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The Impact of Private Ownership, Incentives and Local Development Objectives on University Technology Transfer Performance

Sharon Belenzon and Mark Schankerman

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

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Abstract

We study the impact of private ownership, incentive pay and local development objectives on university licensing performance. We develop and test a simple contracting model of technology licensing offices, using new survey information together with panel data on U.S. universities for 1995-99. We find that private universities are much more likely to adopt incentive pay than public ones, but ownership does not affect licensing performance conditional on the use of incentive pay. Adopting incentive pay is associated with about 30-40 percent more income per license. Universities with strong local development objectives generate about 30 percent less income per license, but are more likely to license to local (in-state) startup companies. In addition, we show that government constraints on university licensing activity are .costly. in terms of foregone license income and the creation of start-up companies. These results are robust to controls for observed and unobserved heterogeneity.

Keywords: incentives, performance pay, universities, technology transfer, licensing, local development

JEL Classifications: O31, O32, O33, F23

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Sharon Belenzon is a Research Economist with the Productivity and Innovation Research Group at the Centre for Economic Performance, London School of Economics. He is also a Postdoctoral Research Fellow at Nuffield College, University of Oxford. Mark Schankerman is an Associate of the Centre for Economic Performance. He is also the first James and Pamela Muzzy Chair in Entrepreneurship at the University of Arizona's Eller College of Management.

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1. Introduction

Empirical studies demonstrate that university research has real effects, enhancing innovation and productivity in private firms. This works through two main channels – pure knowledge spillovers and licensing of university inventions.[1] Patenting and licensing by universities has grown sharply and has become an active public policy issue in the U.S. From 1991-2004, patent applications by U.S. universities rose from 1,584 to 10,517 and license income increased from $218 million to $1.4 billion, which is about six percent of federal R&D financing for universities.[2] This rapid growth was partly associated with the Bayh-Dole Act of 1980, which gave universities ownership of inventions from federally-funded research. Today all research universities have technology licensing offices (TLO's) and intellectual property policies.[3] This paper studies how economic incentives and institutional arrangements affect university technology licensing performance.

Technology transfer involves two distinct activities: innovation by faculty scientists and commercialization by the TLO. Scientists produce both publications and inventions in response to monetary and other incentives (e.g., promotion and tenure rules and intrinsic motivation).[4] Lach and Schankerman (2003) show that royalty sharing incentives for scientists strongly affect innovation and licensing outcomes. The effectiveness of commercialization by university technology licensing offices – which decide whether to patent and license inventions, identify licensees and structure contracts – is shaped by the university's objectives, government constraints, and incentives within the TLO. Improving TLO productivity is especially important because, under prevailing arrangements in the U.S., universities have monopsony control ('right of first refusal') over commercialisation.

[1] Leading studies on the knowledge spillovers from university research include Jaffe (1989) and Adams (1990). On the geographic localisation of such spillovers, see Jaffe, Trajtenberg and Henderson, 1993; and Audretsch and Stephan, 1996. There is also a growing empirical literature on patenting and technology transfer by universities, and by national research laboratories (e.g., Henderson, Jaffe and Trajtenberg, 1998; Jaffe and Lerner, 2001; Thursby and Kemp, 2002; and Siegel, Waldman and Link, 2003).

[2] The figures are computed from information in the *FY 2004 Licensing Survey*, Association of University Technology Managers. The patenting licensing information includes all universities and hospitals that responded to the AUTM surveys in the respective years.

[3] There was some technology transfer prior to the Bayh-Dole Act, though the transaction costs and uncertainty of property rights undermined widespread activity. For a more skeptical view of the contribution of the Bayh-Dole Act to the growth of technology licensing, see Mowery and Zeidonis (2001).

[4] For discussion see Dasgupta and David (1994). Aghion, Dewatripont and Stein (2005) provide an interesting theoretical analysis of the functions of university and private sector research and the implications for incentive structures.

A number of papers have shown that technology transfer performance is influenced by university characteristics and other factors, including university ownership (public versus private), academic quality, local (high-tech) demand conditions and license contract design.(Jensen and Thursby, 2001; Thursby and Kemp, 2002; Thursby and Thursby, 2002; Siegel,Waldman and Link, 2003; and DiGregorio and Shane, 2003; Elfenbein, 2004). These studies explore a variety of different outcome measures, including the number of patents and licenses, license income, and the formation of start-up companies. Our paper extends the literature by focusing more on the 'black box' of productivity within the technology licensing office.

We focus on three key determinants of productivity: performance pay, local development objectives, and government constraints on licensing activity. Labor economists have studied the impact of performance pay on output and earnings in various contexts (Lazear, 2000b, and the literature cited there). To our knowledge, this paper and Lach and Schankerman (2003) are the only studies of how monetary incentives affect performance in not-for-profit organizations, in this case universities. Universities have various objectives in undertaking technology transfer. Survey data used in this paper show that the two main objectives are generating license income and promoting local and regional development, the latter being more prominent in public universities. Institutions that view local economic development as one of their primary functions might perform differently from those that exclusively pursue income maximization. Finally, state governments often impose a variety of constraints – both statutory restrictions and informal political pressure – on licensing activity in public universities. In this paper we quantify the impact of incentives and measure the implicit cost of local development objectives and government constraints in terms of foregone license income.

We develop a simple contracting model of the TLO that focuses on how performance-based incentives, local development objectives and government constraints affect licensing performance. In our model, the TLO worker makes an effort decision which is unobservable to (or unverifiable by) the TLO administration. This effort is devoted to two things: first, identifying inventions with commercial potential (i.e. getting scientists to disclose them) and, second, licensing those inventions to private firms. We assume that the interests of the TLO and the university (administration) are aligned. However, we introduce an agency problem by assuming that there is a divergence of interests between the TLO and its workers. In particular, the TLO has two objectives – maximising total license income plus a premium attached to income generated in the local market. However, workers do not share this local development objective (they are only trying to maximise their income). The TLO provides income sharing incentives to the worker in order to induce greater effort.

The model generates four main empirical predictions. First, the use of performance pay should be more likely when universities give less weight to local development objectives and are less constrained by government. Second, the use of performance pay should increase the level of income per license (and possibly the number of licenses). Third, strong local development objectives should reduce income per license (but possibly increase the number of licenses). Fourth, government constraints should reduce income per license.[5]

We are not the first to model the intermediation role of technology transfer offices. Jensen, Thursby and Thursby (2005) develop a model that emphasises the 'dual agency' role of the TLO, which serves both university scientists and the university administration as principals who have divergent objectives. In their model, scientists first decide whether (and when) to disclose their inventions, and the TLO then decides whether to search for a licensee and negotiate terms for the license. The university administration influences the incentives of the TLO and faculty scientists by establishing policies for the distribution of license income and/or industry-sponsored research. In their model, the decision of scientists to disclose their inventions is influenced indirectly by the effectiveness of the TLO in commercialising inventions, but the TLO does not directly invest resources to identify inventions. Our model introduces this latter element, which the survey evidence indicates is important.[6]

More recent models emphasise the role of the TLO in mitigating imperfect and asymmetric information about the quality of inventions. Macho-Stadler, Perez-Castrillo and Veugelers (2007) build a model in which the TLO, but not potential licensees, is informed

[5]While the model is based on the effort effect of incentives, we recognise (as emphasised by Lazear, 2000a and 2000b) that performance pay can improve productivity both by providing greater incentives for effort and by improving positive sorting of workers. The impacts of performance pay estimated in this paper capture both effects. We do not have any individual level data, and thus cannot separately identify the pure incentive (effort) and sorting effects.

[6]According to the survey evidence, TLOs spend considerable resources to identify potentially commercialisable inventions (Jensen, Thursby and Thursby, 2001). In our more recent and larger survey, described in Section 3, TLO directors rank "identifying suitable inventions" as one of the most important task in terms of their allocation of resources.

about the quality of new inventions and show that reputation building in an infinitely repeated licensing game can sustain an equilibrium in which only profitable inventions are offered and licensed. Finally, in an important paper, Hoppe and Ozdenoren (2005) develop a dynamic games in which intermediaries have an incentive to invest in information acquisition (e.g. about the quality of inventions) and use this information to match inventions to licensees.

These papers have enhanced our understanding of the role of TLOs, but they do not analyse the impacts of performance-based incentives and local development objectives on TLO performance, which are the primary focus of our model. In principle, it should be possible to build a more encompassing model that incorporates both the features we emphasise and those in the aforementioned models, but that is beyond the scope of this paper.

The empirical analysis in this paper is based on new survey data combined with panel data from public sources on 86 U.S. universities for the period 1995-99. The key results can be summarized as follows. First, universities are more likely to adopt performance pay when they are private, when they place less weight on local development objectives and when they are less constrained by state government. This evidence is consistent with the predictions of the theoretical literature on the adoption of incentives in public organizations.[7] However, while private ownership has a large, positive effect on the adoption of incentive pay, ownership has no independent effect on licensing performance, conditional on the adoption of incentive pay. Second, incentives have strong performance effects. Universities that use bonus pay generate, on average, about 30-40 percent more income per license.[8] Taken together, these two findings suggest that it may be possible to get 'private performance' out of public institutions if the right incentives are introduced.

Third, we find that local development objectives are 'costly' in terms of foregone license income. Universities with strong local development objectives generate, on average, about 30 percent less income per license. The standard argument for having a local licensing

[7] This literature shows that high-powered incentives are less likely to be adopted in public organizations because of the problem of multiple principals (Berheim and Whinston, 1986; Holmstrom and Milgrom, 1988; Dixit, 1997), output measurement and monitoring (Prendergast, 2002) and stronger intrinsic motivation in such organizations (Francois, 2000; Besley and Ghatak, 2006).

[8] This estimate is broadly similar to other estimates in the literature, including the well known study of the productivity gains from piece work pay in an automotive glass manufacturing firm (Lazear, 2000b), and more recent work by Bandiera, Barankay and Rasul (2005, 2006).

preference is that it increases localised knowledge spillovers and the agglomeration effects emphasized by the new economic geography literature. We provide some evidence that universities with strong local development objectives are more likely to establish start-up companies in the state rather than outside it. But a full evaluation of whether localised spillovers are stronger for such universities in beyond the scope of this paper. Nonetheless, the large opportunity cost of promoting local development through licensing highlights the importance of comparing this policy to the alternative policy of maximizing licensing income and using the additional income to finance local economic development in other ways (e.g. lower business taxes or direct subsidy programs).

Finally, we find that state government constraints reduce license income – the estimated shadow price of an additional 'effective constraint' (as defined in Section 3) is a 17 percent reduction in license income. Universities that are more strongly constrained are also less likely to license through new start-up companies (rather than existing firms).

The main econometric concern is the potential endogeniety of incentives due to unobserved heterogeneity (e.g. commercial orientation) that affects both the university's licensing performance and adoption of incentive pay. We do not have variation over time in our measures of performance pay and thus cannot use university fixed effects to address this issue. Instead, we adopt the approach developed by Blundell, Griffith and van Reenen (1999) by using information on the pre-sample license income and patenting by the university to capture unobserved heterogeneity. In addition, we control for whether the university is private, which should be correlated with commercial orientation. While the pre-sample patent control is very significant and works in the expected direction, one cannot rule out the possibility that there is some remaining unobserved heterogeneity. To reach more definitive conclusions, we would need information on variation over time, and across universities, in the adoption of incentive pay as well as instrumental variables that affect that adoption decision but not license income, but this kind of information is not available to our knowledge.

The findings in this paper contribute to the policy debate about the effectiveness of university licensing activity, but the paper is not a cost-benefit analysis of the 'commercialisation' of universities. Many scholars have expressed concerns about the potential costs of these developments, including the threat to established norms of open science and the redirection of research away from fundamental science.[9] While important, these issues are beyond the scope of this paper.

The paper is organized as follows. Section 2 presents the model. In Sections 3 and 4 we describe the data and present the empirical specification. Section 5 presents and discusses the implications of the parametric estimates of the model (nonparametric results are included in an appendix), followed by brief concluding remarks.

2. Analytical Framework

The university technology licensing office (TLO) hires a worker who allocates her effort to two tasks. The first is to identify inventions with commercial potential (i.e., getting the faculty to disclose her inventions). University scientists are contractually required to report to the TLO any inventions based on federally-financed research, but the survey evidence strongly indicates that, in practice, TLO licensing officers spend substantial effort eliciting disclosures and thus increasing the "supply" of inventions (Jensen, Thursby and Thursby, 2001; Siegel, Waldman, Atwater and Link, 2003). The second task is to search for potential licensees and negotiate deals on those inventions. We assume that the TLO worker makes these effort decisions simultaneously.[10]

It takes μ_I units of effort to identify an invention with commercial potential. Each of these disclosed invention can be licensed either in the local market (L) or the national market (N). Licensing an invention in market $i = L, N$ takes μ_i^* units of effort and generates revenue λp_i. The parameter $\lambda \in [0, 1]$ captures the severity of any (formal or informal) government constraints on the TLO, which have the effect of reduing the payoff to licensing ($\lambda = 1$ denotes the case of no constraints). We assume that it is more costly to license (search) in the national market, but that it generates a higher payoff: $p_N > p_L$ and $\mu_N^* > \mu_L^*$. We normalize the number of total inventions by faculty scientists to unity.

Let β denote the fraction of effort devoted to licensing inventions in the national market. Then total effort is given by $e = \mu_I + \beta\mu_N^* + (1-\beta)\mu_L^*$. Letting $\mu_i = \mu_i^* + \mu_I$ denote the 'full cost' of finding and licensing an invention in market i, we can write $e = \beta\mu_N + (1-\beta)\mu_L$.

[9] For a thoughtful analysis of these issues, see Dasgupta and David (1994). There is very limited empirical work on the impact of such activity on open science and research orientation. Recent work includes Agarwal and Henderson (2002) and Murray and Stern (2006).

[10] The predictions of the model would not change if we modelled the disclosure and licensing efforts of the worker as sequential rather than simultaneous.

Effort costs are $C(e) = \frac{1}{2}e^2$.

The TLO offers a compensation package involving a wage $w \geq 0$ and a high-powered incentive in the form of a fraction $\alpha \in [0, 1]$ of the licensing revenues.[11] The TLO has two objectives – earning license income and promoting local development. License income is $R = \beta\lambda p_N + (1 - \beta)\lambda p_L$. We model the local development objective by assuming that the TLO places a premium on generating license income from the local area, in addition to the total income it retains, $(1 - \alpha)R$. Letting $\Delta p = p_N - p_L$ and $\Delta\mu = \mu_N - \mu_L$, the objective function is

$$V = (1 - \alpha)\lambda\{\beta\Delta p + p_L\} + \delta(1 - \beta)\lambda p_L - w \tag{2.1}$$

The parameter $\delta \geq 0$ reflects the premium attached to local development. Larger δ denotes a stronger local development objective.

The first best allocation where β.is contractible solves

$$\max_{\beta}\ V = \beta\lambda\Delta p + \lambda p_L + \delta(1 - \beta)\lambda p_L - w \qquad s.t. \quad U(w, \beta) = \ w - \frac{1}{2}(\beta\Delta\mu + \mu_L)^2 \geq U_0$$

where U_0 is the worker's reservation value. This yields

$$\beta^{**} = \max\left\{\frac{\lambda(\Delta p - \delta p_L) - \mu_L\Delta\mu}{(\Delta\mu)^2}, 0\right\}$$

Now suppose that the TLO cannot contract over β.[12] The TLO sets the compensation package (w, α) subject to the incentive compatibility constraint that the worker sets optimal effort. The benefit to the TLO of a higher α is that it induces more effort on high-revenue licensing. The cost is that the TLO retains less of the revenue generated. The trade-off determines the optimal α.

Under incentive compatibility, the worker solves

$$\begin{aligned}\max_{\beta} U(\beta) \quad &= \quad \alpha\lambda\{\beta\Delta p + p_L\} + w - \frac{1}{2}(\beta\Delta\mu + \mu_L)^2 \quad s.t. \ \ U(\beta) \geq U_0 \\ &\implies \ \beta^* = \max\left\{\frac{\alpha\lambda\Delta p - \mu_L\Delta\mu}{(\Delta\mu)^2}, 0\right\}\end{aligned}$$

[11] We assume that the TLO cannot use different sharing rates for revenue raised in the local and national markets (we have no evidence that would allow us to investigate this). We also rule out the possiibility that the worker pays the TLO for employment ($w < 0$) and is compensated by revenue sharing.

[12] This can arise either because the worker's effort is not observable to the TLO or not verifiable to third parties.

Since the worker has no preference for local development, there is a divergence between her objectives and those of the TLO.[13] Note that even if the worker retains all the license income ($\alpha = 1$), $\beta^* > \beta^{**}$ as long as $\delta > 0$. If the TLO has a local development objective, it wants to tilt effort more toward licensing in the local market, relative to the allocation made by the worker. Since we assume the TLO cannot set different revenue sharing rates for license income in local and national markets, the only way the TLO can lower the worker's choice of β is to reduce the high-powered incentive, α.

Given $\beta^*(\alpha)$, the university solves

$$\begin{aligned} \max_{\alpha,w} V &= (1-\alpha)\lambda\{\beta^*(\alpha)\Delta p + p_L\} + \delta(1-\beta^*(\alpha))\lambda p_L - w \\ s.t.\ \ U(\beta^*) &= \alpha\lambda\{\beta^*(\alpha)\Delta p + p_L\} + w - \frac{1}{2}(\beta^*(\alpha)\Delta\mu + \mu_L)^2 \geq U_0 \end{aligned}$$

Assuming the participation constraint binds, the first order condition is

$$V_\alpha = \{\lambda\Delta p - \delta\lambda p_L - (\beta^*(\alpha)\Delta\mu + \mu_L)\Delta\mu\}\frac{\partial\beta^*(\alpha)}{\partial\alpha} = 0 \tag{2.2}$$

which yields the optimal revenue sharing

$$\alpha^* = \max\left\{1 - \frac{\delta p_L}{\Delta p}, 0\right\} \quad \Longrightarrow \quad \frac{\partial\alpha^*}{\partial\delta} \leq 0 \tag{2.3}$$

The optimal revenue share for the worker is non-increasing in the weight the TLO attaches to local development objectives.[14]

In the data we observe whether or not the university adopts performance-based pay, but not the actual revenue sharing parameter, α^*. To examine how the local development objective affects the adoption probability, suppose there is a fixed cost of introducing incentive pay, F. The TLO introduces (optimal) incentive pay if the gain exceeds the cost: $\Delta V(\theta) = V(\alpha^*;\theta) - V(0;\theta) \geq F$, where $\theta = (\delta, p_L, p_N, \mu_L, \mu_N, U_0)$. Using equation (2.2) and recalling that $\beta^* = 0$ when $\alpha = 0$,we get $\Delta V(\theta) = \frac{1}{2}(\beta^*(\alpha^*)\Delta\mu)^2$. It is easy to verify that $\frac{\partial\Delta V(\theta)}{\partial\delta} \leq 0$ and $\frac{\partial\Delta V(\theta)}{\partial\lambda} \geq 0$, which imply:

[13] A preference for local development could arise if workers in technology licensing offices sort across universities on this dimension.

[14] Two points should be noted. First, if $\delta = 0$ the TLO wants to give maximum incentives to the worker, $\alpha = 1$. However, then $V > 0$ only if the TLO charges the worker for the right to work ($w < 0$). If we rule this out, the optimal policy is to set $\alpha < 1$ that satisfies the participation constraint for $w = 0$. Second, the optimal revenue sharing is independent of the constraint parameter λ because we have assumed that the latter affects local and national licensing the same way.

Prediction 1: Universities that care more about local development (higher δ) are less likely to adopt incentive pay.

Prediction 2: Universities that are more constrained (lower λ) are less likely to adopt incentive pay.

We next examine how incentive pay, local development objectives and constraints affect total license income earned by the university, which is what we observe in the data. With optimal incentive pay, the license income generated is $R^* = \beta^*(\alpha^*)\lambda\Delta p + \lambda p_L$. The effect of adopting (optimal) incentive pay is given by $\Delta R = R(\alpha^*; \theta) - R(0; \theta) = \beta^*(\alpha^*)\lambda\Delta p > 0$. This leads to:

Prediction 3: Universities which use incentive pay generate greater license income per license.

Finally, using the expression $R^* = \beta^*(\alpha^*)\lambda\Delta p + \lambda p_L$ and equation (2.3), it is easy to verify that $\frac{\partial R^*}{\partial \delta} \leq 0$ and $\frac{\partial R^*}{\partial \lambda} \geq 0$, where these derivatives take into account the impact of δ and λ on the optimal revenue sharing decision, α^*. These results imply the following two predictions:

Prediction 4: Universities that care more about local development (higher δ) generate less license income per license, conditional on their choice of whether to adopt incentive pay.

Prediction 5: Universities that are more constrained (lower λ) earn less license income per license, conditional on their choice of whether to adopt incentive pay.

In the model above, we have interpreted the local development objective as a preference for generating license income in the local market. A plausible alternative interpretation of a local licensing preference is that the university (TLO) may attach a premium to the *number of licenses* it generates in the local market, rather than the amount of license income in the local market.[15] To analyse this interpretation, we can re-write the objective function for the TLO as

[15] In the survey, 52 universities rank the number of licenses as a very important objective, 24 as moderately important and 10 as relatively unimportant or unimportant (the survey does not distinguish between local and non-local in this respect). The average shares of non-exclusive in total licenses for these groups of universities are, repectively, 88, 82 and 68.

$$V = (1-\alpha)\lambda\{\beta\Delta p + p_L\} + \delta(1-\beta) - w \tag{2.4}$$

Here the local objective component is the term $\delta(1-\beta)$, as compared with the original formulation in equation (2.1) in which it was $\delta(1-\beta)\lambda p_L$. Following the derivations above, it is straightforward to show that Predictions 1-5 continue to hold with this new objective function. However, we obtain an additional prediction with this new formulation: the number of licenses in the local market, denoted by $(1-\beta)$, increases when incentive pay is used, when local development objectives are stronger (higher δ), and when constraints are more severe (lower λ). We will investigate these additional implications in the empirical analysis in Sections 4 and 5.

3. Data Description

This paper combines data from three main sources: (1) a new survey of technology licensing offices in public and private universities in the United States, (2) annual surveys published by the Association of University Technology Managers (AUTM), and (3) patent data from the USPTO (available at the NBER archive).

Survey: We conducted a survey of TLO directors in late 2003. The survey was sent to about 200 U.S. and Canadian research universities that belong to the AUTM, from which we received 102 responses. After matching to other data for the empirical analysis, the final sample consists of 86 universities. We ran sample selection regressions using as controls the sample mean of TLO age, TLO size, license income per active license, number of licenses executed per invention disclosure, and dummy variable for whether the university is private and whether it has a medical school. Only the medical school dummy has a significant (positive) coefficient in the selection equation (pseudo-$R^2 = .13$, p-value$<.001$). Importantly, the response probability is not systematically related to the private status of the university or either of the two measures of licensing performance which we later use in the econometric analysis.

In addition to descriptive information about the TLO, the survey focused on three key areas: (1) the use of performance-based pay (merit pay or bonuses), (2) the relative importance of different objectives in their licensing activity, and (3) informal and formal government constraints on TLO operations.[16]

On incentives, the survey asked whether the TLO uses some form of *performance-based pay* for its professional staff – either merit pay or bonuses. We define a dummy variable for the TLO's that use merit pay and another for bonus pay. These indicators of performance-based pay include both cases where the pay is based on subjective and objective measures of performance, and on the basis of individual or group performance.[17] Bonuses are a more high-powered incentive because they are more directly linked to objective performance outcomes. We do not have any information on the size of performance-related pay.

On objectives, the survey asked to assess the importance of different objectives of the TLO (as very important, moderately important, relatively unimportant or unimportant). These objectives include (but are not limited to) the number of licenses executed, the amount of license income generated, and the promotion of local and regional economic development (i.e., a preference for licensing to local firms, even if it does not maximize licensing revenue). Inspection of the survey data shows that the only objective for which universities differ substantially is local and regional development.[18] For this reason, we focus our attention in this paper on this objective. We define a set of dummy variables that reflect the importance of the local development objective: LOCDEV=High ('very important') and LOCDEV=Medium ('relatively important'); the reference category corresponds to 'relatively unimportant' or 'unimportant'.

Finally, the survey asked about the importance of six different (formal or informal) constraints on licensing operations that are imposed by state government, using the same descriptions as for local development objectives. The constraints cover the choice of licensees, license contract terms, the use of equity stakes (rather than royalties), and provisions regarding confidentiality, indemnification and dispute resolution. We define a variable that counts the number of constraints for which the TLO reports 'moderately important' or

[16]The survey questionaire is available from the authors on request.

[17]For a theoretical analysis of incentives based on objective and subjective performance measures, see Baker, Gibbons and Murphy (1994). Our survey contains some information on these two characteristics, but the data were not rich enough to allow us to differentiate performance-based pay along these dimensions

[18]For the local development objective, 29 universities rank it as very important as compared to 20 who say that it is relatively unimportant or unimportant (the rest rank it as moderately important). By contrast, for the number of licenses executed, 51 universities rank it as a very important objective and only 10 say that it is relatively unimportant or unimportant. This latter characterization also holds for the other objectives in the survey.

'very important'. We have no information when these constraints were introduced.

AUTM: Data on licensing income, the number of new licenses executed, the stock of active licenses, the number of inventions disclosed, and descriptive information about the TLO (size and age) and the university are taken from the Annual Surveys of the Association of University Technology Managers (AUTM). The AUTM surveys cover the period 1991-2001, but for the set of variables we need the usable sample period is 1995-2001.[19] The final data set is an unbalanced panel of 521 observations covering 86 universities. The AUTM data are at the university level aggregated across technology fields; there is no information for separate technology areas or for individual innovations.

USPTO: For each university we construct a "pre-sample" measure of the stock of patents held by each university as of 1990. We use this measure to capture unobserved heterogeneity that may be due to variations across universities in their commercial orientation or capacity. To construct the pre-sample patents, we matched the names of universities in our sample to the complete list of assignees to any patent applications filed (and subsequently issued) in the USPTO during the period 1969-1990.

Technology composition of faculty: We collected information from the National Research Council (part of the U.S. National Academy of Sciences) on the distribution of faculty across hard science departments in order to construct measures of university specialization in different research areas.[20] This information is provided only for U.S. universities. For Canadian institutions we constructed a measure of the faculty size by hand, using the lists of full time faculty for each of the 23 hard science departments covered by the NRC, as provided on the university websites, and then aggregated up to the six categories used in this paper.

High-tech density (TechPole index): We measure high-tech density (to proxy the local

[19] Information on the stock of active licenses (which generate observed license income) is only available for the subperiod 1995-2001. Also note that *licensing income* includes all license fees, running royalties, and the cash value of equity when sold.

[20] The NRC provides full-time faculty size for 23 different doctoral programs, which we aggregate into six science fields. We use the shares of faculty employed in each field to proxy for the research orientation of the university. The fields are: (1) *Biomedical and Genetics* (biochemical/molecular biology, cell and development biology, biomedical engineering and molecular and general genetics), (2) *Other Biological Sciences* (neurosciences, pharmacology, physiology and ecology/evolution and behavior), (3) *Computer Science,* (4) *Chemical Science* (chemistry and chemical engineering), (5) *Engineering* (aerospace, civil engineering, electrical engineering, industrial engineering, material science, and mechanical engineering), and (6) *Physical Sciences* (astrophysics/astronomy, geosciences, mathematics, oceanography, physics, and statistics/biomedical statistics).

demand for licensing) by the TechPole index, constructed by the Milken Institute (Devol and Wong, 1999). The index a composite of the share of national high-tech real output and the concentration of high-tech industries for each U.S. metropolitan area. The index ranges from zero to a maximum value of about 23 for Silicon Valley. We assign each university the index for the metropolitan area nearest to the university location (main campus). For the Canadian universities, we use a *ranking* of the high-tech density of U.S. and Canadian cities and assign each Canadian university the average TechPole index for the next highest and lowest U.S. cities in the ranking.[21]

Table 1 presents descriptive statistics for the sample. Table 2 provides more detailed information about how the key survey variables vary with university ownership, size, and high-tech density. Note first that the use of high-powered incentives is strongly linked to ownership – private universities are much more likely to use some form of incentive pay than public institutions. Incentives are also more common in larger TLO's (where direct monitoring of performance is likely to be more difficult), and in universities located in high-tech areas. Second, private universities are much less likely to pursue local development objectives than public ones, but this does not vary with TLO size or high-tech density. Third, government constraints are important only for public universities (no private university reports more than two constraints being important).

[See Tables 1 and 2]

These facts have two further implications linked to the model's predictions. First, universities that attach low weight to local development objectives (LOCDEV=Low) are twice as likely to adopt the highest powered incentive (bonus pay), as compared to universities with strong development objectives (LOCDEV=High) – 21 versus 10 percent, respectively. Second, universities that are less constrained by government regulations (NumConst<3) are twice as likely to adopt bonus pay as compared to more constrained universities (NumConst≥ 3) – 20 versus 10 percent, respectively. These simple results are consistent with Predictions 1 and 2 of the model.

To investigate further, we conduct Probit estimation of the determinants of adopting bonus incentives (Table 3). We start with a specification that includes only a private

[21] The ranking was taken from "Competing on Creativity, A Report prepared for the Ontario Ministry of Entrerprise, Opportunity and Innovation and the Institute for Competitiveness and Prosperity" (November 2002), by Mric Gertler, Richard Florida, Gary Gates and Tara Vinodrai. Downloaded from www.creativeclass.org/acrobat/jan2003_canada.pdf

ownership dummy, which is positive and significant. The coefficient on the private ownership dummy is robust to adding controls for observed heterogeneity (column 2), and the implied effect of university ownership is large – moving from public to private doubles the probability of using bonus pay (from the mean of 35 to 71 percent). This finding that ownership strongly affects the adoption of incentive pay is robust to adding pre-sample patenting to control for unobserved heterogeneity (column 4).[22] However, it is not possible to disentangle the separate effect of private ownership from those of local development objectives and constraints because of the strong correlation among these variables (column 5). If we drop the private ownership dummy (column 5), we find that incentive pay is negatively and significantly associated with the number of government constraints, but not with local development objectives. This supports Prediction 2, but not Prediction 1, of the model.

[See Table 3]

Before turning to the econometric analysis, we present nonparametric evidence linking incentives, local development objectives and constraints to licensing performance. Figures 1 and 2 present smoothed cumulative distribution functions of income per active license and the number of licenses per invention disclosed (averaged over time) for universities grouped according to whether they use bonus incentives, the strength of local development objectives, and the severity of government constraints. It is clear that the distribution of income per license for universities that use bonus pay stochastically dominates the distribution for those that do not. This also very nearly holds for universities that are less constrained and that place less weight on local development. The effects of bonus pay and constraints are less clear-cut for the number of licenses per invention, but there is some evidence that stronger local development objectives are associated with more licenses per invention. The next sections provide an econometric analysis of these relationships.

[See Figures 1 and 2]

[22] In sharp contrast, we show in Section 5 that private ownership does *not* have any independent effect on licensing outcomes, once we control for the use of incentive pay.

4. Empirical Specification

4.1. License income equation

The baseline specification links licensing income to incentives, local development objectives and constraints, as follows:

$$\log(LicInc)_{it} = \beta_0^I + \beta_1^I \log(LicExec)_{it} + \beta_2^I DumMerit_i + \beta_3^I DumBonus_i$$
$$+\beta_4^I LOCDEV\_Med_i + \beta_5^I LOCDEV\_High_i + \beta_6^I NumConst_i \quad (4.1)$$
$$+\beta_7^I Intervene \times NumConst_i + Z_{it}'\phi^I + \tau_t^I + \epsilon_{it}^I \quad (4.2)$$

where the superscript I refers to the license income equation, and i and t denote university and year, respectively. The variables are defined as follows: $LicInc$ is the annual flow of licensing income, $LicExec$ is the cumulative number (stock) of active licenses held by the TLO, $DumMerit$ is a dummy variable that equals one if the TLO uses merit pay, $DumBonus$ is a dummy variable that equals one if the TLO pays bonuses as part of the compensation scheme, $LOCDEV\_Med$ and $LOCDEV\_High$ are dummy variables denoting medium and strong local development objectives of the TLO (the reference category is no/weak objectives), $Numconst$ is the number of constraints the TLO reports as important or very important, $Intervene$ is a dummy variable equal to one if the TLO reports that the university frequently intervenes in its decision-making, Z is a vector of additional controls, τ_t^I is a complete set of year dummies, and ϵ_{it}^I is an error term. The control variables include the share of faculty in different fields of research, dummies for whether the university is private or public and whether it has a medical school, pre-sample patents and others.[23] The equation is estimated by generalized least squares with standard errors that allow for arbitrary heteroskedasticity and first-order serial correlation (AR(1)).[24]

Based on the analysis in Section 2, we expect the following signs for the coefficients of interest (prediction from the model): $\beta_3^I > \beta_2^I \geq 0$ (Prediction 3), $\beta_5^I < \beta_4^I < 0$ (Prediction 4), and $\beta_6^I < 0$ (Prediction 5). Finally we expect $\beta_7^I > 0$ if the university intervenes to

[23] In some specifications we also control for the number of inventions disclosed (by the faculty) to the university TLO in order to capture the size of the available 'pool' of inventions that can be licensed.

[24] We also estimated the equations using a more general error specification, allowing $AR(2)$ with arbitrary heteroskedasticity. The estimated parameters and standard errors are very similar.

mitigate the effect of government constraints. This would be expected if the university and TLO have aligned objectives, as assumed in the model.

On final point should be noted on the interpretation of the coefficients β_2^I and β_3^I. As emphasized by Lazear (2000a, 2000b), performance based pay can improve performance both by providing greater incentives to existing workers to increase effort and by improving positive sorting (higher productivity workers moving to TLO's that offer performance pay). The coefficients on the merit and bonus pay dummy variables capture both effects. Since we do not have individual-level data, we cannot separately identify the pure incentive (effort) and sorting effects.

There is a concern that the estimates of β_2^I and β_3^I may be upward biased by unobserved heterogeneity, e.g. differences in commercial orientation (This also applies to the equation for the number of licenses below). Because we do not have variation over time in incentive pay, we cannot use university fixed effects here. We adopt the 'pre-sample scaling' approach developed by Blundell, Griffith and Van Reenen (1999) and Blundell, Griffith and Windmeijer (2002). They show that, under the assumption that the unobserved fixed effect can be expressed as a linear function of the observable characteristics, the pre-sample mean of the dependent variable is a sufficient statistic for the unobserved fixed effect. Thus one can use this pre-sample mean as an additional regressor to control for such heterogeneity. In our context, this involves using the pre-sample mean of license revenues to control for unobserved, university fixed effects. We use the mean license income for the period 1991-94 for each university as a control in the regression on the 1995-99 sample. Because of missing observations, we have only 66 universities in this exercise. Therefore, we also use pre-sample data on patenting by each university for the period 1965-90 (both patent counts and citations), which is available for the full sample of 86 universities.[25] Lach and Schankerman (2007) show that pre-sample information on patenting can be used in place of pre-sample information on license income, provided we assume that patenting is also a linear function of the same unobserved heterogeneity that affects license income, which seems very reasonable (see Appendix 2 for details). Finally, we include a dummy variable for whether the university is private or public, since ownership type is likely to

[25]We actually use the log of one plus the number of patent counts, so as not to discard universities with zero pre-sample patents, and add a dummy variable for these observations. It is worth noting that the within-sample (1995-99) correlation between the log of patent counts and the log of license income is high, at 0.67.

be correlated with commercial orientation.

4.2. Number of licenses equation

The baseline specification links the annual flow of licenses executed by the TLO to incentives, objectives and constraints, as follows:

$$\begin{aligned}\log(Licenses)_{it} &= \beta_0^N + \beta_1^N \log(Inventions)_{it} + \beta_2^N DumMerit_i + \beta_3^N DumBonus_i \\ &\quad +\beta_4^N LOCDEV\_Med_i + \beta_5^N LOCDEV\_High_i + \beta_6^N NumConst_i \\ &\quad +\beta_7^N Intervene \times \ NumConst_i + Z_{it}'\phi^N + \tau_t^N + \epsilon_{it}^N \qquad (4.3)\end{aligned}$$

where the superscript N refers to the number of licenses equation. Following the model, we summarize the parameter predictions as follows. First, we expect high powered incentives to improve performance, so $\beta_3^N > \beta_2^N \geq 0$. Second, it is easier for the TLO to monitor the number of licenses a worker generates (from a given stock of inventions), as compared to the license income generated relative to what might have been earned by more effort. Because of this difference, we expect the adoption of any form of incentive pay to have a smaller impact on the number of licenses than on the level of license income: $\beta_2^N < \beta_2^I$ and $\beta_3^N < \beta_3^I$. Finally, we expect the impact of local development objectives on the number of licenses is likely to be positive rather than negative. Universities that care about local development are more likely to license inventions non-exclusively – which generates less license income but a larger number of licenses on the available inventions. The survey evidence confirms this conjecture.[26] Thus we expect $\beta_5^N > \beta_4^N \geq 0$.

4.3. Start-ups equations

We use two equations, one for the number of university startup companies and a second for the location of those startups. Since the number of startups is a count variable, we use a negative binomial specification for both equations. The first links the expected number (annual flow) of university start-ups to the flow of licenses executed, incentives, objectives and constraints:

[26] For the sample as a whole, exclusive licenses account for 64.7 percent of all licenses executed, but the ratio differs significantly with the strength of local development objectives. For universities that do not care at all about local development (LOCDEV=Low), the ratio is 68.1 percent (s.e.=0.19). For universities with a moderate local development objective (LOCDEV=Medium), the share is 66.4 (s.e.=0.22), and for those with strong objectives, it is 60.2 (s.e.=0.23).

$$
\begin{aligned}
E(Startups)_{it} \;=\; & \beta_0^S + \beta_1^S \log(Licenses)_{it} + \beta_2^S \log(Inventions)_{it} + \beta_3^S DumMerit_i \\
& + \beta_4^S DumBonus_i + \beta_5^S LOCDEV\_Med_i + \beta_6^S LOCDEV\_High_i \\
& + \beta_7^S NumConst_i + Z_{it}'\phi^S + \tau_t^S + \epsilon_{it}^S \qquad (4.4)
\end{aligned}
$$

Startups are one mode of licensing (the other is to existing firms). There is no reason that high-powered incentives should affect the choice of licensing mode. The same holds for local development objectives, since a local licensing preference can be pursued with either licensing mode. Thus we expect $\beta_3^S = \beta_4^S = \beta_5^S = \beta_6^S = 0$. However, licensing to startups is typically much more risky than licensing to existing firms. Since the survey indicates that restrictions on indemnification and dispute resolution are the most frequently cited as 'important' constraints, we expect that more constrained universities will be less likely to license via startups – $\beta_7^S < 0$.

The second equation links the expected number of university start-ups established in the state where the university is located to the number of total start-ups, incentives, objectives and constraints:

$$
\begin{aligned}
E(LocalStartups)_{it} \;=\; & \beta_0^L + \beta_1^L \log(Inventions)_{it} + \beta_2^L Start\,\mathrm{ps}_{it} + \beta_3^L DumMerit_i \\
& + \beta_4^L DumBonus_i + \beta_5^L LOCDEV\_Med_i + \beta_6^L LOCDEV\_High_i \qquad (4.5) \\
& + \beta_7^L NumConst_i + Z_{it}'\phi^L + \tau_t^L + \epsilon_{it}^L \qquad (4.6)
\end{aligned}
$$

There is no reason to believe that incentives should affect the locational choice of startups, thus we expect $\beta_3^L = \beta_4^L = 0$..However, strong local development objectives should create a preference for local (relative to out-of-state) startups, so $\beta_6^L > \beta_5^L > 0$. Finally, since government (statutory) restrictions do not typically discriminate between in-state and out-of-state licensees, we expect $\beta_7^L = 0$.[27]

Table 4 summarizes the qualitative predictions of the key variables of interest.

[See Table 4]

[27] If there is informal government pressure to license to local rather than out-of-state startups, then $\beta_7^L > 0$.

5. Econometric Results

5.1. License income

Table 5 summarizes the results for the license income equation. In all regressions we control for the stock of active (non-expired) licenses, so the coefficients in this equation essentially refer to the determinants of the income per license – i.e., the 'quality' of licenses. As column 1 shows, private universities generate higher income per license (about 30 percent more) than public universities. In column 2 we add dummy variables for the use of merit pay and bonuses (the baseline category is no incentive pay). The coefficients indicate that incentive pay strongly affects license income and, as expected, the impact increases with the strength of the incentive. While the point estimates of both coefficients are positive, the effect of bonuses is more than twice as large as for merit pay. We show below that the estimated effects of incentives decline, but remain significant, when we control for observed and unobserved heterogeneity across universities. Importantly, the coefficient on the private dummy is no longer significant once we include the incentive pay variables. That is, private ownership affects licensing performance only because it is correlated with the adoption of high-powered incentives.

[See Table 5]

To control for observed heterogeneity across universities, in column 3 we introduce variables to pick up differences both on the supply and demand sides of the licensing activity. First, we use two controls for the technological orientation of research at the university – a dummy variable for whether the university has an affiliated medical school, and the shares of the full-time faculty in each of six technology areas (biomedical, other biological, chemistry, computer science, engineering and physical sciences). Second, to pick up differences in the local demand for licenses we include a measure of the high-tech density of the city in which the university is located – the TechPole index.

Introducing these controls for heterogeneity reduces the coefficients on incentive pay, as one might expect. The use of merit pay no longer has any effect on license income. However, while the coefficient on the high powered incentive – bonuses – is reduced by about half as compared to column 2, the estimated effect is still large and statistically strong. With these additional controls, the use of bonuses is associated with about a 40 percent increase in license income. The controls for technology orientation and demand are also significant. The coefficient on the medical school dummy is very large, reflecting the commercial importance of biomedical research in universities. The estimated coefficient on the TechPole index confirms that local demand is also important. To illustrate the quantitative implications, the point estimate implies that moving a university from Iowa City to Chicago would be associated with a 12.2 percent increase in income per license $[(3.75 - 0.063) \times 0.033]$; moving it to Boston would further increase income per license by 8.4 percent $[(6.31 - 3.75) \times 0.033]$. The fact that local high-tech density matters is interesting because it is suggests that information and/or transaction costs of licensing are related to geography.[28]

Finally, we control for potential correlation between the adoption of incentive pay and unobserved university heterogeneity. As discussed in Section 4.1, we adopt the approach developed by Blundell, Griffith and van Reenen (1999), which involves using the pre-sample mean of license revenue for each university as an additional regressor to control for such heterogeneity. As discussed earlier, because we have a very short pre-sample time series on license revenues (only 1991-94), we primarily use pre-sample information for 1965-90 on patenting by the university (both patent counts and citations). The results are provided in column 4 of Table 5. The coefficient on the pre-sample patents variable is positive and highly significant. Adding the pre-sample control to the regression reduces the estimated effect of bonus pay, from 0.40 to 0.30, indicating that correlated unobserved heterogeneity is in fact present, but the coefficient remains strongly significant. We also try controlling for unobserved heterogeneity by including the average income per invention disclosure over the period 1991-94 (the regression covers the sample period 1995-99). This reduces the available sample from 86 to only 66 universities (column 5), but using this control gives similar results to those obtained using the pre-sample patents. Since ours is the first attempt to estimate the incentive effect of performance-based pay in universities, we cannot make any direct comparisons to previous research. But it is reassuring that our estimated incentive effect of bonus pay is very similar to the productivity impact of introducing piece-work pay (in automobile windshield installation) in the well-known

[28] The differences in licensing performance are not due to differences across universities in the geographic scope of their search for licensees. The survey asks how widely the TLO typically searches – in the local area, state, nation or globally. The vast majority of universities resport that they search either nationally or globally.

study by Lazear (2000b).[29]

We next use the survey evidence on the importance the TLO attaches to local development objectives (LOCDEV) in its licensing activity. The model predicts that such objectives will be associated both with a lower probability of adopting incentive pay and, at the same time lower levels of license income, conditional on whether or not incentive pay is used. Column 5 presents the specification that includes dummy variables for medium and strong local development objectives. As expected, universities that care most strongly about promoting local development generate less licensing income, and the effect is large – on average, they earn nearly 30 percent less income per license. Controlling for local development objectives marginally reduces the effect of using bonus pay (from 0.30 to 0.27), but the decline in the estimated coefficient is not statistically significant.

In column 6 we add the number of government constraints that the TLO reports are either important or very important (maximum of six constraints) – which we will call effective constraints – and the interaction between this variable and a dummy variable for whether the university (administration) frequently intervenes in the decision-making of the TLO. If the interests of the university and the TLO are aligned, as we assumed in the theoretical model, then university intervention should reduce the negative effect of government intervention on licensing performance. Otherwise, university intervention should worsen TLO performance. The results confirm that government constraints strongly affect performance. The effect of adding another effective constraint is to reduce license income by 17 percent. The median number of such constraints in the sample is 1.6, which implies a reduction in license income of 27 percent.[30] However, there is clear evidence that university intervention mitigates the impact of government constraints (perhaps because the university can help circumvent informal government intervention) – as shown by the point estimate of 0.279 on the interaction term. For universities that intervene, the implied marginal effect of government constraints is not significantly different from zero (the point estimate is $-0.171 + 0.279 = 0.108$ with a standard error of 0.029).

In all of these specifications, we have controlled for the number of active licenses. However, if licensing is done from a larger pool of inventions, we would expect a higher average

[29] Using detailed worker-level data, Lazear (2000b) found that moving from hourly to piece-work pay increased average labor productivity by 44 percent, about half of which was due to increased productivity for existing workers and the other half to positive sorting and other factors.

[30] The minimum number of important constraints reported in the sample is zero; the maximum is six.

level of license income to be generated.[31] To allow for this possibility, in column 7 we add the log of the number of faculty inventions (disclosed to the TLO). The estimated coefficient is positive and significant, consistent with the hypothesis that there are diminishing returns to licensing from a given pool of inventions. Adding the number of inventions does not affect the size of the coefficients on the bonus pay or local development variables. The effect of government constraints is reduced and loses statistical significance, however.

5.2. Number of Licenses

Table 6 presents the results for the annual number of licenses executed per year. In all these regressions, we control for the annual number of inventions disclosed, so the other coefficients in the equation essentially refer to the impact on licenses per invention.[32]

[See Table 6]

A number of interesting findings emerge. First, unlike in the regressions for license income, private ownership has no significant effect on the number of licenses generated from a given pool of inventions (column 1). This finding continues to hold when we introduce various controls for observed and unobserved heterogeneity (columns 2-6). Second, incentives do not have a statistically significant effect on the quantity of licenses, once we control for heterogeneity (columns 3-6). This is striking, since we found strong impacts of bonus pay on income per license. This difference is likely due to the fact that it is relatively easy to monitor a TLO worker's performance in 'quantity' terms – how many licenses are generated from a given number of inventions – but very difficult to evaluate performance in terms of license income because the potential value of each invention is not known ex ante by the TLO management.[33]

The third finding is that local development objectives have a *positive* and significant impact on the number of licenses generated, which is the opposite sign from their impact

[31] This argument assumes that the distribution of potential value of inventions is the same. Our controls for technological specialisation of the faculty and the medical school dummy should help capture differences in value distributions. We also tried adding various measures of faculty quality, such as publications and citations per faculty (taken from the National Research Council), but these variables did not have any significant effect on license income in the regressions.

[32] We also included the size of the TLO (full-time professionals), but it was never statistically significant once we control for the number of inventions from the faculty.

[33] In Appendix 1 we find that when non-parametric estimation techniques are used, high-powered incentives (bonus pay) do have a positive and significant effect on the number of licenses. But the quantitative effect is much smaller than for license income, which is again consistent with the monitoring argument made in the text.

on the level of income per license. Universities with medium local development objectives generate, on average, 12 percent more licenses than those with no such objectives; for strong local development focus, the increase in 28 percent. This probably reflects the fact that strong local development focus is associated with more concern for maximizing the number of licenses rather than license income, as evidenced by greater use of non-exclusive licenses by universities with such objectives.

Fourth, as column 6 shows, government constraints do not have a significant impact on the number of licenses generated. This is in sharp contrast to the significant and large negative impact of such constraints on the income generated per license. This indicates that government constraints impinge on the university's ability to find the most suitable licensee match (from their perspective), but not to license *per se*.

Finally, our controls for heterogeneity in university characteristics are important determinants of the number of licenses per invention. First, the research orientation of the university, as measured by faculty shares in different technology areas, significantly affects licensing. Second, the high tech density of the university location (TechPole) confirms that the local demand for licenses affects the ability of the TLO to strike deals. Interestingly, the point estimates of the TechPole coefficients in the licenses executed equation are almost identical to those in the license income equation – i.e., local demand has essentially the same impact on the quantity and quality dimensions of licensing performance. Finally, we find that universities with medical schools generate, on average, about 11 percent *fewer* licenses per invention, whereas we found that they generate about 50-70 percent *more* income per license.

The key findings for the license income and number of licenses equations also hold when we use non-parametric (propensity score matching) estimation techniques. Details are provided in Appendix 1.

5.3. Number and Location of Startups

Table 7 summarises the estimates for the number and location of start-ups. The results are strongly consistent with our predictions. Turning first to the number of startups, we find that incentives and local development objectives have no significant effect on the choice of licensing mode – i.e., on the number of startups, conditional on the number of new licenses executed. Second, universities which are more strongly constrained generate fewer startups, which is consistent with the greater risk of start-ups relative to licensing to existing firms. Third, private universities license less to startups than public institutions, other things equal. It may be that startups are a more visible metric of activity for public universities. On the location of startups, we find that incentives and government constraints do not affect the choice of location (conditional on licensing to a startup), but local development objectives, and public ownership of universities, are strongly associated with the likelihood that an in-state startup will be licensed.

[See Table 7]

5.4. Potential Bias from Mismeasuring Local Development Objectives

Our survey measure of the strength of local development objectives is likely to contain measurement error (call it ε) for two main reasons. First, the measure is subjective and, while using categories rather than a continuous measure of 'importance' may mitigate reporting error, it is unlikely to eliminate it. Second, it may be hard for TLO directors to distinguish between behaviour that reflects their own local development objectives as opposed to government pressure and constraints to license locally. We now examine how such measurement error is likely to affect our empirical findings.[34]

If we make the standard assumption that measurement error is uncorrelated with either observed covariates or unobserved university heterogeneity (commercial orientation, call it η), then attenuation bias implies that we will understate the effect of local development objectives (LOCDEV). In particular, we will underestimate their negative impact on license income and underestimate their positive impact on the number of licenses. Such biases would strengthen, rather than undermine, our conclusions.

However, in our context it may be plausible to assume that measurement error is correlated with unobserved university heterogeneity. The reason is that such mismeasurement may actually reflect real differences across universities in their local licensing preferences which our survey measure does not capture, rather than random reporting error. These unobserved differences in true local development objectives are likely to be negatively correlated with the commercial orientation of the university, $\sigma_{\varepsilon\eta} < 0$.[35] In this case, we get

[34] We focus on the effects of measurement error in our survey variable on local development objectives, but the arguments also apply to our measure of government constraints.

[35] Recall that the obsserved survey measure of LOCDEV is lower for private universities, which we expect to be more commerically oriented than public institutions (see Table 2).

two sources of bias but they reinforce each other – standard attenuation bias and the negative bias induced by the correlation between ε and η. In addition, it is possible that the observed survey measure itself may be correlated (negatively) with the unobserved university heterogeneity. This endogeneity would also cause us to under-estimate the effects of LOCDEV on both license income and number of licenses.[36]

We can test whether unobserved university heterogeneity, η, is negatively correlated with the observed measure of LOCDEV and/or measurement error in this variable, ε. If it is, then when control for η, we should find that the estimated coefficient on LOCDEV in the license income equation should fall (in absolute value), while its coefficient in the number of licenses equation should rise, as compared to the case where we do not control for η . This is exactly what we find. For license income, the estimated coefficient (standard error) on LOCDEV=High is -0.371 (.131) when we do not include the pre-sample patents control for unobserved university heterogeneity, but it is -0.288 (.131) when we include the control (column 5, Table 5). For the number of licenses, the coefficient on LOCDEV=High is 0.195 (.069) without the pre-sample control, compared to 0.288 (.074) with it (column 5, Table 6). These results indicate negative correlation between unobserved university heterogeneity and either the survey measure of LOCDEV or measurement error in it. However, our key empirical findings do not change when we control for such correlation using the pre-sample patents variable.

Another concern is that measurement error in our measure of local development objectives may be correlated with observable covariates, in particular with whether the university is located in a high-tech area. We would expect any such correlation to be negative, since there is less reason to care about local development in developed, high-tech markets. While our survey variable LOCDEV does not vary with our measure of high-tech density, TechPole (see Table 2), this does not rule out correlation with the unobserved component in local development preferences. In there is such negative correlation, we would get an

[36]To summarise these cases, let the true model be $y = \beta x + \eta + u$ where x is the true measure of local development objectives (other covariates are surpressed here for simplicity), the observed measure is $x^o = x + \varepsilon$ and we assume $\sigma_{\varepsilon x} = \sigma_{\varepsilon u} = 0$. The least sqaures estimate of β, say b, yields

$$p\lim(b - \beta) = -\beta \frac{\sigma_\varepsilon^2}{\sigma_{x^o}^2} + \frac{(\sigma_{x\eta} + \sigma_{\varepsilon\eta})}{\sigma_{x^o}^2}.$$

The first term is the standard attenuation bias. The other term captures bias due to correlation between the unobserved university heterogeneity (commercial orientation) and the true value and unobserved component of local development objectives, which are both likely to be negative.

upward bias in the coefficient on TechPole in the license income equation, but a downward bias on that coefficient in the equation for the number of licenses.[37] It is reassuring that the estimated coefficient on TechPole is of very similar magnitude in both equations (and robust across regression specifications), as a comparison of Tables 5 and 6 shows.

In summary, we conclude that our main empirical findings cannot be explained away by 'measurement error' in our survey measure of local development objectives.

5.5. Potential Bias Arising from Mismeasuring the Timing of Adoption of Incentives

The current research design is not ideal for assessing the impact of incentive pay on performance. Ideally, we would like to study how exogenous changes in the adoption of incentive pay affect performance. Because we do not have any information on when universities adopted incentive pay, our identification comes from cross-sectional variation. To account for possible correlation of the adoption decision with unobserved university heterogeneity, we use the pre-sample patenting activity of the university as a control. If we had information on when incentive pay was adopted, we could use this information to look at the impact of adoption on subsequent changes in performance. But this approach would be problematic too, since the adoption decision cannot be treated as an exogenous, quasi-natural experiment (e.g., the adoption decision might be correlated with expected future demand conditions that affect the profitability of using incentive pay). In the end, one needs to model the timing of the decision to adopt incentive pay, and to have suitable identifying variables that are correlated with adoption but uncorrelated with performance. Because of data limitations, we are unable to take that approach in this paper.

However, we can show that the lack of information about the timing of adoption leads us to *underestimate the true effect of incentives*, once we control for unobserved university heterogeneity. The intuition is simple: we estimate the effect of incentives from the difference in the mean licensing performance for universities with incentive pay and those without, controlling for other covariates. If universities which report having incentive pay as of the survey date (2001) actually adopted it sometime after the beginning of our sample period (1995), then we will mistakenly expect them to have had better licensing

[37] The reason is that the coefficient on the observed variable LOCDEV (and thus presumably also the unobserved component associated with it) is negative in the license income equation, but positive in the equation for the number of licenses executed.

performance throughout the sample. Since their pre-adoption performance will be worse on average – reflecting the true absence of incentives – we will understate the true impact of adopting incentives. We present a formal derivation of this conclusion in Appendix 3.

6. Concluding Remarks

This paper investigates the impact of incentives, local development objectives, and government constraints on the effectiveness of university technology licensing activity. The analysis is based on new survey data on technology licensing offices, together with public information on 86 U.S. universities for the period 1995-99. We develop a simple agency model in which the university technology licensing office pursues two objectives – license income and local development (interpreted as a preference for licensing in the local market) – and uses performance-related (merit and bonus) pay to incentivize workers. The model predicts that local development objectives and government constraints make the adoption of incentive pay less likely and reduce the level of income per license, and that universities which adopt incentive pay generate more income per license. The empirical results are generally consistent with the predictions of the model.

The key results are as follows. First, private ownership has a large, positive effect on the adoption of incentive pay, which is robust to controls for observed and unobserved heterogeneity. In sharp contrast, private ownership has no independent effect on licensing performance, once we control for the adoption of incentive pay. Second, universities that use bonus pay generate about 30-40 percent more income per license, controlling for university 77heterogeneity. This finding shows that incentives can be important for improving performance in both private and public institutions. Third, we find that stronger local development objectives and government constraints are 'costly' in terms of the foregone license income. Universities with strong local development objectives generate about 30 percent less income per license, but at the same time, such universities are more likely to license to an in-state (rather than out-of-state) startup company. This evidence on the opportunity cost of local development objectives highlights the importance of comparing the benefits of local licensing preference to alternative policies, such as maximizing income from university inventions and using the additional license income to finance local economic development in other ways.

Appendix 1. Nonparametric Results

We show here that nonparametric estimation methods (the propensity score matching estimator) confirms the key parametric findings in the text. The matching estimator compares the licensing outcome of interest for universities that have introduced the treatment of interest to those that have not.[38] We study the effects of three treatments – adopting incentives, having strong local development objectives, and being subject to strong government constraints. We use two outcome measures – income per license and the number of licenses per invention disclosure.

Let y_i^1 denote the outcome measure of interest for university i when treatment is applied and y_i^0 when it is not, $D_i = 1$ denotes university i getting the treatment, and y_i is the outcome actually observed. We want to estimate the average causal effect of treatment (on the 'treated' universities), $E(y_i^1|D_i = 1) - E(y_i^0|D_i = 1)$, but $E(y_i^0|D_i = 1)$ is not observed since we do not have information on the same university before and after it introduces incentive pay. The matching estimator assumes that the selection of the treated is random, conditional on observed university characteristics, and computes the counterfactual outcome for university i as $\widehat{y_i} = \sum_j \omega_{ij}(p_i, p_j)y_j$ where j indexes the set of universities in the control (untreated) group, p_i and p_j are the predicted probabilities that universities i and j have the treatment based on their observed characteristics, and ω_{ij} is a weighting metric that decreases with the distance between p_i and p_j. We experiment with two different weighting metrics – the nearest neighbor and kernel methods.

License Income

Panel A in Table 8 presents results on the impact of bonus pay (columns 1-4), local development objectives (columns 5-8) and government constraints (columns 9-12) on the mean of log income per active license for each university.[39] Since the treatment must be binary, for government constraints we analyze the difference between universities that report at least three (out a total of six) constraints as being important or very important, and universities that do not. In each panel we use three alternative specifications for the

[38] For an excellent review of the literature on these techniques, see Imbens (2004).

[39] Two points should be noted. First, in this analysis we drop the variable for merit pay (and focus only on bonus pay) because the the parametric results showed that it did not significantly affect outcomes. Second, we also experimented with alternative license outcome measures that relax the assumption of constant returns to scale in the number of licenses – we use log Income/(ActiveLicenses)$^{\alpha}$. Consistent with the parametric estimates of α in Table 4, we use $\alpha = 0.8$ and $\alpha = 1.2$. The results are similar to those reported in Panel A of Table 6.

first stage of the nonparametric estimation – the set of controls is larger as we move to the right in the panel (see table notes for details).

[See Table 8]

The nonparametric estimates of the impact of bonus pay on income per license are in the range of 30 to 40 percent, and statistically significant (bootstrapped standard errors are reported). These estimates are very similar to the parametric estimates reported in Table 5, and they are not sensitive to the controls used in the first stage estimation. We find that strong local development objectives reduce income per license by about 45-55 percent, and the estimates are again highly significant. These nonparametric point estimates are larger than the parametric estimates but they are not statistically different. Finally, universities which are 'constrained' (the treated group) generate about 30 percent less income per license, on average. The estimates are robust to the controls in the first stage estimation, and statistically significant when we use a wider set of controls. In the subset of treated universities, the mean number of important constraints is 3.9; for the untreated, the mean is 0.81. Thus the nonparametric estimate corresponds to the impact of increasing the number of constraints by 3.09. The implied marginal effect of a constraint is $-0.33/3.09 = -0.11$, which is similar to the parametric estimate of -0.17 in Table 5.

Number of Licenses

Panel B summarises results for the mean number of licenses executed per invention disclosed.[40] Bonus pay has a statistically significant, positive impact on the number of licenses per invention, about 13 percent. This differs from the parametric estimation where we found no significant effect of incentives. However, the nonparametric estimates confirm that the effect of incentives on income per license (the 'quality' of licenses) is about three times larger than on the 'quantity' of licenses (compare columns 1-4 in Panels A and B). This is consistent with our argument that monitoring performance on the quality of licenses is harder than on the quantity, and thus incentives are more important and effective for quality outcomes. Next, we find that local development objectives do not have any material impact on the number of licenses per invention. This is different from our findings with parametric estimation, where there was positive and statistically significant effect. Given the sensitivity of the finding to the estimation procedure, we

[40] We also tried an alternative outcome measures that relax the assumption of constant returns to scale in the number of inventions. We use log Number Licenses(InventionsDisclosed)$^{\beta}$, for $\beta = 0.8$ as indicated by the parametric estimates in Table 5. Results are similar to those reported in Panel B of Table 6.

cannot draw any definite conclusion from theses data on how local development objectives affect the number of licenses. Finally, as with parametric estimation, we find no effect of government constraints on the number of licenses.

Appendix 2. Pre-Sample Patent Information and Unobserved Heterogeneity[41]

The model is

$$y_{it} = x_{it}\beta + \eta_i + u_{it}$$

where $i = 1, ..., N$, $t = 1, ..., T$, y is the logarithm of license income, x includes both time varying and invariant regressors (the latter includes the survey measures of the use of incentive pay, local development objectives, and government constraints), and we only assume $E(u_{it}|x_{it}, x_{it-1}, ..., \eta_i) = 0$ for all t. The unobserved heterogeneity η_i may be correlated with incentive pay and other variables. We use the 'pre-sample scaling method' developed by Blundell, Griffith and van Reenen (1999), which amounts to constructing a sufficient statistic for η_i based on pre-sample information on the dependent variable and then directly controlling for it in the regression.[42] They develop the method for a (non-linear) patent count model. Below we sketch how the method works in our context and how we must adapt it for our purposes.

Let J denote the number of pre-sample observations. Then

$$p\lim\left(\frac{1}{J+1}\sum_{t=0}^{-J} y_{it}\right) = p\lim\left(\frac{1}{J+1}\sum_{t=0}^{-J}(x_{it}\beta + \eta_i + u_{it})\right) = \underset{J\to\infty}{p\lim}\left(\frac{1}{J+1}\sum_{t=0}^{-J} x_{it}\beta\right) + \eta_i$$

The left-hand-side of this equation is the limit of the pre-sample mean of license income for university i.

Using a linear projection argument, we can express each of the observable regressors x_j as a linear function of the unobservable η_i and an error c_{ijt} uncorrelated with η_i :

$$x_{ijt} = \alpha_0 + \phi_j\eta_i + c_{ijt}, \qquad j = 1, \ldots, k$$

with $E(c_{ijt}) = 0$ and $E(\eta_i c_{ijt}) = 0$.

Note that if all the $\phi_j's$ are zero then there is no endogeneity problem. Thus, if x_{ijt} is endogenous at least one of the ϕ_j's is non-zero. We assume that the projection parameters

[41] This appendix is taken from Lach and Schankerman (2007). It is included here for completeness and for the convenience of the referee..

[42] They also show that one can use pre-sample information on the regressors, but we do not have such information.

are constant over time.[43] This representation implies

$$\begin{aligned}\frac{1}{J+1}\sum_{t=0}^{-J}x_{it}\beta &= \frac{1}{J+1}\sum_{t=0}^{-J}\sum_{j=1}^{k}x_{ijt}\beta \\ &= \alpha_0\sum_{j=1}^{k}\beta_j+\eta_i\left(\sum_{j=1}^{k}\phi_j\beta_j\right)+\frac{1}{J+1}\sum_{t=0}^{-J}\sum_{j=1}^{k}c_{ijt}\beta_j\end{aligned}$$

Provided a law of large numbers apply to $\frac{1}{J+1}\sum_{t=0}^{-J}c_{ijt}$ so that $\underset{J\to\infty}{p\lim}\frac{1}{J+1}\sum_{t=0}^{-J}c_{ijt}=0$, we get

$$\begin{aligned}\underset{J\to\infty}{p\lim}\frac{1}{J+1}\sum_{t=0}^{-J}x_{it}\beta &= \alpha_0\sum_{j=1}^{k}\beta_j+\alpha_1\eta_i+\underset{J\to\infty}{p\lim}\frac{1}{J+1}\sum_{t=0}^{-J}c_{ijt}\beta_j \\ &= \alpha_0\sum_{j=1}^{k}\beta_j+\alpha_1\eta_i\end{aligned}$$

where $\alpha_1=\sum_{j=1}^{k}\phi_j\beta_j$.[44]

We can then write

$$m_{yi}\equiv\underset{J\to\infty}{p\lim}\left(\frac{1}{J+1}\sum_{t=0}^{-J}y_{it}\right)=\alpha_0\sum_{j=1}^{k}\beta_j+(1+\alpha_1)\,\eta_i$$

and solving for η_i,

$$\eta_i=-\frac{\alpha_0\sum_{j=1}^{k}\beta_j}{1+\alpha_1}+\frac{1}{1+\alpha_1}m_{yi}$$

This equation says that the pre-sample mean of log license income is a sufficient statistic for η_i. Substituting into the original model we get the estimating equation

$$y_{it}=x_{it}\beta+\frac{1}{1+\alpha_1}m_{yi}+u_{it}$$

where the constant term $-\frac{\alpha_0\sum_{j=1}^{k}\beta_j}{1+\alpha_1}$ is absorbed into the constant term of the original model. In the actual estimation the pre-sample mean of y is used instead of its probability limit m_{yi}.

The problem in our context is that we do not have pre-sample information on license income. However, we do have pre-sample information on the patenting activity for each

[43]This assumption is made to simplify the exposition and it will hold if the $x's$ are drawn from the same distribution at every t. The method can be extended to time-varying coefficients under an additional convergence assumption.

[44]Note that there are no time-invariant components in c_{ijt} – they are captured by η_i – and that some weak serial dependency is possible as long as a law of large numbers can be applied.

university. In order to use pre-sample patents instead of pre-sample license income we make the additional assumption that patenting is also a linear function of the unobserved heterogeneity, η. That is, we assume

$$p_{it} = z_{it}\lambda + \sigma\eta_i + v_{it}$$

where p is the log of patents (or patent citations) and the regressors z may have common components with x. Since the decision by the TLO to patent an invention is based on expected returns from commercialising the invention, this assumption that patenting depends on η seems very reasonable.

Retracing the previous steps but using p instead of y, using tildes to denote coefficients in this derivation for patents, and letting $m_{p_i} = p\lim_{J\to\infty} \frac{1}{J+1}\sum_{t=0}^{-J} p_{it}$, we have

$$\eta_i = -\frac{\widetilde{\alpha}_0 \sum_{j=1}^{k} \lambda_j}{\sigma + \widetilde{\alpha}_1} + \frac{1}{\sigma + \widetilde{\alpha}_1} m_{pi}$$

and substituting into the original model, we get the estimable equation

$$y_{it} = x_{it}\beta + \frac{1}{\sigma + \widetilde{\alpha}_1} m_{pi} + u_{it}$$

where the constant term $-\frac{\widetilde{\alpha}_0 \sum_{j=1}^{k} \lambda_j}{\sigma + \widetilde{\alpha}_1}$ is absorbed into the constant term of the original model.

This is the equation we estimate in the paper, using the pre-sample mean of patents (or patent citations) instead of its probability limit m_{pi} to control for the correlation with unobserved heterogeneity.

Appendix 3. Bias from Mismeasuring the Timing of Adoption of Incentives

In this appendix we show that any mismeasurement in the timing of adoption of incentives leads us to underestimate the true effect of incentives on performance. For simplicity, and to highlight the intuition, we focus on the incentives variable and ignore other observable covariates. We can introduce them, but at the cost of considerable complexity.

We write the true model as

$$y_{it} = \alpha + \beta D_i + \eta_i + u_{it}$$

where $D_i = 1$ if university i has adopted incentive pay, η_i denotes unobserved university heterogeneity, $E(u_{it} \mid D_i) = 0$ and $E(\eta_i \mid D_i) \neq 0$. The latter covariance introduces endogeneity bias, discussed in Appendix 2. We include it here for completeness.

We know whether the university adopted incentive pay as of the date of the survey, 2001, but not the date of adoption. We assume that universities do not revert (during the sample period) once they have adopted incentive pay. Let G_0 denote the set of N_0 universities for which $D_i = 0$, and G_1 denote the set of N_1 universities for which $D_i = 1$ (we denote $N = N_0 + N_1$). Let G_{11} denote the subset of N_{11} universities in G_1 that adopted incentive pay prior to the sample period, and G_{10} denote the subset of N_{10} universities in G_1 that adopted incentive pay at some point during the sample period (1995-1999). We do not know which universities fall into the subsets G_{10} and G_{11} – i.e. we do not observe when universities adopted incentive pay. To begin, we assume that these N_{10} universities had the same incentive pay they reported in 2001 for the whole sample period, 1995-99, but later will show what happens if we relax this assumption.

The estimated coefficient on the dummy variable D can be written as the difference between the mean of the dependent variable (over i and t) for universities with $D = 1$ and those with $D = 0$, say $y_{1.}$and $y_{0.}$., respectively. Writing these out,

$$y_{0.} = \frac{1}{TN_0} \sum_{t=1}^{T} \sum_{i \in G_0} (\alpha + \eta_i + u_{it}) = \alpha + \eta_{0.} + u_{0.}$$

where $\eta_{0.}$ and $u_{0.}$ denote the means of unobserved heterogeneity and the disturbance for all universities in G_0. Similarly,

$$\begin{aligned}
y_{1.} &= \frac{1}{TN_1}\sum_{t=1}^{T}\{\sum_{i\in G_{10}}(\alpha+\eta_i+u_{it})+\sum_{i\in G_{11}}(\alpha+\beta+\eta_i+u_{it})\} \\
&= \alpha+\frac{N_{11}}{N_1}\beta+\frac{N_{10}}{N_1}\eta_{10.}+\frac{N_{11}}{N_1}\eta_{11.}+\frac{N_{10}}{N_1}u_{10.}+\frac{N_{11}}{N_1}u_{11.}
\end{aligned}$$

where $\eta_{10.}$ (respectively, $\eta_{11.}$) is the mean value of η for universities that adopted incentive pay during the sample period (respectively, before the sample period), and similarly for $u_{10.}$ and $u_{11.}$ The term involving β represents the fact that universities adopting incentives before the sample should have a higher value of y than universities adopting at the end of the sample. The estimated effect of incentive pay is $b = \Delta y = y_{1.} - y_{0.}$. Thus

$$p\lim_{N}\ (b-\beta)=\frac{-N_{10}}{N_1}\beta+\left\{\frac{N_{10}}{N_1}\eta_{10.}+\frac{N_{11}}{N_1}\eta_{11.}-\eta_{0.}\right\}$$

The first term in this equation is the bias due to mismeasuring when universities adopt incentive pay. The important conclusion is that we underestimate β, and the bias depends on the fraction of universities with $D = 1$ that adopted incentive pay during the sample period rather than at the end as we assume. In addition, there is a second bias due to correlation between the adoption decision and η. This is the endogeniety bias we discussed at length in the text. It captures the difference between the mean fixed-effect of adopters and non-adopters, which we assume to be positive (i.e., $\eta_{11} > \eta_{10} > \eta_0$ as more commercially oriented universities adopt earlier). Once we control for unobserved heterogeneity, this endogeneity bias should disappear.

Finally, we can show that the bias due to mismeasurment of adoption timing is smaller (but still negative) when we relax the assumption that in-sample adoption is made at the end of the sample by all N_{10} universities. Letting $t_i^* \leq T$ denote the adoption date for university i, the equation for $y_{1.}$ becomes

$$\begin{aligned}
y_{1.} &= \frac{1}{\sum_{i\in G_{10}}(T-t_i^*)+TN_{11}}\left\{\sum_{i\in G_{10}}\sum_{t=t_i^*}^{T}(\alpha+\eta_i+u_{it})+\sum_{i\in G_{11}}\sum_{t=1}^{T}(\alpha+\beta+\eta_i+u_{it})\right\} \\
&= \alpha+\frac{TN_{11}}{\sum_{i\in G_{10}}(T-t_i^*)+TN_{11}}\beta \\
&\quad +\frac{1}{\sum_{i\in G_{10}}(T-t_i^*)+TN_{11}}\left\{\sum_{i\in G_{10}}(T-t_i^*)\,\eta_{10.}+TN_{11}\eta_{11.}+\sum_{i\in G_{10}}(T-t_i^*)\,u_{10.}+TN_{11}u_{11.}\right\}
\end{aligned}$$

Using this equation, the expression for the bias is

$$\begin{aligned} p\lim_{N}\ (b-\beta) &= \frac{-\sum_{i\in G_{10}}(T-t_i^*)}{\sum_{i\in G_{10}}(T-t_i^*)+TN_{11}}\beta \\ &+\left\{\frac{\sum_{i\in G_{10}}(T-t_i^*)}{\sum_{i\in G_{10}}(T-t_i^*)+TN_{11}}\eta_{10.}+\frac{TN_{11}}{\sum_{i\in G_{10}}(T-t_i^*)+TN_{11}}\eta_{11.}-\eta_{0.}\right\} \end{aligned}$$

This bias reduces to the earlier case we analysed when $t_i^*=0$ for all i. It is easy to see that the negative bias from the mismeasurement of the timing of adoption is smaller (in absolute value) when $t_i^*>0$ for some i. Also note that the positive, endogeneity bias is also smaller than the previous case because $\eta_{10.}<\eta_{11.}$ and $\frac{N_{11}}{N_1}<\frac{TN_{11}}{\sum_{i\in G_{10}}(T-t_i^*)+TN_{11}}$.

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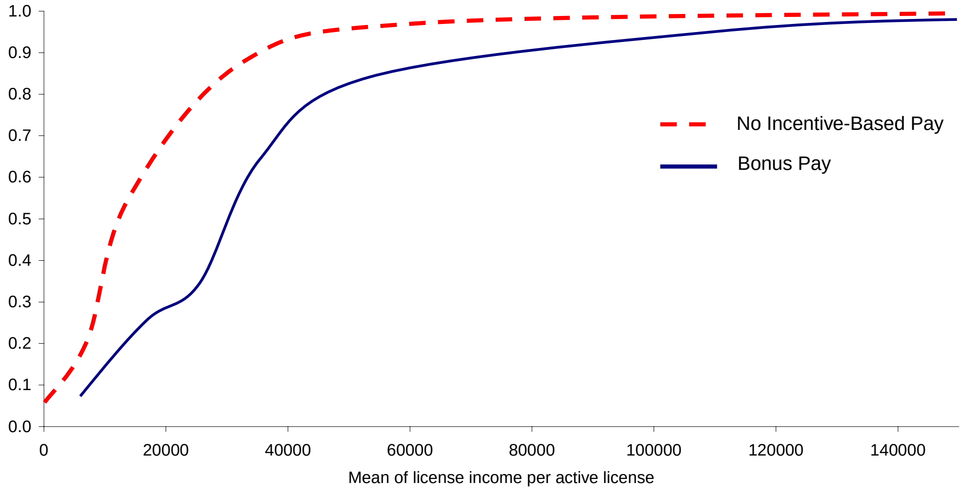
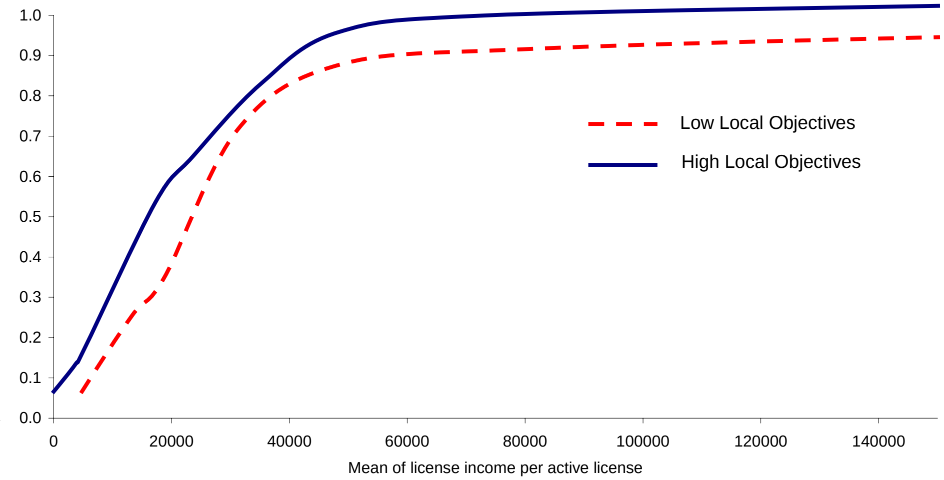
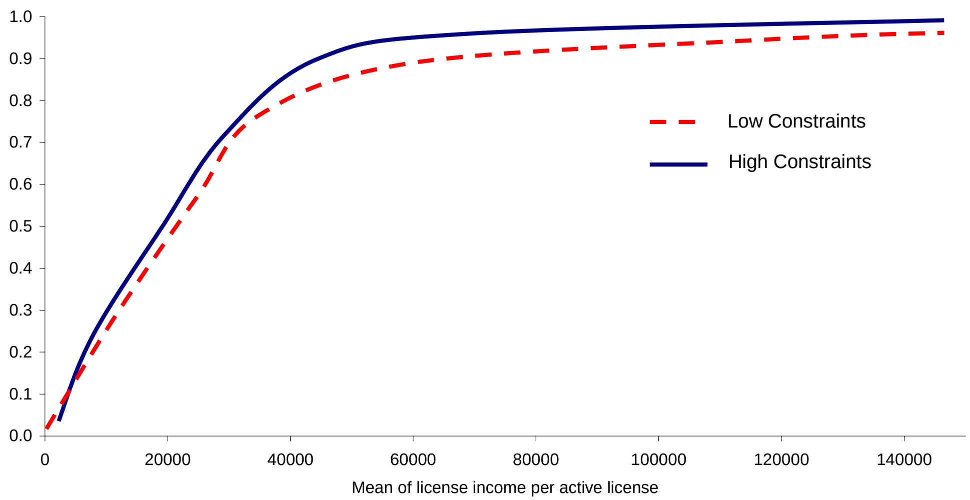
Cumulative distribution for mean of license income per active license: the effect of Performance-Based Pay



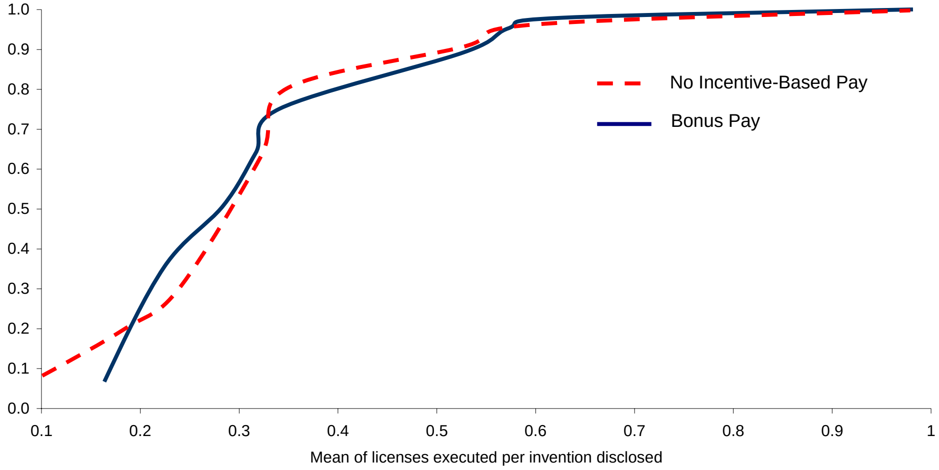
Cumulative distribution for mean of license income per active license: the effect of Local Objectives



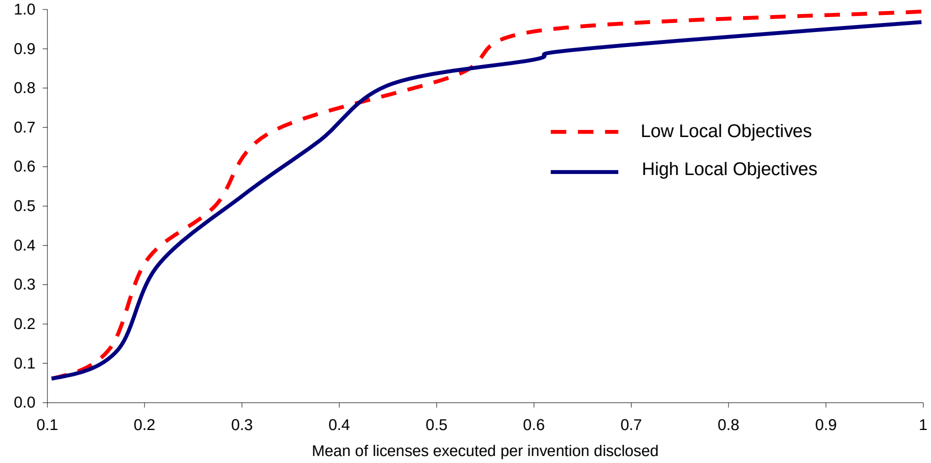
Cumulative distribution for mean of license income per active license: the effect of Constraints



Cumulative distribution for mean of licenses executed per invention disclosed: the effect of Performance-Based Pay



Cumulative distribution for mean of licenses executed per invention disclosed: the effect of Local Objectives



Cumulative distribution for mean of licenses executed per invention disclosed: the effect of Constraints

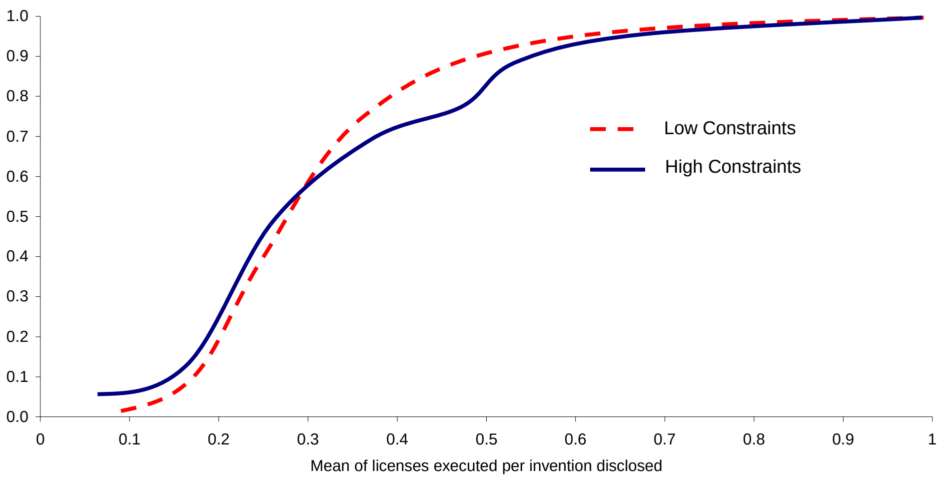


Table 1

Descriptive statistics for main variables

Variable	Mean	Median	Standard deviation	Min	Max
Licensing income, '000	5686	1289	14362	0	148938
Licenses executed	29.1	16	33.9	0	218
Inventions disclosed	87.7	66	78.4	0	476
Licensing income per active license	38.9	15.6	143.2	2.9	1327
Licenses executed per invention disclosed	5.2	3.5	5.5	0.31	27.6
Full-time TLO employees	6.8	4.8	5.9	0.5	27.7
TLO age	12	9	13.3	1	71
TechPole	1.7	0.38	3.19	0.001	23.7
Total Startups	2.8	2	3.74	0	31
University Startups	2.5	1	3.47	0	25
Pre-sample patents stock	169.1	65	326.8	0	2492
Dummy for Private	0.28	0	0.45	0	1
Dummy for Merit Pay	0.41	0	0.49	0	1
Dummy for Bonus Pay	0.17	0	0.38	0	1
Dummy for LOCDEV=Medium	0.43	0	0.49	0	1
Dummy for LOCDEV=High	0.34	0	0.48	0	1
NumConst	1.5	1	1.6	0	6
Dummy for MedSchool	0.66	1	0.48	0	1

Note: monetary values are in thousands of 1996 US dollars.

LOCDEV measures the weight the university attaches to local/regional development objectives in its licensing activity. NumConst is the number of state government constraints that the university reports as being moderately or very important (based on six different constraints listed in the survey).

Table 2

Incentives, Local Development Objectives and Government Constraints

Variable	Number of universities	Dummy for Private	Full-time TLO employees	TechPole
Incentives				
No incentives	36	0.14	4.70	1.23
Merit pay	35	0.37	6.90	1.14
Bonus pay	15	0.40	9.60	3.53
Local objectives				
LOCDEV=Low	20	0.45	5.82	1.62
LOCDEV=Medium	37	0.30	7.19	1.64
LOCDEV=High	29	0.14	6.06	1.52
Gov't constraints				
NumConst<3	66	0.36	7.40	1.64
NumConst≥3	20	0.00	3.60	1.44

LOCDEV measures the weight the university attaches to local/regional development objectives in its licensing activity. NumConst is the number of state government constraints that the university reports as being moderately or very important (based on six different constraints listed in the survey).

Table 3

The determinants of adoption of high-powered incentives

Dependent variable: Dummy for Performance-Based Pay, Probit estimation (86 universities)

	(1)	(2)	(3)	(4)	(5)
Dummy for Private	0.812***	0.935***	0.851**	0.641	
	(0.0331)	(0.373)	(0.404)	(0.437)	
Dummy for LOCDEV=Medium				-0.285	-0.360
				(0.393)	(0.392)
Dummy for LOCDEV=High				0.148	0.043
				(0.399)	(0.408)
NumConst				-0.141	-0.215**
				(0.113)	(0.102)
TechPole		0.003	-0.035	-0.022	0.014
		(0.055)	(0.053)	(0.061)	(0.065)
Dummy for MedSchool		0.381	0.132	0.077	0.029
		(0.371)	(0.400)	(0.415)	(0.412)
Technology area faculty shares		Yes***	Yes**	Yes*	Yes*
		(F=15.78)	(F=11.22)	(F=10.58)	(F=10.06)
Pre-sample patents stock			0.249**	0.254**	0.252**
			(0.109)	(0.110)	(0.108)
Dummy for Canada		-0.305	0.005	0.056	-0.027
		(0.555)	(0.597)	(0.564)	(0.525)
Pseudo R^2	0.055	0.182	0.231	0.253	0.237

Standard errors (in brackets) are robust to arbitrary heteroskedacity and serial correlation. *, **, *** denote statistical significance at the 1, 5 and 10 percent levels, respectively.

LOCDEV measures the weight the university attaches to local/regional development objectives in its licensing activity. NumConst is the number of state government constraints that the university reports as being moderately or very important (based on six different constraints listed in the survey).

Table 4

Econometric predictions

	License income	Number of licenses	Total startups	Local startups
Performance-Based Pay	Positive	Positive	Zero	Zero
Local Objectives	Negative	Positive	Zero	Positive
Constraints	Negative	Zero	Negative	Zero

Table 5

The effect of incentives, objectives and constraints on licensing income

Dependent variable: log(licensing income), GLS estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(active licenses)	1.256***	1.184***	1.028***	0.917***	0.959***	1.028***	1.012***	0.760***	0.725***
	(0.038)	(0.042)	(0.052)	(0.057)	(0.058)	(0.054)	(0.058)	(0.064)	(0.065)
Dummy for Private	0.315***	0.161	0.094	0.156	0.077	0.015	0.212	0.117	0.299*
	(0.103)	(0.108)	(0.146)	(0.144)	(0.142)	(0.145)	(0.157)	(0.142)	(0.154)
Dummy for Merit Pay		0.324***	-0.022	-0.111	-0.079	0.069	-0.011	0.037	-0.016
		(0.089)	(0.109)	(0.118)	(0.117)	(0.109)	(0.123)	(0.118)	(0.166)
Dummy for Bonus Pay		0.778***	0.401***	0.304**	0.274**	0.380***	0.468***	0.493***	0.495***
		(0.126)	(0.128)	(0.139)	(0.139)	(0.132)	(0.155)	(0.131)	(0.161)
Dummy for LOCDEV=Medium					0.005	-0.004	-0.145	-0.170	0.073
					(0.117)	(0.122)	(0.131)	(0.117)	(0.137)
Dummy for LOCDEV=High					-0.288**	-0.371***	-0.317***	-0.261**	0.015
					(0.131)	(0.131)	(0.133)	(0.119)	(0.159)
NumConst							-0.171***	-0.061	-0.231***
							(0.058)	(0.051)	(0.082)
NumConst x Univ Intervene							0.279***	0.195***	0.317***
							(0.046)	(0.042)	(0.078)
Pre-sample patents stock				0.159***	0.120***		0.088**	0.049	-0.034
				(0.038)	(0.036)		(0.038)	(0.036)	(0.044)
Dummy for MedSchool			0.803***	0.645***	0.587***	0.717***	0.712***	0.481***	0.771***
			(0.109)	(0.115)	(0.112)	(0.110)	(0.116)	(0.105)	(0.143)
TechPole			0.049***	0.037**	0.041***	0.053***	0.026	0.033***	0.044***
			(0.019)	(0.019)	(0.017)	(0.017)	(0.017)	(0.013)	(0.017)
Technology area faculty shares			Yes***	Yes***	Yes***	Yes***	Yes***	Yes***	Yes***
			(F=21.64)	(F=19.69)	(F=21.79)	(F=21.09)	(F=23.05)	(F=22.71)	(F=27.16)
log(inventions disclosed)								0.549***	
								(0.073)	
Pre log(licensing income)									0.352***
									(0.067)
Dummy for Canada	-0.355	-0.288	-0.609**	-0.463	-0.463	-0.561*	-0.523*	-0.297	0.099
	(0.248)	(0.256)	(0.299)	(0.308)	(0.317)	(0.315)	(0.305)	(0.291)	(0.211)
Number of universities	86	86	86	86	86	86	86	86	66
Number of observations	518	518	518	518	518	518	518	518	422

Standard errors (in brackets) are robust to arbitrary heteroskedacity and serial correlation (GLS estimation with heteroskedasticity between panels and AR(1) serial correlation within panels). *, **, *** denote statistical significance at the 1, 5 and 10 percent levels, respectively. All regressions include a complete set of year dummies.

LOCDEV measures the weight the university attaches to local/regional development objectives in its licensing activity. NumConst is the number of state government constraints that the university reports as being moderately or very important (based on six different constraints listed in the survey). 'Univ Intervene' is a dummy that receives the value of 1 if the TLO says that the university 'usually' or 'always' intervenes in the decision-making of the TLO. Pre log(licensing income) is computed over the period 1991-1995 for 66 universities for which such information exists.

Table 6

The effect of incentives, objectives and constraints on number of licenses executed

Dependent variable: log(licenses executed), GLS estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(inventions disclosed)	0.855***	0.849***	0.838***	0.754***	0.744***	0.800***	0.756***	0.583***
	(0.026)	(0.028)	(0.031)	(0.039)	(0.039)	(0.030)	(0.039)	(0.054)
Dummy for Private	0.089	0.072	-0.039	-0.101	-0.042	0.072	0.017	0.027
	(0.059)	(0.065)	(0.068)	(0.069)	(0.071)	(0.068)	(0.075)	(0.070)
Dummy for Merit Pay		0.023	0.058	0.039	0.023	0.044	0.055	0.113
		(0.069)	(0.075)	(0.073)	(0.073)	(0.070)	(0.075)	(0.080)
Dummy for Bonus Pay		0.136*	0.123	0.069	0.068	0.098	0.113	0.235***
		(0.078)	(0.079)	(0.079)	(0.078)	(0.075)	(0.081)	(0.081)
Dummy for LOCDEV=Medium					0.127*	0.025	0.117*	0.110*
					(0.068)	(0.065)	(0.068)	(0.069)
Dummy for LOCDEV=High					0.288***	0.195***	0.282***	0.233***
					(0.074)	(0.069)	(0.073)	(0.078)
NumConst							0.038	-0.018
							(0.033)	(0.039)
NumConst x Univ Intervene							0.007	0.059
							(0.031)	(0.038)
Pre-sample patents stock				0.088***	0.098***		0.096***	-0.029
				(0.024)	(0.024)		(0.024)	(0.029)
Dummy for MedSchool			-0.091	-0.120*	-0.129**	-0.096	-0.116*	-0.071*
			(0.067)	(0.069)	(0.067)	(0.065)	(0.068)	(0.078)
TechPole			0.037***	0.037***	0.034***	0.036***	0.032***	0.014***
			(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Technology area faculty shares			Yes***	Yes***	Yes***	Yes***	Yes***	Yes***
			(F=41.95)	(F=38.56)	(F=40.75)	(F=50.51)	(F=43.53)	(F=22.11)
Pre log(licenses executed)								1.039***
								(0.146)
Dummy for Canada	-0.089	-0.100	-0.443***	-0.239	-0.324*	-0.501***	-0.163	0.121
	(0.119)	(0.118)	(0.175)	(0.176)	(0.180)	(0.185)	(0.193)	(0.146)
Number of universities	86	86	86	86	86	86	86	66
Number of observations	518	518	518	518	518	518	518	422

Standard errors (in brackets) are robust to arbitrary heteroskedacity and serial correlation (GLS estimation with heteroskedasticity between panels and AR(1) serial correlation within panels). *, **, *** denote statistical significance at the 1, 5 and 10 percent levels, respectively. All regressions include a complete set of year dummies.

LOCDEV measures the weight the university attaches to local/regional development objectives in its licensing activity. NumConst is the number of state government constraints that the university reports as being moderately or very important (based on six different constraints listed in the survey). 'Univ Intervene' is a dummy that receives the value of 1 if the TLO says that the university 'usually' or 'always' intervenes in the decision-making of the TLO. Pre log(licenses executed) is computed over the period 1991-1995 for 66 universities for which such information exists.

Table 7

The effect of incentives, objectives and constraints on number of licenses executed

Dependent variable: Total Startups and Local Startups, Negative Binomial estimation

	Total Startups			Local Startups		
	(1)	(2)	(3)	(4)	(5)	(6)
log(inventions disclosed)	0.667***	0.655***	0.649***	0.512***	0.534***	0.571***
	(0.103)	(0.102)	(0.092)	(0.071)	(0.074)	(0.083)
log(licenses executed)	0.249***	0.247***	0.238***			
	(0.078)	(0.079)	(0.073)			
Total Startups				0.111***	0.112***	0.105***
				(0.020)	(0.021)	(0.022)
Dummy for Private	-0.105	-0.107	-0.210**	-0.326***	-0.322***	-0.378***
	(0.120)	(0.118)	(0.104)	(0.081)	(0.080)	(0.098)
Dummy for Merit Pay	-0.034	-0.039	0.068	0.035	0.045	0.043
	(0.127)	(0.129)	(0.119)	(0.092)	(0.092)	(0.096)
Dummy for Bonus Pay	-0.186	-0.192	-0.154	0.012	0.024	-0.093
	(0.155)	(0.159)	(0.138)	(0.090)	(0.091)	(0.110)
Dummy for LOCDEV=Medium	-0.150	-0.147	-0.166	0.177	0.176*	0.173*
	(0.169)	(0.165)	(0.125)	(0.106)	(0.105)	(0.104)
Dummy for LOCDEV=High	-0.007	-0.003	-0.096	0.233**	0.232**	0.200**
	(0.176)	(0.172)	(0.126)	(0.122)	(0.123)	(0.110)
NumConst	-0.132***	-0.128**	-0.149***	-0.044	-0.049	-0.042
	(0.054)	(0.057)	(0.054)	(0.049)	(0.049)	(0.053)
NumConst x Univ Intervene	0.067	0.065	0.073	0.006	0.009	0.003
	(0.052)	(0.053)	(0.054)	(0.047)	(0.047)	(0.049)
Pre-sample patents stock		0.128	-0.011		-0.023	-0.033
		(0.041)	(0.036)		(0.026)	(0.027)
Dummy for MedSchool			-0.148			0.033
			(0.103)			(0.091)
TechPole			0.031***			0.016
			(0.010)			(0.010)
Technology area faculty shares			Yes*			Yes
			(F=9.62)			(F=5.47)
Number of universities	86	86	86	86	86	86
Number of observations	518	518	518	518	518	518

Standard errors (in brackets) are robust to arbitrary heteroskedacity and serial correlation (GLS estimation with heteroskedasticity between panels and AR(1) serial correlation within panels). *, **, *** denote statistical significance at the 1, 5 and 10.

LOCDEV measures the weight the university attaches to local/regional development objectives in its licensing activity. NumConst is the number of state government constraints that the university reports as being moderately or very important (based on six d

Table 8

Non-parametric propensity-score estimation: 86 Universities												
	Panel A						Panel B					
	Mean of log(licensing income per invention disclosed)						Mean of log(licenses executed per invention disclosed)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dummy for Bonus Pay	0.432**	0.386**					0.138*	0.118*				
	(0.159)	(0.099)					(0.058)	(0.059)				
Obs=0	71	71					71	71				
Obs=1	15	15					15	15				
Dummy for LOCDEV=High			-0.548**	-0.421**					0.065	0.038		
			(0.275)	(0.256)					(0.055)	(0.060)		
Obs=0			57	57					57	57		
Obs=1			29	29					29	29		
Dummy for NumConst≥3					-0.335	-0.341*					-0.045	-0.038
					(0.195)	(0.161)					(0.059)	(0.046)
Obs=0					20	20					20	20
Obs=1					66	66					66	66
Weighting method	Kernel	Nearest-neighbour	Kernel	Nearest-neighbour	Kernel	Nearest-neighbour	Kernel	Nearest-neighbour	Kernel	Nearest-neighbour	Kernel	Nearest-neighbour

Bootstrapped standard errors are in brackets. *, **, *** denote statistical significance at the 1, 5 and 10 percent levels, respectively.

Obs=1 is the number of observations for which the "treatment" applies (e.g., the universities that have bonus pay). Obs=0 is the number of observations for the "untreated" universities. In the second stage, observations are weighed using the kernel method.

The first stage regression for the Dummy for Bonus Pay is as reported in column 2 of Table 2. Analogous specifications are used for Dummy for LOCDEV=High and Dummy for NumConst≥3. That is, for LOCDEV=High, we include the bonus pay dummy and delete the LOCDEV dummies; for NumConst≥3, we include the bonus pay dummy and delete the NumConst variable.

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