

Innovation and Institutional Ownership*

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Abstract

We find that institutional ownership in publicly traded companies is associated with more innovation (measured as cited-weighted patents), even after controlling for a possible endogeneity of institutional ownership. To explore the mechanism through which this link arises, we build a model that nests managerial laziness with career-concern considerations, where institutional ownership *increases* the incentives managers have to innovate by reducing the career risk of innovative projects. While the lazy manager hypothesis predicts a substitution effect between institutional ownership and product market competition, the career-concern one allows for complementarity. Our finding that the effect of institutional investors on innovation increases with product market competition supports the career-concern model. This model is also supported by our finding that CEOs are less likely to be fired in the face of profit downturns when institutional ownership is higher. **JEL No.** O31, O32, O33, G20, G32

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Innovation is the main engine of growth. But what determines a firm's ability to innovate? Innovating requires taking risk and forgoing current returns in the hope of future ones. Furthermore, while any type of financing is plagued by moral hazard and adverse selection, the financing of innovation is probably the most affected ones (Arrow, 1972), since the information that needs to be conveyed is the hardest one to be communicated to outsiders. For this reason it is very important to study the governance of innovation.

While the ability to diversify risk across a large mass of investors makes publicly traded companies the ideal locus for innovation, managerial agency problems might undermine the innovation effort of these companies. In publicly traded companies, the pressure for quarterly results may induce a short term focus (Porter, 1989). And the increased risk of managerial turnover (Minton and Kaplan, 2008) might dissuade risk-averse chief executive officers from this risky activity. Finally, innovation requires effort and lazy managers might not exert enough of it. Hence, it is especially important to study the governance of innovation in publicly traded companies, which account for a large share of the private investments in R&D.

The most important phenomenon in corporate governance in the last 30 years is the rise in institutional ownership. While in 1970 institutions owned only 10% of publicly traded equity, by the end of 2005 they owned more than 60%. Thus, in this paper we focus on the role of institutional ownership on the innovation activity of publicly traded companies. Did the rise in institutional ownership increased short-termism, undermining the innovation effort? Or did it reassure managers, making them more willing to strike for the fence? To answer these questions we assemble a rich and original panel dataset of over 800 major US firms over the 1990s containing time-varying information on patent citations, ownership, R&D and governance.

We show that there is a robust positive association between the level of insti-

tutional ownership and innovation. Institutions have a small and positive impact on R&D, but a larger effect on the *productivity* of R&D (as measured by future cite-weighted patents per R&D dollar). This relationship is not due to a selection mechanism, where institutions choose to own the most innovative companies, because we show that even an exogenous increase in institutional ownership, as the addition of a stock to the S&P500, has a positive effect on innovation.

To uncover the source of this relationship we build a model that nests the two main reasons for this positive effect. The simplest explanation is managerial slack: managers may prefer to live a quiet life but institutional investors may force them into innovating. An alternative explanation is based on career concerns. Innovation carries a risk for the CEO: if things go wrong for purely stochastic reasons, the board will start to think he is a bad manager and may fire him. This generates a natural aversion to innovation. If incentive contracts cannot fully overcome this, increased monitoring can improve incentives to innovate by “insulating” the manager against the reputational consequences of bad income realizations. According to this view, institutional owners, which own a large share of the firm and hence have incentives to monitor, will encourage innovation. The lazy manager hypothesis predicts that product market competition and institutional ownership are substitutes: if competition is high then there is no need for intensive monitoring as the manager is disciplined by the threat of bankruptcy to work hard. In contrast, the career concern model predicts that more intense competition reinforces the positive effect of institutional investment on managerial incentives.

We find that the positive relationship between innovation and institutional ownership is stronger when product market competition is more intense (or when CEOs are less “entrenched” due to protection from hostile takeovers), which is consistent with the career concerns hypothesis and inconsistent with the “lazy manager” one.

Another implication of the career concern model is that the decision to fire the CEO is less affected by a decline in profitability than in the presence of large institutional investors. We find that to be the case. While in the absence of a large institutional investor a decline in profit leads to a high percentage probability of the CEO being dismissed, this probability drops when institutional investors own a substantial fraction of the stock.

Finally, we try to uncover which institutions have the biggest impact on innovation by using Bushee (1998) classification. We find that quasi-indexed institutions have no effect on innovation, while dedicated and transient institutions (to use Bushee's classification) have an equally positive effect on innovation.

While there is a large literature on the effect of financing constraints on R&D (for surveys see Bond and Van Reenen (2007) and Hall (2002)), there is very little on the relation between institutional ownership and innovation. Notable exceptions are Francis and Smith (1995), who find a positive correlation between ownership concentration (which includes institutions) and R&D expenditures and Eng and Shackell (2001), who find a positive correlation of institutions with R&D. In a similar vein, Bushee (1998) finds that cuts in R&D following poor earnings performance are less likely the greater is the degree of institutional ownership. Unlike all these papers, we focus on the actual productivity of the innovation process, rather than on the quantity of input (R&D expenses). In addition, our use of an instrument allows us to exclude the possibility that this relationship is due to institutions' ability to select the most productive firms. Finally, our model allows us to probe deeper into the fundamental agency problem that causes this relationship.

Our paper is organized as follows. Section 1 presents the data, Section 2 the econometric framework, Section 3 the main empirical results on institutional ownership and innovation. The model is described in Section 4 and its additional

predictions on competition and managerial exit are tested in Section 5. Section 6 offers some concluding comments.

1. Data

We assemble a panel data of firm-level data on innovation and institutional ownership from a variety of sources. Our starting point is Compustat, which contains accounting information for all U.S. publicly listed firms since the mid 1950s. While Compustat contains information on R&D expenditures, it does not contain patent data. We get these by using the NBER match between Compustat and the U.S. Patent and Trademark Office data. This contains detailed information on almost three million U.S. patents granted between January 1963 and December 1999 and all citations made to these patents between 1975 and 2002 (over 16 million)¹. Since the value of these patents differ greatly, to capture their importance we weight them by citations.

For information on institutional ownership we use the text files of Compact Disclosure. Ownership data includes the number of institutional owners, the number of shares issued and the percent of outstanding shares held by each institution². The ownership data covers 91,808 firm-year observations between 1991 and 2004 (prior to 1991 there are some inconsistencies in the reporting of the ownership data which is why this is our first year). We then matched these data with Bushee (1998) classification of institutions, to investigate whether there are

¹See Bronwyn Hall, Adam Jaffe and Manuel Trajtenberg (2001) and Adam Jaffe and Manuel Trajtenberg (2002). We used Bronwyn Hall's update of the citation files which runs through to 2002.

²All institutional organizations, companies, universities, etc. are required to file a Form 13-F with the SEC on a quarterly basis if they have greater than \$100 million in equity assets under discretionary management. All common stock holdings of 10,000 or more shares or having a value of \$200,000 or more must be reported. Throughout this paper an institutional owner is defined as an institution that files a 13-F.

differential effects by the type of institutional owner.

Third, for information on CEO firing, exits in general and other managerial characteristics we use the data constructed by Ray Fisman, Rakesh Khurana and Matthew Rhodes-Kropf (2005) based on careful reading of the financial press and the S&P ExecuComp database.

Finally, for information on corporate governance and state laws against hostile takeovers we use the *Investor Responsibility Research Center* (IRRC) which publishes detailed listings of corporate governance provisions for individual firms (see Paul Gompers, Andrew Metrick and Joy Ishii, 2003 and Maria Pinnelle, 2000).

These datasets do not overlap perfectly so our baseline regressions run between 1991, the first year of clean ownership data, and 1999, the last year when we can realistically construct citation weighted patent counts. Although the exact number of observations depends on specific regression, the sample for which we run the cite-weighted patents equation contains 6,208 observations on 803 firms. Descriptive statistics are contained in Table 1. We see that our firms are large (3,700 employees and \$608,000 in sales at the median). As is well-known the citation and patents series are very skewed. For example, the mean number of cite-weighted patents is 176 per firm-year, but the median number of cites is only two.

1.1. Nonparametric analysis

We first take a preliminary, non-parametric look at the data in Figures 2 and 3. Figure 2 presents the non-parametric relationship between the log of raw patent counts and the proportion of firm's equity owned by institutions. Figure 3 presents the same graph but using our preferred future citation weighted patents measure. On both graphs we show a line of the local linear regression estimated by the lowest smoother with a bandwidth of 0.8. There is clearly a positive correlation

between the two variables which appears to be broadly monotonic, although the positive relation does not appear until institutions own at least 25% of the shares.

2. Econometric modeling strategy

2.1. Modeling Innovation

Consider the first moment of the relationship between a count-based measure of innovation (i.e. future/forward cite-weighted patents), $CITES_{it}$, of firm i in period t and our measure of institutional ownership (the proportion of stock owned by institutions)³. The conditional expectation ($E(.|.)$) of innovation is:

$$E(CITES_{it}|x_{it}) = \exp(\alpha INSTIT_{it} + \beta x_{it} + \eta_i + \tau_t) \quad (2.1)$$

where x_{it} are other control variables⁴, η_i is a firm-specific idiosyncratic effect and τ_t is a full set of time dummies. Note that we will show the importance of different conditioning variables. In particular, we consider specifications with and without controlling for the R&D stock. When the R&D stock is included in equation (2.1) α indicates whether firms with higher $INSTIT_{it}$ have a greater ability to obtain innovations from their R&D stock (“R&D productivity”). When we drop R&D from the right hand side α will reflect both this effect and any additional effect of institutions in raising investment in R&D.

We adopt the log-link formulation because of the count-based nature of the data. Different assumptions concerning the error term will generate alternative estimators even though the first moment (2.1) is the same. Our baseline is the Poisson model where the mean equals the variance. Since all models will allow

³See Richard Blundell, Rachel Griffith and John Van Reenen (1999) and Jerry Hausman, Bronwyn Hall and Zvi Griliches (1984) for discussions of count data models of innovation.

⁴We consider a range of control variables suggested by the existing literature on models of innovation and models of institutional ownership. For example we condition on size and the capital-labor ratio (see inter alia Hall et al, 2005, and Gompers and Metrick, 2001).

the standard errors to have arbitrary heteroscedacity and autocorrelation (i.e. by clustering the standard errors by firm) the exact functional form of the error distribution is not so important. The variance of the Negative Binomial under our specification is:

$$V(CITES_{it}) = \exp(\alpha INSTIT_{it} + \beta x_{it} + \eta_i + \tau_t) + \vartheta \exp(2(\alpha INSTIT_{it} + \beta x_{it} + \eta_i + \tau_t))$$

where the parameter, ϑ , is a measure of “over-dispersion”.

We introduce firm fixed effects, η_i , into the count data model using the “mean scaling” method introduced by Richard Blundell, Rachel Griffith and John Van Reenen (1999). This relaxes the strict exogeneity assumption underlying the model of Jerry Hausman, Bronwyn Hall and Zvi Griliches (1984) who introduced the fixed effect Poisson model (analogously to the within-group estimator for linear panel data models). Essentially, we exploit the fact that we have a long pre-sample history (of up to 25 years per firm) on patenting behavior to construct the pre-sample average of cite-weighted patents. This can then be used as an initial condition to proxy for unobserved heterogeneity under certain conditions (in particular, the first moments of the variables must be stationary). Although there will be some finite sample bias, Monte Carlo evidence shows that this pre-sample mean scaling estimator performs well compared to alternative econometric estimators for dynamic panel data models with weakly endogenous variables⁵.

Following standard procedures we use patents that are ultimately granted dated by year of application and we weight these by future citations through to 2002. To deal with the censoring of patents we have done two things. First, we estimate only until 1999 allowing for a three year window of future citations for the last cohort of patents in the data. Second, we include a full set of time

⁵Richard Blundell, Rachel Griffith and Frank Windmeijer (2002) discuss this extensively using the patents-R&D relationship for a much earlier version of the Compustat data.

dummies which controls for the fact that patents taken out later in the panel have less time to be cited than patents taken out earlier in the panel⁶.

An advantage of these count data models is that we take the zeros explicitly into account. We compare the results of these models with OLS estimates on the sample of firms with non-zero patenting, i.e.

$$\ln CITES_{it} = \alpha INSTIT_{it} + \beta x_{it} + \eta_i + \tau_t + v_{it} \quad (2.2)$$

and with models that use the arbitrary re-scaling and substitute the dependent variable with $\ln(1 + CITES_{it})$.

2.2. Identification

Although we lag all variables by one year, the coefficient on institutional ownership may be biased for many reasons. The main concern is that institutions select firms to invest in on the basis of characteristics that are observable to them but not to us. For example, institutions might invest in firms when they anticipate a surge in their production of innovation. The second problem is that our measure of institutional ownership might be noisy. Besides recording and classification mistakes, the main concern is that institutions might behave in a very different way. By using the total amount of institutional ownership, rather than the amount of institutional ownership held by "active" institutions, we are likely to underestimate their effect.

To address the endogenous selection process we follow Clay (2001) and use the inclusion of a firm in the S&P500 as an instrument. An S&P500 firm is more likely to be owned by institutions for at least three reasons. First, openly indexed funds that track the S&P500 will be forced to invest in this company. Second,

⁶We also experimented with re-normalizing citations taking into account the year in which the patent was taken out (see Bronwyn Hall et al, 2005). These delivered similar results to the unadjusted citations results presented here.

even non-indexed funds are usually benchmarked against the S&P500 so there is an incentive for them to be over-exposed to companies in the S&P500. Thirdly, fiduciary duty laws - such as ERISA - have been shown to influence portfolio selection through their implied endorsement of broad indexing⁷.

Stocks are added to the S&P because they represent well a certain sector, not for their expected performance. Standard and Poor's explicitly states that "the decision to include a company in the S&P 500 Index is not an opinion on that company's investment potential." Hence, the S&P500 inclusion is unrelated to the fundamental performance of firms and thus seems to satisfy the exclusion restriction for a valid instrument.

We implement the instrumental variable estimator in two ways. First, we consider the two-stage least squares results. Although this is relatively uncontroversial for continuous variables, it is problematic for the count data models (which have a mass point at zero). For this reason our preferred results use a control function approach (see Richard Blundell and James Powell, 2001). Under exogeneity of $INSTIT_{it}$ we have the moment condition:

$$E(v_{it}|INSTIT_{it}, x_{it}, \eta_i, \tau_t) = 1$$

where v_{it}^p is the error term in equation (2.1). This will not hold under endogeneity of $INSTIT_{it}$. We assume that the instrument z_{it} obeys the reduced form:

$$INSTIT_{it} = \pi z_{it} + \beta^o x_{it}^o + \eta_i^o + \tau_t^o + v_{it}^o$$

with

$$E(v_{it}^o|x_{it}^o, \eta_i^o, \tau_t^o) = 1$$

⁷See Diane Del Guccio (1996), John Wei and Stephen Pruitt (1989) or Kenneth Froot, David Scharfstein and Jeremy Stein (1992) for supportive evidence.

so that controlling for v_{it}^o in the conditional moment condition is sufficient to remove the endogeneity bias. In estimation we use the extended moment condition

$$E(CITES_{it}|X_{it}, v_{it}^o) = \exp(\alpha INSTIT_{it} + \beta x_{it} + \eta_i + \tau_t + \rho(v_{it}^o)) \quad (2.3)$$

where $\rho(v_{it}^o)$ is a non-parametric function of v_{it}^o (empirically we used a polynomial series expansion). A simple test for exogeneity is the joint significance of the residuals in equation (2.3).

3. Main empirical findings

3.1. Innovation and institutional ownership

Table 2 contains the first set of results where we measure innovation by patent counts weighted by the number of citations they receive in the future (“CITES”)⁸. Columns (1) and (2) report the OLS estimates, where $\ln(\text{CITES})$ is the dependent variable (so we drop observations with zero cites). Columns (3) through (8) are proper count data models where we include all the zeros and avoid arbitrary transformations⁹. Columns (3) through (5) report the estimates using Poisson regressions, while columns (6) through (8) report the negative binomial (Negbin) ones¹⁰.

Across all the columns of Table 2 the coefficient on institutional ownership lies between 0.005 and 0.010. A marginal effect of 0.007 implies that an increase of

⁸We obtained quite similar results just using raw patent counts so we generally omit presenting the results.

⁹See below in Appendix Table A3 for an alternative where we consider $\ln(1 + \text{CITES})$ as an alternative dependent variable and obtain similar results.

¹⁰Note that Negbin is more general than Poisson as we relax the assumption that the variance is equal to the mean. However, since we allow a general error structure when clustering the standard errors (i.e. they are robust to arbitrary autocorrelation and heteroscedacity) this is not so critical (see Blundell, Griffith and Van Reenen, 1995, 1999 for a discussion).

ten percentage points in institutional ownership (e.g. from the mean of 45.5% to 55.5%) is associated with a seven percent increase in the probability of obtaining an additional cite-weighted patent (i.e. from the mean of 176 cite weighted patents to 188). This seems a result of economic as well as statistical significance. In our sample period between 1991 and 1999 the average level of institutional ownership for our firms rose from 40% to 50%, so ten percentage points is a reasonable change to consider.

Column (1) of Table 2 simply presents the OLS regressions of $\ln(\text{CITES})$ on institutional ownership with controls for the $\ln(\text{capital/labor})$ ratio, $\ln(\text{sales})$, four-digit industry dummies and time dummies. As shown by Figures 2 and 3, there is a positive and significant association between innovation and the firm's share of equity owned by institutions. Column (2) includes the firm's R&D stock which, as expected has a positive and significant association with patent citations (see, e.g. Bronwyn Hall et al, 2005). Conditioning on R&D slightly reduces the coefficient of institutional ownership (from 0.006 to 0.005) suggesting that the main effect of ownership is to alter quality and/or productivity of R&D rather than through simply stimulating more R&D. If we use $\ln(\text{R\&D})$ as a dependent variable instead of patents, institutional ownership has a significant and positive association with firm R&D investment (even after controlling for fixed effects) although the magnitude of this effect is small (see Appendix Table A1). Thus, previous studies which have focused on R&D as the sole measure of innovation have underestimated the importance of institutions.

Columns (3) and (4) of Table 2 repeat the specifications of the first two columns but use a Poisson count data model. Since the zeros can now be used the number of observations increases by about half (from 4,025 to 6,208). The coefficient on institutional ownership remains significant with a larger marginal effect of 0.08 when we condition on R&D. Column (5) includes the controls for fixed effects

following the method of Blundell et al (1999) using the pre-sample history of citations to control for correlated unobserved heterogeneity. The fixed effects are highly significant, but only reduce the marginal effect of institutions to 0.007 and the coefficient remains significant. The final three columns repeat the Poisson specifications but use the more general Negative Binomial model (which relaxes the assumption of the equality between the variance and the mean). The qualitative results are very similar: institutional ownership has a positive and significant marginal effect. Note that using the Hausman et al (1984) approach to controlling for fixed effects in count data models leads to similar results for the coefficient on institutional ownership. In an identical specification to column (8) the coefficient is 0.005 with a standard error of 0.002.

3.2. Controlling for endogeneity

As discussed above, we use a firm’s membership to the S&P500 index as an instrument for institutional ownership to address the possible endogeneity of this variable. Table 3 reports the results. The first column reproduces the basic Poisson results of Table 2 column (3) for reference. Column (2) presents the first stage where we regress institutional ownership on a dummy equal to unity if the firm was in the S&P500 (and all the other controls). As expected the instrument is positive and highly significant. Institutions own 9.2 percentage points more of the equity in firms that are included in the S&P500 Index than we would expect from the observable characteristics of these firms.

The third column presents the estimates where we use the control function method outlined in the econometric section¹¹. Interestingly, the ownership variable remains significant with a coefficient that is much larger than column (1). At

¹¹This uses just a first order term in the polynomial for the control function. The second order term was insignificant (p-value =0.274). The coefficient on institutional ownership was 0.035 (standard error = 0.015) when both terms of the control function were included.

face value, this result suggests that we are underestimating the positive effect of ownership on innovation by treating institutions as exogenous.

The next three columns of Table 3 repeats the specifications but include fixed effects. Column (4) shows the standard result treating institutional ownership as exogenous and column (5) has the first stage. The external instrument remains highly significant. In column (6) we use the control function approach to deal with the endogeneity of institutional ownership and again, the coefficient on ownership remains positive and significant with a much higher marginal effect than column (4). This is consistent with some attenuation bias towards zero in the OLS results. Note, however, that exogeneity is not rejected at the 5% level in column (6) whereas it is rejected at the 1% level in column (3). This suggests that the fixed effects deal with a substantial part of the endogeneity bias, and to the extent it is a problem (exogeneity is still rejected at the 10% level in the final column) the bias causes us to underestimate the importance of institutions.

While the inclusion to the S&P500 should be orthogonal to a firm's future performance, it is not completely random. Standard & Poor's wants to insure that the index is representative and that it is relatively stable over time. Hence, it avoids choosing companies that are at serious risk of bankruptcy and prefers large companies with a good past performance. In order to be included in the S&P500 index, thus, a company must have been small in the past (which explains why it was not already in the index) and large today. Given these rules, it is not surprising that companies that are added on average experience very large stock returns in the three years preceding their inclusion. As a result, the apparent effect of S&P500 addition on innovation could be spurious, due to the fact that stock performance anticipates the rise in innovation. Note that this is a very tough test, as innovation is positively associated with stock prices (see Hall et al, 2005 for direct evidence) thus making it hard to identify an independent effect of

institutional ownership on innovation.

To rule out this possibility, in the final column of Table 3 we control for the cumulative stock returns over the previous three years as an additional variable. Consistent with a correlation between run up and innovation, we find that the run up has a positive and statistically significant coefficient on innovation. Yet, the coefficient of institutional ownership falls only slightly: from 0.029 to 0.023 and remains statistically significant at the 5% level. Thus, the result does not appear to be driven by simultaneous "good news" about the firm.¹²

Another concern with our IV strategy is that the treatment firms (which joined the S&P500) are not well matched with the rest of the sample (the implicit control group). To examine this we use a propensity score matching technique. We estimate the propensity to join the S&P500 as a function of the exogenous firm characteristics (including fixed effects). Very few firms that are members of the S&P500 have a predicted probability below 0.24 (roughly the sample median). Hence, we trim the sample below this threshold so that treatment and control have common support and re-estimate the IV results on this sub-sample. The results (not reported) are very similar: we estimate a treatment effect of 0.026 (standard error = 0.013) on this sub-sample of 3,099 observations compared to 0.029 (standard error = 0.013) on the full sample of 6,028.

Finally, to further validate the quality of the instrument we perform a small event studies on the cite-weighted patents around the time a stock is added to the S&P500 index. We use a window of 7 years, three years prior to the year when the firm was added, the year itself and three years after the firm was added (a similar story emerges from adding or subtracting an extra year to the window).

As Figure 4 shows cite-weighted patents increase in the two years following

¹²In an unreported regression we controlled for Tobin's Q instead of cumulative returns. The coefficient on institutional ownership remains very similar (0.027) and retains its statistical significance at the 5% level.

the addition to the S&P500 index. Three years after the addition, the number of cite-weighted patents increased by almost 3, a 43% increase with respect to the median.

3.3. Simply an effect of ownership concentration?

To what extent the effect found is driven by an omitted variable: ownership concentration. To address this problem directly in unreported regressions we included various measures of ownership concentration in our baseline specification. For example, we constructed a variable measuring the proportion of equity held by the top five shareholders. This ownership concentration measure enters positively and (weakly) significantly into an innovation specification that does not include any measure of institutional ownership, but its effect is driven to zero when we insert also the institutional ownership variable. For example, in Table 2, column (5) the coefficient (standard error) on the concentration measure was 0.004 (0.003) and the institutional ownership variable remained positive and significant (coefficient of 0.007 with a standard error of 0.002). If we drop institutional ownership from the regression, however, the coefficient (standard error) on ownership concentration rises to 0.005(0.003), which is significant at the 5% level.

This result suggests that our findings are not driven by the omission of an ownership concentration variable, but the other way around: the existing findings of the positive effects of ownership concentration may be due to the failure to distinguish between institutional and non-institutional ownership. This is reasonable. If there are some fixed costs in setting up effective monitoring across firms, institutions, which typically hold large blocks in several companies, they can exploit these economies and monitor more effectively. Second, the market can more easily infer from the selling behavior of institutions, which have fewer liquidity reasons to sell, than from the trading of individuals.

Overall, all these results point in the direction of a positive effect of institutional ownership on innovation. What remains to be explained is why that is the case. We attack this problem in the next section.

4. The model

4.1. Basic framework

Consider the following variant of Holmstrom (1982)'s career concerns model. There are two periods, $t = 1, 2$. The firm is run by a manager with unknown ability $\theta \in \{\underline{\theta}, \bar{\theta}\}$. The prior beliefs about θ are that:

$$\Pr(\theta = \bar{\theta}) = \Pr(\theta = \underline{\theta}) = 1/2.$$

For notational simplicity we normalize $\underline{\theta}$ at zero.

At the beginning of period 1, the manager decides whether or not to innovate. We denote the innovation decision by $i \in \{0, 1\}$. If the manager does not innovate ($i = 0$), then her project is assumed to be uninformative about her ability in the sense that the revenue realization in period 1 is uncorrelated with ability. We normalize this revenue at zero.

If the manager decides to innovate ($i = 1$), she must incur an innovation cost I and then the period 1 revenue realization is equal to:

$$y_1 = \begin{cases} 1 & \text{with probability } p \\ 0 & \text{with probability } 1 - p \end{cases}$$

if the manager is of high ability (that is with $\theta = \bar{\theta}$), and to

$$y_1 = \begin{cases} 1 & \text{with probability } \alpha p \\ 0 & \text{with probability } 1 - \alpha p \end{cases} ,$$

where (i) $\alpha < 1$, so that a lower ability manager is less successful at innovating than a higher ability manager; and (ii) $p = 1\pi$, where π is the probability that the innovation is imitated. The parameter π measures the degree of product market competition, so where competition I more intense innovation I less likely

4.2. A career concern model

In the main part of the model we will assume, following Holmstrom (1982), that the manager is concerned about the impact that her decision will have on the market perception about her ability. Absent an institutional investor, the market infers the manager's ability from observing the period 1 revenue realization. Thus, by innovating, the manager exposes herself to the risk of losing her job. This in turn limits her incentive to innovate in the first place. In the presence of an institutional investor who monitors (i.e., collect independent information about the quality of the manager), the market can infer the manager's type also from the institutional investor's action. For simplicity, in the model we assume that the institutional investor's action is to decide whether to keep the manager. In reality, things are more subtle. Unhappy institutional investors do not fire the manager directly (since generally they have no representative on the board), but can pressure behind the scene the board to do so. Alternatively, they can exercise their exit option and sell, causing the stock price to drop and triggering the board to act. Either way informed institutional investors' action reveals the manager's type to the market independently from period 1 revenue realization.

The timing of moves is as follows: (i) the manager first decides whether to innovate (and pay I); (ii) the institutional investor learns about the manager's ability, provided she invests a monitoring cost K ; (iii) the first period revenue is realized and based on that realization the market updates its assessment of the manager's ability; (iv) the manager decides whether to stay with the firm, based on the comparison between her expected wage in period 2 if she remains inside the firm versus what she can expect if she reallocates to another sector.

To complete our description of the model we make three assumptions:

Assumption 1: The market for managers is fully competitive, and the second period wage of a manager is equal to her expected ability conditional upon the

information acquired in period 1.

This assumption is identical to that made in Holmstrom (1982).

Assumption 2: The institutional investor acquires perfect information about the manager's ability only if the manager innovates

In the context of the model this assumption is justified by the fact that only innovation reveals the manager's ability, since it is only when the manager innovates that the revenue realization depends upon her ability. Realistically, the implicit assumption is that the investor can monitor the manager while she undertakes the innovative strategy and assess her ability independent of the revenue realization. If not innovative strategy is undertaken, there is no opportunity for the investor to learn whether the outcome is due to luck or skill.¹³ After gathering this additional information, the investor decides whether to have the manager fired.

Assumption 3: Managerial ability is sector-specific, thus what happens on her current job is uncorrelated with the manager's ability if she moves to another sector.¹⁴ Moreover, a manager who reallocates to another sector incurs a switching cost equal to δ .

Assumption 3 implies that every time a manager is fired and reallocates to another sector she has a new draw of the distribution of talents, so that her expected utility equals to:

$$\underline{w} = \frac{1}{2}\bar{\theta} - \delta.$$

This is also the manager's reservation wage on her current job.

¹³As we discuss below, if the investor were able to learn about the manager's ability regardless of whether she innovates institutional ownership would have a negative effect on innovation, which is the opposite of what we observe in the data.

¹⁴Below we analyze the polar case where skills are fully non-sector specific.

4.3. Equilibrium wage and innovation without institutional investor

We first consider the benchmark case where no information is acquired by the institutional investor. We solve the model by backward induction. Suppose that the manager has decided to innovate. Then, based on the revenue realization in period 1, the market updates its beliefs about managerial ability using Bayes' rule. Consequently, the manager's wage in period 2 if she remains in the firm, is given by:

$$w_2(y_1) = \Pr(\theta = \bar{\theta}/y_1)\bar{\theta}.$$

If $y_1 = 1$, then

$$\Pr(\theta = \bar{\theta}/y_1 = 1) = \frac{p}{p + \alpha p} = \frac{1}{1 + \alpha}.$$

We thus get:

$$w_2(y_1 = 1) = \frac{\bar{\theta}}{1 + \alpha}.$$

Similarly,

$$w_2(y_1 = 0) = \Pr(\theta = \bar{\theta}/y_1 = 0)\bar{\theta} = \frac{1 - p}{2 - p - \alpha p}\bar{\theta}.$$

Assumption 4:

$$\frac{\bar{\theta}}{1 + \alpha} > \frac{1}{2}\bar{\theta} - \delta = \underline{w} > \frac{1 - p}{2 - p - \alpha p}\bar{\theta}.$$

This assumption implies that the manager will leave the firm whenever her first period revenue performance is low. Note that we always have

$$\frac{1}{1 + \alpha} > \frac{1}{2} > \frac{1 - p}{2 - p - \alpha p},$$

so that there is a non-empty set of parameters $(\alpha, \underline{w}, p)$ which satisfy Assumption 4.

Now, moving back to the initial stage of the game, the manager will decide to innovate if and only if:

$$U(i = 0) < U(i = 1) - I,$$

where

$$U(i = 0) = \frac{1}{2}\bar{\theta}$$

is the ex ante utility conditional upon not innovating (if the company is surpassed by a rival in innovation, the manager goes back to the labor market and gets her expected value, minus a relocation cost δ), and

$$U(i = 1) = \left(\frac{1}{2}p + \frac{1}{2}\alpha p\right)\frac{\bar{\theta}}{1 + \alpha} + \left[\frac{1}{2}(1 - p) + \frac{1}{2}(1 - \alpha p)\right]\underline{w}. \quad (4.1)$$

The first term in the first line of $U(i = 1)$ is the ex ante probability of a high revenue realization¹⁵ times the second period wage conditional upon a high revenue realization $w_2(y_1 = 1)$. The second term is the ex ante probability of a low revenue realization times the manager's expected payoff from moving to another firm.

Thus

$$U(i = 1) = \frac{1}{2}p\bar{\theta} + \frac{1}{2}(2 - p - \alpha p)\underline{w}.$$

In particular, note that

$$U(i = 1) - I > U(i = 0)$$

whenever I and π are not too large.

4.4. Institutional investment and innovation

We now introduce the institutional investor into the analysis. By learning the true managerial ability, the institutional investor avoids having to keep a low ability

¹⁵That is the ex ante probability of $\theta = \bar{\theta}$ (i.e. $\frac{1}{2}$) times the probability of a high revenue conditional upon $\theta = \bar{\theta}$ (i.e. p) plus the probability of $\theta = \underline{\theta}$ (i.e. $\frac{1}{2}$) times the probability of a high revenue conditional upon $\theta = \underline{\theta}$ (i.e. αp)

manager. Let Π denote the net expected gain from getting rid of a low ability manager before the period 1 income realization.¹⁶

If the investor owns a fraction ψ of the firm's shares¹⁷, he will choose to pay the cost K of learning the manager's ability whenever

$$\psi\Pi > K.$$

Thus, if the investor's share of profits ψ is sufficiently high, he will pay the learning cost K . In this case, the manager's expected utility from innovating becomes¹⁸

$$U(i = 1 : \text{monitor}) = \frac{1}{2}\bar{\theta} + \frac{1}{2}\underline{w}.$$

We can establish:

Proposition 4.1. *Monitoring by an institutional investor, which occurs when the investor's share of the firm's profits is sufficiently large, increases the manager's gain from innovating. This positive effect is increased with higher product market competition π .*

¹⁶This gain is computed as follows. First, the wage saving in period 2 from identifying a bad manager beforehand, is equal to $\alpha pw_2(y_1 = 1)$. The expected gain of getting rid of a low ability manager and replacing her by a new manager, is thus equal to this expected wage savings plus the expected gain from finding a new manager

$$\Pi = \frac{1}{2}\alpha pw_2(y_1 = 1) - \frac{1}{2}\alpha p + \frac{1}{2} \cdot \frac{1}{2}(p - \bar{\theta})$$

or

$$\Pi = \frac{1}{2}\alpha p \left(\frac{\bar{\theta}}{1 + \alpha} - 1 \right) + \frac{1}{4}(p - \bar{\theta}),$$

which is positive for α sufficiently small.

¹⁷The paper takes a partial equilibrium approach by taking the investor's share ψ as exogenously given. Endogeneizing ψ would involve introducing new considerations such as risk-pooling or the enhancement of managerial initiative, into the model.

¹⁸When the institutional investor monitors, the manager gets $\bar{\theta}$ if she is found out to be of high ability and \underline{w} if she is found out to be of low ability.

Proof: We have:

$$\Delta U = U(i = 1 : \text{monitor}) - U(i = 1) = \frac{1}{2}[\bar{\theta}(1 - p) - (1 - p - \alpha p)\underline{w}].$$

That $\bar{\theta} > \underline{w}$ implies immediately that ΔU is positive. Furthermore,

$$\frac{d}{d\pi}(\Delta U) = \frac{1}{2}[\bar{\theta} - (\underline{w} + \alpha\underline{w})]$$

is positive since Assumption 4 has $\frac{\bar{\theta}}{1+\alpha} > \underline{w}$. This establishes the proposition.

Corollary 4.2. *Innovation takes place for a larger range of innovation costs I when the manager is monitored by an institutional investor and the more so the higher competition.*

Proof: This results immediately from the fact that innovation takes place whenever

$$U(i = 1 : \text{monitor}) - U(i = 0) > I.$$

Thus, institutional investment stimulates managerial innovation by insulating the manager against the reputational risk from a bad revenue realization, and this effect is stronger when the degree of product market competition is higher (measured by the imitation probability π).

Remark 1: Consider what happens if the institutional investor finds out about the manager's ability irrespective of whether the manager innovated. In this case we have:

$$U(i = 0 : \text{monitor}) = \frac{1}{2}\bar{\theta} + \frac{1}{2}\underline{w} = U(i = 1 : \text{monitor}).$$

But then the manager is deterred from innovating altogether, since

$$U(i = 1 : \text{monitor}) - U(i = 0 : \text{monitor}) = 0 < I.$$

Remark 2: Let us compare the above analysis with what happens if managerial skills are fully transferable (i.e., completely non sector specific). In this case, in the absence of an institutional investor the ex ante utility of a manager who innovates is equal to

$$U(i = 1) = \frac{1}{2}p\bar{\theta} + \frac{1}{2}(2 - p - \alpha p)\frac{1 - p}{2 - p - \alpha p}\bar{\theta} = \frac{1}{2}\bar{\theta} = U(i = 0),$$

i.e., it is identical to the expected utility of a manager who does not innovate. Similarly, in the presence of an institutional investor who monitors the ex ante utility conditional upon innovating is equal to

$$U(i = 1 : \text{monitor}) = \frac{1}{2}\bar{\theta} = U(i = 0).$$

In this case, thus, monitoring by the institutional investor does not affect at all the manager's incentives to innovate. The reason is very simple. In a model where managers are risk neutral, the source of career concern for a manager arises from the cost she faces in reallocating her talent across sectors (δ). If such a cost disappears, the career concern disappears as well and so does the effect of the monitoring undertaken by the institutional investor. To reproduce the effect in a world with fully general skills, however, it would suffice to assume that the manager is risk averse.

Remark 3: In the model so far, innovation increases the probability of imitation. Now consider the following variant where innovation allows the firm to escape competition. In this variant, the firm is imitated with probability 2π in the absence of innovation, so that

$$U(i = 0) = (1 - 2\pi)\frac{1}{2}\bar{\theta} + 2\pi\underline{w}.$$

In this case, an increase in competition π increases the net gain ($U(i = 1) - U(i = 0) - I$) of an innovating manager in the absence of institutional investor. But it

increases by even more the net gain ($U(i = 1 : \text{monitor}) - U(i = 0) - I$) of an innovating manager monitored by an institutional investor. Thus the introduction of an institutional investor magnifies the escape competition effect of innovation, which in turn reinforces the complementarity between institutional investment and competition.

4.5. Contrasting with the "lazy manager" story

An alternative explanation to that developed so far, inspired by Hart (1983) and Schmidt (1997), is that monitoring by institutional investors, together with the managers' fear of losing the private benefits of remaining on the job, would force the latter to innovate if they are a priori reluctant to do so.

To nest this idea into the same model we assume that the manager draws private benefit B from remaining on the job, but that innovating entails a private cost K to her. Other than that, the manager does not respond to monetary incentives, whether explicit or implicit. Finally, we assume that the institutional investor will monitor with probability m (which is a function of the size of the stake it owns). When the investor monitors, it can observe whether the manager has innovated and can decide whether to fire her. As a result, the investor can use the firing threat to force the manager to innovate. More specifically, the manager will choose to innovate whenever:

$$B - K > B(1 - \pi)(1 - m).$$

As before, the higher m the more likely it is that the manager will innovate. However, now, a higher imitation probability π will reduce the marginal effect of m on the manager's net gain from innovating, namely $[B - K - B(1 - \pi)(1 - m)]$. Thus, unlike in Proposition 1, more competition on the product market will reduce the effect of institutional investment on managerial innovation.

5. Testing the predictions of the model

5.1. Institutional ownership and product market competition

So far we have documented a positive effect of institutional ownership on innovation. Both the career concern model and the lazy manager story deliver the prediction that institutional ownership encourages managers to innovate. Where the two approaches differ is in the interaction between institutional ownership and product market competition. In the career concern model the two are *complements* (i.e. the positive effect of institutions on innovations should be stronger when competition is higher). By contrast, in the lazy manager story competition and institutions are *substitutes* (see Neil Dryden, Stephen Nickell and Daphne Nicolitsas, 1997). Indeed, in highly competitive environments there should be little managerial slack and therefore little need for greater monitoring by institutions or other mechanisms (e.g. Schmidt, 1997; Bloom and Van Reenen, 2007).

Table 4 analyzes what the interaction between institutional ownership and product market competition is empirically. As a measure of product market competition we use $1 - \text{the Lerner Index in the firm's three digit industry}$. The first column reproduces our baseline fixed effects Poisson model of citations (column (5) of Table 2), including also our measure of product market competition. Competition has a positive association with innovation, although the effect is not significant, while institutional ownership remains positive and significant.¹⁹

Column (2) introduces an interaction term between ownership and competition which is positive and significant, consistent with competition and institutional owners being complements. We then split the sample into observations with high

¹⁹As with Aghion et al (2005) there is some (weak) evidence of an inverted U relationship between innovation and competition. If we include a term in the square of the (inverse) Lerner Index it is negative, whereas the linear term remains positive. This quadratic term is insignificant, however with a coefficient of -6.852 and a standard error of 24.554.

and low competition based on the median of the Lerner Index. In column (3) where competition is high, the coefficient on institutional ownership is large, positive and significant whereas in column (4) where competition is low the coefficient in institutional ownership is small and insignificant (0.009 vs. 0.002).

We illustrate these findings by plotting the implied value of patent citations at different levels of institutional ownership in Figure 5. This shows that it is only in the high competition regime that there is an important effect of institutions on innovation.

A concern might be that we have allowed the Lerner Index to change over time, so instead we consider a time invariant measure, averaging the Lerner over our sample period. We repeat the specifications using this alternative measure in the final four columns with very similar results. For example, the interaction term between competition and institutional ownership in column (6) remained positive and significant (coefficient of 0.087 with a standard error of 0.033). We also estimated the Lerner correcting for capital intensity as in Aghion et al (2005) and Nickell (1996). Again, the interaction term remained positive and significant (coefficient of 0.104 with a standard error of 0.043).

At face value, Table 4 seems inconsistent with the “lazy manager” interpretation of the empirical findings and consistent with the simple career concerns model outlined in the previous section.

5.2. CEO entrenchment and institutional ownership

A further implication of the “lazy manager” hypothesis is that the benefits of institutional ownership should be felt most sharply where agency costs are higher and managers are more “entrenched”. Apart from competition there are several settings where we might think agency costs are less likely to allow managers to slack. First, where the market for corporate control is strong (e.g. via a credible

threat of a hostile takeover), this should also discipline CEOs. Second, if shareholders have more power this should mean that the firm is more “democratic” and the power of the CEO less entrenched. As before, under the lazy manager hypothesis institutional ownership should have more of an effect when managers are entrenched, while under the career concern hypothesis the impact of institutional ownership on innovation should be weaker when managers are entrenched.

To measure the degree of entrenchment of CEOs it has become standard to use the index introduced by Paul Gompers et al (2003), which is built upon the number of antitakeovers provision in place (including relevant state antitakeover statutes). The shortcomings of this measure is that most of these devices were introduced in the late 1980s, when hostile takeovers were rampant, and become effectively useless with the demise of hostile takeovers. Nevertheless, that boards were willing to approve these statutes provide an indication of the degree of control of the CEO over the board.

Table 5 investigates the interaction between managerial entrenchment and institutional ownership. As a measure of entrenchment, the first four columns use the index for state takeover laws and the last four columns the Gompers Index of CEO power. The first column looks at the linear effects of institutional ownership and state laws protecting firms from takeovers. The coefficient on institutional ownership is positive whereas that on the entrenchment variable is negative (but insignificant). Column (2) includes an interaction which has a positive and significant coefficient. This is the opposite of the lazy manager story: institutional ownership is more effective when managers are less entrenched. Column (3) estimates the model on the sub-sample when the legal index is below the median level of entrenchment, while column (4) uses the sub-sample when managers are more entrenched. Consistently with column (3), the coefficient on institutional ownership is large and significant in the sub-sample where managers are not entrenched

whereas it is small and insignificant when state laws protect managers.

Column (5) of Table 5 shows that ownership is still positively correlated with innovation even when we condition on the Gompers Index. The Gompers Index is negatively and weakly significantly associated with innovation. In column (6) the interaction between institutional ownership and the Gompers Index is negative and significant in column (2). This suggests that institutions are more important when managers are less entrenched (at least as measured by the Gompers' index of CEO power). When we split the sample by the median value of the Gompers Index, institutional ownership looks equally important in both sub-samples. So there is certainly no evidence of substitution between institutional ownership and entrenchment

So again, the evidence from Table 5 (like that of Table 4) appears to be inconsistent with the lazy manager interpretation of the positive effect of institutional ownership on innovation, and more in line with the career concern one.

5.3. Institutional ownership and managerial turnover

A third prediction of the career concern model is that managerial turnover should be less sensitive to performance in the presence of institutional investors. By contrast, under the lazy manager story institutional ownership should not reduce the impact of bad realization of profits on the probability of managerial turnover. If anything it should increase that impact because it makes it easy to resolve the collective action problem in firing the manager.

Table 6 presents evidence on the interaction between profitability and institutional ownership on forced managerial turnover. We use the data from Fisman et al (2005)²⁰ which has information on CEO firings and other dismissal constructed from detailed readings of contemporary accounts in the financial press such as the

²⁰We would like to thank Ray Fisman for kindly supplying the data to us.

Wall Street Journal. Since this covered only the larger S&P500 firms until 1995, we only have a sub-sample of our main dataset (249 firms)²¹. The dependent variable in Table 6 is whether a CEO was fired. We estimate this specification by probit Maximum Likelihood. We start by replicating Fisman et al (2005). In particular, in the first column we regress whether the CEO was fired that year on the lagged change in profitability (profits normalized by assets). Like them, we find that higher profitability growth is associated with a (weakly) significantly lower probability the CEO will be fired. Column (2), then, interacts the profitability variable with the proportion of equity owned by institutions. The coefficient on this interaction is positive and significant and indicates that firms with greater institutional ownership are significantly *less likely* to fire their CEOs when there is “bad news”. This is in line with the Career concern model presented above and inconsistent with the lazy manager story. Since Figure 2 suggested that institutional ownership mattered when more than 25% of the stock was owned by institutions, instead of the continuous variable in column (3) as interaction term we use an indicator variable equal to one if institutional owners controlled more than a quarter of shares. The results are very similar.

Column (4) presents a robustness test obtained by restricting the sample to the post 1991 period. If anything the results are stronger. Since CEOs leave their job also voluntarily, as a control we can test whether institutional ownership affects also these voluntary departures. To do so, we change the dependent variable in column (5) to be only voluntary departures (i.e. all exits except firings). Consistent with our interpretation the coefficient on the interaction term is insignificant (and has actually reversed signs). So despite the smaller sample

²¹Given this much smaller sample size we use ownership in the first year of our sample (1991). This enables us to use more of the CEO firing data. We assume ownership does not change much for four years prior to 1991 and after 1991 and estimate on 1988-1995 in column (1) of Table 6. We show our results are robust to using a shorter time window in column (4).

size, Table 6 is broadly consistent with our careers concern model suggesting that institutional ownership partially insulates CEOs from short-term pressures (in so doing encouraging them to invest in risky innovation).

5.4. Disaggregating the type of Institutional Ownership

We can gather additional insights on the mechanism through which institutional ownership affects innovation by differentiating among institutions on the basis of their style of investing. Bushee (1998) classifies institutional investors in three groups: "quasi-indexed" (institutions that are widely diversified and do not trade much), "dedicated" (institutions whose holdings are more concentrated, but do not trade much), and "transient" (institutions whose holdings are diversified but trade often in and out from individual stocks).

We follow this classification.²² In our sample quasi-indexers own 25% of firm equity, dedicated owned 10% and transients own 8%.

Table 7 presents the results from using this information. Column (1) presents the baseline results on the sub-sample where we were able to obtain this classification. It shows that the results remain quite stable: there is still a positive and significant association between institutional owners and innovation. In column (2) we divide the institutional ownership variable into the three groups. The coefficients on the dedicated and transient institutions are positive, significant and similar to each other (we cannot reject that they take the same coefficient, p-value =0.671). By contrast, the coefficient on the quasi-indexed institutions is close to zero and insignificant. In the final column we illustrate this by including the standard institutional ownership variable from column (1) and the proportion of equity owned by quasi-indexed institutions. The coefficient on quasi-indexed

²²We are very grateful to Brian Bushee for providing us with this data. See Data Appendix for how Bushee constructs these.

institutions is negative and highly significant, indicating that there is a zero effect from increasing their share of equity; by contrast the marginal effect of other institutions is 0.014 and significant.

The absence of any effect of quasi-indexed funds is broadly consistent with the model we present. The fact that dedicated institutions are not much better than transient institutions is perhaps more surprising. One possible interpretation is that for institutional investor to have an impact they need to have either significant voice (as dedicated institution) or a strong exit option (as transient ones). Quasi-indexed seem to have neither.

6. Conclusions

Given the importance innovation has on growth and the wealth of nations, it is paramount to understand the incentives to innovate at the firm level. This paper tries to do so by studying the relationship between innovation and institutional ownership.

Contrary to the view that institutional ownership creates a short-term focus in managers, we find that their presence boosts innovation, even after accounting for an increase in R&D and the endogeneity of institutional ownership. This positive impact could derive from the disciplinary effect of institutions on lazy managers or from the reassurance they provide to managers concerned about their career. Thanks to a simple model that nests these two hypotheses, we are able to derive three implications able to distinguish between them. In all three cases, the data seems to support the career concern model and reject the lazy manager one.

If confirmed these results suggest that risk considerations at the managerial level play an important role in preventing innovation. Given the positive externality innovation entails, it might be useful to think about public policies able to reduce the innovation risk for managers of publicly traded companies.

This paper has also interesting implications for corporate governance in general. If career concerns, not the desire to live a quiet life or to build an empire are the main source of managerial agency problems, then many of the public policy prescription changes. For example, boards composed mostly of outsiders can jeopardize the ability of the board to separate luck from skill in the CEO performance, increasing her risk aversion and jeopardizing innovation (see also Adams and Ferreira, 2005).

There are many directions this research could and should be taken. One potentially important omission is that we have abstracted away from the impact institutional owners may have on the design of incentive contracts to overcome the disincentives to innovate (and how this interacts with competition). This would be a fruitful line of future research currently pursued by Gustavo Manso (2008) and Richard Holden (2008).

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Data Appendix

A. Main Dataset

We combine several firm level panel datasets. Because we are using patents (weighted by total future citations) as our key measure of innovation, we rely on the matching of the US Patents and Trademark Dataset (USPTO) with Compustat lodged at the NBER (see Bronwyn Hall et al, 2001, and Jaffe and Trajtenberg, 2002, for details). The matching was performed based on the ownership structure in 1989, so our sample is of a cohort of firms who were publicly listed in 1989 or entered subsequently. We follow these firms through the 1990s (including those who subsequently died). We use the updated version of the NBER match containing patent citations through to 2002 (downloaded from Bronwyn Hall’s website). All patents granted between 1963 and 1999 are included (just under 3 million patents) and citation information is available from 1975 to 2002 (over 16 million citations). The need to have some patent data is the main reason why our sample is much smaller than the full Compustat sample.

The second dataset we draw on is the text files from Compact Disclosure. This is an electronic version of the 13-F forms that all institutional organizations are obliged to lodge at the SEC on a quarterly basis if they have at least \$100m in equity assets under discretionary management. The data includes the numbers of institutional owners, the number of share issues and the percentage of outstanding shares held by each institution (our key measure of institutional ownership). This dataset is not wholly consistent before 1990, so we use ownership data from 1991 onwards. The ownership data covers almost all the firms in the Compustat-USPTO match (we lose only three observations due to ownership changes in 1990), so the merging of the two datasets is straightforward. Compact Disclosure identifies five types of institutional owners: banks, insurance companies, investment companies, independent investment advisors and “other” which includes internally managed pension funds, colleges and universities, foundations and other miscellaneous institutions and endowments (law firms, private investment partnerships, etc.).

The merged dataset consists of 1,078 firms and 7,923 observations between 1991 (the first year of the ownership data) and 1999 (the last year of the patent data). We are able to use lags of patent information back to 1969, however, so our patent stock variables include all this past information. Since our preferred regressions use fixed effects we condition our sample on firms who received at least citations and had at least two years of non-missing data on all variables between

1991 and 1999 over this period. This leaves us with 6,208 observations on 803 firms which is our baseline sample.

Descriptive statistics are in Table 1.

B. Other datasets for robustness tests

In the robustness tests we also use other firm-level datasets. These datasets cover sub-samples of the firms in our database, so this is the reason why the number of observations is smaller in these regressions.

B.1. Entrenchment of managers

For information on governance we use the *Investor Responsibility Research Center* (IRRC) which publishes detailed listings of corporate governance provisions for individual firms in Corporate Takeover Defenses. The data on state takeover legislation is from Pinnell (2000). Paul Gompers et al (2003) construct an index of CEO power (relative to shareholders) as the sum of up to 24 unique provisions to do with how incumbent managers can be protected. We split out the state law sub-index of Gompers Index which is the simple average of the existence of six different laws.

B.2. CEO Firings Data

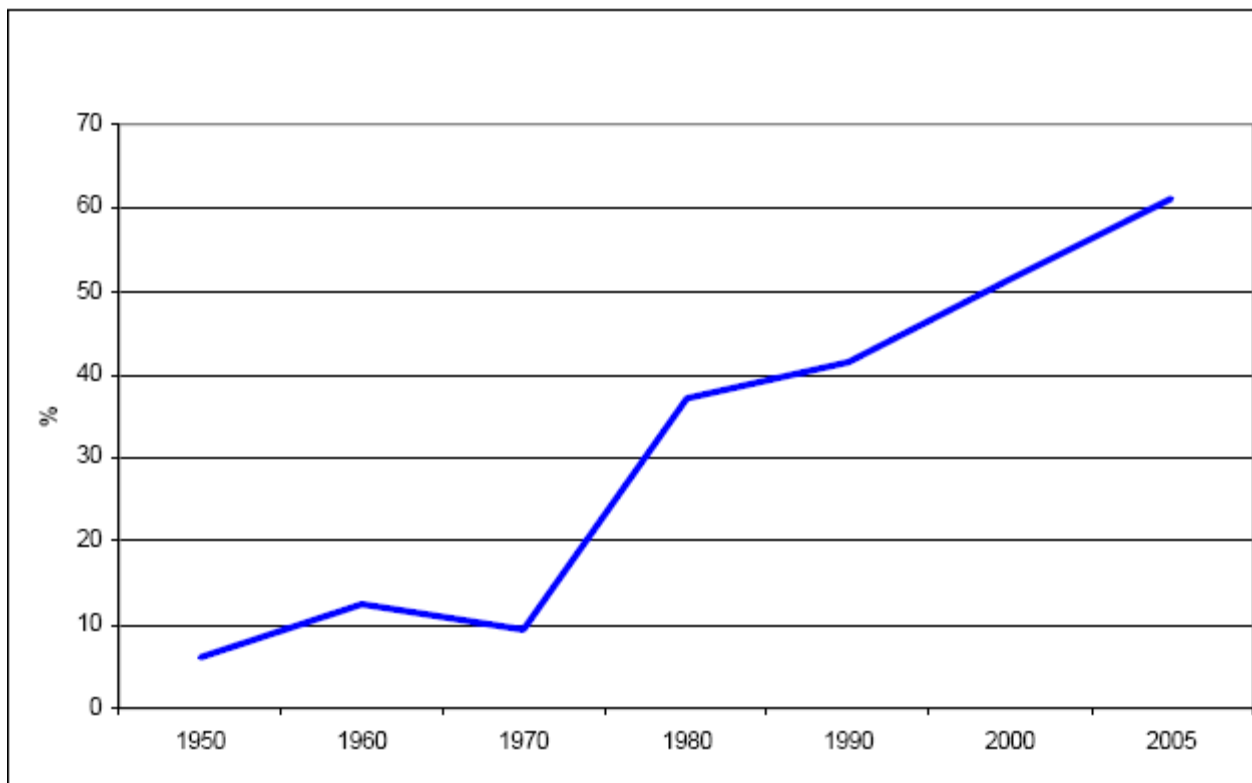
This data is from Fisman, Khurana and Rhodes-Kropf (2005). They followed a sample of largest firms in 1980 (the publicly traded Fortune 500 companies plus the 100 largest commercial banks, 100 largest financial services firms, 100 largest retail firms and 50 largest transportation firms) until 1995. The key variable they construct is whether the CEO was forcibly removed from his job, as opposed to another form of exit (e.g. if retired or ill). They do this by examining all CEO departures prior to the age of 61. They then use reports from the *Wall Street Journal* and *New York Times* to distinguish the type of exit. For information on managerial characteristics (such as CEO tenure) we use the S&P ExecuComp database. We are grateful to Ray Fisman for supplying us with this data. We measure profitability following Fisman et al (2005) by the ratio of operating profits divided by the sum of current assets and property, plant and equipment, and like them we trim the change of profitability for outliers. Tenure is the number of years a CEO has held this position.

B.3. Disaggregation by type of Institutional Owner

It is possible to distinguish the name of the institutional owner from Compact Disclosure. Following Bushey (1998, 2001) we divide all institutions into three types: quasi-indexers, transient and dedicated. Bushey determined which firms fall into which category by using a factor analysis method where a larger group of institutional ownership characteristics are reduced to three: BLOCK (whether the institution tends to have large blockholdings or is very diversified), PTURN (whether the portfolio held is stable or turns over rapidly) and MOMENTUM (whether the institution reduces shareholding quickly in response to "bad news"). Using these three factors he creates three clusters of institutional ownership types. "Quasi-indexers" have low values of all three factors: they are diversified, have low turnover and are relatively insensitive to bad news. "Dedicated" investors have high blockholdings in single firms, low portfolio turnover and are insensitive to "bad news". The final group of "transients" have low blockholdings in any one firm, high turnover and high momentum. Brian Bushey kindly supplied us with the data breaking institutional owners into these three classes for more recent data that we could match in to our sample.

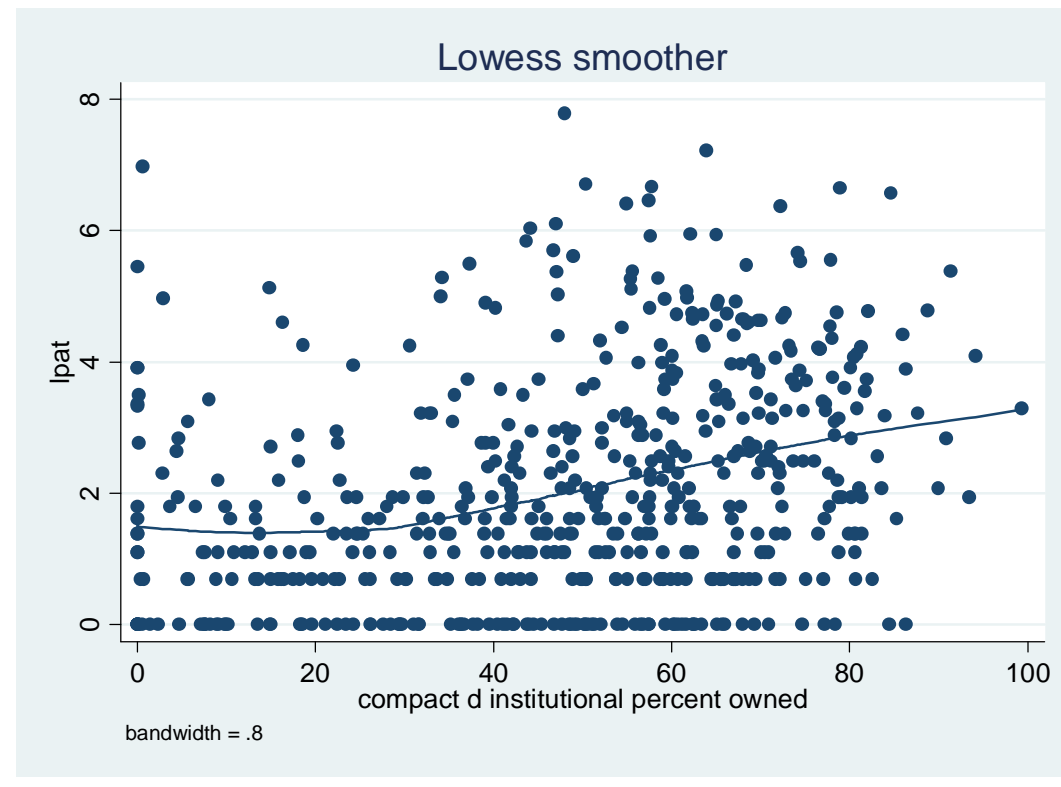
Using this categorization we can calculate for each year, what proportion of a firm's shares are held by each of these institutional investors. To ensure that the data is consistent with use only observations where our measure of institutional ownership and Bushey's were within 5% of each other (the correlation is over 0.99).

Figure 1: Proportion of US stock market held by institutional owners, 1950-2005



SOURCE: Federal Reserve Board Flow of Funds Report (various years)

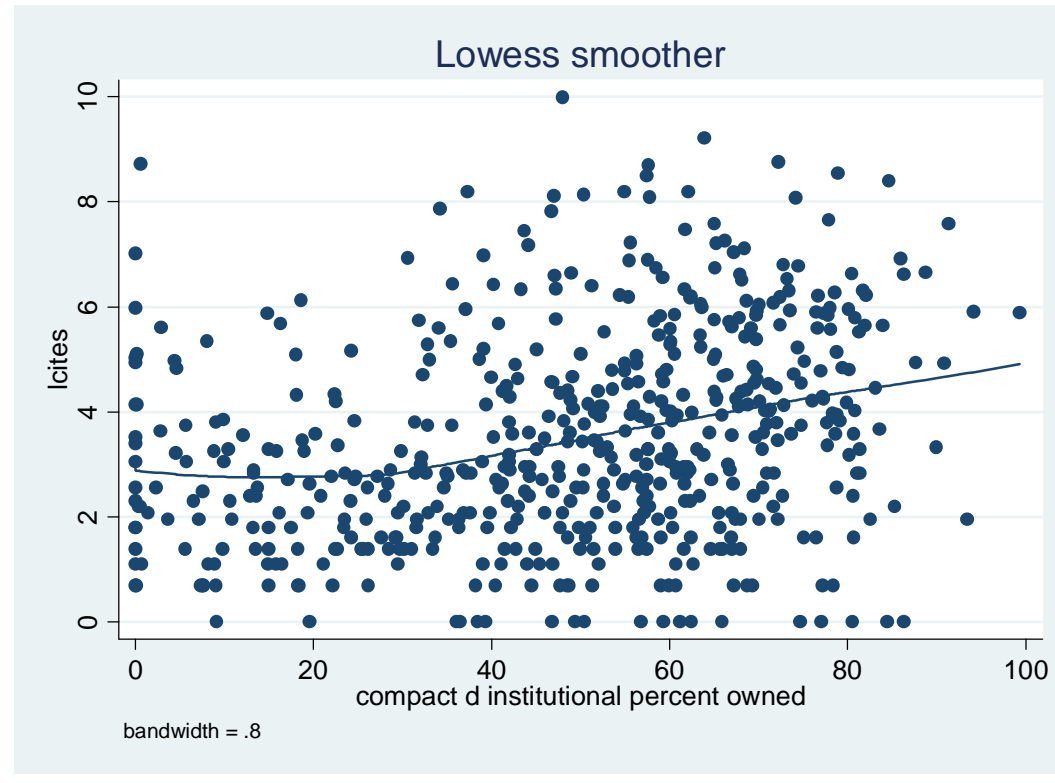
Figure 2:
Nonparametric Regression of count of a firm's patents and the proportion of a firm's voting equity owned by Institutions



NOTES: This Figure presents the non-parametric (local linear) regression of the firm patent counts and the proportion of equity owned by institutions (the graph is from 1995 in the middle of our sample period)

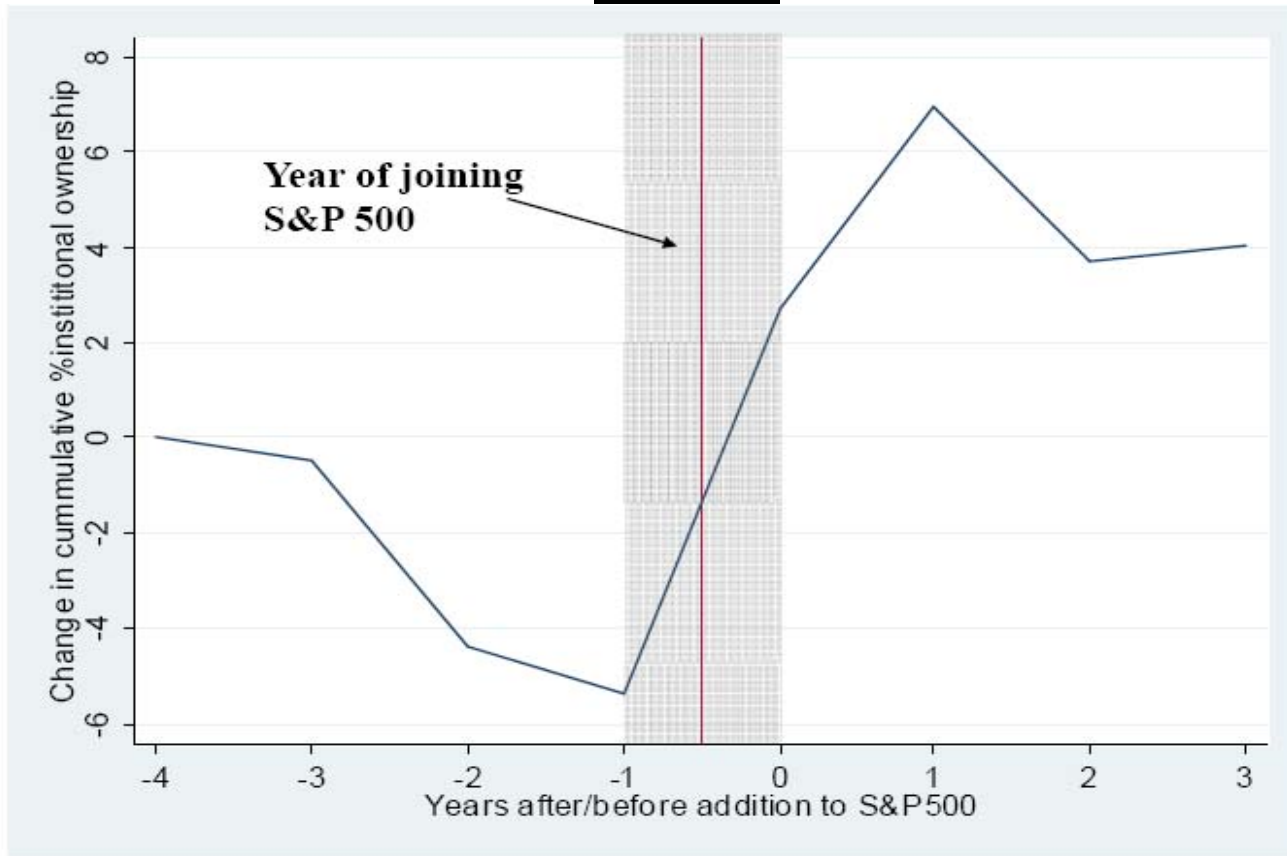
Figure 3:

Nonparametric Regression of CITES (ln(Patent Citations)) and the proportion of a firm's voting equity owned by Institutions



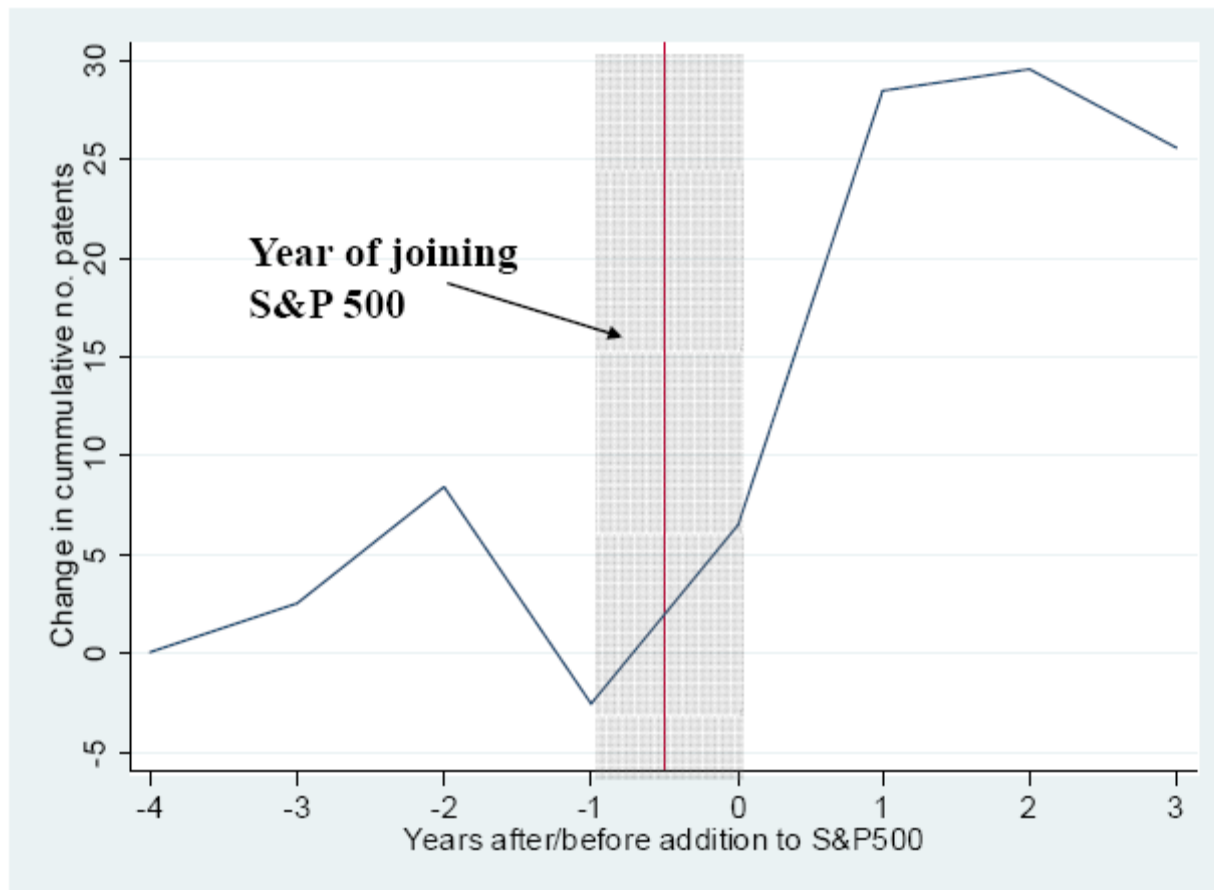
NOTES: This Figure presents the non-parametric (local linear) regression of firm patents weighted by future citations and the proportion of equity owned by institutions (the graph is from 1995 in the middle of our sample period)

Figure 4: Change in the cumulative proportion of institutional ownership before and after a firm is added to the S&P500 (7 year window)



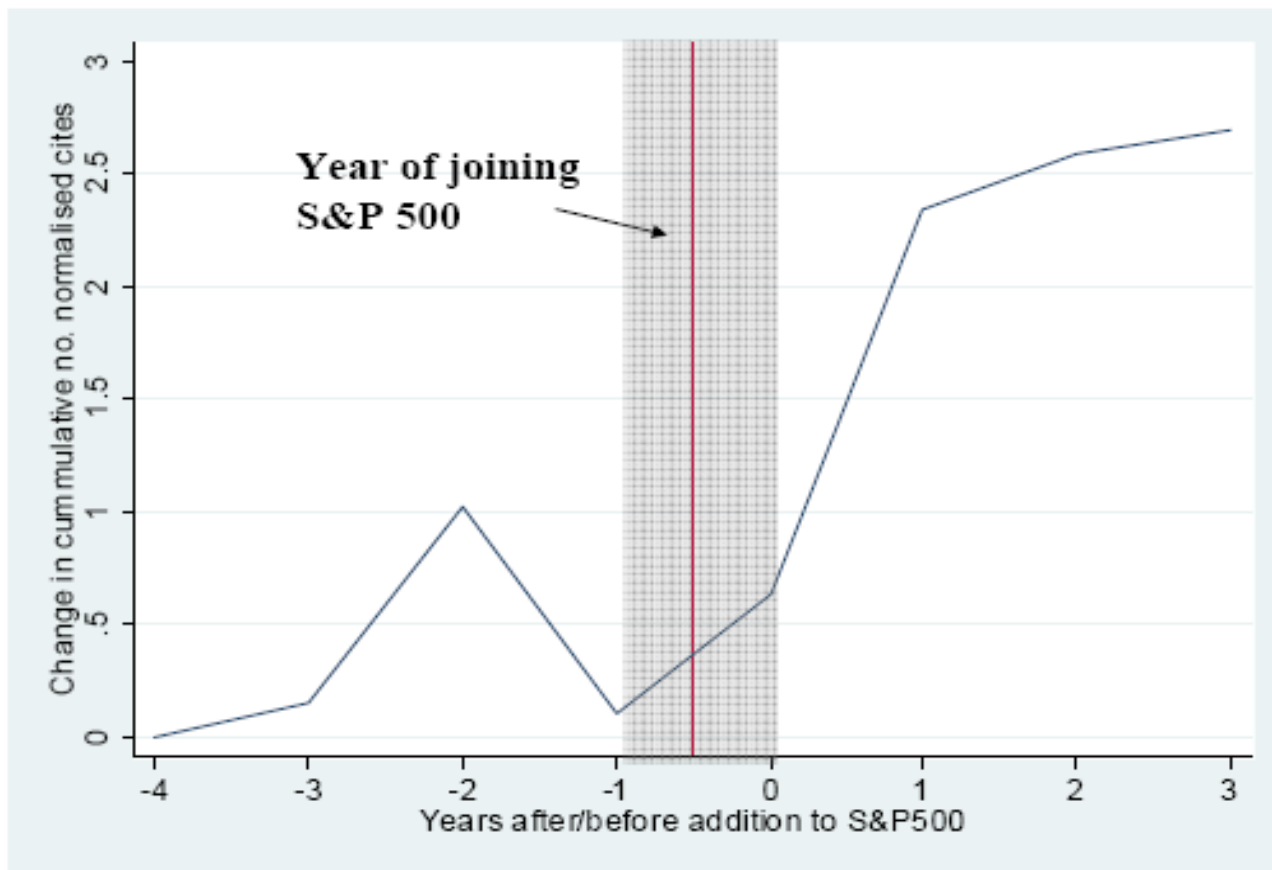
NOTES: The graph shows the cumulated mean change in the proportion of equity owned by institutions up to three years before and three years after a firm becomes a member of the S&P 500 Index (years -1 to 0 is the year the firm was added). For example, in the year a firm joined the S&P 500 8.1 percentage points more of its stock became owned by institutions. The following year institutional owners increased this proportion by 4.2 percentage points, and so on.

Figure 5: Change in the cumulative innovation before and after a firm becomes added to the S&P500 (7 year window)



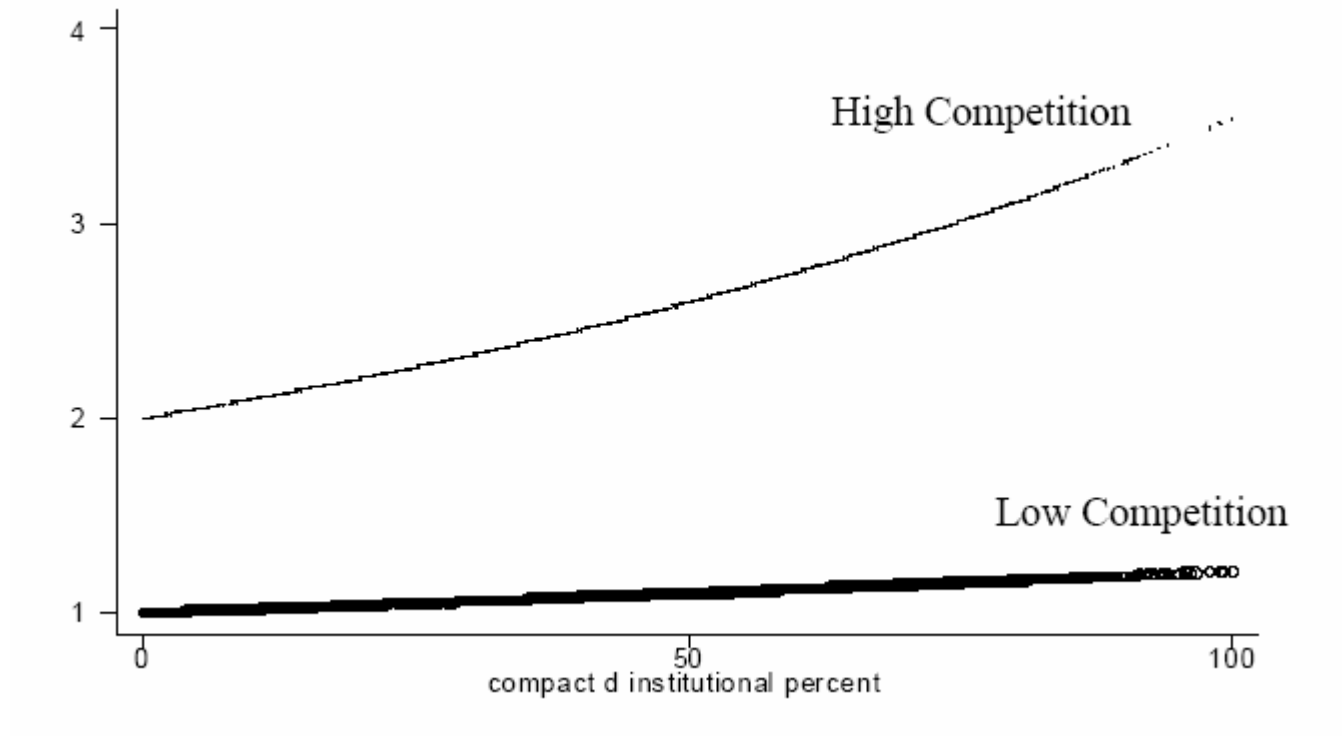
NOTES: The graph shows the cumulated mean change in the number of patents up to three years before and three years after a firm becomes a member of the S&P 500 Index (years -1 to 0 contains the point at which the firm was added).

Figure 6: Change in the cumulative innovation before and after a firm becomes added to the S&P500 (7 year window)



NOTES: The graph shows the cumulated mean change in the number of cite-weighted patents up to three years before and three years after a firm becomes a member of the S&P 500 Index (years -1 to 0 contains the point at which the firm was added). The cites measure is normalized on the yearly average.

Figure 7:
Predicted relationship between the increase in the number of cites and the proportion of equity owned by institutions



NOTES: This Figure presents the predicted number of cites as a function of the proportion of equity owned by institutions for firms in high competition industries (upper line) and lower competition (lower line). The estimates are taken from the Poisson model of columns (3) and (4) of Table 4.

TABLE 1: DESCRIPTIVE STATISTICS

VARIABLE	Mean	Standard deviation	Median	Min	Max	Source	Observations
(Future) Cite-weighted patent counts	176	923	7	0	23,121	USPTO	6,208
Patents	24	105	2	0	2,405	USPTO	6,208
% Institutional Ownership	45.5	23.1	48.2	0	100	SEC	6,208
Employment (1000s)	16.0	45.4	3.7	0.05	756.3	Compustat	6,208
Sales (\$m)	3,475	10,750	608	0.019	174,694	Compustat	6,208
R&D (\$m)	126	528	9.0	0	8900	Compustat	6,208
1-Lerner Index	0.861	0.044	0.871	0.488	0.974	Compustat	6,208
Index of State Laws blocking hostile takeovers	31.0	22.9	16.7	0	100	IRRC and Gompers et al (2003)	1,139
CEO Power Index	9.7	2.9	10	2	18	IRRC and Gompers et al (2003)	1,357
CEO Firing	0.04	0.20	0	0	1	Fisman et al (2005)	1,897
CEO exit (not firing)	0.09	0.018	0	0	1	Fisman et al (2005)	1,897
CEO Tenure	7.6	6.7	6	0	47	Fisman et al (2005)	1,897
Profits/Assets	0.093	0.052	0.087	-0.064	0.577	Compustat	1,897

NOTES: Data is taken from the sample of 6,208 observations (803 firms) used for the regression of citations/patents sample unless otherwise stated.

TABLE 2: INSTITUTIONAL OWNERSHIP AND INNOVATION (CITE-WEIGHTED PATENTS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimation Method	OLS	OLS	Poisson	Poisson	Poisson	Negative Binomial	Negative Binomial	Negative Binomial
Dependent variable	Ln (CITES)	Ln (CITES)	CITES	CITES	CITES	CITES	CITES	CITES
Share of Equity owned by institutions	0.006*** (0.002)	0.005** (0.002)	0.010*** (0.002)	0.008*** (0.002)	0.007*** (0.002)	0.009*** (0.002)	0.008*** (0.002)	0.006*** (0.002)
ln (R&D Stock)		0.337*** (0.040)		0.493*** (0.140)	0.009 (0.107)		0.448*** (0.039)	0.178*** (0.029)
Ln(K/L)	0.433*** (0.094)	0.261*** (0.085)	0.483*** (0.136)	0.346** (0.165)	0.440*** (0.132)	0.613*** (0.106)	0.343*** (0.087)	0.264*** (0.076)
Ln(Sales)	0.568*** (0.037)	0.310*** (0.045)	0.920*** (0.041)	0.349*** (0.117)	0.184** (0.063)	0.493*** (0.047)	0.229*** (0.058)	0.127*** (0.038)
Fixed Effects controls	No	No	No	No	Yes	No	No	Yes
Observations	4,025	4,025	6,028	6,208	6,208	6,208	6,208	6,208
Firms	803	803	803	803	803	803	803	803

NOTES: ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level. CITES is a count of a firm's patents weighted by the number of future citations. Coefficients are from count data models with standard errors clustered by firm (in parentheses). All regressions control for ln(sales), ln(capital/sales) ratio), and a full set of four digit industry dummies and time dummies. Estimation period 1991-1999 (citations up to 2002); Fixed effects controls using the Blundell, Griffith and Van Reenen (1999) mean scaling estimator.

TABLE 3: INSTITUTIONAL OWNERSHIP AND INNOVATION - CONTROLLING FOR ENDOGENEITY OF OWNERSHIP

Dependent variable: CITES	(1)	(2)	(3)	(4)	(5)	(6)
Estimation Method	Poisson	OLS (First Stage)	Poisson and control function	Poisson	OLS (First Stage)	Poisson and control function
Dependent variable	CITES citation weighted patent counts	Share of Equity owned by institutions	CITES citation weighted patent counts	CITES citation weighted patent counts	Share of Equity owned by institutions	CITES citation weighted patent counts
Share of Equity owned by institutions	0.010*** (0.002)		0.043*** (0.012)	0.007** (0.002)		0.029** (0.013)
S&P500		9.238*** (0.788)			8.872*** (0.805)	
Exogeneity test (p-value)			0.007			0.087
FE controls	No	No	No	Yes	Yes	Yes
Observations	6,208	6,208	6,208	6,208	6,208	6,208
Firms	803	803	803	803	803	803

NOTES: ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level. Columns (1)-(6) control for ln(sales), ln(capital/employment), 4-digit industry dummies and time dummies. Estimation period is 1991 -1999. S&P500 is a dummy variable equal to unity if the firm is a member of the S&P 500 Index. FE controls use the Blundell et al (1999) method in columns (4)-(6) and within groups in (7)-(9). Exogeneity test is a Hausman test.

TABLE 4: ALLOWING THE INSTITUTIONAL OWNERSHIP EFFECT TO VARY WITH PRODUCT MARKET COMPETITION

Dependent variable: CITES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Competition Measure	Lerner varies over time	Lerner varies over time	Lerner varies over time	Lerner varies over time	Lerner constant over time	Lerner constant over time	Lerner constant over time	Lerner constant over time
Sample	Pooled	Pooled	High Product Market Competition (1-Lerner) > 0.871)	Low Product Market Competition (1-Lerner) < 0.871)	Pooled	Pooled	High Product Market Competition (1-Lerner) > 0.871)	Low Product Market Competition (1-Lerner) < 0.871)
(Share of Equity owned by institutions) *		0.082** (0.035)				0.087** (0.033)		
Share of Equity owned by institutions	0.007** (0.002)	-0.064** (0.030)	0.009** (0.002)	0.002 (0.003)	0.007*** (0.003)	-0.068*** (0.028)	0.009*** (0.001)	0.002 (0.001)
Competition	0.343 (2.329)	-3.694 (3.330)	4.664 (3.943)	1.376 (4.939)				
Observations	6,208	6,208	3,085	3,123	6,208	6,208	3,085	3,123
Firms	803	803	542	637	803	803	542	637

NOTES: ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level. The dependent variable is future cite-weighted patents. Each column is a separate Poisson regression as in Table 2 column (5): all regressions control for year dummies, ln(sales), ln(capital/labor), ln(R&D stock), four digit industry dummies (in columns (1)-(4) and three digit in columns (5)-(8)) and fixed effects using Blundell et al (1999) method. Standard errors are clustered at the three digit industry level. Product market competition constructed as (1 - Lerner Index) where Lerner is calculated as the median gross margin from the entire Compustat database in the firm's three digit industry.

TABLE 5:
ALLOWING THE INSTITUTIONAL OWNERSHIP EFFECT TO VARY WITH MANAGERIAL “ENTRENCHMENT”

Dependent variable: CITES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Measure of Entrenchment	State Laws against hostile takeovers				Gompers Index of managerial power over shareholders			
Sample	Pooled	Pooled	Low Entrenchment: Few Laws block takeovers (Index less than or equal to 16.7)	High Entrenchment: Many State Laws block takeovers (Index greater than 16.7)	Pooled	Pooled	Low Entrenchment (Gompers’ Index greater less than 10)	High entrenchment (Gompers Index greater than or equal to 10)
(Share of Equity owned by institutions) *		-0.039**						
(State Laws blocking hostile takeovers)		(0.016)						
(Share of Equity owned by institutions) *						-0.003**		
(Gompers’ Index)						(0.001)		
Share of Equity owned by institutions	0.007***	0.017***	0.010***	0.004	0.008***	0.032***	0.009***	0.008**
State Laws blocking hostile takeovers	(0.003)	(0.005)	(0.003)	(0.004)	(0.003)	(0.010)	(0.003)	(0.004)
Gompers’ Index	-0.003	0.021***	-0.022**	0.0002				
	(0.004)	(0.008)	(0.011)	(0.0075)	-0.050*	0.105*	0.013	-0.105
					(0.026)	(0.061)	(0.043)	(0.066)
Observations	1,139	1,139	675	464	1,357	1,357	613	744
Firms	406	406	243	165	539	539	277	309

NOTES: ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level. The dependent variable is future cite-weighted patent regressions. Each column is a separate Poisson regression as in Table 2 column (5): all regressions control for year dummies, ln(sales), ln(capital/labor), ln(R&D stock), industry dummies (three digit) and fixed effects using Blundell et al (1999) method. Standard errors are clustered at the firm-level. State Takeover law index is an average of 6 different state laws that make it harder to launch a hostile takeover bid. Gompers Index is an average of up to 26 provisions in the firm’s charter. The entrenchment measures are based on data from IRRC in 1993, 1995 and 1998.

TABLE 6: THE IMPACT OF POOR PERFORMANCE ON CEO FIRING PROBABILITY IS LOWER WITH MORE INSTITUTIONAL OWNERS

Dependent variable	(1) CEO Fired	(2) CEO Fired	(3) CEO Fired	(4) CEO Fired	(5) Unforced CEO exit
$\Delta(\text{Profits/Assets})_{t-1}$	-0.479* (0.251)	-1.604*** (0.496)	-1.274*** (0.362)	-1.668** (0.690)	0.715 (1.224)
(Share of Equity owned by institutions)* $\Delta(\text{Profits/Assets})_{t-1}$		0.025** (0.010)			
Share of Equity owned by institutions ^a		-0.037 (0.023)			
(Share of Equity owned by institutions>25%)* $\Delta(\text{Profits/Assets})_{t-1}$			1.057** (0.456)	1.364* (0.790)	-0.513 (1.294)
Share of Equity owned by institutions>25%			-0.033** (0.021)	-0.039 (0.029)	0.033 (0.022)
Observations	1,897	1,897	1,897	1,178	1,178
Firms	249	249	249	249	249
Years	1988-1995	1988-1995	1988-1995	1991-1995	1991-1995

^a Coefficient and standard error multiplied by 100

NOTES: ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level. The dependent variable is 1 if CEO was fired and zero otherwise. CEO firings are from Fisman et al (2005). All regressions include a full set of time dummies and a quadratic in the tenure (in post) of the CEO. Estimation is by probit ML, marginal effects are shown above standard errors (in parentheses) that are clustered by firm. Share of equity owned by institutions is based in 1991 (first year we have ownership data). “Unforced CEO exists” are when the CEO leaves but is not fired (e.g. for reasons of retirement or death). See text and Data Appendix for full description.

TABLE 7: DISAGGREGATING INSTITUTIONAL OWNERSHIP

	(1)	(2)	(3)
Share of Equity Owned by institutions	0.006** (0.002)		0.014*** (0.004)
Share of Equity Owned by quasi-indexed institutions		0.001 (0.004)	-0.014* (0.007)
Share of Equity Owned by “dedicated” institutions		0.012** (0.006)	
Share of Equity Owned by “transient” institutions		0.016** (0.007)	
Observations	3,157	3,157	3,157
Firms	678	678	678
Years	1991-1998	1991-1998	1991-1998

NOTES: *** = significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level. The dependent variable is the number of patents weighted by future citations. Poisson models with controls for fixed effects (Blundell et al, 1999), ln(sales), ln(capital/labor ratio), ln(R&D stock) and full set of time dummies and four digit industry dummies. Standard errors clustered by firm. All specifications identical to Table 2 column (5) except we also control for ln(employment). The definitions of different institutional ownership types follows Bushee (1998) – see Data Appendix for details.

TABLE A1: R&D AND INSTITUTIONAL OWNERSHIP

	(1)	(3)	(4)
Estimation Method	OLS	OLS	OLS
Dependent variable	Ln (R&D Expenditure)	Ln (R&D Expenditure)	Ln (R&D Expenditure)
Share of Equity owned by institutions	0.038** (0.003)	0.006*** (0.001)	0.002** (0.001)
controls		Ln(capital-labor ratio), 4 digit industry dummies	Ln(capital-labor ratio), fixed effects
Observations	4,922	4,922	4,922
Firms	653	653	653

NOTES: ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level.

Columns control for ln(sales) and time dummies. All standard errors clustered by firm. Estimation period 1992-1999.

TABLE A2: PRODUCTIVITY AND INSTITUTIONAL OWNERSHIP

	(1)	(2)	(3)	(4)
Estimation Method	OLS	OLS	OLS	OLS
Dependent variable	Ln(Sales)	Ln(Sales)	Ln(Sales)	Ln(Sales)
Share of Equity owned by institutions^a	0.035*** (0.007)	0.031*** (0.006)	0.031*** (0.006)	0.008** (0.004)
R&D stock	-	-	0.028** (0.011)	0.040* (0.023)
Labor	1.026*** (0.014)	0.636*** (0.042)	0.636*** (0.042)	0.504*** (0.045)
Capital		0.350*** (0.038)	0.350*** (0.038)	0.326*** (0.039)
Fixed Effect	No	No	No	Yes (Within Groups)
Observations	6,208	6,208	6,208	6,208
Firms	803	803	803	803

^a Coefficient and standard error multiplied by 10

NOTES: ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level. Coefficients estimated by OLS with , standard errors clustered by firm (in parentheses). Controls for ln(capital), ln(employment), four digit industry dummies and time dummies. Estimation period is 1991-1999.

TABLE A3: OWNERSHIP AND INNOVATION INSTRUMENTAL VARIABLE REGRESSIONS; ALTERNATIVE TRANSFORMATION OF DEPENDENT VARIABLE

	(1)	(2)	(3)
Estimation Method	OLS	OLS (First Stage)	IV
Dependent variable	Ln (1+CITES) citation weighted patent counts	Share of Equity owned by institutions	Ln (1+CITES) citation weighted patent counts
Share of Equity owned by institutions	0.007** (0.002)		0.122** (0.035)
S&P500		7.8254*** (0.724)	
Observations	6,208	6,208	6,208
Firms	803	803	803

NOTES: ***=significant at the 1% level, **=significant at the 5% level, *=significant at the 10% level. Columns control for ln(sales), ln(capital/employment), ln(R&D stock/employment), 4-digit industry dummies and time dummies. All standard errors clustered by firm. Estimation period 1992-1999. S&P500 is a dummy variable equal to unity if the firm is a member of the S&P 500 Index.