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Heuristic Rules in the Field:

Evidence from Royalty Shares in Scientific Teams

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Abstract

Using field data from a large U.S. technology transfer organization with over $50 million in annual revenue, we investigate four related issues regarding the sharing of licensing revenues by academic teams. First, we find that the main empirical regularity is a heuristic-based allocation of shares 1/n, equal shares to all unique inventors in a single invention team, and the use of the partition dependence (PD) rule, whereby inventors receive equal share within an invention and shares across inventions included in the same contract are equal. Second, when we examine the performance consequences of such equal sharing, we find it is negatively related to performance. Third, using both matched sample estimations and examining strategic switchers, i.e., the case of inventors who switch between equal and unequal sharing, we find that self-selection rather than shirking explains the negative performance. Finally, the pattern of their switching is random in time—i.e., there is no movement toward unequal rules over time so inventors are not learning to use unequal rules.

Most inventions, especially the most valuable ones, are now created by teams of academic scientists (Henderson, Jaffe, & Trajtenberg, 1998; Singh & Fleming, 2010; Wuchty, Jones, & Uzzi, 2007). How academic inventing teams share potential royalty income from a license is an important question. Most licensed academic inventions are at embryonic stage and require substantial effort from inventors subsequent to licensing (Jensen and Thursby, 2001), and the inventors have competing demands on their time, including teaching and other research projects.

Alchian and Demsetz (1972) hypothesize that groups distribute incentives to inspire optimal contributions by their members. Another view, in the judgment and decision-making literature, is that individuals and groups seek to conserve cognitive energy and adopt simple distribution rules, such as allocating equal shares to all inventors.[1] It remains uncertain whether such simple rules are effective motivators or impose a cost by reducing motivation. In a field study, we gathered data on how academic inventor teams at a large U.S. technology-transfer organization with over $50 million per year in revenue share licensing revenues. We ask a set of five related questions: (1) Do teams containing members with heterogeneous experience and talent split potential proceeds from their efforts using heuristic rules? (2) When are teams less likely to rely on heuristic rules? (3) What are the performance consequences of using heuristic rules, if any? (4) Is differential performance between heuristic royalty regimes and non-heuristic or unequal royalty regimes driven by self-selection, by shirking, or both? and (5) Do strategic switchers, i.e., inventors who switch between heuristic and non-heuristic regimes, learn to discard heuristic rules over time?

A long tradition primarily of laboratory studies in the judgment and decision-making literature shows that decision makers sometimes rely on simple rules of thumb, or heuristics, and ignore relevant information. But more recently, scholars in this stream of literature have been taking insights from the laboratory to study field data. A few papers that have combined experimental and field studies have shown that people use heuristics to decide how many hours they want to work (Camerer, et al.,1997), betting on winning or losing streaks of basketball teams (Camerer and Weber, 1999), allocate funds between risky gambles (Fox and Clemen, 2005; Fox and Rottenstreich, 2003; Langer and Fox, 2003), retirement accounts (Benartzi and Thaler, 2001), and businesses within companies (Bardolet, Fox, and Lovallo, 2011). For example, using both experimental and field evidence, Benartzi and Thaler (2001) found naïve diversification in defined contribution savings

[1] In this paper we take a narrow definition of heuristics. We treat the 1/n rule and partition dependence rule as heuristics. There could be other rules, for instance, the lead inventor gets a higher share. We treat only the rules that appear to ignore heterogeneous abilities of inventors, for instance in our setting 1/n rule which is equal allocation to each inventor, as a heuristic rule. We treat any other rules that may have been based on ability of the inventors as not a heuristic. It is possible that some teams are perfectly homogeneous and a case could be made for such teams that the 1/n rule may be optimal.

plans, such that investors followed a "1/n strategy," dividing their contributions equally across their plan's funds. Depending on the variety of assets in a mutual fund plan—for instance, either two equity and one bond option or one equity and two bond options—this simple strategy leads to very different allocations for similar people. A more thorough review of this literature is available in Kahneman (2011), Kahneman and Fredrick (2005), and Pruitt (1981).

A more complex rule than the 1/n rule is the partition dependence (PD) rule, which implies that allocations are made hierarchically based on the order they are observed by decision makers (Fox and Rottenstreich, 2003). For example, in experimental settings using experienced executives as subjects, Bardolet, Lovallo, and Fox (2011) found participants allocated capital to divisions of a hypothetical firm in radically different proportions based on the order that the same objective information was presented. When executives were provided with information grouped by three geographic divisions and then by one to three product subdivisions in each of the geographic divisions, they first allocated equally to each geographic division and then divided each share by the number of product subdivisions within the geographic area. When executives were provided with information in the opposite order, by product divisions and then by geographic subdivisions, they allocated equally to each product division and then equally to each geographic subdivision. Thus, for the same hypothetical company with the same information, different division groupings resulted in widely different allocations. As such, the effects of an observed pattern on allocation varied not because of rational differences in the worthiness of projects but because of where managers' attention was first focused. Due to the coarseness of the data, Bardolet et al. (2011) were not able to test the partition dependence hypotheses on field or archival data. In this study, we test partition dependence with field data.

In this paper we extend the examination of the 1/n and PD rules, hereafter "N or PD." Prior N or PD work has focused on individual decision makers. More specifically, most prior evidence for PD has come primarily from laboratory studies wherein a single individual estimates probabilities or allocates funds to projects. Recent work on PD has extended this to study field experiments using sports events spanning several weeks and horse race predictions by individual decision makers (Sonnemann, Camerer, Fox, and Langer, 2013). In this paper, we suggest that groups also use N or PD rules to divide the returns from their joint effort. In our context, groups divide royalty shares, which are both rewards for previous work *and* incentives for future work.

This paper makes three contributions to extant literatures. First, whereas the prevalence of the 1/n rule has been found in groups, this paper offers the first field evidence of the prevalence of the PD rule among teams distributing rewards and incentives.[2] We suggest that when multiple inventions are

[2] Royalties are a combination of rewards for past input and incentives for future effort.

bundled and licensed, inventions rather than the inventors are the first naturally occurring partitions that come to mind. Hence, if teams strictly use PD heuristic rule, allocations to inventions should be equal regardless of the quality of the inventions and also equally to inventors in each of those inventions. Our results support this prediction.

Second, we use a bargaining model suggested by Hellman and Wasserman (2011) to predict when teams deviate from N or PD to share royalty income. As predicted by the model, we find that larger teams and teams consisting of individuals with successful experience are less likely to engage in equal splitting of royalty income than other teams. Inventions that earn high royalty income after licensing are less likely to be licensed using N or PD rules. Thus, we find evidence both for the use of simple rules to share royalty income *and* for the rational account provided by the bargaining model.

To investigate whether the underperformance of inventions in heuristic regimes is driven by self-selection or shirking, we follow a stringent matching method, "coarsened exact matching" (CEM), developed by Iacus et al (2009), to match licenses with and without N or PD royalty sharing regimes. Using a matching theory prevalent in innovation studies (Azoulay et al, 2009; Singh and Agarwal, 2011), we match licenses that have an equal sharing rule with other licenses with similar quality of inventors and invention but do not use a heuristic sharing rule.[3] We then examine the difference in performance of similar quality inventions at the time of licensing, including those that used N or PD rules and those that did not. The implication of such a matching procedure is that, after matching, any difference in performance for two nearly equal quality of inventions and with similar quality inventors is due to the treatment effect of the royalty sharing regime used. We find that N or PD rules for allocation of rewards are not inefficient after accounting for low-quality inventions being assigned to N or PD regime. In other words, the difference in performance is due to self-selection, and not due to shirking. Finally, we find that individuals do not learn over time to refrain from using non-heuristic regimes. The evidence we finds suggests that the use of non-heuristic regimes depends simply on items like the potential size of the royalty prize at stake- the greater the amount of money at stake, the more likely inventors are to adopt non-heuristic regime.

1. Research Site

For our research site we selected a technology transfer office (TTO) at a large U.S. university. This university has one of the largest TTOs in the U.S. with income over $50 million and is well respected for its patenting and licensing capabilities. The data for this study were collected in 2007, when one of the authors regularly visited the TTO and interviewed intellectual property managers,

[3] Again, there are many types of heuristic rules possible, in this paper we are only referring to N or PD as heuristic rules.

licensing managers, legal counsel, and the senior management team to develop a deeper understanding of the TTO and its processes.

The TTO documents all invention disclosures made by the university faculty. Once an inventor approaches the TTO with a claim of an invention with potential commercial value, a file with a unique identifier number is created, and an intellectual property manager (IPM) is assigned to the case. The IPM interviews the inventors to elicit detailed information about the invention and its commercial potential. Based on the interviews, the IPM writes a report on whether the TTO should file for IP protection. All new disclosures are discussed at a monthly meeting at which all IPMs, licensing managers, legal counsel, and senior management of the TTO are typically present. Once the decision on IP protection has been made, the licensing managers are included in detailed discussions with inventors on strategies to effectively market the IP. The legal counsel then prepares the disclosure for patent protection filing with the U.S. Patent and Trademark Office and/or in other countries.

The sample consists of 415 licensed contracts from 1990 to 2004 that include two or more inventors. The graduate office does an "equity review" to identify all inventors who contributed an "inventive step"—i.e., some original conjecture. Hence, some objective vetting of inventors does occur. However, the inventors decide among themselves how great a share in a licensed invention each should receive, and they communicate this decision to the TTO. Each contract lists how the inventors' portion of the revenue received by the TTO from the licensing firm will be distributed among the inventors. Outsiders and even the TTO are generally uncertain about how great a share an inventor should receive. For instance, a TTO manager reports:

> (T)here is some question in my mind as to who is truly an inventor here. X clearly conceived and directed the work. Y is a past student from fall of 1997, Z (a lab technician), did experiments to establish the appropriate levels of lactate, anti-oxidant and colorant. Y's potentially inventive contribution involved her identification of monasticin as a desirable colorant, as X was not familiar with it. X's current student, V, has done work to optimize concentration of the ingredients, but does not appear to have made an inventive contribution thus far.

The licensing manager corresponds with the inventors before the signing of the licensing agreement and incorporates the inventors' decision. There are 644 unique inventors in the sample.

2. How often are N & PD rules used to distribute income from royalties?

1/n rule. A rational perspective might argue that when a significant amount of money is at stake, the use of heuristic rules to share rewards should be minimal. On the other hand, the behavioral view suggests that the use of heuristic rule to share rewards is invariant to stake size. The contrasting theories give qualitative different predictions but no specific point estimates (Camerer & Lowenstein, 2004). Harris and Joyce (1982) offer evidence from a laboratory study on the prevalence of the 1/n rule to distribute incentives among group members. They find that groups shared income equally 60% of the time and allocated expenses equally 70% of the time, leading to unequal incomes. In a sample containing a representative population of U.S. adults founding nascent ventures, the 1/n rule was prevalent, with 65% of the teams sharing equity equally (Kotha and George, 2012). This is a much higher rate than in a sample of venture-capital-backed entrepreneurial teams, wherein approximately 34% of teams spilt equity equally (Hellman and Wasserman, 2011). Hence, for a field study, an *ex ante* expectation of the range 1/n usage is large, falling anywhere from 34% to 65% based on prior evidence.

In our sample, of the 415 licensed contracts, 278 include only one invention; the remaining 137 contracts have two or more inventions that are bundled and licensed (see Figure 1). The number of single partition inventions is 278, of which nearly 81% are equally shared among the inventors, showing that 1/n explains the vast majority of royalty share distribution perfectly—a much higher prevalence of the use of 1/n rule than found in prior work on groups sharing incentives. The rate we find in our sample is also much higher than the prevalence of 1/n rule found by Benartzi and Thaler (2001), who reported that 21% to 34% of individuals in a laboratory study chose equal allocation of their savings to stocks and bonds. One implication of this descriptive result might be that the prevalence of 1/n rule is amplified when decisions are made by a group rather than by individuals.

-INSERT FIGURE 1 HERE-

To confirm the descriptive results for 1/n, we estimate the share an inventor receives with control variables for heterogeneity in inventor human capital in addition to individual and period fixed effects. We predict the share an inventor receives in an agreement. The *inventor share* is greater than zero and less than 100%. The explanatory variables are *publications experience*, and *invention experience*. We count the number of published articles by an inventor prior to the date of the focal invention, and then subtract the average publications of other inventors on the team, the intuition being that if an inventor-i has a higher number of publications than his team members, then this variable will be larger. Hence the expectation would be the greater the relative publication experience of an inventor over his team members, the greater the share of royalty income that the inventor receives. *Invention experience* is the difference between the average of invention experience of the other inventors in the team and the experience of the focal inventor, whose share in the royalty income we are estimating. The theory explanatory variable is *1/n*, which is the share a focal inventor receives as predicted by 1/n rule. In Table 1 we report the descriptive statistics and correlations of these variables.

-INSERT TABLE 1 HERE-

We follow Bardolet et al. (2011) in predicting the share each focal inventor receives and use the share predicted by the 1/n rule as an explanatory variable. The intuition here is that once human capital variables of the inventors are accounted for, then simple rules are irrelevant to the share an inventor receives. We used inventor fixed effects to control for unobserved time-invariant inventor factors and also used year indicators to control for unobserved period effects[4]. We report the results of these estimations in Table 2. We find that the share predicted by the 1/n rule is positive and significant in Model 2 (b=.72; p<.01), confirming the descriptive data that the 1/n rule is the most common method of allocating royalty income shares, even after controlling for the experience of inventors, publication record of inventors, and the performance of inventors' prior inventions.

Partition dependence rule. Recall that the PD rule suggests that decision makers are influenced by the first naturally occurring partitions that come to the decision maker's notice. For instance, Fox and Rottenstrich (2003) asked subjects in a laboratory study, "What is the probability that Sunday will be hotter than any day of the week?" This question suggests to decision makers a two-fold comparison: is Sunday hotter than each other day or not? Hence, they assigned 50% likelihood of it being hotter than other days. By comparison, asking them "What is the probability that Sunday will be the hottest day of the week?" suggests a seven-fold comparison, which results in decision makers correctly assess the probability to be 1/7. In another study, Langer and Fox (2003) replicate the work of Benartzi and Thaler (2001) and then extend it to show that an individual's allocation varied by the order in which vendors and the number of funds were offered. Similarly, as noted above, Bardolet et al. (2011) found that senior executives were influenced by the grouping of the information for capital budget allocation of a hypothetical corporation by either geography divisions or product divisions, resulting in widely different allocations without any change in information content. Hence, prior laboratory evidence suggests that decision makers divide equally among the first hierarchical possibility that they notice and then subdivide again equally within subcategories within an allocation.

The evidence from PD studies suggest a general rule that can be expressed as follows: If there are "m" unique partitions in the first hierarchical level that are salient to decision makers, then whatever is being allocated will be first shared equally among all "m" partitions. If there are "n"

[4] It is worthwhile to stress that in field data fixed effects for inventors allow us to account for individual differences that are trait like: risk seeking, optimism etc., which are unobserved.

unique sub-partitions that come second to decision makers' attention, in each of the "m" partitions, then the number of first partitions—m with index $j = \{0,1,...,m\}$. ; number of sub-partitions in a partition j: n_j. ; an indicator variable $d_{ij} = \{0,1\}$—takes on value 1 if a unique sub-partition "i" is represented in a set of j. In this case, the simple partition rule would result in a unique sub-partition, i, receiving the following share of whatever is being allocated:

$$s_i = \sum_{j=1}^{m} \frac{d_{ij}}{mn_j}.$$

A numerical example from Bardolet et al. (2011) can be used to illustrate this general rule. If a hypothetical company were grouped by geography and then products—for instance, United States (Home, Beauty, Health), Europe (Home, Beauty Care), and Latin American (Home Care)—then each of the three geographic divisions (United States, Europe, and Latin America) would be allocated 33.33% of the available capital. The subdivisions in Home Care would get 61.05% of the total budget, one third of the U.S. budget, one half of Europe's budget, and Latin America's entire budget (1/3*33.33+1/2*33.33+1*33.33=61.05%). Whereas if the company were organized by product divisions and then by geographic subdivisions, i.e., Home Care (U.S., Europe, Latin America), Beauty Care, and Health Care, then Home Care would receive a budget of 33.33% each, which then would be split equally by the number of geographical subdivisions under each product division. The implication again would be that the hierarchal structure of the hypothetical organization influences outcomes without any change in the information regarding the particular business outlook for a product/geography category (or vice versa).

Partition dependence in our research setting. In the research setting we found that several inventions are bundled and licensed in one contract. These inventions have one or more common inventors. A simple 1/n rule would predict that the number of unique inventors in all of the inventions licensed in an agreement be counted and be given equal shares. A partition dependence prediction would seek out the first level of hierarchy that comes to decision makers' notice and provide equal allocation at that level. The question then becomes, is the unique inventors the focal point or is the focal point the number of unique inventions followed by the number of inventors in each of those inventions?

Our interviews of the licensing managers at the TTO suggested that the TTO and the licensee firm first established which discrete inventions were needed to practice a technology gainfully, as suggested by this description from a licensing manager:[5] *"The basic flow is that the potential licensee is going to have an interest in a technology. That may be one patent, that may be ten patents, they have to evaluate that – so often you go under a confidentiality agreement and there's a period where they need to evaluate the technology and then they finally get to a point where they understand its potential."* Hence, we suggest that discrete inventions are the first hierarchical partition that comes to a decision maker's notice. Therefore, according to the PD rule, each discrete invention in a license will get an equal share of the licensing income. The next level determines how to compensate the inventors. Again, if the PD rule guides decision making, then all the unique inventors of a particular invention will share equally in the allocation. If an inventor works on more than one invention, then her shares in each discrete invention are summed to arrive at her share for a licensed contract.

The number of multiple partition contracts is 137. In such contracts, the PD rule explains 77% of all royalty income distribution among inventors perfectly. Thus, the behavioral rule of PD explains a vast majority of royalty income allocation in bundled contracts.

-INSERT FIGURE 1 HERE-

A partition dependence explanation predicts that when two or more inventions are bundled, it is not the 1/n rule but the partition dependence rule that predicts a focal inventor's share. We test this in a sub-sample of agreements with two or more inventions in Models 5, 6, and 7. We find the 1/n rule is a significant predictor without the partition dependence rule in Model 6 ($b=.56$; $p<.01$). However, when the partition dependence rule is introduced, the predicting power of the 1/n rule ($b=.045$) disappears, and it is the partition dependence rule ($b=.84$; $p<.01$) that is a significant predictor, as shown in Model 5. The results of these estimations show that, over and above human capital variables, 1/n and partition dependence rules predict the shares a focal inventor receives for the vast majority of the number of inventions.

-INSERT TABLE 2 HERE-

The main results thus far are that the 1/n rule perfectly predicts royalty income distribution in 81% of the single invention contracts and that the PD rule predicts perfectly the shares of each inventor in 77% of all contracts when multiple inventions are bundled and licensed together.[6] Perhaps

[5] Note each of the discrete inventions may not be equally valuable. Take for example a basic compound discovery which is usually more important that the method to extract it or a specific field of use, although all three may be required for practice of the invention.

[6] The point to note regarding the partition dependence allocation is that it is not obvious why two or more heterogeneous inventions should be treated as equal value and each individual inventor in such inventions get an equal share. The simple fairness rule would predict that the shares should be divided equally among unique inventors across all inventions in a bundled license (Messick, 2008).

it is pertinent here to mention a descriptive result on the income earned in the sample by N or PD licenses. If the percentage was approximately 80% of the total income then it would suggest that the type of regime used to share rewards and ultimate performance of the inventions does not matter. In our sample the income earned by N or PD licenses is only 41%. The non N or PD licenses are approximately 20% of the total deals and account for 60% of the total revenue. This calls for explanations of when teams do not use N or PD and the reason for lower share of total income of N or PD licenses.

3. When do some teams not use 1/n or PD rules?

Bargaining model. We use predictors suggested by the bargaining model as a starting point to explain when N and PD rules are less likely to be used (Hellmann and Wasserman, 2011). In the bargaining model, bargaining costs arise either from time wasted on bargaining or a psychological dislike of bargaining. Hence, when the expected value of a project is low, then equal shares are more likely, as there is less incentive to bargain about how team members should share income from a project. Second, an assumption of the model is that even if one individual team member demands to bargain, then bargaining occurs and reveals the marginal contribution of team members to the project. Third, given that a project is valuable and worth the bargaining effort, then bargaining unearths each individual's marginal contribution to the team and therefore results in unequal allocation. This model suggests the use of the aforementioned N or PD rules is less likely under the following circumstances: i) the team size is large, as the chance of any single member asking for a negotiation to allocate incentives is greater in a larger team; ii) there is greater heterogeneity among team members; and iii) the expected value of the project is higher.

We use the following variables to measure constructs from the bargaining model. Team size is the number of inventors in a license. Human capital heterogeneity is measured by *invention* and *publication* heterogeneity of the inventors in a license. For the expected value of a project, we use the following proxies: the *citations received* by the patents underlying an invention, the *prior performance* of the inventors' inventions, and the size of the *licensee firm*. The size of the licensee firm is a proxy for the potential income that could be earned from a license. Large firms with presence in multiple geographically markets may provide more income. We also use other control variables in the estimations, such as grants, which include the dollar amount of funding received by the inventors' department, the number of inventions bundled in a contract, and the proportion of inventors in a license who previously had worked together. The prior relationship between inventors is an important control. For one the search costs to find out marginal contribution may be lower as the inventors know each other's potential contributions from prior relationship. Second the psychological distaste for bargaining among relations may be higher. Hence controlling for prior relationships between the inventors is important. An indicator variable is used to show whether an invention is interdisciplinary—that is, if all inventors are from the same discipline or from different disciplines. Since it possible that bargaining costs may vary between same disciple teams and interdisciplinary teams it is important to control for this difference (Kotha, George, Srikanth, 2013). A variable to control for the stage of an invention uses the number of citations that an invention's patent has made to other patents. Early stage inventions are more risky and if an invention builds on other established work it is less risky. The expertise of the licensee firm is an indicator variable that takes a value of 1 if the firm has patents; otherwise, it is zero. We then estimate the probability that a contract adopts one of the N or PD rules to distribute royalty shares to inventors using the aforementioned explanatory variables. *N or PD royalty sharing regime* is an indicator variable that takes a value of "1" if 1/n in single invention contracts and partition dependence in multiple invention contracts predict royalty shares of inventors perfectly; otherwise, it is "0." The intuition is that if an explanatory variable is positive (negative) and significant, then it suggests when inventors are more (less) likely to adopt the 1/n or PD rule.

Table 3 includes the summary statistics of the independent and control variables used in the estimation in two panels: not N or PD and N or PD. Recall that there are a total of 415 contracts in our sample, of which 85 are not assigned to an N or PD royalty income sharing regime. The average team size for non-N or PD regime contracts is 6.3 and 3.3 for N or PD (significant at $p<.001$), consistent with the bargaining model prediction. There is no difference between N or PD and non-N or PD contracts in publication and invention experience heterogeneity among team members in a contract. The prior performance of non-N or PD teams , measured by the prior income earned by the inventors is twice as high as the prior performance of N or PD contract team members (significant at $p<.001$), suggesting that teams with prior successful inventions are less likely to choose an N or PD regime, again consistent with the bargaining model prediction.

-INSERT TABLES 3 & 4 HERE-

Next we test the descriptive results from the correlation analysis in a multivariate analysis using OLS estimation, a Logit estimation leads to similar results, with the dependent variable taking a value of 1 if the royalty sharing regime in a contract is N or PD. We report these results in Table 4. All estimations have domain and year fixed effects. Team size variable is negative and significantly related to the choice of N or PD regime ($b=-.056$; $p<.01$), consistent with the bargaining model prediction. Human capital heterogeneity variables—invention experience heterogeneity ($b=.0068$; $p<.01$) and publication experience heterogeneity ($b=.11$;$p<.01$)—are both positive and significant, implying that an increase in heterogeneity in a team increases the probability that the team would adopt an N or PD regime. This result is contrary to the bargaining model, which suggested that greater heterogeneity in the human capital of team members should cause team members to be less likely to choose N or PD regime. There is a negative relationship between the prior success of team members with commercialization and choice of N or PD regime (b=-.0011; p<.05). Inventions licensed to large licensee firms are less likely to use N or PD allocation (b=-0.10; p.<01). There is no statistical relationship between patent citations and choice of an N or PD allocation.

In our sample there is a consistent pattern of results for the average and heterogeneity in human capital variables. When the average human capital of a team is higher, it is more likely that such a team will adopt N or PD regime. On the other hand, when heterogeneity in human capital of a team is high, then the team is less likely to adopt N or PD regime. What could cause this pattern? We speculate that higher human capital leads to higher valued inventions, and, hence, inventors may be more willing to bargain when the stakes are higher. Why does heterogeneity not follow the prediction of the bargaining model? Could it be that heterogeneous teams invent lower valued inventions? In subsequent estimations wherein we examine the performance consequence of a contract regime we find that the heterogeneity in number of prior inventions among team members is not significant predictor of the income an invention earns and publication differences among team members is a weak positive predictor. Therefore we cannot draw the inference from our data that heterogeneous teams invent lower valued inventions. We discuss these results in greater detail in our conclusion and call for studies to explain this finding.

Some other results are worth noting beyond the theory variables. Teams that have a higher number of members who share prior collaborations are more likely to adopt N or PD regimes (b=.12; p<.01). Since the bargaining model has both the cost of effort needed to determine marginal contribution and the psychological distaste for bargaining, it could be argued that in repeated teams, psychological distaste for engaging in bargaining is high, though relative contributions can be easily identified by repeated team members (Rick, Weber, Camerer, 2007), or it could be the case that shirking is monitored better when there are multiple interactions or that logrolling across inventions even out over time. Similarly, continuing inventions could have overlap of content and inventors, and they are also more likely to have N or PD regimes (b=.066; p<.01). Barring the heterogeneity in human capital variables, other theory and control variables support the intuition from the bargaining model regarding when teams deviate from N or PD regimes.

4. What are the performance consequences of the use of 1/n or PD rules, if any?

Recall that the rational view would suggest that the use of N or PD rules may suppress the effort needed from inventors and result in poor performance, per the classic economic model of moral hazard in teams (Alchian and Demsetz, 1972) unless by random chance perfect incentives align with heuristic rules. This model suggests that when effort is hard to observe and costly, as well as when the profits of effort are equally shared among team members, each team member will have an incentive to contribute lower-than-profit-maximizing effort. The typical assumption is that the cost of effort is entirely borne by an individual and is a non-linear increasing function. At low levels of effort, the cost of effort is low for an individual. When high levels of effort are required, an individual pays the cost of effort, but the returns on this effort are equally shared. Hence, the individual may not receive a return that is greater than the cost of her effort, leading to a situation wherein team members do not contribute optimal societal effort that maximizes revenue. Indeed, evidence from laboratory studies suggest that team members tend to devote less than optimal societal effort when rewards are equally shared (Nalbantian and Schotter, 1997). If we assume that teams that chose to provide a higher share of returns to individuals who have the most value to offer, such that the effort garnered is maximized, then equal shares may diminish the desire of the most valuable team member to contribute effort (Alchian and Demsetz, 1972). Hence, from a societal point of view, if N or PDs lead to the muting of effort exerted by inventors that could otherwise have been exerted, then N or PD regimes are a drag on project performance. This negative relationship between an N or PD regime and performance of a project would be apparent even after controlling for the ex-ante quality of a project. That is, if two equal-quality projects were selected and one was assigned to N or PD and the other to not N or PDs, the N or PD regime project would have a lower ultimate performance than the non-N or PD regime project. Therefore, the shirking model would predict that the negative relationship between the choice of N or PD-based royalty sharing regimes and the performance of the project will not be fully mediated by the ex-ante quality of the project.

Contrary to the shirking view above, from the perspective of the bargaining model (Hellmann and Wasserman, 2011), teams that adopt 1/n or PD rules may not perform any worse than those that adopt a different rule. In the bargaining model, the ex-ante expectation of project performance, i.e. "stake," explains the switch between the use of N or PD and non-N or PD rules. When stakes are low, it is less likely that an inventor will engage in explicit bargaining, resulting in the use of 1/n or PD rule (Hellmann and Wasserman, 2011). Hence, N or PD regimes are more likely for low-valued ventures than high-valued ventures, resulting in the self-selection of low-valued ventures to N or PD royalty regimes (Hellmann and Wasserman, 2011). Therefore before we examine the shirking view, we must account for the fact that inventors with low values inventions may self-select into N or PD regime. However, the key point to note is that in the bargaining view a scientist is unlikely to shirk subsequent to choosing whether to use an N or PD regime to share royalty income. Hence, the bargaining view would predict that once one account's for the fact that low quality inventions are self-selected to N or PD regime the performance of the project will be no worse off due to the choice of N or PD regime. To summarize the above discussion the bargaining view would predict that the negative relationship between the choice of an N or PD-based royalty income shares and performance of the project will be mediated by the quality of the project. In other words, once the ex-ante quality of the project is controlled for, then there will be no negative relationship between an N or PD-based regime and the performance of the project. Thus from the society's point of view only after we had accounted for self-selection of low valued inventions to N or PD regime and then if there is still a negative relationship between N or PD contract choice and performance of the invention then this is evidence of shirking by team members.

We first test a simple association between an N or PD regime and performance of the licensed invention. In Table 5, Model 1, we first estimate a simple OLS regression with the natural log of revenue received from an invention as the dependent variable and the regime as an indicator variable. The N or PD regime takes a value of 1 if the regime is based on an N or PD, otherwise it is zero. The definitions and descriptive statistics of all the variables used in this estimation are the same as those in Table 3. Notice that in Table 3 the average non-N or PD contract yields nearly five times the revenue of an N or PD-based contract (see Table 3). This result is confirmed in OLS estimations. We find that the N or PD regime is negatively related to performance of a contract (b=-2.20; p<.01; Table 5).

-INSERT TABLE 5 HERE-

The negative relationship between the use of N or PD royalty income sharing and performance of the invention, while consistent with the economic view, leads to a few intriguing questions. First, is it possible that inventors with low-value projects self-select to N or PD regimes? Second, do inventors in N or PD regimes expend less effort than they would have if only a different regime had been chosen? Finally, is it possible that both self-selection and some muting of effort occur?

4.1 Is it selection, shirking, or both? Coarsened matched sample regression of performance of 1/n and PD contracts

Examining whether or not shirking occurs in this context is complicated by our use of field data. We propose to tackle this challenge as follows. First, we will show how different the inventions in the N or PD are from inventions that are not licensed as N or PD just prior to invention licensing. We will use the human capital of the inventors, quality and stage of the project, and capabilities and size of the licensing firm. If inventions in N or PD and not N or PD are similar on these dimensions before licensing, then presumably the incentive regime adopted is the "only" variable left that influences performance. Hence, we need to measure how similar or different the inventions in N or PD are from not N or PD.

If the inventions in N or PD are very different than not N or PD, then it is imperative that we reduce this imbalance through matching. The goal should be for the imbalance to be as low as possible without reducing the sample to only a few observations. We then will measure the performance of N or PD inventions that are matched with similar not N or PD inventions. If the variable N or PD is still negative and a significant predictor of performance of the invention, then this is consistent with the shirking interpretation.

Furthermore, since matching is more an art than a science, we would also like to know how the above result changes if a different matching criteria is used. We relax the matching criteria by eliminating only one variable from the set at a time. Again, in the new set of predictions, we would like the imbalance between N or PD and not N or PD before licensing to be as low as possible. Below, we report the outcome of the process outlined above.

Self-selection. A critical concern is that the negative relationship between licenses with N or PD incentive regime and performance of such licenses is endogenous. That is, the question is whether lower-ability inventors or those with lower-quality inventions chose an N or PD incentive regime. This then could fully explain the negative relation between the adoption of an N or PD incentive regime and the subsequent poor performance of the licensed invention. To rule out the effects of such self-selection, the innovation literature suggests using appropriate stringent matching of licenses that have, at the time of licensing, a similar level of inventor(s) and invention quality (Azoulay, Graff Zivin, and Manso, 2011; Singh and Agarwal, 2011).

Measures. We reviewed the literature to identify measures of quality of the inventors and measures of the invention's quality at the time of licensing. Inventors' quality could be measured as experience with inventing, prior collaborations between inventors in a team, inventors' academic publications, and the prior performance of the inventions. The expectation is that inventors who have higher human capital are less likely to choose an N or PD incentive regime. Invention quality may vary independently of the inventors; that is, inventors with high ability may sometimes create low-quality inventions, and vice versa. Hence, we measure the economic potential of the invention using the number of prior citations that the patent underlying the invention received and the stage of the invention. Furthermore, we also match licenses based on the quality of the licensee firms, the intuition being that inventions licensed to large or high-capability licensee firms would perform better than those licensed to smaller licensee firms. Hence, we include in the matching algorithm the size and expertise of the licensee firm.

Matching process. Recall that the objective of the matching process is to compare two equal-quality inventions at the time of licensing, one that happens to be assigned to N or PD regime and the other to not N or PD regime. How similar are the N or PD and non-N or PD licenses in our sample before the matching process? A measure developed by Iacus et al (2009), "imbalance," measures the level of similarity in the sub-samples. If two sub-samples are perfectly similar, then the imbalance score is "0" and if the two sub samples are very different than the score is "1." The starting imbalance score "L" is 0.74 in our data. This suggests that the sample of N or PD and not N or PD inventions are very different on observable measures of quality. We run the coarsened matching procedure with the eight matching variables described above. The matching procedure chooses cases that have the least imbalance in the N or PD and non-N or PD regime sub-samples. Hence, the matching process drops observations that are completely dissimilar. Post matching, we end up with 118 cases of licenses without the N or PD regime matched to 48 cases of licenses with the N or PD regime, and the imbalance reduces to 0.35, a 47% drop. We do not use one-to-one matching, as the sample size is too small; the cases that do not use N or PD sharing rules are only 21% of the total starting sample. For the sake of robustness, we rerun the results with one-to-one matching, and our result for the treatment variable (N or PD regime) is unchanged. In Table 6, we report summary statics of the matched sample by licenses with N or PD and without N or PD regimes. Even after matching, we can see that inventor experience and inventor publications are still different in the N or PD and not N or PD sub-samples. Recall that matching is not perfect; our aim is to reduce imbalance as much as possible without whittling away the size of the sample.

-INSERT TABLE 6 HERE-

Results of matched estimations. In Table 7 we report the results estimations in the full sample without matching and in the matched sample. Models 1 and 2 are a full sample without and with the N or PD regime indicator variable, respectively. In Model 2's full sample, the N or PD regime indicator, is negative and a significant predictor of the license's performance (b=-1.89;p<.001). In the matched sample seen in Model 4, the N or PD regime indicator is negative but not significant (b=-.81; p=0.34). Notice that within the bar for inventor experience and inventor publications, there are no variables that are statistically different within this matched sample (Table 7: Model 3 and Model 4). This reinforces the fact that the matching has succeeded in balancing the ex-ante differences in project-level quality based on observable factors. Conditional on the matching process working, the results in Table 7, Model 4 are consistent with a self-selection explanation. That is, inventors with low-performing projects choose to use the N or PD rule, and the evidence does not support shirking as an explanation.

-INSERT TABLE 7 HERE-

Sensitivity of the N or PD performance result to the matching process. We check the sensitivity of the matching process by dropping each of the eight matching variables one at a time and then rerunning the matching process and estimating the performance of N or PD contracts. We report these results in Table 7A. Only in Model 6, when we drop the stage of the invention as a matching variable, do we find that the N or PD variable is negative and a significant predictor of revenues earned (b=1.47; p=.02). However, note the efficiency of the matching process. The initial imbalance was 0.66; post imbalance it was 0.59, which is the worst matched of all the samples. Recall that in the full model (Table 7: Model 4) with all the eight matching variables, the starting imbalance was .74 and dropped to .35 post matching. This inspires much more confidence that, ex ante, the inventions in N or PD and not N or PD are more similar than matched estimation in Table 7A, Model 6. This suggests that, post matching, the contracts in the N or PD and not N or PD are still very different.

Hence, it is not possible to claim ex ante that the inventions had the same quality. Wherever the matching has done a reasonable job of reducing the ex-ante imbalance (as can be inferred from the low imbalance score post matching), we find that the coefficient of N or PD is not significant, although it is negative. Thus, our results cannot support shirking.

-INSERT TABLE 7A HERE-

4.2 Alternative explanations: Are there "types" of inventors? Do inventors learn when to use N or PD?

Project level versus long-term analysis. The unit of analysis we employed in this paper to test the performance implications of the N or PD regime is itself a project. However, a case can be made that individuals who adopt an N or PD strategy for a project may attract several more collaborators, and the sum of the income from larger number of collaborations in the entire sample period is greater than the income in the entire sample period for those who do not adopt an N or PD, as they may have a lower number of collaborations, and, hence, lower period income. To examine this explanation, we divide inventors into three categories: only N or PD, both, and never N or PD. We found that inventors who use only N or PDs have the lowest total income in the sample period. Inventors who used only non-N or PD had higher total income in the sample period. The highest income was for those inventors who used both N or PD and non-N or PD regimes (see Figure 2).

Strategic switchers. In our sample, inventors can be classified into three broad types: those who always use N or PDs (298 cases), those who never use N or PDs (52 cases), and those who switch between N or PDs and non-N or PDs (65 cases). It could be that inventors who switch between N or PDs and non-N or PD have a better expectation of the ex-post performance of the projects. These inventors switch to non-N or PDs when they expect high performance and use N or PDs when they expect lower performance (Hellmann and Wasserman, 2011). Consistent with this insight, we found that inventors who switch between N or PDs and non-N or PDs, hereafter referred to as "*strategic switchers,*" had an income of $60,446 when they use non-N or PD royalty sharing rules and $15,322 when they use N or PDs (see Figure 2). This finding reinforces the self-selection argument over the shirking argument, as otherwise it would be necessary to construct and believe in an explanation where inventors shifted between shirking rather than royalty regimes, such that the same inventor would shirk on one project and devote effort to another project systematically depending on regime.

-INSERT FIGURE 2 HERE-

To take the above insight further, we run the performance estimation using the refined inventor types: never N or PD, strategic switchers, and always N or PD. We report these results in Table 8. Model 1 is the baseline model with the simple N or PD regime indicator variable used in the performance estimations in Table 7. In Model 2, we replace this variable with the inventor type: never N or PDs, always N or PDs, and strategic switchers. The comparison category is the group of inventors in the sample period who have never used the N or PD rule to share royalty income. When compared to those inventors who never use the N or PD rule, those who always use the N or PD rule perform worse (b=-2.21, p<.001). However, the key point to note is that the performance of strategic switchers (b=-1.21) is not statistically different from those who never use the N or PD rule Therefore strategic switchers appear to perform just as well as those who always chose not N or PD even though strategic switchers are switching between N or PD and not N or PD

-INSERT TABLE 8 HERE-

In Model 3 we refine the strategic switchers into two categories: cases when they did or did not use N or PD. Again we compare these categories with those who never used N or PD in the sample period. First, the result of the difference between never and always N or PD is the same as in Model 2. Those who use N or PD always perform lower than those who never use N or PD (b=-2.18, p<.001). We are more interested in finding out what happens to strategic switchers when they use or do not use N or PD rules. As compared to those who never use N or PD, the coefficient of strategic switchers when they used N or PD is weakly significant (b=-1.73; p<.07). Thus, when strategic swicthers use the N or PD rule, they earn less income as compared to those who never use the N or PD rule. This explanation is consistent with both the shirking and self-selection arguments, as we had not performed matching on similar projects. Once we match and rerun the analysis, this weakly negative relationship is not significant.

Learning. The shirking model would suggest that inventors learn from the negative experience of using N or PD and subsequently choose shares that are not N or PD. By contrast, the bargaining model would suggest that such shifts would be based on the value of the invention and other variables listed. If the null assumption is that inventions with high and low value are randomly sequenced in time, then shifts that occur with the value of the invention would have a random pattern. We pick the most experienced inventors who exhibited a more pronounced switching pattern between the use of N or PD rules and not N or PD in the sample period; their choices are listed in Figure 3. There is no discernible pattern that explains why inventors switch with time. Therefore, learning about the drawback of equal shares does not explain the choice of incentive selection as predicted by the shirking model. Recall the switching is consistent with high-valued inventions by strategic switchers being licensed as not N or PD (see Figure 2 for average value of an invention in a regime).

-INSERT FIGURE 3 HERE-

We test this intuition using a non-parametric Wald–Wolfowitz run test (Swed & Eisenhart, 1943). The test uses the pattern of the number of adjacent ‘0’ or ‘1’ and compares this against the null hypothesis that this pattern is random. For example, consider a toss of a coin represented by 1 if heads and 0 if tails, then patterns as 1010101010 and 111000111, which have 10 and 3 runs, respectively. Runs are sequence of similar outcomes. The number of runs and how long a sequence lasts can be used to measure if it is random. The intuition being too few runs, too many runs or excessive long runs are deviations away from randomness. Obviously, the more the number of observations the easier it is to say if a sequence is random or not. We classify the choice by a lead inventor, who is a strategic switcher, to use N or PD as '1' and not N or PD as '0'. We order the choice of regime as represented by '1' or '0'sequentially by time, with the older coming first. Hence we observe a sequence of 0 and 1 for each of these inventors. We test the randomness of the sequence of 0 and 1 for each inventor. We report these results in Table 9. Only two inventors appear to have a pattern of choice that is non-random. Notice also that the number of observations for each inventor is only a few. Thus, we use an alternative test. At its heart is a comparison of the observed pattern with a hypothetical pattern suggested by the learning argument.

It would be straightforward to assume that an inventor can make a relative comparison between the use of N or PD and not N or PD only if he has experienced both choices himself. After making this assumption, we follow what a simple learning argument would suggest for the choice of contract regime. A learning argument would suggest that the first time an inventor has not used N or PD after having used N or PD, then the inventor can make relative comparisons. In the relative comparisons, the inventor may learn about the advantages of not using N or PD. Hence, the inventor should henceforth not use N or PD. Therefore, the learning rule then gives a 'conjectural choice' pattern of N or PD and not N or PD for each inventor. The rule is the first time a pair of alternative choices is present; thereafter, the inventor should not chose N or PD. We then use the observed choice and the conjectural choice suggested by the learning view to predict the income earned by the invention. We find that when we use the two variables, observed choice and learning-rule-based choice, to predict the value of an invention, it is only the observed choice that predicts the invention value ($p<.07$) and not the learning rule ($p<.4$). This confirms again that strategic switchers shift with the value of the invention rather than due to the fact that they have learnt that N or PD regimes had shirking problems. Hence, our data suggests that shifts occur more with the value of a project rather than from learning from experience with a royalty income sharing regime. Thus, we conclude that switching is random in time but not random in project value.

-INSERT TABLE 9 HERE-

Fairness. In this paper we cannot tell if inventors in the equal and unequal shared rewards condition thought the allocations were fair. However, the most obvious alternative causal mechanism to the cognitive conservation of effort leading to 1/n allocation that we had advanced is that inventors are guided by fairness norms (Fehr & Fischbacher, 2003; Messick, 2008; Pillutla and Murnighan, 1996). Fairness and cognitive conservation of effort leading to 1/n are indistinguishable when it comes to sharing royalties in single invention contracts. However, when multiple inventions are licensed in a contract, then fairness norms would indicate each unique inventor would get an equal share. It is hard to argue that two or more unequal value inventions should get equal shares first, as predicted by the partition dependence. Hence, we offer evidence from the multiple invention contracts that is consistent with conserving cognitive effort on the part of the decision makers rather than concerns of pure fairness guiding royalty income allocations. However, the deep literature on fairness distinguishes between procedural and allocative fairness (Folger and Konovsky, 1989) and suggests that procedural fairness requires that decision makers follow fair rules even in the face of unequal outcomes. It could be that the use of PD is procedurally fair but leads to unequal allocation at the individual level. This question is beyond the scope of this paper and the data available.

Tradeoffs. Another explanation is that inventors who accept N or PD regime are focused on academic work and, hence, are willing to accept N or PD royalty income shares. This explanation is consistent with the bargaining cost hypothesis (Hellmann and Wasserman, 2011) that inventors prefer to focus on academic work rather than take time away from or impinge on academic collaborations. If this were the case, then those who use N or PD should be particularly productive academic researchers. Yet we found that the academic productivity of inventors who used only N or PD regime or never used N or PD regime in the sample period to be no different than that of other inventors. Rather, it is strategic switchers who used both N or PD and non-N or PD regimes in the period who have the highest scientific productivity significance level (see Figure 4). This finding again is consistent with the idea that no side payments are occurring in the publication domain to make up for the use of N or PD in the commercial domain. More importantly, the finding is consistent with the idea that those with the best knowledge self-select in N or PD and non-N or PD regimes as the expected royalties grow.

-INSERT FIGURE 4 HERE-

To briefly summarize the results, we find that the use of N or PD is highly prevalent, comprising 80% of the cases in our sample, and that the use of N or PD is negatively correlated with the performance of the invention as the share of revenues from N or PD is only 41% of the total revenues in the sample. We explored two explanations for this negative relationship: shirking or self-selection by inventors with lower-quality projects to N or PD royalty sharing agreement. The preponderance of the evidence suggests that self-selection rather than shirking explains the negative relationship. Furthermore, strategic switchers are not learning not to use N or PD but choosing royalty regimes based on the expected size of the royalties.

5. DISCUSSION

Somewhat surprisingly, the results of this paper are consistent with both a behavioral and rational perspective. On the one hand, N or PD is the dominant sharing mechanism in the vast majority of both single and multiple royalty contracts. Furthermore, these rules are used when serious money is at stake, much more than in experiments. However, consistent with a rational bargaining model, unequal shares result when the stakes are very large, the count of bargainers is high, or inventors have successful licensed in the past.

Another unanticipated finding of this paper is the “strategic switching” behavior of some inventors in the sample period. We found that some inventors chose to have N or PD regime when the potential income from the invention is low. When potential income from the invention is high, however, they distributed income unequally. These “strategic switchers” have the highest income in the sample period as well as the highest academic productivity in terms of publications and citations. Some elements of this strategic switching behavior are anticipated by Hellman and Wasserman (2011), yet we found subtle but important differences in the evidence. First, the average income of strategic switchers is $15,322 when they share royalty incomes equally, significantly more than the average income of inventors who always share equally ($9,957). This finding suggests that those presumed to be “good” at negotiating should have a lower cost of engaging in negotiation. Hence, we would expect that when strategic switchers share equally, their inventions should have the lowest performance. By contrast, when they share expected income equally, their inventions perform better than those of inventors who always share income equally. Second, team heterogeneity on relevant human-capital dimensions was posited to be negatively related to the choice to equally share income, but we find that team heterogeneity is a positive predictor of equal sharing of royalty income. These important differences aside, the central finding that the same individuals switch to unequal incentives when more money is at stake is consistent with the bargaining model by Hellmann and Wasserman (2011).

5.1 Implications of our results

This study is the first to test partition dependence usage by groups using field data. We find that when multiple inventions are bundled, potential income is equally divided among inventions and then equally to each inventor within a project 77% of the time. This prediction is consistent with theory and evidence developed primarily in laboratory studies using individuals to predict probabilities of events. Recent lab work using experienced managers also finds that when they allocate capital in their individual capacity, they are prone to first allocate by the partition that is prominent first—either geography or product—and then to subdivisions with each category equally.

A second finding of this paper is that an overwhelming majority of all deals in the sample, 79%, have equally shared royalty income, yet they comprise only 40% of the sample's total value. Inherent in that descriptive statistic is the implication that, on average, equally shared deals perform lower than deals that are not equally shared.

We developed predictions for why some deals and not others would be shared equally and the performance consequences of the deal due to a particular type of incentive distribution. Our results confirm that lower-quality inventions are assigned to equal sharing of royalty income. Conditional on matching inventions of the same quality, and assuming that these equal-quality inventions are randomly assigned to either equal or unequal sharing of regimes, the results of our matched sample estimation support the view that type of royalty income sharing distribution in itself does not mute or amplify performance of the deal.

One of the null expectations was that homogenous teams would be more likely to equally share incentives than heterogeneous teams because the marginal contribution of each team member would presumably be nearly the same. The results of the estimation that predicted when teams would have equally or unequally shared incentives finds that heterogeneity in team-member invention experience and publication experience is more likely to result in such teams adopting equal incentives, contrary to a *priori* intuition. When we probed this result further to see if there was specialization—i.e, team members having high human capital on different dimensions—we found this was not the case; inventors with high publications also had high invention experience. Therefore, there was no expertise specialization in a team, an intriguing result that calls for future work. Teams that on average have higher human capital are more likely to share royalty income unequally, consistent with the explanation that the inventions of higher-quality teams have a greater economic potential. Hence, when more money is a stake, members are more likely to negotiate reward distribution, and any negotiation is more likely to result in some deviation from perfectly equal distribution of royalty income. A fruitful area for future laboratory and field research would be to examine why heterogeneous teams are more likely to have equal incentives than homogenous ones.

5.2 Equality Norm of Science

Given that scientists are inculcated in norms of scientific behavior (Merton, 1973), norms of equality may induce them to treat one another's contributions as equal. We conducted extensive interviews of licensing managers, legal counselors, and senior management at the research site. We also reviewed invention reports, correspondence, and other documents to understand the processes at the research site. We found in the reports of managers at the TTO a case that illustrates the generosity norm of scientists*:*

> [I]nventor X would like to include his technician as an inventor, saying that without her, the work would not have been accomplished. Similarly, inventor X pursued this work because of Y's suggestion. Y is a professor at another university. Inventor X believes that both the technician and Y should get a share of the income.

Consider two other cases reviewed by the TTO officer wherein inventors were more generous than necessary:

- "X lists Y as an inventor on her IDR. Y's contribution was providing small quantities of the ILK inhibitor KP392. He did not participate in the conception of the idea, and I feel that his inclusion as an inventor may be doubtful."
- "Professor X would like to include Y and Z as inventors. However, his description at our meeting of their contributions did not seem to rise to the level of inventorship."

Based on such cases, we might conclude that scientists are more generous than other professionals due to scientific norms. The 80% of equal shared projects in our sample is much higher than that of entrepreneurs sharing ownership equally (60%) and joint venture partners sharing investments (67%), although it should be noted that less capital may be at stake in scientist endeavors. In addition, field evidence shows that scientists routinely give up higher-paying jobs for their research careers (Stern, 2004). Hence, scientists in our sample may be so focused on research and teaching that they find bargaining over income share to be more psychologically distasteful and time consuming than other samples (Hellmann and Wasserman, 2011).

That said, the PD method of sharing royalty income often leads to unequal shares due to the number of inventions bundled and the number which an individual is listed as an inventor. Suppose there are two inventors, A and B, and two inventions bundled in a contract, 1 and 2. Assume that inventor A is listed as an inventor for both inventions and inventor B is listed only for Invention 1. The PD rule predicts that equal shares will be given to Invention 1 and 2 and then equal shares to each inventor for each invention. As a result, Inventor A receives 75% (25% from Invention 1 + 50% from Invention 2) of the total contract revenue, and Inventor B receives 25% shares of the royalty income.

Since Inventor B is listed as inventor on only one invention, Invention 1, he gets half of the Invention 1's share of royalties. Invention 1 gets 50% share of the royalties as there are a total of two inventions, each of which get 50%. Therefore, the PD rule results in unequal final allocations unless all inventors engage in each invention. In our data, the use of the PD rule results in the lead inventor receiving 34% and other inventors 12% of a contract income, on average (see Figure 5). Therefore, the PD rule provides higher shares to lead inventors.

-INSERT FIGURE 5 HERE-

5.3 Limitations

This study is not without limitations. Chiefly, any single result from field data is open to multiple interpretations of the causal mechanisms that lead to the result; hence, researchers using field data apply the threshold of a pattern of results taken together supporting one view rather than another. We find deviations from N or PDs when more money is at stake, as predicted by a model of bargaining costs. A set of results that completely support the behavioral or the economic view would have made the findings more definitive. One key inference from our results, once we account for low-quality inventions being systemically assigned equal shares to inventors, is that scientists do not appear to shirk. Future studies that measure effort in more direct ways could investigate this insight, as we are unable to using the existing field data.

Another limitation of this study is our extrapolation from the theory of partition dependence, which has primarily been shown in laboratory studies of single individuals judging probabilities or allocating resources to a group distribution task. We suggest and find evidence for the partition dependence prediction. As field data cannot perfectly isolate a single causal mechanism (Camerer, 2012), a laboratory study on the prevalence of partition dependence among groups and limits to partition dependence would be highly desirable.

5.4 Contribution

We examine two competing views on how income from royalty is shared in self-forming teams and the consequences of incentive regime on the performance of projects. We find that nearly 80% of all deals use N or PD rules. We also provide field evidence that partition dependence influences choice of royalty shares an inventor receives. Prior work on partition dependence has mostly used laboratory studies and has examined a single decision maker judging probabilities or allocating investments. Teams deviate from an N or PD choice when they have prior successful inventions. There is a negative relationship between projects with N or PD regime and performance. Our matched sample estimations reveal that the negative relationship between N or PD regime and performance is absent once the self-selection of lower-quality projects to N or PD regime has been accounted for. This result is important, as we focus on the inventions of academic scientists, whose breakthroughs often influence several domains and improve societal welfare. If scientific discoveries are not turned into products and services due to misaligned incentives among academic inventors, then society is worse off.

We found a negative correlation between the use of N or PD rules to share royalty income and the performance of such inventions. The bulk of the evidence we studied to determine whether this negative relationship is due to self-selection or shirking by inventors suggests the former explanation is appropriate; only a weakly significant result in a poorly matched sample is consistent with the shirking explanation. Thus, we conclude that in our setting, the use of N or PD incentive regimes does not impose a significant cost on society in large part because the most productive scientists know when and when not to deviate from equal sharing.

REFERENCES

Alchian, A. A., & Demsetz, H. (1972). Production, information costs, and economic organization. *The American Economic Review*, *62*(5), 777-795.

Azoulay, P., Graff Zivin, J. S., & Manso, G. (2011). Incentives and creativity: evidence from the academic life sciences. *The RAND Journal of Economics*,42(3), 527-554.

Bardolet, D., Fox, C. R., & Lovallo, D. (2011). Corporate capital allocation: a behavioral perspective. *Strategic Management Journal*, 32(13), 1465-1483.

Benartzi, S., & Thaler, R. H. (2001). Naive diversification strategies in defined contribution saving plans. *American Economic Review*, 79-98.

Camerer C. Field studies: Cabs and basketball. Accessed on 1 Dec Sept. 2012 <http://www.hss.caltech.edu/~camerer/web_material/fs.html>

Camerer, C., Babcock, L., Loewenstein, G., & Thaler, R. (1997). Labor supply of New York City cabdrivers: One day at a time. The Quarterly Journal of Economics, 112(2), 407-441.

Camerer, C. F., & Loewenstein, G. (2004). Behavioral economics: Past, present, future. Advances in behavioral economics, 3.

Camerer, C. F., & Weber, R. A. (1999). The econometrics and behavioral economics of escalation of commitment: a re-examination of Staw and Hoang's NBA data. Journal of Economic Behavior & Organization, 39(1), 59-82.

Fehr, E., & Fischbacher, U. (2003). The nature of human altruism. *Nature*,425(6960), 785-791.

Folger, R., & Konovsky, M. A. (1989). Effects of procedural and distributive justice on reactions to pay raise decisions. *Academy of Management journal*, 32(1), 115-130.

Fox, C. R., & Clemen, R. T. (2005). Subjective probability assessment in decision analysis: Partition dependence and bias toward the ignorance prior. *Management Science*, *51*(9), 1417-1432.

Fox, C. R., & Rottenstreich, Y. (2003). Partition priming in judgment under uncertainty. *Psychological Science*, *14*(3), 195-200.

Harris, R. J., & Joyce, M. A. (1980). What's fair? It depends on how you phrase the question. *Journal of Personality and Social Psychology*, *38*(1), 165.

Hellmann, T. F., & Wasserman, N. (2011). *The First Deal: The Division of Founder Equity in New Ventures* (No. w16922). National Bureau of Economic Research.

Henderson, R., Jaffe, A. B., & Trajtenberg, M. (1998). Universities as a source of commercial technology: a detailed analysis of university patenting, 1965–1988. Review of Economics and Statistics, 80(1), 119-127

Iacus, S. M., King, G., & Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political analysis*, 20(1), 1-24.

Jensen, R., & Thursby, M. (2001). Proofs and Prototypes for Sale: The Licensing of University Inventions. *American Economic Review*, 240-259.

Kahneman, D. (2011). *Thinking, fast and slow*. Farrar, Straus, and Giroux.

Kahneman, D., & Frederick, S. (2005). A model of heuristic judgment. *The Cambridge handbook of thinking and reasoning*, 267-293.

Kotha, R., & George, G. (2012). Friends, family, or fools: Entrepreneur experience and its implications for equity distribution and resource mobilization. *Journal of Business Venturing*.

Kotha, R., George, G., & Srikanth, K. (2013). Bridging the mutual knowledge gap: coordination and the commercialization of university science. Academy of Management Journal, 56(2), 498-524.

Langer, T., & Fox, C. R. (2004). Naïve diversification in allocation among risky prospects: Partition-dependence, unit-dependence, and procedure-dependence. *Unpublished manuscript, University of Mannheim*.

Messick, D. M. (2008). 2 Equality as a decision heuristic. *Psychological perspectives on justice: Theory and applications*, 11.

Merton, R. K. (1973). The sociology of science: Theoretical and empirical investigations. *University of Chicago Press*.

Nagin, D., Rebitzer, J., Sanders, S., & Taylor, L. (2002). Monitoring, motivation and management: The determinants of opportunistic behavior in a field experiment (No. w8811). *National Bureau of Economic Research*.

Nalbantian, H. R., & Schotter, A. (1997). Productivity under group incentives: An experimental study. *The American Economic Review*, 314-341.

Pillutla, M. M., & Murnighan, J. K. (1996). Unfairness, anger, and spite: Emotional rejections of ultimatum offers. *Organizational Behavior and Human Decision* Processes, 68(3), 208-224.

Pruitt, D. G. (1981). Negotiation Behavior--Organizational and Occupational Psychology.

Rick, S., Weber, R., & Camerer, C. F. (2007). Knowledge Transfer in Simple Laboratory Firms: The Role of Tacit vs. Explicit Knowledge. *Department of Social and Decision Sciences Working Paper.*

Singh, J., & Agrawal, A. (2011). Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Science*, 57(1), 129-150.

Singh, J., & Fleming, L. (2010). Lone inventors as sources of breakthroughs: Myth or reality?. *Management Science*, *56*(1), 41-56.

Sonnemann, U., Camerer, C. F., Fox, C. R., & Langer, T. (2013). How psychological framing affects economic market prices in the lab and field. Proceedings of *the National Academy of Sciences*, 110(29), 11779-11784.

Swed, F. S., & Eisenhart, C. (1943). Tables for testing randomness of grouping in a sequence of alternatives. *The Annals of Mathematical Statistics*, 14(1), 66-87.

Wuchty, S., Jones, B. F., & Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, *316*(5827), 1036-1039.

Figure 1: Structure of Equal and Unequally Shared License Revenue between Inventors

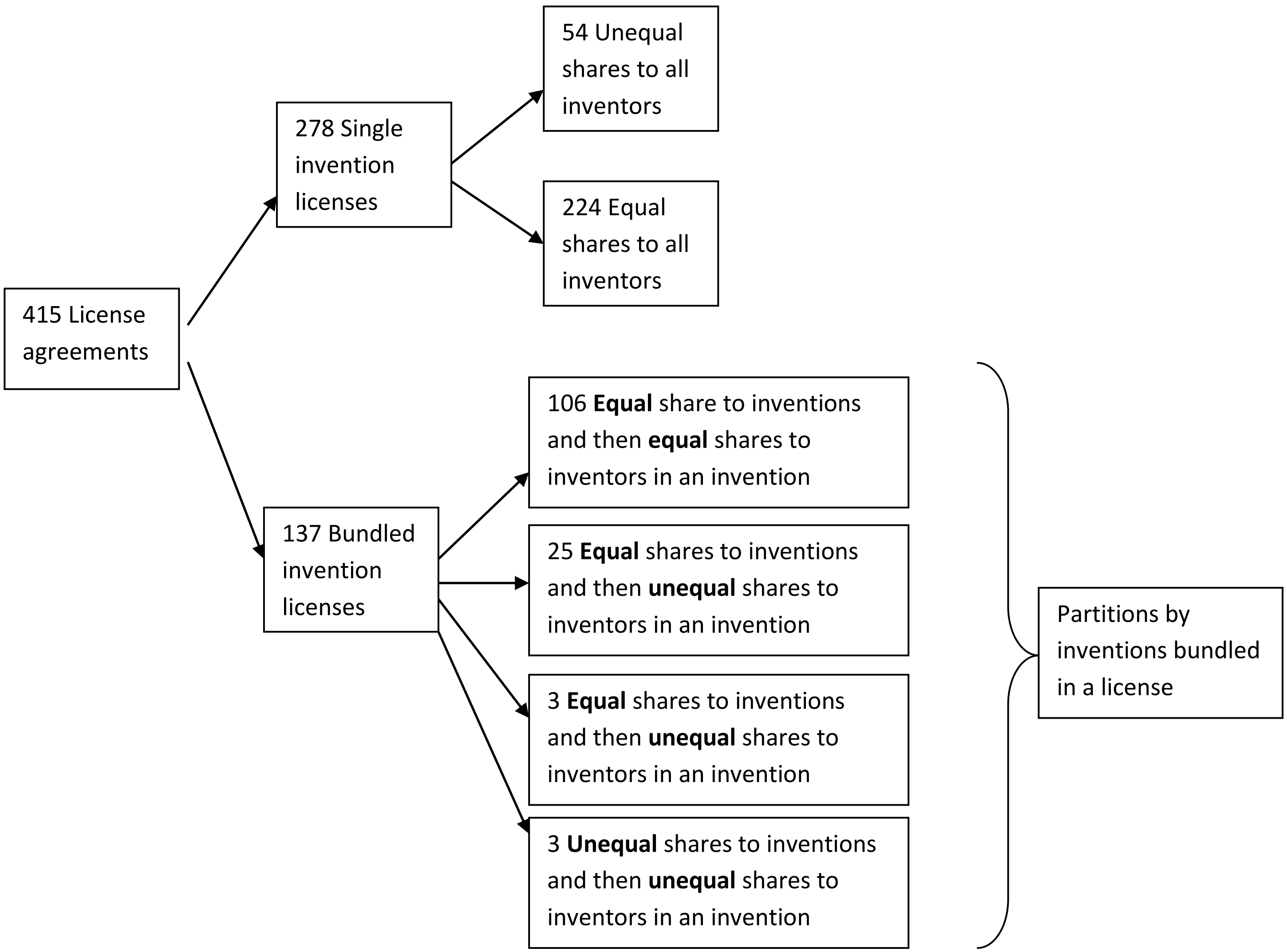

Table 1: Summary statistics and correlations

Inventor share is the share an inventor receives in a license. The other variables are as follows: *publications*, the natural log of cumulative publications that an inventor has minus the average for the team; *invention experience*, the total experience the inventor has prior to the licensing of the current agreement minus the average for the team; *one-by-N* is the inventor's share, predicted by 1 divided by the number of unique inventors in a licensed agreement; *partition dependence,* the share predicted by the division of a licensed agreement by number of unique inventions in the licensed agreement and then by the number of unique inventors in each of those licensed inventions.

	Variables	mean	sd	min	max	1	2	3	4	5
1	Inventor share	0.3	0.2	0.0007	0.83	1				
2	Publications	-0.3	1.4	-4.3	3.4	0.327***	1			
3	Experience	-0.2	1.0	-3.8	3.8	0.403***	0.619***	1		
4	Size	6.1	5.5	2	26	-0.636***	-0.242***	-0.349***	1	
5	1/N Rule	0.3	0.1	0.038	0.5	0.828***	0.175***	0.263***	-0.769***	1
6	Partition Dependence	0.3	0.2	0.004	0.83	0.950***	0.328***	0.429***	-0.669***	0.866***

N=1723; * p<.10, ** p<.05, *** p<.01

Table 2: Inventor Fixed Effects Estimations of Share an Inventor Receives in a Licensed Agreement
The dependent variable for the analysis is the share an inventor receives in a licensed agreement. If the license has more than one invention bundled into it, then it is the sum of the shares across all inventions that an inventor is part of in an agreement. Explanatory variable are as follows: *publications,* the natural log of cumulative publications that an inventor has minus the average for the team; *invention experience*, the total experience the inventor has prior to the licensing of the current agreement minus the average for the team; *one-by-N,* inventor's share, predicted by 1 divided by the number of unique inventors in a licensed agreement; *partition dependence*, the share predicted by the division of a licensed agreement by the number of unique inventions in the licensed agreement and then by the number unique inventors in each of those licensed inventions. *Year fixed effects* are included but not reported. Models 1, 2, and 3 use the full sample. Model 4 is the sub-sample with one invention per contract. In Model 4, 1/N rule and partition dependence rule are the same; hence, partition dependence is dropped as an explanatory variable in Model 5. Models 5, 6, and 7 are the subsample with two or more inventions per contract.

Dependent variable: Inventor's share of revenue (%)	All inventions			Single invention	Multiple inventions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Difference in publications	-0.012	0.0066	0.0031	-0.0070	0.017**	0.021*	0.017**
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Difference in invention experience	-0.012	-0.011*	-0.0030	-0.027***	-0.0018	-0.00097	-0.0019
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
1/n rule		0.72***	0.043*	1.00***	0.045	0.56***	
		(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	
Partition rule			0.94***		0.84***		0.87***
			(0.02)		(0.04)		(0.03)
Constant	0.29***	0.071**	0.013	-0.0088	0.052**	0.100***	0.057**
	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)
r2	0.032	0.49	0.80	0.77	0.68	0.36	0.68
N	1735	1735	1735	934	801	801	801

Standard errors in parentheses; * p<.05, ** p<.01, *** p<.001

Table 3: Summary Statistic at the Level of Invention

Performance is the amount of money that an invention receives. *Grant windfall* is the log of the dollars received in the domain of the inventors in a year. *Team size* is the number of inventors in an invention. *Number of inventions bundled* is the total number of inventions bundled and licensed together. *Prior collaborations* are the proportion of inventors in a team that had prior inventions together. *Invention experience* is the average number of inventions disclosed by the inventors. *Publications* is the average number of publications of the inventors. *Interdisciplinary* is when all inventors come from the same domain or different domains. *Prior performance* is the income from licensing prior to focal invention. *Cites received* are the forward patent citations received. *Late-stage inventions* measure the citations made to other patents. *Continuing invention* describes whether the current invention is stand-alone or related to prior inventions by the inventors. *Licensee size* is whether the licensee is a public company. *Licensee expertise* is whether the licensee has patents in the domain of the focal invention.

	Not N or PDs (N=85)		**N or PDs** (N=330)		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	T-test
Performance ('000)	125,612.9	660430.0	22,850.5	77597.7	**
Grant windfall (lg)	188.7	84.7	126.6	91.9	***
Team size	6.3	5.0	3.3	1.8	***
Number of inventions bundled	4.0	7.2	1.8	1.8	***
Prior collaborations	0.1	0.2	0.2	0.4	***
Invention experience	11.3	24.2	3.8	8.0	***
Invention experience s.d.	8.4	19.0	3.9	12.7	
Publications	3.4	0.7	2.7	0.9	***
Publications s.d.	3.4	0.8	3.4	1.0	
Interdisciplinary	0.2	0.2	0.3	0.4	
Agreement type	0.5	0.5	0.3	0.5	***
Prior performance	82.5	57.5	41.0	47.9	***
Cites received	0.2	1.0	0.3	0.9	
Late stage invention	0.2	0.6	0.3	0.7	
Continuing invention	1.4	3.2	0.9	1.6	
Licensee size	0.5	0.5	0.2	0.4	***
Licensee expertise	0.3	0.5	0.4	0.5	**

Table 4: OLS Estimation of Choice of N or PD Regime
(All variables are defined in Table 3)

Dependent variable: N or PD (1/0)	Model 1	
Grant windfall	-0.0012***	(0.00)
Team size	-0.056***	(0.01)
Number of inventions bundled	-0.017	(0.01)
Prior collaborations	0.12***	(0.04)
Invention experience	-0.0073**	(0.00)
Invention experience s.d.	0.0068***	(0.00)
Publications	-0.11***	(0.02)
Publications s.d.	0.11***	(0.02)
Interdisciplinary	-0.040	(0.05)
Prior performance of inventors	-0.0011**	(0.00)
Citations of patent	0.011	(0.02)
Late stage	0.010	(0.03)
Continuing invention	0.066***	(0.02)
Licensee size	-0.10***	(0.04)
Licensee expertise	0.0057	(0.04)
Constant	1.50***	(0.37)
r2	0.50	

Standard errors in parentheses; * p<.10, ** p<.05, *** p<.01

Table 5: Results of Performance Estimations
(All variables are defined in Table 3)

	OLS Performance	
N or PD	-2.20***	(0.65)
Grant windfall	-0.0025	(0.00)
Team size	-0.066	(0.12)
Number of inventions bundled	-0.19	(0.15)
Prior collaborations	2.23***	(0.55)
Invention experience	-0.0068	(0.04)
Invention experience s.d.	0.020	(0.03)
Publications	-0.0050	(0.29)
Publications s.d.	-0.48*	(0.27)
Interdisciplinary	-0.34	(0.63)
Prior performance of inventors	0.0044	(0.01)
Citations of patent	0.73***	(0.26)
Late stage	0.077	(0.32)
Continuing invention	0.34	(0.22)
Licensee size	1.28***	(0.49)
Licensee expertise	0.022	(0.44)
Constant	10.5**	(4.63)
r2	0.30	

Standard errors in parentheses; * p<.10, ** p<.05, *** p<.01

Table 6: Summary Statistics of the Matched Sample
(All variables are defined in Table 3)

Variable	N or PD (118)				Not N or PD (48)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Prior collaborations	0.1	0.4	0.0	1.0	0.1	0.2	0.0	1.0
Inventor experience	9.5	28.2	0.0	179.0	20.3	48.9	0.0	179.0
Inventor publications	70.3	87.2	2.0	552.0	114.2	138.9	23.0	552.0
Prior performance	27.6	44.1	0.0	158.0	67.4	61.5	0.0	156.0
Quality of invention	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Late stage invention	0.0	0.1	0.0	1.6	0.0	0.3	0.0	1.8
Licensee size	0.2	0.4	0.0	1.0	0.3	0.5	0.0	1.0
Licensee capabilities	0.3	0.5	0.0	1.0	0.3	0.4	0.0	1.0

Table 7: Results of Performance Estimations with and without matched sample
(All variables are defined in Table 3)

	Full Sample				**Matched Sample**			
	Model 1		Model 2		Model 3		Model 4	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Constant	-8.63*	(5.17)	-7.76	(5.09)	-6.19	(5.72)	-6.00	(5.73)
Prior collaborations	1.91***	(0.50)	2.23***	(0.50)	-0.83	(1.11)	-0.77	(1.11)
Inventor experience	0.012	(0.01)	0.0089	(0.01)	0.080**	(0.03)	0.081**	(0.03)
Inventor publications	-0.0086**	(0.00)	-0.0078**	(0.00)	-0.026**	(0.01)	-0.026**	(0.01)
Prior performance	0.0093*	(0.01)	0.0054	(0.01)	0.0029	(0.01)	0.0013	(0.01)
Quality of invention	0.63***	(0.24)	0.68***	(0.23)	0	(0.00)	0	(0.00)
Late stage invention	-0.20	(0.32)	-0.12	(0.31)	-3.03	(2.20)	-3.05	(2.20)
Licensee size	1.69***	(0.47)	1.45***	(0.47)	0.91	(0.95)	0.88	(0.95)
Licensee capabilities	-0.15	(0.43)	-0.056	(0.42)	-0.62	(0.84)	-0.66	(0.84)
N or PD (1/0)			-1.89***	(0.53)			-0.81	(0.85)
Domain fixed effects	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
r2	0.28		0.30		0.32		0.32	
N	415		415		166		166	

Standard errors in parentheses;* p<.05, ** p<.01, *** p<.001

Table 7A: Results of Performance Estimations with and without matched sample

(All variables are defined in Table 3)

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Prior collaborations			-0.13	(1.10)	0.67	(0.93)	0.21	(0.95)	-0.22	(1.05)	-0.19	(0.98)	-0.79	(0.99)	-0.81	(1.07)
Inventor experience	0.081**	(0.03)			0.0097	(0.02)	0.057**	(0.02)	0.035*	(0.02)	0.050**	(0.02)	0.040**	(0.02)	0.071**	(0.03)
Inventor publications	-0.026***	(0.01)	-0.0042	(0.01)			-0.024***	(0.01)	-0.017*	(0.01)	-0.014**	(0.01)	-0.020**	(0.01)	-0.022**	(0.01)
Prior performance	0.0041	(0.01)	0.0068	(0.01)	-0.0076	(0.01)			0.0063	(0.01)	-0.0052	(0.01)	0.011	(0.01)	0.00017	(0.01)
Quality of invention	0	0.00	0	0.00	0	0.00	0	0.00			0	0.00	0	0.00	0	0.00
Late stage invention	-2.95	(2.15)	-3.77*	(2.22)	-4.17*	(2.34)	-1.85	(1.44)	-0.62	(1.48)			-1.85	(1.47)	-3.33	(2.17)
Licensee size	1.42*	(0.78)	0.92	(0.97)	0.89	(0.97)	0.88	(0.80)	0.96	(0.89)	0.76	(0.83)			1.2	(0.90)
Licensee capabilities	-0.49	(0.73)	-0.56	(0.85)	-0.29	(0.70)	-0.14	(0.76)	-0.67	(0.78)	-0.23	(0.63)	-0.72	(0.72)		
N or PD (1/0)	-1.01	(0.79)	-0.74	(0.86)	-1.04	(0.75)	-1	(0.64)	-1.14	(0.80)	-1.47**	(0.66)	-1.18	(0.75)	-0.87	(0.81)
Domain fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Matched case: not N or PD	49		46		48		68		51		53		61		749	
Matched cases: N or PD	128		117		161		179		127		172		127		123	
Imbalance after matching	0.41		0.32		0.22		0.57		0.29		0.59		0.25		0.33	
Imbalance before matching	0.72		0.73		0.69		0.63		0.72		0.66		0.7		0.72	

Standard errors in parentheses; * p<.10, ** p<.05, *** p<.01

Figure 2: Period Income for an Inventor by type of Regime

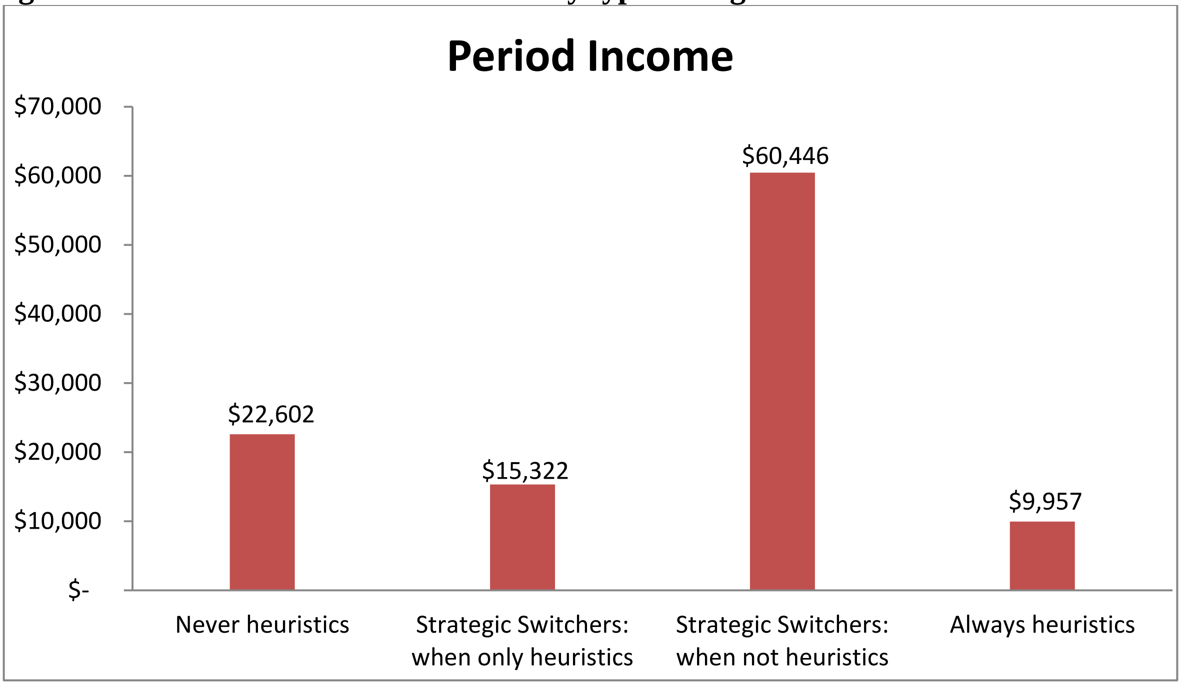

Table 8: Results of Performance Estimations with Inventor Type

(All variables are defined in Table 3)

	Model 1		Model 2		Model 3	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Prior collaborations	2.23***	(0.50)	2.20***	(0.50)	2.24***	(0.51)
Inventor experience	0.0089	(0.01)	0.0091	(0.01)	0.0088	(0.01)
Inventor publications	-0.0078**	0.00	-0.0075**	0.00	-0.0076**	0.00
Prior performance	0.0054	(0.01)	0.0048	(0.01)	0.0049	(0.01)
Quality of invention	0.68***	(0.23)	0.75***	(0.24)	0.72***	(0.24)
Late stage invention	-0.12	(0.31)	-0.11	(0.31)	-0.11	(0.31)
Licensee size	1.45***	(0.47)	1.57***	(0.47)	1.49***	(0.47)
Licensee capabilities	-0.056	(0.42)	-0.0065	(0.43)	-0.029	(0.43)
N or PD(1/0)	-1.89***	(0.53)				
Strategic Switchers			-1.21	(0.80)		
Always N or PD			-2.21***	(0.65)	-2.18***	(0.65)
Strategic Switchers: N or PD					-1.73*	(0.95)
Strategic Switchers: not N or PD					-0.61	(0.99)
Domain fixed effects	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	
r2	0.22		0.24		0.24	

Standard errors in parentheses; * p<.10, ** p<.05, *** p<.01

Figure 3: Revenues By Type of Regime and By Inventor's Experience

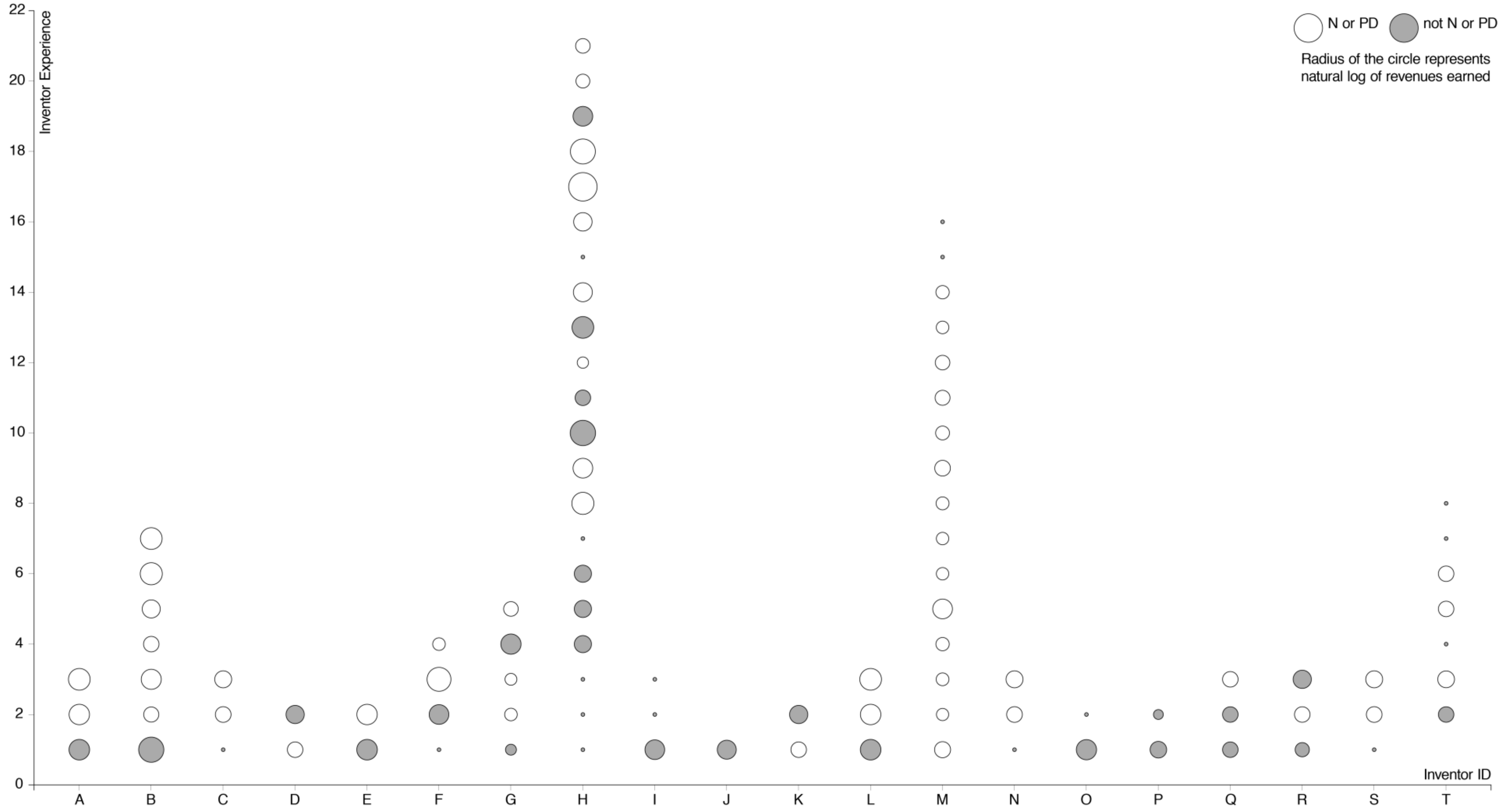

Table 9: Test of Randomness of Choice between N or PD by Strategic Switchers

Inventor ID	Observations	N(runs)	Prob>|z|
3	3	2	0.48
5	7	2	0.11
6	3	2	0.48
12	2	2	--
13	2	2	--
15	4	3	0.32
16	5	4	0.51
18	44	2	**0.001**
21	21	12	0.33
28	3	2	0.48
33	2	2	--
38	3	2	0.48
47	16	2	**0.01**
50	3	2	0.48
51	2	2	--
60	3	2	0.48
62	3	2	0.48
63	3	2	0.48
64	7	2	0.11

Figure 4: Period Publications

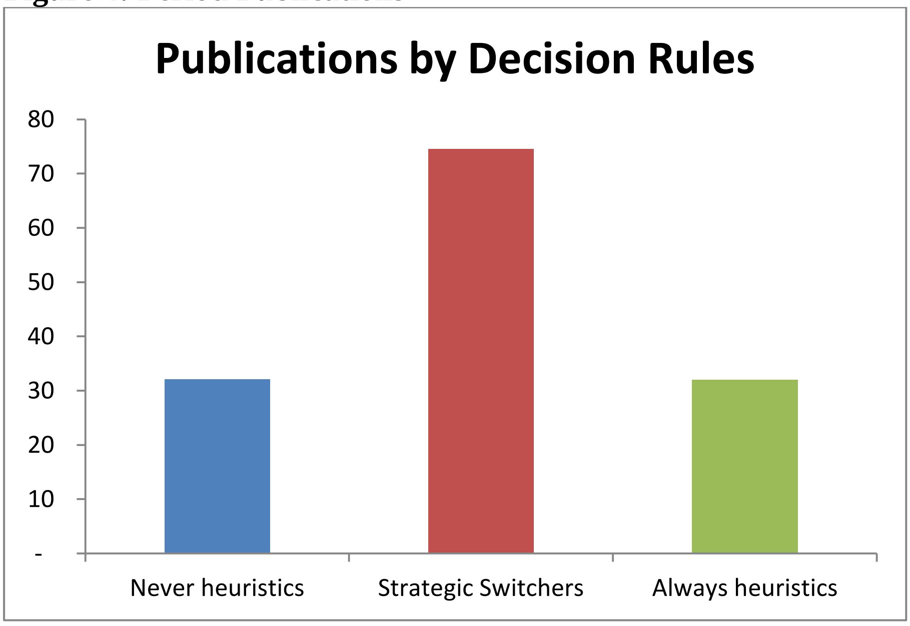

Figure 5: Share in a PD Contract of a Lead and Other Inventors