$

Investment occurs during the crisis but not before it if

$$-\mu_b \geq \varepsilon > -P - \mu,$$

conditional on the political benefits being sufficiently large so that $P > \mu_b - \mu$. The error term lies in the region with probability $\int_{-P-\mu}^{-\mu_b} f(\varepsilon)d\varepsilon$. In section 2, we saw that there was a reasonably large increase in observed government funding to R&D investment during the crisis relative to investment before it, so the probability is quite large.

From equation (2), the probability that a investor would fund a project but a manager would not is $\int_{-P-\mu}^{-\mu} f(\varepsilon)d\varepsilon$. Since $\mu_b > \mu$, it follows that

$$\int_{-P-\mu}^{-\mu} f(\varepsilon)d\varepsilon > \int_{-P-\mu}^{-\mu_b} f(\varepsilon)d\varepsilon > 0$$

and so there is a quite large probability that a project would be financed if external finance is necessary but not financed if internal finance is the source. It follows that there is a quite large change in expected investment when the project moves from being entirely internally dependent to entirely externally dependent. Assuming innovative outputs are positively related to investment, we then have the following hypothesis:

H2: For US universities during the financial crisis, dependence on external finance will increase the innovative output of project classes.

The effect of the intangibility ratio on university innovation during the crisis is analysed in a similar way as for company innovation. We again assume intangible assets *N* rise with the level of investment so $dN/dI > 0$, and innovative outputs *P* increase with intangible assets, so $dP/dN > 0$. The limits on the region in which investors invest more than managers in equation (2) are both independent of tangible assets *T*, so investment *I* during the crisis is independent of *T*, and $dT/dI = 0$.

The derivative of innovative outputs with respect to the intangibility ratio can be expanded as before to

$$\frac{dP}{d(N/(T+N))} = \left(\frac{dN}{dP} \frac{dI}{dN} \frac{d(N/(T+N))}{dI} \right)^{-1}$$

or

$$\frac{dP}{d(N/(T+N))} = \frac{dP}{dN} \frac{dN}{dI} (T+N) \left(\frac{dN}{dI} \left(1 - \frac{N}{T+N} \right) - \frac{dT}{dI} \frac{N}{T+N} \right)^{-1}$$

or

$$\frac{dP}{d(N/(T+N))} = \frac{dP}{dN} \frac{dN}{dI} (T+N) \left(\frac{dN}{dI} \left(1 - \frac{N}{T+N} \right) \right)^{-1}$$

since $dT/dI = 0$. The terms $\frac{dP}{dN}$, $\frac{dN}{dI}$, $T+N$, and $\left(1-\frac{N}{T+N}\right)$ are all positive, so

$$\frac{dP}{d(N/(T+N))} > 0.$$

So, university innovative outputs grow as the intangibility ratio rises. We therefore have the following hypothesis:

H3: For US universities during the financial crisis, higher intangibility ratios will increase the innovative output of project classes.

3.3 Control variables

The main variables for testing our hypotheses will be external financial dependence and the asset intangibility ratio, whose construction we will describe in section 4. We also include several control variables in the analysis. Together with lagged innovative outputs, they are used to capture other influences on the change in innovation during the crisis, including the effect of demand shifts due to the associated recession. In this subsection, we present the expected effect of the control variables on innovation.

The novelty of the type of innovated product

The financial crisis may have been associated with either of two Schumpeterian hypotheses, namely creative accumulation or creative destruction (Archibugi et al 2013a). Under the creative accumulation hypothesis, innovations are incremental and due to established innovators. They are the innovators who persist during the crisis, and we may expect them to build on their existing work with more established products. Thus, the age of the product type could be positively associated with changes in the volume of innovation. Under the creative destruction hypothesis, innovations are radical and occur in new areas. The financial crisis created instability and weakened the position of existing innovators. The crisis would be a time of new product type introduction, so that the age of the product type could be negatively associated with change in the amount of innovation. We do not take a prior position on which hypothesis best describes innovation during the crisis, and leave the data to determine the result.

R&D intensity

R&D intensity is measured as R&D divided by sales. Between 2008 and 2009, R&D funding for companies reduced (National Science Board (2012), appendix table 4-3). As a result, they had lower funds for sustaining research in previously initiated projects and for bringing partially finished projects to completion. The difficulties may have been most acute for expensive and risky R&D intensive projects. Thus, during the financial crisis we may expect bigger declines in commercial innovation for companies undertaking more R&D intensive projects. Universities had increased R&D funding indicating that the effect of R&D intensity would increase, but the impact would be moderated by their primary non-commercial objectives.

Capital to labour ratio

Large investments are made in R&D in the US (see section 2.1), and single successful innovative products can be very costly (see DiMasi et al (2003), Adams and Brantner (2006), and DiMasi and Grabowski (2007) for the costs of pharmaceuticals). Human skill and ingenuity is important in the innovation process, and employee remunerations are a large cost in it. For example, in 2008 the total wage bill for US corporate R&D workers was around $114 billion[3] compared with total business R&D investment of $291 billion (see section 2.1). We do not have any strong prior expectations of whether a high capital to labour ratio for a production process will be associated with higher or lower innovation rates. During the financial crisis, capital was rationed and innovation projects dependent on capital may have been hindered more than those with greater dependence on labour. Innovative output from such projects may have declined. However, as we do not expect a strong initial relation between innovation and the capital to labour ratio, the decline may be weak. Kroszner et al (2007) finds the capital to labour ratio has an insignificant effect on industrial value added growth changes between financial crisis periods and the periods preceding them.

[3] National Science Board (2012), table 3-7 puts average annual salaries for science and engineering workers at $80,170 in 2010. Table 3-13 gives total company R&D workers at 1,424,000 in 2008. We multiply to give a total wage bill of $114 billion.

4 Data

4.1 Preparation

In this section, we present the data used in our empirical testing[4]. It comes from two sources, the US Patent and Trademark Office (USPTO) online patent database and Compustat financial data. The cross-sectional unit of analysis is patent class, a USPTO classification of inventions according to technological type. There are 473 such classes, given directly in the USPTO data. For the Compustat financial data, we aggregate the data by industry code and then use the code to map into patent class. The patent class thus serves as a means of identifying technological and financial characteristics of innovation undertaken by US companies and US universities. By construction, the quantities derived from the Compustat data (external dependence, intangibility, R&D intensity, and the capital to labour ratio) allow for the industrial composition of their patent class.

USPTO data

The USPTO online patent database contains details of patent applications in the US unless the applicant has explicitly requested privacy prior to grant. Patent applications are published eighteen months after the applicant files for a patent. The database records applicant name, country of residence of the organisation or person to whom the application is issued, the application date, and the patent class of the invention. We accessed the data in March 2014.

Compustat data

We use data from all companies on Compustat for constructing our financial measures. Rajan and Zingales (1998) and Kroszner et al (2007) also use the full set of Compustat companies in preparing measures of external dependence, which results in the statistics reflecting the finances of US publicly quoted and larger companies. Our measures are all ratios of financial quantities, and are used for companies and universities operating commercially by undertaking patenting. Conceivably the relevant ratios of financial quantities in commercial operations run by US universities may be different from those in US companies. If true, then our hypothesis testing remains valid if the adjustment factor between the financial ratios of companies and

[4] The data and STATA code used in estimation are available from the author on request.

university commercial operations is constant across different innovation projects. Moreover, we run separate estimates for companies and universities, so there are no interpretational ambiguities for a combined coefficient.

Our statistics for Compustat data are grouped by two digit Standard Industrial Classification (SIC) System codes. As our cross-sectional unit for estimation is the USPTO patent class, we map from SIC based statistics to patent class based statistics using the concordance file between the two classifications provided by USPTO (2008b). The mapping to patent class is not unique as there are multiple subclasses which may be allocated different SIC codes, so we calculate average statistics over subclasses. For every patent class, the percentage of each SIC code corresponding to the class is calculated. The statistics for the patent class are derived as the sum of the percentage weighted statistics for the individual SIC codes. The formulas take the form

$$S_C = \sum_i \frac{n_{C,i}}{\sum_j n_{C,j}} S_i$$

where S_C is the statistic for patent class C, S_i is the statistic for SIC code i, $n_{C,i}$ is the number of subclasses in class C corresponding to SIC code i, and the summations run over all SIC codes.

As a means of determining the financial conditions under which an innovation was produced, the mapping is inevitably inexact. The difficulty arises from the allocation of patents to specific industries, as noted by Jaffe and Palmer (1997) in their matching of patents to industrial environmental cost data. An invention may have been produced by an innovator whose core operation is not in the SIC code allocated to the invention. So the invention may have been produced in financial conditions that differ from those that apply to companies producing under the allocated SIC code. We assume that any mismatches occur as random noise in the data and do not distort our results.

Our statistics S_i derived from Compustat data (external dependence, intangibility, R&D intensity, and the capital to labour ratio) all take the form of ratios and depend on the SIC code *i*. To calculate them, we first calculate the corresponding statistics $S_{i,j}$ for each SIC code and company code *j*. They are calculated as ten year averages over 2000-9, with for example the intangibility ratio given by

$$S_{i,j} = \frac{\sum_{k=2000}^{2009} \nu_{i,j,k}}{\sum_{k=2000}^{2009} \tau_{i,j,k} + \nu_{i,j,k}}$$

where $\nu_{i,j,k}$ are the total intangible assets for company coded *j* in year *k* operating in industry *i*, and $\tau_{i,j,k}$ are the total tangible assets over the same period. The statistic S_i for the SIC code are then the median of $S_{i,j}$ over all companies.

Variables

Patent counts

We use counts of patent applications as our measure of innovation within each patent class and split by innovator type, using USPTO data. Patents have long been used as such a measure (Scherer 1965, Schmookler 1962), and their advantages and disadvantages extensively discussed (Archibugi and Pianta, 1996; Basberg, 1987; Hagedoorn and Cloodt, 2003). The extent to which patents measure innovation may differ by innovator type. Universities may have a lower proclivity to patent their innovation than companies because of their largely different objectives (Bozeman, 2000). We may nevertheless infer that a contraction due to the crisis in the number of innovations, and in particular in the number of innovations produced with a commercial orientation, will generally be associated with a reduction in the number of patents for any innovator type.

We collect monthly data for the period from January 2006 to December 2009, giving 348,000 patents in total. There is an 18 month delay between filing and publication of applications, but as our data was collected in March 2014 the delay does not affect included applications. Applications that are made with a request of privacy, and are due to be successfully granted, and take more than four years to process may not be included in the data (with potentially greater effect on patent counts in later months). However, we expect the numbers to be small because the mean delay between patent application and issue or abandonment was 32 months in 2008 (USPTO (2008a), workload table 4) so that the large majority of applications would have been handled four years after they were made. Moreover, any omissions will not change the comparative results across innovators.

There is no single US country code to allow us to identify all US applicants on the USPTO database, but it does record the US state in which an American applicant is resident. We sum the patent counts for each state to obtain a patent counts for the whole US. The academic origin of applicants is not recorded on the USPTO database. We separate academic and non-academic applicants by searches on the applicant name. A representative subset of academic applicants is identified by searching the name for the words “university”, “college”, “school”, or “institute of technology”. These search terms identify most of the primary institutional names for academic applicants, including the largest patenters[5]. Some academic institutions may patent under secondary names omitting these terms, and these patents will be included in our non-academic counts. As the number of company patents far exceeds university patents, the contamination of company patent counts will be very limited.

External dependence

External dependence is calculated as the ratio of capital expenditures not financed by net operating cash flow to capital expenditure. The Compustat code for capital expenditures is *capx*, and for net operating cash flow is *oancf*, so the formula for external dependence is $(capx - oancf)/capx$. The list of external dependence values by patent class is available at our website in .csv format[6].

Intangibility

Intangibility is the ratio of intangible assets to total assets. The Compustat code for intangible assets is *intan*, and for total assets is *at*.

[5] http://www.uspto.gov/web/offices/ac/ido/oeip/taf/univ/total_counts/univ_ct_list_2012.htm
[6] http://ebasic.easily.co.uk/02E044/05304E/Ext_dep_by_patent_class.csv

The novelty of the innovated product class

The novelty of the innovated product type is measured by the date at which the USPTO introduced the corresponding patent class. The earliest establishment date is 1899 for patent classes including wood turning products and envelopes. The latest introduction date is 2007 for combinatorial chemistry technology.

The USPTO class introduction date is likely to measure the novelty of a type of innovated product only with a delay. It may not be immediately clear that the early patents in the product type represent a major departure from existing product types, and their citations will necessarily locate them within existing classes. The USPTO may only wish to introduce a new class only when a sufficient number of relevant patents is reached, and the identification and decision processes will not be immediate. Our econometric method will absorb into the constant term the average delay between the date at which a product type was first innovated and the date at which the corresponding USPTO class was introduced[7].

R&D intensity

R&D intensity is calculated as the ratio of R&D to sales. The respective Compustat codes are *xrd* and *sale*.

Capital to labour ratio

The capital to labour ratio is calculated as fixed assets divided by number of employees. The Compustat code for fixed assets is *ppent*, and for employees is *emp*.

Time

Time is measured in months since April 2001 (the first month of data availability), with April 2001 = 1.

4.2 Summary statistics

In table 1 we see summary statistics for the financial and other characteristics of the innovation undertaken by each innovator type. The mean external dependence of company innovation is lower than university innovation. For the classes in which

[7] Thanks to Pia Weiss for pointing out the likely difference between innovation date and patent class introduction date, and suggesting reasons for it.

companies innovate, internally generated funds are around 164 percent of total capital expenditures in US commercial conditions, while for universities the amount is 124 percent. The mean level of asset intangibility in those classes is similar for both innovator types at 14 and 15 percent. The mean establishment dates of the patent classes in which they operate is also similar, in the second half of the 1970s. Both innovate in the oldest and newest classes. The R&D intensity is higher in classes in which companies innovate compared with those in which universities innovate. The capital to labour ratio is lower for the projects of companies than those of universities.

Table 1

Summary statistics for innovation portfolios of each innovator type

	US companies			US universities		
	Mean	Min	Max	Mean	Min	Max
External dependence	-0.64	-5.55	0.84	-0.24	-5.49	0.84
Intangibility	0.14	0	0.66	0.15	0	0.66
Date established	1975	1899	2007	1978	1899	2007
R&D intensity	0.0029	0	0.0866	0.0017	0	0.0865
Capital/labour	115.3	0	2783.3	173.3	0	2783.3

Notes: mean values are weighted by patent counts.

4.3 Changes in aggregate patent counts during the crisis

Figure 1 shows aggregate patent counts by US companies. There are 326,000 patents in total over the period 2006-9, and the aggregate patenting appears to slow down around the end of 2007. To demonstrate the change in broad terms, the patent counts from the period 2006-7 are regressed on a time trend by OLS, and then the same is done for the period 2008-9. The two fitted lines are superimposed on the graph. The change in level and trend between the two periods is clear. Figure 2 shows aggregate patent counts for US universities; there are 22,000 patents over the whole period. Their patenting seems to change after the start of the financial crisis, in both level and trend.

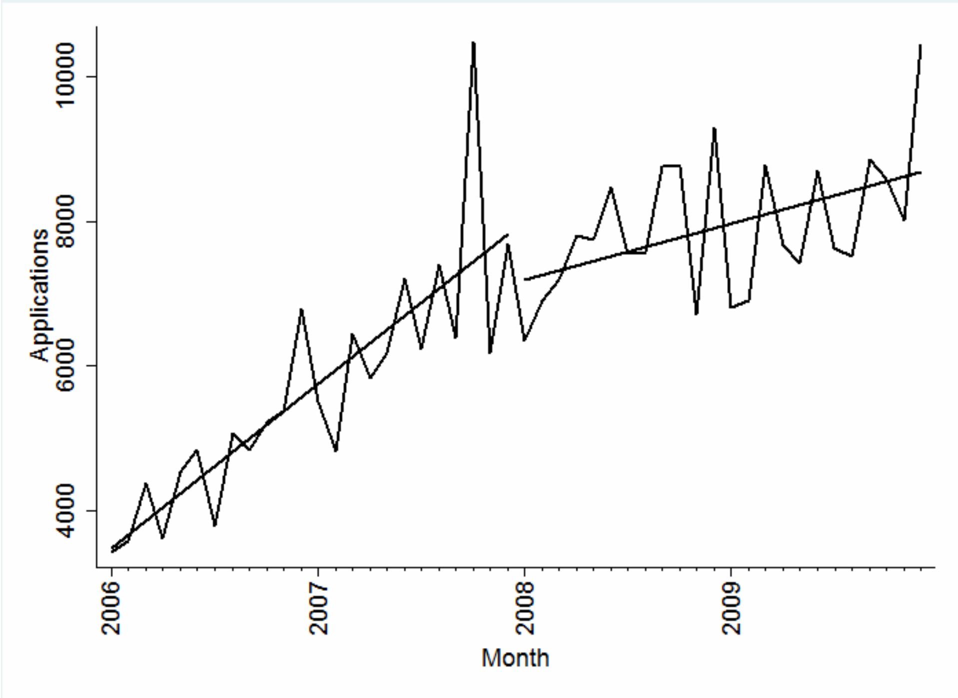

Figure 1. Aggregate patent counts by US companies with OLS lines fitted for 2006-7 and 2008-9.

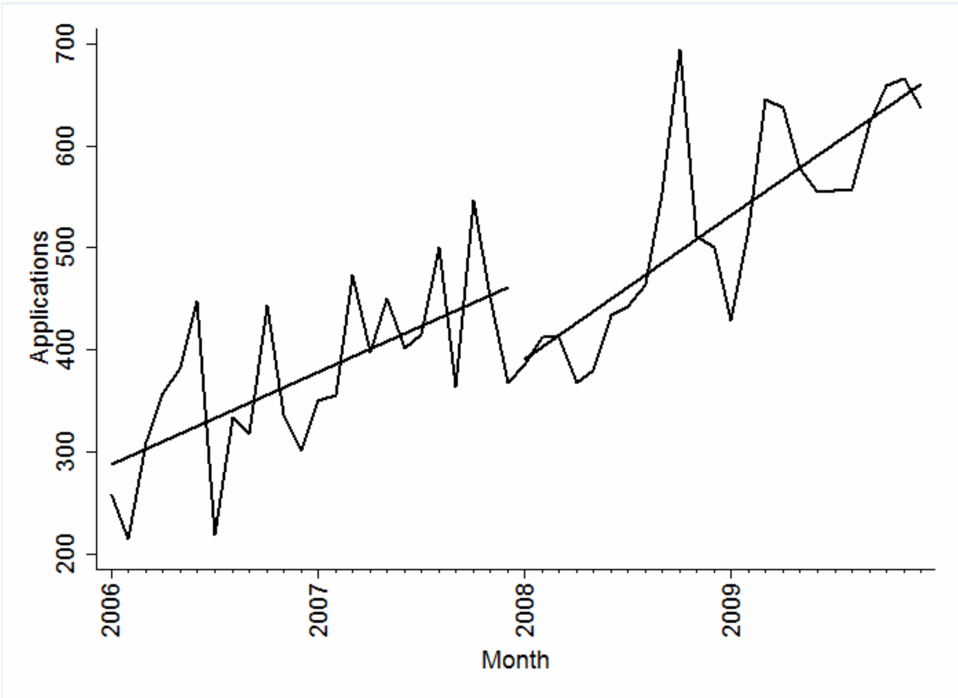

Figure 2. Aggregate patent counts by US universities with OLS lines fitted for 2006-7 and 2008-9.

To examine whether the change in aggregate patent rates for US companies is significant, we ran F tests for the constant and trend coefficient in the pre-break and post-break periods being jointly equal, allowing for possible break dates between January 2007 and December 2009. The most likely break date is at the end of 2007, giving us confidence to take December 2007 as a change date in the subsequent analysis.

To demonstrate the changes for patent classes around the financial crisis, we ran negative binomial estimations for patent counts in each class in the periods 2006-7 and 2008-9, with the logarithm of the expected value linearly dependent on time (this procedure forms part of the estimation method we describe for our full analysis in section 5). Predicted patent counts in January 2008 were calculated from the estimation results for both periods, giving us a set of predicted patents for the 2006-7 estimates and a set for the 2008-9 estimates. Figure 3 plots the predicted patents from the US company data as kernel densities. The solid line shows the predictions from the 2006-7 estimates, and the dashed line shows the predictions from the 2008-9 estimates. The 2008-9 density is a compression towards zero of the 2006-7 density, representing a general reduction in patenting.

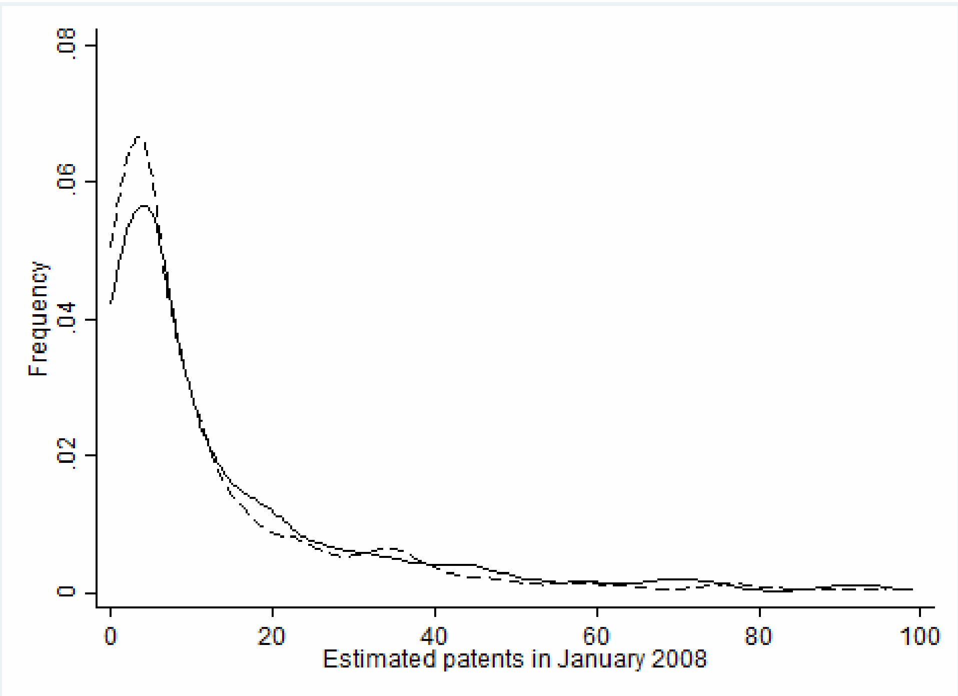

Figure 3. Kernel density of estimated patents in January 2008 across patent classes. *Notes*: the solid line is for estimates from 2006-7 and the dashed line is for estimates from 2008-9. US company data is used.

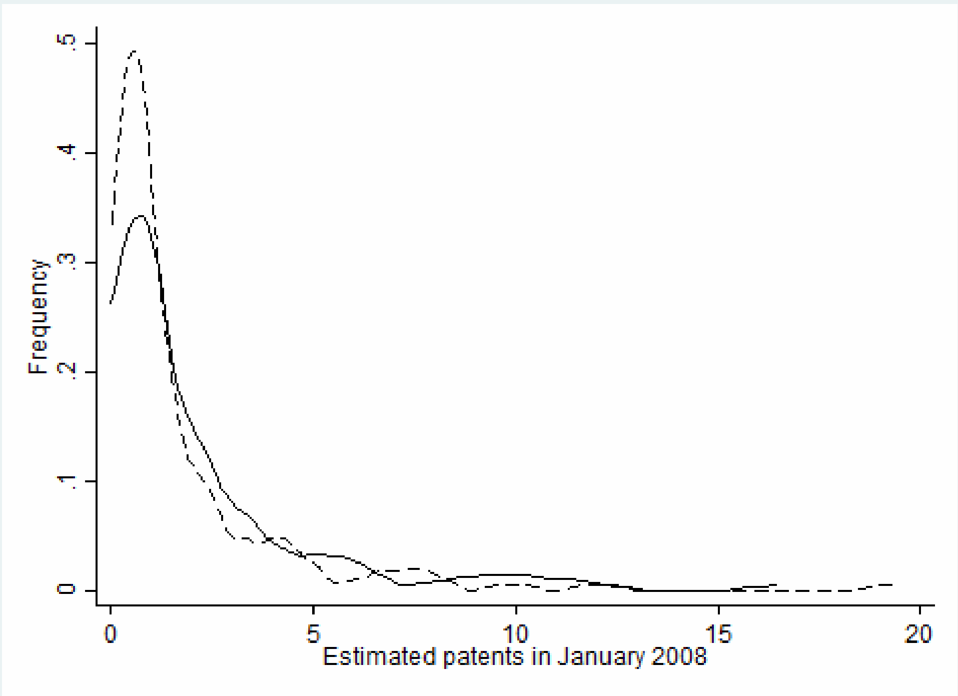

Figure 4. Kernel density of estimated patents in January 2008 across patent classes. *Notes*: the solid line is for estimates from 2006-7 and the dashed line is for estimates from 2008-9. US university data is used.

In figure 4, we see the corresponding densities for US universities. The number of patent classes predicted to have just a single patent increases in the 2008-9 estimates, and there is again a broad compression towards zero, indicating a reduction in patenting.

5. Empirical method

In this section we present our testing and estimation method. We assume a multiplicative model for predicted patent counts conditional on the information available during the crisis, relating it to the predicted patent counts prior to the crisis and an adjustment factor influencing the relation between the two. The adjustment factor is exponential and guarantees positive patent counts, as is standard in the empirical literature (Cameron and Trivedi, 1998). The functional form is

$$p_{i,t} \mid I^{+} = \alpha \ (p_{i,t} \mid I^{-})^{\beta} \ \exp(\gamma + \Gamma' X_i + u_i) \qquad (3)$$

where $p_{i,t} \mid I$ are predicted patent counts in patent class *i* at time *t* and conditional on information set *I*, I^{+} is the information available during the crisis, I^{-} is the information available before the crisis, α, β and γ are constants with $\alpha > 0$, X_i is a vector of time-invariant patent class characteristics, Γ is a vector constant with the same dimension as X_i, and u_i is a zero mean normal error.

Hypotheses H1 and H2 examine how external dependence affects the change in innovation during the crisis for different innovator types. Equation (3) may be written as

$$(p_{i,t} \mid I^+)/(p_{i,t} \mid I^-) = \alpha \ (p_{i,t} \mid I^-)^{\beta-1} \ \exp(\gamma + \Gamma' X_i + u_i)$$

The left hand side of the equation is the ratio of patents predicted during the crisis to those predicted before the crisis, and so measures innovation change. We test hypothesis H1 by looking at the significance of external dependence on the right hand side of the equation when company data is used, and hypothesis H2 by looking at the sign and significance of external dependence when university data is used. Hypothesis H3 examines how intangibility ratios affect innovation, and we test it by looking at the sign and significance of the intangibility ratio on the right hand side of the equation when university data is used.

Taking logs of equation (3) we have

$$\ln(p_{i,t} \mid I^-) = \ln \alpha + \beta \ln(p_{i,t} \mid I^+) + \gamma + \Gamma' X_i + u_i . \qquad (4)$$

This specification for examining the crisis' effect is similar to that used in Archibugi et al (2013a), where the change in innovation between two years is measured. We could bring our specification even closer to their model by comparing changes in patents in successive time periods, t and $t + 1$. However, we prefer to examine an instant effect, rather than a delayed one. The reason is that any crisis effect may tend to correct itself over time especially in patent classes where it has been severe, so that an estimation using successive periods may not capture the full crisis effect. Moreover, we prefer to use extended evidence of patenting behaviour to estimate mean patenting rates rather than patent rates in one period, in order to reduce measurement volatility. As a prediction method for calculating $p_{i,t} \mid I^+$ and $p_{i,t} \mid I^-$, we could use averages or sums over successive periods (for example, to give annual rates of innovation, as in Archibugi et al (2013a)), which would be acceptable in the absence of trends in the data. However, trends in patenting in each class are likely. So we use an equivalent method to averaging, but one which allows for trends. We calculate the predicted patents $p_{i,t} \mid I^{+}$ and $p_{i,t} \mid I^{-}$ in class i at time t by running two sets of negative binomial regressions for counts in each patent class:

$$\log(P_{i,t}) = \varphi_i + \psi_i\, t\,, \qquad (5)$$

$P_{\mathrm{i,t}}$ ~ negative binomial,

where $P_{\mathrm{i,t}}$ are patent counts in class i at time t, and φ_{i} and ψ_{i} are class specific constants. Patenting in each class may be generated by distinct processes and be at different life stages, and so we make no assumptions about the commonality of parameters across classes in generating predictions.

The estimation is performed first over the 24 month period from January 2006 to December 2007, which we call the pre-crisis period, and then over the period from January 2008 to December 2009, which we term the crisis period. We exclude any patent classes in which the number of patents is ten or less over the whole 2006 to 2009 period. Once we have the regression coefficients, we take $p_{i,t} \mid I^{-}$ to be the predicted value at time t from the early period equation, and $p_{i,t} \mid I^{+}$ to be the predicted value from the late period equation.

We estimate equation (4) using OLS across classes i with robust standard errors, with the predicted patents evaluated in January 2008. The influence of extreme patent class values is eliminated by excluding any classes in which the predicted January 2008 patent counts from either the 2006-7 or 2008-9 periods exceed 100 for US companies, and 20 for US universities. The exclusion is of less than the top seven percent of values for each innovator type.

We also estimate a modified version of equation (4) using cumulative patents over a time period T,

$$\ln \sum_{t \in T} p_{i,t} \mid I^- = \ln \alpha + \beta \ln \sum_{i \in T} p_{i,t} \mid I^+ + \gamma + \Gamma' X_i + u_i . \qquad (6)$$

The values for cumulative predicted patents are produced by predicting two sets of cumulative patents over the period *T*, using estimates from equation (5) based on the data from 2006-7 to predict $\sum_{t \in T} p_{i,t} \mid I^-$ and from 2008-9 to predict $\sum_{t \in T} p_{i,t} \mid I^+$. In the OLS estimation of equation (6), we exclude classes with early estimated or late estimated cumulative patents exceeding 5000 for companies, and 500 for universities. Less than the top five percent of values are excluded for each innovator type.

6 Results

6.1 Immediate and cumulative effects of the financial crisis

In this section we present our results, starting with the crisis' immediate and cumulative effects on innovation in table 2. The first two columns present regression results where the determined variable is the logarithm of the patent count in January 2008 as predicted using data from 2008-9. In column one, we see the results for US companies. External dependence has an insignificant effect on the count, consistent with hypothesis one was that there would be no significant link between the two. Column two gives coefficients for US universities. External dependence is significantly associated with increased patenting during the crisis, consistent with hypothesis two, while intangibility is significantly associated with increased patenting during the crisis, as anticipated in hypothesis three.

Columns three and four look at regressions with the logarithm of cumulative predicted patents as determined variable. Column three has results for companies. External dependence has a significant positive effect on the cumulative patenting over 2008-9, indicating that the effect in January 2008 becomes more positive over time. Column four presents results for universities, with a significant positive links between cumulative patenting and both external dependence and intangibility. The same links are observed in January 2008.

Table 2

Determinants of the logs of the predicted patent count at the start of the crisis and the sum of the predicted patent counts during the crisis

Dependent variable:	Log late predicted patents in January 2008		Log late predicted patents cumulated over 2008-9	
	US companies	US universities	US companies	US universities
	OLS regressions			
	(1)	(2)	(3)	(4)
External dependence	0.0254	0.1990*	0.0858**	0.2439**
	0.0306	0.1012	0.0415	0.103
Intangibility	-0.0857	1.1103**	0.305	1.0084**
	0.2238	0.4257	0.3645	0.4088
Log early predicted patents	0.9497***	0.6994***	0.7663***	0.4038***
	0.0329	0.0617	0.036	0.0505
Establishment date	-0.0008	-0.0057**	0.0011	0.0018
	0.0009	0.0025	0.0014	0.003
R&D intensity	-2.9369	-7.8922*	-5.2830*	-9.7988*
	2.1868	4.7325	2.8048	5.6922
Capital to labour ratio	-0.0002**	-0.0006**	-0.0002*	0.0001
	0.0001	0.0003	0.0001	0.0002
Constant	1.488	11.0805**	-1.225	-1.6421
	1.7817	4.9167	2.646	6.0256
R^2	0.87	0.62	0.77	0.46
Observations	369	140	372	134

Notes: Robust standard errors are shown below the coefficients.

* Ten percent significance.

** Five percent significance.

*** One percent significance.

6.2 Results split by age of patent class

Table 3 presents estimations split by the age of the patent class, with new patent classes established after 1990 and old patent classes established before 1991. This division gives a reasonable approximation for the split between high technology and other technology. The results for new classes are shown in columns one and two. Coefficient estimates for US companies are presented in column one, where external dependence is insignificantly associated with patenting. The results for US universities are in column two, where neither external dependence nor intangibility is associated with patenting. The small sample size will have influenced the low coefficient significance.

Table 3

Determinants of the logs of the predicted patent count in January 2008, by patent class age

	Dependent variable: log late predicted patents in January 2008			
	New classes		Old classes	
	US companies	US universities	US companies	US universities
	OLS regressions			
	(1)	(2)	(3)	(4)
External dependence	-0.0428	0.0186	0.0224	0.2162*
	0.118	0.3345	0.0313	0.1102
Intangibility	0.1676	0.7474	-0.2079	1.1014**
	0.9583	1.3296	0.2272	0.468
Log early predicted patents	1.1308***	0.6025***	0.9223***	0.7856***
	0.072	0.1117	0.0364	0.0767
Establishment date	-0.0065	0.0296	-0.0002	-0.0078**
	0.0233	0.0342	0.001	0.0036
R&D intensity	4.0078	-17.9753	-2.8549	-6.7787
	4.2495	10.7814	2.3566	4.7261
Capital to labour ratio	-0.0001	-0.0009***	-0.0001	-0.0003
	0.0001	0.0002	0.0001	0.0002
Constant	12.2738	-59.3178	0.4251	15.1319**
	46.257	68.3041	1.9659	6.9697
R^2	0.92	0.6	0.86	0.67
Observations	61	43	308	97

Notes: Robust standard errors are shown below the coefficients.

* Ten percent significance.

** Five percent significance.

*** One percent significance.

Columns three and four give estimates for data based on old patent classes. Column three shows that for US companies there was no significant association between external dependence and patenting. A significant positive relation is shown for US universities in column four. The association is also significant and positive between external dependence and patenting. Hypotheses one, two, and three all hold for patenting in old classes.

6.3 Estimates based on OLS predictions of patenting

In calculating the results in section 6.1, the predicted patent counts are derived from negative binomial estimation within each patent class, so they grow exponentially over time. In this section, we calculate results in which the predictions are derived from OLS estimations in each class, with linear growth in patenting over time. The extra caution comes at the cost of allowing negative patenting in classes and of a discrete non-symmetric random variable being approximated by a normal variable; however, as section 7 will show, the aggregate OLS behaviour predicts actual patenting after the crisis more closely than aggregate negative binomial predictions.

We continue to estimate results from our main cross sectional regressions given by equations (4) and (6). However for predicting patents within classes we replace the negative binomial equation (5) with an OLS equation

$$P_{i,t} = \varphi_i + \psi_i \ t + v_{i,t} \ ,$$

where φ_i and ψ_i are class specific constants and $v_{i,t}$ is a zero mean normal variable. The estimation is performed over the period from January 2006 to December 2007, then over January 2008 to December 2009. We again exclude any patent classes in which the number of patents is ten or less over the whole 2006 to 2009 period. Once we have the regression coefficients, we use predictions from the early period and late period estimations as variables in our main regressions.

Table 4 contains our results, with the first two columns presenting coefficient estimates when the dependent variable is the logarithm of predicted January 2008 patents. In column one, US company data is used and external dependence is found to have an insignificant association with patenting, as expected from hypothesis one. Column two shows that for US universities there is a significant positive relation between external dependence and patenting, consistent with hypothesis two. The relation between intangibility and the patent count is significant and positive, as hypothesis three anticipated. Overall, the evidence provided for hypotheses 1, 2, and 3 is strong here as in the main table 2.

Table 4

Determinants of the logs of the predicted patent count at the start of the crisis and the sum of the predicted patent counts during the crisis; prediction by OLS

Dependent variable:	Log late predicted patents in January 2008		Log late predicted patents cumulated over 2008-9	
	US companies	US universities	US companies	US universities
	OLS regressions			
	(1)	(2)	(3)	(4)
External dependence	0.0329	0.2534**	0.0689**	0.2781***
	0.0319	0.1001	0.0289	0.0667
Intangibility	-0.1108	1.1115**	0.3049	0.8959***
	0.2471	0.4496	0.2076	0.3237
Log early predicted patents	0.9447***	0.8276***	0.8857***	0.6662***
	0.0394	0.0446	0.0393	0.0567
Establishment date	-0.0006	-0.0042*	-0.0002	-0.0026
	0.001	0.0024	0.001	0.0022
R&D intensity	-4.1775	-7.2524	-3.5887	-9.0298***
	2.8012	4.5322	2.188	3.2574
Capital to labour ratio	-0.0001*	-0.0005***	-0.0002***	-0.0003**
	0.0001	0.0001	0.0001	0.0002
Constant	1.3011	8.1784*	0.8929	6.4551
	1.9036	4.6957	1.8581	4.31
R^2	0.88	0.74	0.89	0.68
Observations	386	134	373	129

Notes: Robust standard errors are shown below the coefficients.

* Ten percent significance.

** Five percent significance.

*** One percent significance.

Columns three and four report estimates where the dependent variable is the logarithm of patents cumulated over 2008-9. In column three we see that for companies there is a positive relation between external dependence and cumulative patenting. Column four employs university data, and shows that there is a significant positive association between cumulative patenting and both external dependence and intangibility. As a whole, the findings are similar to those in table 2 where negative binomial projections are used.

7. Counterfactuals

The growth of unregulated debts among financial institutions has been presented as a major contributing factor to the 2007-8 crisis (Brunnermeier, 2009; Calomiris, 2008), and market-based solutions have been advanced to alter and constrain the behaviour of financial institutions (Acharya et al, 2009). They offer the possibility of insulating the financial and real economies from systemic build up of risk, such as that emerging from the sub-prime mortgage market. More stringent measures would reduce the role of the financial markets in funding companies, but the direction of international travel has been towards increased market based development. A movement towards a more commercial approach has been seen in US universities as well, for regulatory, technological, administrative, and financial reasons (Mowery et al, 2001).

In this section, we investigate the effect of alternative responses to portfolio characteristics on innovation during the crisis. In our first counterfactual companies continue to work on the same projects as before, and the patenting in January 2008 and over 2008-9 is calculated as if they were experiencing the same output response to those projects as universities. Our second counterfactual examines outcomes when universities adopt the response of companies. Calculations are performed based on the parameters estimated in table 2.

The statistics we examine are expected late predictions calculated from equations (4) and (6), minus the early predictions, and summed across all patent classes:

$$\sum_i (E(\overline{p_{i,t} \mid I^+}) - p_{i,t} \mid I^-)$$

and

$$\sum_i (E(\overline{\sum_{t \in T} p_{i,t} \mid I^+}) - \sum_{t \in T} p_{i,t} \mid I^-)$$

where E denotes the expectations operator, $\overline{Y}$ denotes the fitted value of Y, and the other notation is as for equations (3) and (6). The expected predicted patents counts are calculated as

$$E(\overline{p_{i,t} \mid I^{+}}) = \alpha \ (p_{i,t} \mid I^{-})^{\beta} \ \exp(\gamma + \Gamma' X_i) E(\exp(u_t))$$

and

$$E(\overline{\sum_{t \in T} p_{i,t} \mid I^{+}}) = \alpha \ (\sum_{t \in T} p_{i,t} \mid I^{-})^{\beta} \ \exp(\gamma + \Gamma' X_i) E(\exp(u_t))$$

where the additional notation is as below equation (3). The exponential error term is calculated as

$$E(\exp(u_t)) = \exp(0.5\sigma^2)$$

where σ is the root mean squared error from the estimations in table 2. For the counterfactuals, we replace one or more of the coefficients and exponentiated error term from the estimated equation with the coefficients and error from the alternative equation. In the summations, we do not sum over elements with extreme predicted values, using the same definitions of extreme values as in section 5.

Table 5 presents our results, with the top panel showing patenting in January 2008 and the bottom panel showing cumulative patenting over 2008-9. Columns one and two use negative binomial predictions, while columns three and four use OLS predictions. In column one we see the consequences of the crisis response to the characteristics of US company innovation becoming like that experienced by US universities. The top panel shows the immediate effect. There is a substantial impact on patenting in January 2008, with 2,300 fewer patent applications. In the low panel, the cumulative effect of the change is shown. The decline in US company patenting goes from 111,000 applications to 195,000 applications, representing an additional loss of innovation outputs of 84,000 applications.

Table 5

Patenting change during the crisis on switching to a different institution's response parameters while maintaining the original institution's innovation portfolio

Estimation method	Negative binomial		OLS	
From parameters and innovation portfolio of	US companies	US universities	US companies	US universities
To parameters of	US universities	US companies	US universities	US companies
In January 2008				
Expected patent crisis change before adjustment	-558	-54	-262	-34
Expected change after all adjustment	-2890	-6	-2,359	22
Cumulative over 2008-9				
Expected patent crisis change before adjustment	-110,912	-11,455	-46,367	-2,419
Expected change after all adjustment	-194,716	-5,589	-95,092	-1,337

In the counterfactual in column two, US universities are fully integrated in the market and their patenting changes as if they were US companies during the crisis. From the top panel, it can be seen that adopting the alternative responses is associated with an increase in patenting of 48 applications. The lower panel shows that the cumulative effect over 2008-9 of adopting the alternative responses is large relative to base patenting; the decline in innovation goes from 11,500 applications to 5,600 applications, so there are an extra 5,900 patents. Columns three and four show that OLS estimated effects of changing responses are qualitatively similar to negative binomial estimated effects.

Our counterfactuals find that US university responses diminish patenting for US companies, while US company responses increase patenting for US universities. Company responses ensure greater innovation given the portfolio characteristics of companies and universities. Their advantage occurs both in relation to the financial external dependence of innovation projects, and other factors including market demand.

8. Conclusion

In this paper we have looked at how the innovator type affected innovation during the 2007-8 financial crisis. Our theoretical and empirical results indicate that, at the start of the crisis, the effect of external financial dependence on the change in patent counts was insignificant for projects undertaken by companies but significantly positive for projects undertaken by universities. Higher proportions of intangible assets were associated with increased university patenting. The effects were similar over the 2008-9 period, although external financial dependence gained a significant positive association with company patenting. Similar effects are shown for innovative projects in technology classes introduced before 1991; the results for newer classes are not as strong but may be influenced by a relatively small sample size.

Counterfactuals indicate that if US company patenting responded in the same way as university patenting its decline would have been greater. Conversely, US universities would have had smaller declines if they had the same patenting response as US companies. We have not considered the possibility of innovation portfolio characteristics being selected in response to the funding used, which would alter counterfactual patent count changes. An analysis of endogenous selection could start from the theoretical basis described in the managerial literature on multiple interactions and influences between enterprise capabilities, competitive environment, and strategy (Henderson and Mitchell, 1997).

Our results echo those of Paunov (2012), who found that use of public funds by Latin American companies was associated with less discontinuation of their innovative projects during the crisis, whereas use of private funds was not significantly associated with it. Our data inspection and theoretical model suggest that the results can be explained by the increase of aggregate public R&D funding and moderate persistence of aggregate private R&D funding, at least in the US. The question then arises, why did private innovation funding not collapse during the crisis? Campello et al (2010) present a possible explanation, by finding that while total international company investment did fall sharply during the crisis, capital investments were relatively robust. Future work could establish whether innovation projects are accorded a protected status during crises, and whether particular types of projects are given more protection than others.

Although we did not dwell on the matter in the main text, it is interesting to note that persistence of innovation in each patent class was much higher for companies than for universities. One possible explanation is that universities are more willing to break radically with their past innovation during crises, perhaps acting as agents of creative destruction to a greater extent than companies (see Archibugi et al (2013a) and Archibugi et al (2013b)). Universities may have fewer institutional constraints stopping them from becoming radical innovators. However, groundbreaking innovations may be put by the USPTO into the same patent class as less significant innovations in the short term, because of delays in introduction of new classes. So short term patent classification is an imperfect way of recognising technological shifts. Moreover, an alternative institutional explanation for the persistence gap is possible, in that universities are able to retreat from the market in a way that is not possible for companies. Further study could clarify the reasons for the gap.

Our theoretical and empirical results suggest policy applications relating to the selection of solutions to informational and control problems in the principal-agent relations that arise in innovation. Solutions using financial markets may be susceptible to collapse during financial crises, and when they occur or are threatened it may be preferable to adopt elements of the non-market solutions used in university funding by industry or government, including direct or peer monitoring rather than commercially intermediated monitoring, and sharing technologies and profits between the funding and funded parties. However, the value of these relations during a crisis is dependent on the political commitment to fund innovation. If this commitment is lacking – which it generally was in crises prior to 2007-8 – then university relations may perform worse than company relations as funding conduits. Moreover, even during the crisis of 2007-8, company commercial innovative outputs were maintained at a higher level than university outputs. If maintenance of such outputs is sought by policymakers, universities could learn from the productive process of companies during crises. We leave it to future work to determine the exact nature of the lessons.

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