So You Discovered an Anomaly…Gonna Publish It?

An investigation into the rationality of publishing market anomalies

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Abstract

If publishing an anomaly leads to the dissipation of its profitability, a notion that has mounting empirical support, then publishing a highly profitable market anomaly seems to be irrational behavior. This paper explores the issue by developing and empirically testing a theory that argues that publishing a market anomaly may, in fact, be rational behavior. The theory predicts that researchers with few (many) publications and lesser (stronger) reputations have the highest (lowest) incentive to publish market anomalies. Employing probit models, simple OLS regressions, and principal component analysis, we show that (a) market anomalies are more likely to be published by researchers with fewer previous publications and who have been in the field for a shorter period of time and (b) the profitability of published market anomalies is inversely related to the common factor spanning the number of publications the author has and the number of years that have elapsed since the professor earned his Ph.D. The empirical results suggest that the probability of publishing an anomaly and the profitability of anomalies that are published are inversely related to the reputation of the authors. These results corroborate the theory that publishing an anomaly is rational behavior for an author trying to establish his or her reputation.

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I. Introduction

If a finance professor discovers a strategy, say a profitable anomaly to market efficiency, that yields consistent abnormal returns, why would he publish it? Basic principles of economics dictate that any economic activity that produces abnormal profits attracts attention, which eventually leads to new entry into the activity. The new competition then drives profits down until the activity offers only normal profits over the long run.

Ackerman, McEnally, and Ravenscraft (1999) offer some support for this notion in the realm of investing. They report that hedge funds that cease voluntarily reporting performance are either abysmally low or exceptionally high performers. The cessation of reporting by exceptional performers is consistent with the idea that they don't want to attract attention and have their strategies reverse engineered into the disappointing oblivion of merely normal profits.

A new anomaly to market efficiency that yields abnormal profits could easily be classified as an "economic activity that produces abnormal profits." Any anomaly that produces abnormal returns should attract attention and lead to an increased number of investors trading on the anomaly. As the number of investors using the anomaly increases, the profitability of the anomaly should eventually dissipate until it yields profits exactly commensurate with the risk involved. This is expected even when the purveyor of the anomaly is as secretive as possible. Publishing it in some medium that would give a large number of investors immediate access to the anomaly would presumably tremendously expedite the dissipation of its profitability.

Publishing a profitable market anomaly, then, seems to be absurdly irrational behavior. Yet in spite of the apparent irrationality, numerous articles have been published introducing profitable market anomalies (see Schwert (2002) and Russell and Torbey (2002) for surveys of the subject of market anomalies and Roll (1983) and

Jegadeesh and Titman (1993) for examples of typical market-anomaly articles).[1] Indeed, we observe many articles introducing and discussing anomalies, but we have observed no articles seeking to explain why a rational finance professor would be willing to publish an anomaly in the first place.

To us, what is more perplexing than the existence of market anomalies is the fact that anyone, and especially a finance professor who presumably understands how to invest and is interested in making money, is willing to publish them once discovered. Could it be that the group of individuals who arguably subscribe most ardently to the assumption of rational economic participants are themselves exhibiting irrational behavior in the act of publishing profitable market anomalies? The primary contribution of our work is to get to the bottom of this potentially troubling question.

Our specific contribution is to introduce and empirically test a theory that outlines conditions under which the publishing of a market anomaly is rational behavior. The model predicts that publishing an anomaly to market efficiency is rational behavior if the professor authoring the article has relatively few publications and little reputation in the field. The theory, however, poses a very interesting implication for the academic side of finance: it suggests that the most accomplished finance professors have the highest incentive not to publish profitable anomalies to market efficiency.

In answering the above research question, this paper contributes both to the literature on market efficiency and anomalies to market efficiency. It also contributes to the field of metafinance, which Cooley (1994) defines as the study of the nature, structure, and behavior of finance. We present the theory and assumptions in Section II and discuss the empirical implications in Section III.

We then analyze the primary empirical implication of the model, that anomalies to market efficiency are most likely to be published by professors who are relatively young in their careers and have not yet established a strong reputation in the field, in Sections IV and V. We close with a discussion and conclusions in Section VI.

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[1] There have also been articles about how profitable market anomalies are, how persistent they are, and what does or does not explain them (see, for instance, George and Hwang (2004), Dimson and Marsh (1999), Jegadeesh and Titman (2001), Schwert (2002), Grundy and Martin (2001) and Cooper, Guitierrez, and Hameed (2004)). But I can find no articles that address the fundamental question of why finance professors are willing to publish them in the first place.

II. The Theory and Assumptions

Foundational Assumptions

We develop and propose the following model with the intent of arriving at a set of empirical implications and predictions from the model that can, in fact, be tested. Accordingly, as we define variables in the model, we are less concerned with how easily the variables can be quantified and more concerned with how accurately the variables represent the assumptions of the model, which we hope conform to reality as far as assumptions in economic models can be expected to, while still maintaining overall model tractability. Two primary assumptions buttress the model and deserve brief discussion prior to formal development of the model:

> *ASSUMPTION 1*: Once an anomaly to market efficiency is published, its profitability diminishes so that the only anomalies a finance professor can profitably implement are those he does not publish.
>
> *ASSUMPTION 2*: A finance professor's opportunities to accept employment as a professional money manager or to start his own hedge or mutual fund are directly correlated with his reputation.

The first assumption is based on the discussion of the basic principles of competitive free markets in the introduction. Empirical work has already been done corroborating this idea. Dimson and Marsh (1999) present evidence that both in the U.S. and the U.K. the size effect conspicuously dissipates or even reverses subsequent to the publicizing of the anomaly in both countries. The authors disclaim the intent and findings of their paper by stating, "…we are not suggesting that the reversal of the small-cap premium is a consequence of its discovery and dissemination. Instead, our evidence suggests that the reversal resulted from a change in fundamentals, not just a change in sentiment." But the timing of the dissipation and reversal of the size effect in both countries reported in their paper adds credibility to the assumption that publishing an anomaly leads to its downfall.

Marquering Nisser, and Valla (2006) take a less apologetic stance. They show that since initial publication, the weekend effect, the holiday effect, the time-of-the month effect, and the January effect have all disappeared. Their results suggest that publication does, indeed, lead to an anomaly's demise.

Similarly, Schwert (2002) finds that the size effect, value premium, weekend effect, and dividend-yield effect all have dissipated since initial publication. Schwert notes two possibilities explaining the dissipation of the anomalies: either they were anomalously isolated to the sample period in which they were identified or they were exploited by practitioners causing their gradual disappearance. His second explanation is consistent with the foundational assumption of our model that publishing an anomaly contributes to the dissipation of its profitability.[2]

Related to the second foundational assumption, anecdotal evidence suggests reputation does, in fact, play a role in the probability of landing a lucrative position as a professional money manager. Examples of finance professors who have been or currently are employed as professional money managers or compensated advisors to professional money managers include Mark Carhart, Eugene Fama, Kenneth French, Sandy Grossman, Josef Lakonishok, Robert Merton, Richard Roll, Stephen Ross, Ourron Scholes, Andrei Shleifer, Robert Vishney, and others still. While this list does nothing to statistically validate the assumption, it offers enough incentive to proceed with the analysis.

The Model

We begin formal development of the theory with the assumption that a finance professor's utility (U) is a Cobb-Douglas[3] function of two variables: wealth (W) and reputation (R).

$$U(W,R) = W^{\alpha} R^{\beta} \tag{1}$$

Researchers using the Cobb-Douglas utility function often impose the constraint that $0 \le \alpha \le 1$ and that $\beta = 1 - \alpha$ (see Douglas (1976)). Since these constraints ensure

[2] Schwert (2002) reports that the January effect has persisted, though to a lesser degree, since initial publication. Further, momentum seems to have actually strengthened since initial publication. However, the majority of the evidence supports the assumption that anomalies seem to dissipate and even disappear after publication.

[3] Tversky and Kahnemann (1991) list Cobb-Douglas as one of the commonly used utility functions.

that the utility function satisfies the general axioms of consumer choice, we also adopt them in our model. [4,5]

We assume that a finance professor's reputation is a log function of his publication record (P). The variable P takes into account both the quality and quantity of his published research and is on the scale of one to infinity (one meaning he has no publications).[6] P is also raised to the power of a positive constant parameter, λ_R, within the natural log.

$$R(P) = \ln(P^{\lambda_R}) \tag{2}$$

The log relationship, along with the positive constant parameter λ_R and lower bound on the value of P, ensures that the first derivative of reputation (R) with respect to publication (P) is positive while the second derivative is negative – indicating that the marginal impact of publication on reputation is positive but decreasing as P increases. This captures the notion that the first few top articles do more for one's reputation than does the 30th. For example, how much would another Journal of Finance article increase Eugene Fama's reputation? How much would a Journal of Finance article increase our reputation (as of this writing, we have none)? We argue it would marginally improve our reputation more than it would his. The constant parameter λ_R allows flexibility in the magnitude of the influence of publication on a professor's reputation.[7]

Next, we assume that wealth (W) is the sum of a professor's salary (S), which is the compensation paid to the professor from the university or college, and outside income (O), which includes income from investing and compensation from service as a professional money manager.

$$W(S,O) = S + O \tag{3}$$

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[4] The constraint that $\beta = \alpha - 1$ is not necessary for the function to satisfy the axioms of consumer choice. (Nor is it necessary for the development of the model in this paper.) The only constraints necessary to ensure satisfaction of the axioms of consumer choice are that $\alpha < 1$ and $\beta \leq 1$ or $\alpha \leq 1$ and $\beta < 1$.

[5] The Cobb-Douglas function was first introduced in 1928 (Cobb and Douglas (1928)) to model production functions and has since been used extensively to model utility functions.

[6] P is on the scale $1 - \infty$ to prevent reputation from taking a negative value.

[7] Since the form of equation (2) is used throughout the model with other variables, we graphically represent the relationship in Appendix A.

we assume salary is a linear function of reputation with the positive constant, δ_S, as the slope.

$$S = \delta_S R \tag{4}$$

One may argue that salary should be a log function of reputation to capture a positive but decreasing marginal relationship. This is unnecessary, however, since reputation is a log function of a single variable – publishing (P). So one may more accurately think of salary as a log function of publishing by substituting equation (2) into equation (4) to obtain equation (5).

$$S = \delta_S \ln(P^{\lambda_R}) \tag{5}$$

Similar to the relationship between publication and reputation, equation (5) suggests that a professor's first few top articles contribute more marginally to his salary than does his 30th. This is supported by Swidler and Goldreyer (1998) who report that the first top publication for an assistant professor increases the present value of his lifetime earnings by $33,754 on average. His second and third top publications increase the present value of his total earnings by $32,820 and $31,886, respectively. Their results validate the assumption of a positive but diminishing marginal relationship between publication (P) and salary (S). For tractability, we present salary as a linear function of reputation, instead of as a log function of publishing. The constant positive parameter, δ_S allows for flexibility in the magnitude of the influence of reputation on salary.[8]

We assume outside income is a function of reputation (R) and the profitability (π) of the professor's unpublished research, which is on the scale of one to infinity (one meaning the unpublished strategy offers no profits).[9] Specifically, his outside income is assumed to be a log function of the profitability of his unpublished work raised to a constant positive parameter, λ_O. This log term is then multiplied by his reputation times a constant positive parameter, δ_O.

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[8] I also impose the constraint that $P^{\lambda_R} > 1$, which would ensure that the term $\ln(P^{\lambda_R})$ is positive, thus guaranteeing salary (S) > 0. Since P is already constrained to be equal to or greater than 1, this amounts to imposing the constraint that $\lambda_R > 1$.

[9] π is on the scale $1 - \infty$ to prevent outside income from assuming a negative value.

$$O(\pi) = \delta_O R \ln(\pi^{\lambda_O}) \tag{6}$$

The log function, along with the positive constant parameters δ_O and λ_O and lower bound on the value of π, serves the same role as outlined above – ensuring a positive first derivative and negative second derivative. The constant positive parameters λ_O allows flexibility in the magnitude of the influence of the profitability of unpublished work on a professor's outside income, while the constant positive parameter δ_O allows flexibility in the magnitude of the influence of reputation on outside income.

The inclusion of reputation in the function is critical and represents the foundational assumption that the possibility of a finance professor working as professional money manager is positively related to reputation. This has anecdotal support as discussed earlier.

The collective intuition behind equation (6) is that a finance professor needs reputation (R) to get the opportunity to work as a professional money manager and he needs profitable strategies to substantially gain from that employment. According to the foundational assumption outlined earlier, the only plausible profitable strategies assumed in the model are those the professor has developed but not published (π).

We next perform a few simple substitutions to represent the utility function in a workable form. We first substitute equations (4) and (6) into equation (3) to obtain equation (7) and arrange terms to arrive at equation (8).

$$W(S,O) = \delta_S R + \delta_O R \ln(\pi^{\lambda_O}) \tag{7}$$

$$W(S,O) = R[\delta_S + \delta_O \ln(\pi^{\lambda_O})] \tag{8}$$

Now we substitute equation (8) into equation (1) to arrive at equation (9) and perform some simple algebraic manipulations to obtain equations (10) and (11):

$$U(W,R) = \{R[\delta_S + \delta_O \ln(\pi^{\lambda_O})]\}^{\alpha} R^{\beta} \tag{9}$$

$$U(W,R) = [\delta_S + \delta_O \ln(\pi^{\lambda_O})]^{\alpha} R^{\alpha+\beta} \tag{10}$$

$$U(W,R) = A^{\alpha} R^{\alpha+\beta} \tag{11}$$

$$\text{where A} = [\delta_S + \delta_O \ln(\pi^{\lambda_O})] \tag{12}$$

Equation (11) becomes the key utility function that will serve as the focus of the analysis. The primary question of interest is at what point a finance professor is more motivated to publish than he is not to publish. If this condition exists, it would be rational to publish a market anomaly. In mathematical terms, under what conditions does the marginal utility from publishing exceed the marginal utility from not publishing?

$$\frac{\partial U}{\partial \pi} < \frac{\partial U}{\partial P} \tag{13}$$

In order to answer this question, we need the partial derivative of utility with respect to both P and π, which we calculate in detail in Appendix B. For brevity, we present the final results below. Since a professor will choose to publish only when equation (13) holds, we substitute into equation (13) the partial derivatives obtained in Appendix B to obtain equation (14):

$$\left(\alpha A^{\alpha-1}\right)\left(\frac{\delta_O \lambda_O}{\pi}\right) R^{\alpha+\beta} < A^{\alpha}\left[(\alpha+\beta) R^{\alpha+\beta-1}\right]\left(\frac{\lambda_R}{P}\right) \tag{14}$$

We now rearrange the inequality to more clearly ascertain under what conditions equation (13) holds:

$$\left(\frac{R^{\alpha+\beta}}{R^{\alpha+\beta-1}}\right)(P)\left(\frac{\alpha}{\alpha+\beta}\right)\left(\frac{\delta_O \lambda_O}{\lambda_R}\right) < \left(\frac{A^{\alpha}}{A^{\alpha-1}}\right)(\pi) \tag{15}$$

After some simple algebraic reduction, equation (15) becomes:

$$RPk < A\pi \tag{16}$$

$$\text{where } k = \left(\frac{\alpha}{\alpha+\beta}\right)\left(\frac{\delta_O \lambda_O}{\lambda_R}\right) \tag{17}$$

The most intelligible interpretation of (16) is obtained by holding the right-hand variables constant – i.e., assuming that the profitability of a strategy (π) and its influence on wealth without regard to reputation (A) are constant. Holding the right-hand variables constant, then, what decreases the left side of equation (16)? I.e., what conditions on the left-hand side of equation (16) would increase a finance professor's incentive to publish his strategy?

The left side of equation (16) decreases as R, P, δ_O, λ_O, and α decrease and as λ_R and β increase. So low values of R, P, δ_O, λ_O, and α, along with high values of λ_R and β, lead to a higher incentive for a finance professor to publish. Since R is a function of P, both R and P are low when a professor is not well published in terms of both quality and quantity. α is low and β is high (since $\beta = 1 - \alpha$) when a professor places greater proportional utility on reputation than on wealth. δ_O and λ_O are low when the marginal contribution of not publishing (π) to wealth is low while λ_R is high when the marginal contribution of publishing (P) to reputation is high.[10] However, δ_O and λ_O are also on the right side of the inequality, so interpretation of their effect on the net incentive or disincentive to publish is less clear.

III. Model Implications

The results are generally intuitively acceptable. A professor is most inclined to publish when the following hold (a) he has little reputation (R is low), meaning he is not well published (P is low), (b) he derives more proportional utility from reputation than from wealth ($\alpha > \beta$), or (c) the marginal impact of publishing on reputation is relatively high compared to the marginal impact of not publishing on wealth ($\delta_O\lambda_O < \lambda_R$). Conditions (b) and (c) are fairly straightforward and involve, in our opinion, little controversy. Condition (a), however, merits further discussion.

The good news from condition (a) is that the model arrives at a condition that is prevalent in the real world (a finance professor having little reputation and few publications) under which it is perfectly rational for a utility maximizing professor to publish a market anomaly. Condition (a) also suggests, however, that a professor who is widely published and has a strong reputation will gain little marginal benefit from an additional publication containing a profitable strategy he has developed. He will, instead,

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[10] Since the first derivative of reputation (R) with respect to publishing (P) is $\frac{\lambda_R}{P}$ and the first derivative of wealth (W) with respect to not publishing (π) is $\frac{\delta_O R \lambda_R}{\pi}$.

derive more marginal utility from using the information in unpublished form to increase his wealth through the opportunity to act as a professional money manager, which opportunity is made available to him because of his well-established reputation and publication record.

While condition (a) is intuitively acceptable, it is also academically troubling. The model predicts that the best and brightest minds in academia, defined by their record of publication, have the strongest incentive not to publish their work, especially if their personal utility is disproportionately derived from wealth ($\alpha > \beta$ in equation (1)). And the result seems to have some anecdotal support (see the list presented earlier of finance professors who have been or are employed as professional money managers).

This may actually be bad for market efficiency as well. When a professor publishes his profitable strategy, a large number of investors presumably become aware of and trade on the strategy, which causes a relatively rapid dissipation in the profits of the strategy. Conversely, when a professor doesn't publish the strategy, very few investors initially trade on the strategy, so that its profitability persists. Only over time do investors infer the unpublished strategy and trade on it. So the outcome of the model may be bad both for academia and for market efficiency.

Fortunately, the theoretical model outcome offers a clear, testable empirical implication. The finance professors with the greatest incentive, and for whom it is most rational, to publish profitable anomalies to market efficiency or advances to asset pricing models are those with relatively lesser reputations. Since reputation in the model is a direct result of publications, the model predicts that anomalies are most likely to be published by authors with relatively few publications. Such professors will have lesser reputations and, therefore, fewer or no opportunities to work as professional money managers. Hence, they derive more reputational utility from publishing the information than they would wealth utility from not publishing the information and using it in their own personal trading. Another observable variable that likely correlates positively with reputation is the years since a professor received a Ph.D. Professors who are newer to the field will likely have lesser reputations on average. Accordingly, the model predicts that anomalies to market efficiency are most likely to be published by professors with a relatively small record of publications and who are newer to the field. We empirically analyze this implication in Sections IV and V.

The theoretical model also contains at least one other empirically testable point. The model suggests that the finance professors who are most likely to start their own hedge or mutual funds or to be employed as professional money managers are those with strong publishing records, since such professors will presumably have higher reputations and, therefore, more opportunities to work as professional money managers. We leave this point, however, for future work.

IV. Analysis of Empirical Implications – Data and Methods

In this section we analyze the primary implication of the model outlined in Section II – that anomalies to market efficiency on average are expected to be published by finance professors with lesser reputations. Determining adequate proxies for reputation are critical to the success of the analysis.

Since reputation in the theoretical model is driven by publications, we assume that the publication record of an author is one viable proxy for reputation. However, it is not clear what affects reputation the most. Is it the total publications or only the top publications? We include both non-top publications and top publications (to be defined later) in the analysis. Another viable proxy is the years since an author received his Ph.D. While it is conceivable that a newcomer may quickly establish a strong reputation, it is more likely that establishing a reputation takes time. Accordingly, a second proxy for reputation is the years since an author received his Ph.D.

The testing, then, requires data regarding the number of publications of finance professors in the study. Heck and Cooley (2005) use similar data to identify the most prolific authors in finance. They compile an extensive database of authorship data by reviewing all articles published in 72 finance journals since 1953. Heck has established an electronic database (econlibrary.com), which gives users access to his extensive data for an annual subscription fee. We rely on his database to obtain publication data for all finance professors in our study.

To test the primary empirical implication of the model we identify the first authors who published the most well-known market anomalies. The list of well-known anomalies comes from work in the first essay of Colby Wright's dissertation and from a survey piece on the subject by Russell and Torbey (2002). Table 1 presents the anomalies used in the analysis that follows along with the authors identified as the first to publish the anomalies. A total of 33 anomalies are used included in the sample for this study.

Deciding what qualifies as an anomaly requires some subjectivity. Generally, we rely on the survey articles mentioned above to identify candidates. We augment this list of candidates with our own reading of the literature, especially in years since the surveys were published. In order to enter the sample, an anomaly also has to contain a potentially implementable trading strategy. This generally precludes any anomalies from the sample that show abnormal returns over a relatively short event window, unless investors can easily foresee the event.

In a few instances we allow two articles to represent a single anomaly. There are three reasons for this. First, it was difficult to determine which authors were the first to publish the anomaly. Second, there were subsequent authors who improved or highly modified the anomaly. Third, the first article to introduce the anomaly was published in an obscure source that might not have been widely read by investors.

After generating the sample of anomalies, we then determine how many top (JB, JF, JFE, JFQA, and RFS) and non-top (all other journals in the Heck's database) publications the authors had previous to the publication of their anomaly and how many years had passed between the year they received their Ph.D. and the year they published the anomaly. For each anomaly article, we next randomly select one other article from the same issue and journal in which the anomaly was published. This article is intended to serve as a benchmark.[11] Therefore, the only restriction is that the benchmark article cannot introduce or advance an anomaly to market efficiency. For this benchmark article, we similarly determine how many top and non-top publications the authors had previous to the publication of the article of interest and how many years had passed between the year they received their Ph.D. and the year of they published the article in the sample.

[11] The optimal benchmark would be anomalies that were not published. However, this is infeasible to obtain, so we satisfy ourselves with a benchmark dataset consisting of non-anomaly publications.

We record an observation for each article-author combination. E.g., if there are three authors for a single article, this translates into three observations. We are left with a dataset containing an observation for every author-article combination. Each observation either represents an anomaly-related publication or a benchmark publication. We then employ a simple univariate probit model to assess the relationship between the probability of an article presenting an anomaly to market efficiency and the publication record of the authors previous to the anomaly publication and the number of years between their receiving their Ph.D. and publishing the article.

The theory presented earlier in the paper also suggests that professors who derive a disproportionate amount of their utility from reputation (professors who have a high β in the Cobb-Douglas utility function in equation (1)) are more likely to publish anomalies. Since it is not possible to determine every author's α and β from equation (1), we rely on the notion that professors with extremely high βs, ex-ante, in equation (1) should publish more on an ex-post basis than those who have lower βs.

Accordingly, we include a binary variable and two interaction terms in the probit analysis. The binary variable takes the value of one if the author is *not* on any of Cooley and Heck's (2005) top 50 most prolific authors lists and zero if the author is on any one of those top 50 lists (henceforth the binary variable is simply NTOP50). The two interaction terms in the regression are the interaction of NTOP50 with the previous top publications variable and with the previous non-top publications variable.

The unconventional defining of the binary variable makes the estimates of the two interaction terms more intelligible. Assuming that authors with high βs in equation (1) are more likely to be on the prolific authors list than those with low βs, the interaction terms effectively eliminate the high β authors (the most prolific authors) from the analysis by forcing their previous publications to be zero and leaving only the previous publications data for professors with low βs (authors not on the prolific authors lists).

As a further proxy for a professors' β in the Cobb-Douglas utility function presented in equation (1), we also include two other control variables. The first control variable is the total non-top publications for each author subsequent to the publication of the article representing the observation. The second control variable is the total top publications for each author subsequent to the publication of the article representing the observation. The idea behind these control variables is that authors with relatively high βs in equation (1) are expected to continue publishing even after the anomaly publication, while those with lower βs are less concerned with continuing to publish once their reputation is established sufficiently.

At least two other factors may help explain why finance professors publish anomalies. First, anomalies discovered jointly by two or more researchers may have a higher probability of being published. Even though one researcher may wish not to publish the anomaly, he may be unable to dissuade his colleague from publishing it. To control for this, we add a variable to the probit model that indicates the number of authors on the paper.

Second, the profitability of the anomaly may be inversely related to the probability of its being published. Finance professors who discover anomalies that are only marginally profitable may be more inclined to publish their anomalies than those who discover highly profitable anomalies. We are unable to control for this possibility in the probit model because the non-anomaly observations have no equivalent variable. We do, however, perform further testing exploring this possibility.

Including the two variables of interest, one binary variable, two interaction variables, and the control variables, the probit model takes the following functional form:

$$\begin{aligned} A_i = \alpha &+ \beta_1 PNP_i + \beta_2 PTP_i + \beta_3 YEARS_i + \beta_4 AUTH_i + \beta_5 NTOP50_i + \\ &\beta_6 PNP_i \bullet NTOP50_i + \beta_7 PTP_i \bullet NTOP50_i + \\ &\beta_8 SNP_i + \beta_9 STP_i + \varepsilon_i \end{aligned} \tag{24}$$

A_i takes the value of one if article/author combination i introduces a market anomaly and zero if article/author combination i represents a benchmark observation. PNP_i and PTP_i are the number of non-top publications and top publications, respectively, the author had previous to the article representing the observation. $YEARS_i$ is the years between the year author i received his Ph.D. and the year he published the article associated with the observation. $AUTH_i$ is the number of authors who wrote the article representing the observation. $NTOP50_i$ takes the value of 1 if the author is not on any of the top 50 most prolific authors lists presented by Cooley and Heck (2005). SNP_i and

STP_i are the non-top publications and top publications, respectively, of author i subsequent to the publication representing the observations.

PNP_i and PTP_i and their corresponding interaction terms are critical in the analysis. We perform all tests using a number of different definitions for each of the variables. We begin with raw data – simply the aggregate number of non-top publications and top publications prior to the publication representing the observation (hereafter PNP_i and PTP_i, respectively). We then divide the variables by the number of years between the publication of the observation article and the year the author received his Ph.D. to create a per year representation of the two variables (hereafter $PNPY_i$ and $PTPY_i$, respectively). Lastly, we orthogonalize the previous non-top publications per year variable to the previous top publications per year variable. This is accomplished by using the residual from a regression of the previous non-top publications per year on previous top publications per year to create a previous non-top publications per year variable (hereafter $RESIDPNPY_i$) that is uncorrelated with the previous top publications per year. For robustness, we also replace NTOP50 with NPAL, which takes the value of 1 if the author is not on any of the prolific authors lists in Cooley and Heck (2005) and zero otherwise.

Before outlining the priors for each of the coefficient estimates, recall that the model implication derived above implies that the incentive to publish an anomaly is increasing as reputation (R) and publications (P) decrease and as proportional utility derived from reputation (β) increases. Further, R is a function of P. But P is a variable that represents the joint effects of both quantity and quality of an author's publications. The model, however, makes no attempt to disentangle the effects of quality and quantity of one's publications. For this reason, it is useful to consider that the true driver of the disincentive to publish an anomaly is reputation. Whatever increases reputation should decrease the incentive of a researcher to publish a profitable anomaly. It seems reasonable to assume that top publications have a greater effect on reputation than do non-top publications, so one might cautiously assume, ex-ante, that the variables related to top publications will show stronger significance than variables related to non-top publications.

With this in mind and recalling that the model predicts anomalies are more likely to be published by authors with lesser reputations and fewer previous publications, we expect the estimates for β_1, β_2, β_3, β_6, and β_7 to be negative in order to support the model implication. Further, in absolute terms we expect the magnitude of the coefficients related to top publications to exceed the magnitude of the coefficient related to non-top publications ($|\beta_2| > |\beta_1|$ and $|\beta_7| > |\beta_6|$), although this is not necessary to support the primary model implication. Since β_4, β_5, β_8, and β_9 are control variables, we make no predictions regarding their coefficient estimates.

Clearly, the profitability of an anomaly will have an impact on the willingness of a researcher to publish it. Presumably the profitability of an anomaly is inversely related to the probability of its being published. I.e., researchers are more reluctant to publish highly profitable anomalies since they might more successfully use them in their own trading. If this is true, we might expect that only those researchers with lesser reputations or high βs in equation (1) would be willing to publish highly profitable anomalies.[12] To test this hypothesis, we regress the profitability of each anomaly on the exact same variables in equation (24) plus four binary variables to control for the method of risk adjustment used by the original authors of the anomaly.

$$\begin{aligned}\pi_i = \alpha + \beta_1 PNP_i + \beta_2 PTP_i + \beta_3 YEARS_i + \beta_4 AUTH_i + \beta_5 NPAL_i + \\ \beta_6 PNP_i \bullet NTOP50_i + \beta_7 PTP_i \bullet NTOP50_i + \beta_8 SNP_i + \beta_9 STP_i + \\ \beta_{10} MATCHED + \beta_{11} APM + \beta_{12} CAR + \beta_{13} LS + \varepsilon_i\end{aligned} \quad (25)$$

π_i takes the value of the geometrically annualized abnormal profitability of the anomaly. Most anomaly papers present a measure of the abnormal profitability to the strategy over some sample period. Some present an average monthly measure, while some present an average annual measure. We simply use the average geometrically annualized abnormal return reported in the anomaly paper.

We also include four binary variables to control for the method used in each paper to adjust for risk. The risk adjustment methods are grouped into five categories: (1) no risk adjustment, (2) a matched-firm approach (MATCHED), (3) risk adjustment using an

[12] There may be a practical relationship at work here as well. The only anomaly papers authors with little or no reputation can publish are those that prove highly profitable, while authors with well established reputations can publish anomalies that are less profitable.

asset pricing model (APM), (4) risk adjustment using an event study methodology (CAR), and (5) risk-adjustment using a long-short strategy (LS). We include binaries for MATCHED, APM, CAR, and LS.

The sample used to estimate equation (25) does not include all the anomalies included in the estimation of equation (24). The primary reason for an anomaly dropping out of the sample is if that anomaly is unable to provide a clearly inferable trading strategy. For instance, Hirshleifer and Shumway (2003) show that the performance of stock markets around the world is directly related to the amount of sunshine in the city where the stock exchange is located. There is no theoretical asset pricing justification for this relationship, thus qualifying it as an "anomaly." However, there is also no easily inferable trading strategy that an investor could feasibly implement based on this strategy. Hence, this anomaly is included in the estimation of equation (24) but not in the estimation of equation (25). Out of the 33 anomalies used to estimate equation (24), 27 are used in estimating equation (25).

Assuming that the profitability of an anomaly is affected by the same factors that drive the incentive to publish an anomaly, We expect the same signs on the coefficient estimates in equation (25) that we outlined for equation (24). The basic rationale is that professors with lesser reputations and with fewer publications are more willing to publish highly profitable anomalies in an attempt to establish their reputations, while well established professors with higher reputations are only willing to publish anomalies with lower relative profits that could not be practically profitable for them personally.[13]

V. Analysis of Empirical Implications – Results

Table 2 reports the mean and median values of the explanatory variables in equations (24) and (25), including all robust definitions of the explanatory variables. The table reports the difference in means and medians between the anomaly and matched subsamples for each variable and compares the actual signs of the differences to the signs of the differences predicted by the theoretical model outlined earlier in the paper. Of the

[13] Some have suggested that a potentially important determinant of whether a professor would publish an anomaly is whether he has earned tenure prior to the potential publication. While acknowledging the merits of this point, I believe it is reasonable to assume that whether a finance professor has earned tenure is strongly positively correlated with the number of publications he has, which is the primary variable of interest in the model. For this reason, I forego including tenure as a control variable.

35 variables for which the differences between the matched and anomaly samples are reported in Table 2, the theoretical model of the paper provides predictions for 25.

The differences in the mean and especially the differences in median values reported in Table 2 consistently support the primary model implication. The signs of 24 out of the 25 differences in means are consistent with the model predictions, two of which are significant at the 10% level or better. The sign of only one difference contradicts the model, and it is not significant. 15 out of 25 differences in medians are consistent with the model predictions, while only two of the 25 differences in medians contradict the model (eight of the differences in medians are zero). Out of the 15 differences in medians that agree with the model predictions, six are significant at the 10% level or better, while neither of the two contradictory median differences is significant.

The six significant median differences are: (1) anomaly authors have a median of 0.52 previous total publications per year (PPY), while matched authors have a median of 0.88 previous total publications per year; (2) anomaly authors have a median of one previous non-top publication (PNP) compared to two for matched authors; (3) anomaly authors have a median of 0.2 previous non-top publication per year (PNPY) compared to 0.35 for matched authors; (4) a median of six years has elapsed between the time an anomaly author received his Ph.D. and the year he published the article representing the observation (YEARS) compared to eight years for matched authors; (5) anomaly authors not on any of Cooley and Heck's (2005) top 50 most prolific authors lists have a median of one previous publication (PP x NTOP50) compared to two previous publications for matched authors meeting the same criterion; (6) and anomaly authors not on any of Cooley and Heck's (2005) top 50 most prolific authors lists have median previous total publications per year (PPY x NTOP50) of 0.29 compared to 0.67 for matched authors.

The summary message of Table 2, which supports the theoretical model outlined earlier, is that anomaly papers are published by authors (a) who are newer to the field and (b) who have fewer previous publications (whether it be total publications, non-top publications, or top publications and regardless of whether the variables are measured on the aggregate or per year).

Before estimating equation (24), we first estimate 25 iterations of a simple single-variable probit model. The dependent variable takes the value of one if the observation relates to an anomaly and zero otherwise. In each iteration, we use one of the 25 variables in Table 3 Essay Means and Medians, for which the theoretical model makes a prediction.

Note first, however, that Table 2 reveals noticeable differences between means and medians suggesting the mean values are being influenced by extreme observations. Since regression analysis is sensitive to this problem, we estimate all regression models on three samples. The first sample (Full Sample) is the full sample. The second sample (Lower 95%) is truncated to exclude the top 5% of the observations based on the variable serving as the independent variable in the model. For example, if the independent variable is total previous publications, the Lower 95% sample excludes those observations in the top 5% of total previous publications. The third sample is truncated to exclude the top 10% of the observations based on the variable serving as the independent variable. Obviously, the latter two samples suffer less from the discrepancy between means and medians. The reason for truncating the sample only on the high end is that the explanatory variables are bounded by zero on the low side, so the extreme values affecting the mean are all on the high end.

Some of have questioned the wisdom in using truncated samples as opposed to simply taking the natural log of the affected variables. Truncating further aids in controlling for professors who have high β in equation (1). For instance truncating at the 5% level based on previous total publications removes both anomaly and matched authors with previous publications in the top 5% of the sample. Presumably, these professors represent the professors with the highest βs in the sample. Therefore, truncating thusly both helps mitigate the disparity between the means and medians and helps further control for high-β professors.

Results from estimating the 25 single-variable probit models are reported in Table 3. Similar to Table 2, the signs of almost all the coefficients are negative as predicted by the theoretical model. Also not surprisingly, the significance increases as the extreme observations are excluded from the analysis. Only two of the 25 variables are significant using the full sample, while five of the 25 variables are significant using the sample truncated at the 90% level. The five significant variables are: previous total publications per year, previous non-top publications per year, previous top publications per year, the interaction of the previous non-top publications and NTOP50, and the interaction of the previous non-top publications per year and NPAL.

Results from estimating equation (24) on the Full, Lower 95%, and Lower 90% samples are presented in Table 4. Results from specifications using the raw, per year, and orthogonalized definitions of the explanatory variables are presented in Panels A, B, and C, respectively. Panel D presents the correlation matrix of the independent variables using the raw versions of the variables.

The collective results from Table 4 provide mild support for the primary model implication. Specifically, using the sample truncated at the 10% level, the previous top publications per year variable is negative and significant using both the per-year definitions (third column of Panel B) and the orthogonalized definitions (third column of Panel C) of the independent variables. The signs of the other coefficient estimates, however, do not consistently align with model expectations as they do in previous tables. Further, and not surprisingly, the parameter estimates of the variables of interest in estimations using the full sample, which are affected by the previously highlighted discrepancy between the means and medians, show no significance.

The general lack of statistical significance and the inconsistency in the signs of the parameter estimates, however, may have a simple explanation. Relatively high correlation between some of the independent variables in the model, as shown in Panel D of Table 4, may be creating instability in the parameter estimates and making identification of statistical significance difficult.

There is an easily anticipated, strikingly consistent pattern revealed by the correlation matrices. Regardless of how it is defined, the previous non-top publications variable is strongly correlated with the interaction of the previous non-top publications variable and NTOP50. The correlations between these two variables are 0.82 (Table 4), 0.78 (unreported), and 0.93 (unreported) for the aggregate, per year, and orthogonalized versions of the variables, respectively. Similarly, the previous top publications variable is moderately correlated with the interaction of the previous top publications variable and NTPO50. The correlations between these two variables are 0.55 (Table 4), 0.67

(unreported), and 0.67 (unreported) for the aggregate, per year, and orthogonalized versions of the variables, respectively. Also, the YEARS variable is moderately correlated with the previous non-top publications and previous top publications variables. Correlations range from 0.32 (unreported) to 0.63 (Table 4) for these bi-variate pairs.

While these strong bi-variate correlations are not unexpected, they pose the threat of multicollinearity, with its attendant parameter estimate variance inflation, which causes instability in parameter estimates and masks significance. It seems prudent to re-estimate equation (24) excluding highly correlated variables. Accordingly, we re-estimate equation (24) while including only those variables that are not highly correlated. I.e., we estimate it while including previous non-top publications and previous top publications but excluding the years variable and the interaction variables. We also estimate it while including the interaction terms but excluding the years variable and previous non-top publications and previous top publications.

For brevity we report only the results from these re-estimations using the per year and orthogonalized definitions of the independent variables on the Lower 95% and Lower 90% samples.[14] The Lower 95% and Lower 90% samples are generated by truncating based on the explanatory variables of interest in the model. I.e., if the model includes only previous non-top publications per year and previous top publications per year, along with control variables, the samples are truncated based on the previous non-top publications per year and the previous top publications per year. The results using the per year definitions of the independent variables are presented in Panel A of Table 5. Panel B reports the results using the orthogonalized definition of the variables.

The primary supporting result of Table 5 is that the coefficients of variables pertaining to prior top publications per year (whether by itself or interacted on NTOP50) are reliably negative and statistically significant. Consistent with the primary implication of the model, the analysis suggests that anomaly papers are more likely to be written by authors with relatively fewer prior top publications per year. While none of the other explanatory variables of interest significantly support the primary implication of the model, it is noteworthy that none of them significantly contradict the model.

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[14] Complete results are available upon request. The unreported results are qualitatively similar but with lesser statistical significance.

It is worth noting that two control variables are reliably significant in the analysis. NTOP50 and the subsequent top publications per year are positive and significant. These are control variables, and therefore have little bearing on the model itself. However, their magnitude and significance beg investigation. We leave this for future work but offer a few qualitative comments.

These variables are intended to control for the proportional utility that authors place on reputation (β in equation (1)). Admittedly, finding an adequate proxy for β in equation (1) is a difficult task. The manner in which we defined NTOP50 suggests that if these two variables proxy for a common underlying factor, the signs should be opposite. The congruency in the signs suggests that they may not proxy for a common underlying factor.

The positive and significant coefficient estimate for NTOP50 indicates that anomaly papers are more likely be written by authors who are not on any of the top 50 most prolific authors lists. This would be consistent with the notion that anomalies are written by authors with few previous publications and who don't publish prolifically after publishing an anomaly.

However, the positive and significant coefficient estimate for the subsequent top publications per year variable somewhat contradicts this notion. It suggests that authors who publish anomalies subsequently publish top journal articles at a relatively high pace. The contradiction, however, may be reconciled by the considering the possibility that once an author publishes an anomaly, his reputational capital and aspirations evolve such that he will settle for nothing less than top journal publications. I.e., he may have embraced any type of journal article prior to the anomaly paper as he fought to build reputation, but subsequent to the anomaly, he only cares to publish in top journals. Additionally, publishing a recognizable anomaly may generate name recognition that makes it easier for the author to publish in top journals in the future. Again, however, we leave this as a topic for future work.

Similar to our analysis of equation (24), we begin our analysis of equation (25) by estimating 25 iterations of a simple regression model. The dependent variable is the annualized profitability of the anomaly as described earlier. In each iteration, we use one of the 25 variables in Table 3 Essay Means and Medians, for which the theoretical model makes a prediction, and we also include the four binary variables described earlier to control for the fact that the profitability of the anomalies in the study were obtained using differing risk-adjustment procedures.

Results from the 25 iterations are presented in Table 6. The results from these simple regressions also support the primary implication of the theory outlined earlier. Specifically, the signs of 24 of the 25 variables are consistent with the predictions of the model. Of the 24 consistent signs, 10 are significant at the 10% level or better.

Since previous testing revealed that multicollinearity is an issue with the initial specification of equation (25), we move directly to estimations of equation (25) that avoid the inclusion of highly correlated variables. We first perform these estimations on the full sample. Since the sample size for the testing involving equation (25) is about half that of the full sample, which is not large to begin with, we are hesitant to truncate the sample. Accordingly, instead of truncating the sample to mitigate the disparity between the means and medians, we simply perform the estimations on the sample in which the independent variables of interest, except the binary variables, have been redefined as the log transformation of the original variables. Although this log-transformed sample does not augment the attempts to control for high-β professors like the truncated samples do, it at least reduces the disparity between the means and medians while retaining as many observations as possible.

Results from estimating equation (25) exclusive of highly correlated independent variables are reported in Table 7. For brevity, we report only the results using the per-year (Panel A) and orthogonalized (Panel B) definitions of the independent variables of interest. The results from Table 7 are consistent with the theory but statistically unconvincing. The signs of the independent variables of interest are generally of the predicted sign. Specifically, the coefficient estimates for years, previous non-top publications, previous top publications, and the interaction variables are generally negative, which supports the predictions of the model. However, none of these coefficient estimates are significant. The only significant variables are the control variables: authors, the matched-firm risk adjustment binary variable, and the long-short risk-adjustment binary variable.

Given the consistency in signs, however, perhaps the lack of significance is a function of the relatively few degrees of freedom. Since we are unable to increase the degrees of freedom through an expansion of the sample, we increase the degrees of freedom by decreasing the number of explanatory variables in the model. This can be easily accomplished and with compelling justification.

All previous publications variables and the YEARS variable are intended to proxy for the same variable in the theoretical model outlined earlier. Specifically, the model asserts that reputation is driven by publications. Reputation and publications in the model are inextricably connected – they represent the single driving factor behind the incentive to publish an anomaly. Accordingly, it makes sense to reduce the previous publications variables and the YEARS variable to a single common factor. Similarly, the subsequent publications variables and NTOP50 are intended to proxy for the same underlying factor in the model – the proportional utility a professor derives from reputation in the Cobb-Douglas utility function. Accordingly, it makes sense to reduce the subsequent publications variables and NTOP50 to a single common factor. This is accomplished through the use of principal components analysis.

We reduce the specifications reported in Table 7 using principal components analysis. In each specification in Table 7 we replace the independent variables of interest with the first principal component of those same independent variables of interest. We also replace the subsequent publications variables and NTOP50 with the first principal component of those variables.

As an example, the first specification in Panel A of Table 7 includes the following variables: years, authors, NTOP50, previous non-top publications per year, previous top publications per year, subsequent non-top publications per year, subsequent top publications per year, and the four risk-adjustment dummies. After performing the principal components analysis, this specification is altered such that the YEARS, previous non-top publications per year, and previous top publications per year are replaced by the first principal component of those three variables. Additionally, the subsequent non-top publications per year, subsequent top publications per year, and NTOP50 are replaced by the first principal component of those three variables. This effectively replaces six independent variables with two principal components. It buys additional degrees of freedom in the testing and firmly aligns intuitively with the theory outlined earlier since the variables combined to form the principal components are intended to proxy for common underlying factors.

We present the factor loadings and eigen values of the first principal component of the relevant combinations of variables in Table 8. We also include the eigen value of the second principal component of each combination of variables. The table manifests some desirable properties. First, the eigen values of almost all of the first principal components are above one, while the eigen values of the second principal components are universally below one. Therefore, Table 8 clearly demonstrates that use of only the first principal component is justified.[15] Second, the factor loadings of the previous publications variables and the years variable are all positive. This is a indication that these variables are, indeed, proxying for a common underlying factor (presumably reputation). Third, the factor loadings on the subsequent publications variables are positive, while the factor loadings of NTOP50 are negative. This is encouraging as we anticipated a negative relationship between subsequent publications and NTOP50 if they proxy for a common underlying factor (presumably β from equation (1)).

We present the results from the regression estimations using principal components in Table 9. For brevity, we report results using the original non log-transformed sample.[16] Panel A reports results using the raw definitions of the variables, Panel B reports results using the per year definitions of the variables, and Panel C reports results using the orthogonalized definitions of the variables. Since the number of authors variable proves strongly significant in Table 7, we estimate specifications of the regression both including and excluding the authors variable.

The results presented in Table 9 strongly support of the theory outlined earlier. The principal components related to the previous publications and YEARS variables are universally negative and significant in specifications excluding the authors variable. When the authors variable is included, the magnitude of these principal components are noticeably reduced, but they universally remain negative and generally retain their significance. Specifically, the principal components based on the previous publications

[15] The Kaiser-Guttman rule suggests that only factors with eigen values greater than one are valid for extraction (See Guttman (1953) and Kaiser and Rice (1974)).
[16] Results using the log-transformed variables are qualitatively similar and available upon request.

interacted on NTOP50 remains negative and universally significant even in the presence of the authors variable.

Although applying economic interpretation to principal components is tenuous, we can conclude that the common factor among the previous publications and years variables is negatively related to the profitability of the anomaly. If the common factor may be interpreted as reputation, we may conclude that a lesser reputation is associated with a higher profitability in the published anomaly. This is consistent with the prediction of the model that authors with lesser reputations have more incentive to publish anomalies.

The summary conclusions from the empirical testing of the predictions of the theoretical model of the paper are as follows. The model predicts that the incentive to publish anomalies is inversely related to reputation, which is directly driven by publications. Accordingly, anomalies should be published by authors with fewer publications and who are newer to the field.

The comparison of anomaly and matched authors support the predictions of the model. The difference in means and especially medians between anomaly authors and matched authors reveals that anomaly authors have been in the field for a much shorter period of time than matched authors. Further, anomaly authors have fewer previous publications than do matched authors. The single-variable probit analyses also support the predictions of the model. Anomaly papers are more likely to be written by authors with fewer publications and who have been in the field for a shorter period of time. The probit model including multiple independent variables (except for those that are highly correlated) identify the previous top publications per year as the most significant explanatory variable in distinguishing anomaly papers from matched papers. Specifically, anomaly papers are more likely to be written by authors with fewer top publications per year, which corroborates the notion that anomalies are written by authors with lesser reputations.

We also hypothesize that the variables that are inversely related to the incentive to publish an anomaly should have the same relationship with the profitability of a published anomaly: more profitable anomalies should be published by authors with fewer publications and who are newer to the field.

Analyses regressing the profitability of published anomalies on these variables support the theory. The regressions, including a single explanatory variable of interest, along with binary variables to control for the method of risk adjustment used to identify the anomaly, produce coefficient estimates that are consistently negative and significant for the previous publications variables and for the years since obtaining a Ph.D. The regressions including various combinations of the explanatory variables result in coefficients whose signs are consistent with the theory but whose significance is less convincing. When replacing the explanatory variables with their first shared principal component and control variables with their first shared principal component, the first principal component from the explanatory variables of interest, which presumably proxies for reputation is reliably negative and significant. This is evidence that the profitability of an anomaly is inversely related to the common underlying factor between the previous non-top publications, previous top publications, and years since obtaining a Ph.D. of the author(s) who published the anomaly. If this common underlying factor can be interpreted as reputation, these results support the theory outlined above.

VI. Conclusion and Discussion

Why do finance professor publish anomalies? On the surface, it seems like irrational behavior. But this is too disturbing a notion – to believe that finance professors are systematically engaging in irrational behavior when they publish anomalies – for us to embrace. Employing a simple utility function driven by wealth and reputation and constrained by a few seemingly realistic assumptions we demonstrate that publishing an anomaly can actually be quite rational. The theory predicts that finance professors with the greatest incentive, and for whom it is most rational, to publish an anomaly are those (a) with little reputation (b) with few publications, and (c) who derive a disproportionately high amount of utility from reputation compared to wealth.

We empirically test the primary implication of the theory through the use of probit and regression analyses. The results suggest that authors who publish anomalies have fewer publications, especially fewer top publications per year, than non-anomaly authors publishing in the same journal. Additionally, authors who publish anomalies have been in the field for a shorter period of time than their non-anomaly counterparts.

The profitability of an anomaly is inversely related to the number of publications that an author has at the time of the publication of the anomaly and the number of years the author has been in the field. Moreover, the profitability of an anomaly is strongly inversely related to the first principal component of the previous publications of the author and the number of years the author has been in the field. If this principal component may be interpreted as reputation, we can conclude that authors with lesser reputations are much more likely to publish highly profitable anomalies, a conclusion that is consistent with the theory outlined in the paper.

Why do finance professors publish anomalies? According to the theory outlined here, which seems empirically supported, they publish anomalies because they are fighting to build reputation and by publishing the anomaly they gain more utility through the joint effect on their reputation and wealth than they would by keeping the anomaly proprietary and trading on it for their own personal gain. In other words, they publish anomalies because they are rational utility maximizers. It should be somewhat relieving to discover that the group of researchers who widely employ assumptions of rationality in their work are themselves rational on this point.

Unfortunately, this implies that some of the brightest minds in our field, some of the most widely published authors in finance, have the highest incentive *not* to publish any market anomalies they may find. So while finance professors appear to be rational utility maximizers, we should not expect to see the kingpins of our field publishing highly profitable anomalies, unless their utility functions are highly skewed toward reputation. The potential for silence from our top authors on this particular topic is discouraging but not shocking.

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Table 1 – Anomalies and Authors

This table presents the anomalies used in the empirical testing of the paper. It also presents the authors who first introduced the anomaly and the year in which the paper was published.

#	Anomaly	Author 1	Author 2	Author 3	Author 4	Year
1	52-week high	George	Hwang			2004
2	Changes in analyst recommendations	Jegadeesh	Kim	Krische	Lee	2004
3	Changes to analyst target prices	Brav	Lehavy			2003
4	Christmas Day Effect	Lakonishok	Smidt			1984
5	Dispersion in estimates	Diether	Malloy	Scherbina		2002
6	Dividend Yield	Campbell	Shiller			1988
7	Dividend Yield	Fama	French			1988
8	Dividends Drift	Healy	Palepu			1988
9	Ind Momentum	Moskowitz	Grinblatt			1999
10	January Effect	Rozeff	Kinney			1976
11	January Effect w/ Small Firm Effect	Keim				1983
12	January Effect w/ Small Firm Effect	Reinganum				1983
13	Momentum	Jegadeesh	Titman			1993
14	Monday Effect	Cross				1973
15	Monday Effect	French				1980
16	New Year's Day Effect	Roll				1983
17	Oct - March Seasonality	Ogden				2003
18	PE	Basu				1977
19	Post Earnings Announcement Drift	Ball	Brown			1968
20	Post IPO blues	Loughran	Ritter			1995
21	Post Listing blues	Dharan	Ikenberry			1995
22	Post Merger blues	Asquith				1983
23	Post SEO blues	Speiss	Affleck-Graves			1995
24	Pre Holiday Effect	Ariel				1990
25	Qualitative content	Asquith	Mikhail	Au		2005
26	Repurchases	Ikenberrry	Lakonishok	Vermaelen		1995
27	Reversal	DeBondt	Thaler			1985
28	S&P 500 Effect	Harris	Gurel			1986
29	S&P 500 Effect	Shleifer				1986
30	Sentiment	Baker	Wurgler			2006
31	Size Effect	Banz				1981
32	Size Effect	Reinganum				1981
33	Sunshine Effect	Hirshleifer	Shumway			2003
34	Turn of the Month Effect (first 3 days)	Lakonishok	Smidt			1988
35	Turn of the Month Effect (last day)	Ariel				1987
36	Value Line Effect	Black				1973
37	Value Line Effect	Stickel				1985
38	Value Premium	Rosenberg	Reid	Lanstein		1985
39	Value Premium	Stattman				1980
40	Stock Split	Ikenberrry	Ramnath			2002

Table 2 – Differences in Means and Medians
Anomaly vs. Matched Authors

This table reports the mean and median values of all the possible explanatory variables in equations (24) and (25) for both the anomaly observations and for the matched observations. The differences in the mean values between the anomaly and matched samples are tested using a simple pair-wise t-test, while the differences in the median values are tested using a simple non-parametric median two-sample test. The variables reported are defined in the first column of the table.

	N		Mean				Sign		Median				Sign	
Variable	Anom.	Matched	Anom.	Matched	Dif	Sig.	Actual	Expected	Anom.	Matched	Dif.	Sig.	Actual	Expected
Previous Total Publications (PP)	68	71	7.59	7.75	-0.16		-	-	2.00	4.00	-2.00		-	-
Previous Total Publications per Year (PPY)	60	54	0.71	0.91	-0.20		-	-	0.52	0.88	-0.37	**	-	-
Previous Non-Top Publications (PNP)	68	71	3.84	4.44	-0.60		-	-	1.00	2.00	-1.00	**	-	-
Previous Non-Top Publications per Year (PNPY)	60	54	0.34	0.49	-0.15		-	-	0.20	0.35	-0.15	*	-	-
Residual Previous Total Publications (RPP)	68	71	-0.45	0.43	-0.88		-	-	-1.91	-1.55	-0.37		-	-
Residual Previous Non-Top Publications per Year (RPNPY)	60	54	-0.06	0.07	-0.13		-	-	-0.25	-0.17	-0.09		-	-
Previous Top Publications (PTP)	68	71	3.75	3.31	0.44		+	-	1.00	1.00	0.00			-
Previous Top Publications per Year (PTPY)	60	54	0.37	0.42	-0.05		-	-	0.26	0.33	-0.08		-	-
Subsequent Publications (SP)	68	71	13.09	12.58	0.51		+	-/+	4.00	7.00	-3.00		-	-/+
Subsequent Publications per Year (SPY)	68	71	0.77	0.72	0.04		+	-/+	0.50	0.50	0.00			-/+
Subsequent Non-Top Publications (SNP)	68	71	8.04	9.45	-1.41		-	-/+	2.00	4.00	-2.00	**	-	-/+
Subsequent Non-Top Publications per Year (SNPY)	68	71	0.45	0.53	-0.08		-	-/+	0.25	0.28	-0.03		-	-/+
Subsequent Top Publications (STP)	68	71	5.04	3.13	1.92	*	+	-/+	1.50	1.00	0.50		+	-/+
Subsequent Top Publications per Year (STPY)	68	71	0.32	0.20	0.12	**	+	-/+	0.11	0.09	0.02		+	-/+
Residual Subsequent Publications (RSP)	68	71	-1.51	1.45	-2.96		-	-/+	-5.47	-4.47	-1.00		-	-/+
Residual Subsequent Non-Top Publications per Year (RSNPY)	68	71	-0.07	0.07	-0.14		-	-/+	-0.26	-0.14	-0.12	*	-	-/+
Years Between Obtaining PhD and Publishing Paper (Years)	60	54	8.20	8.26	-0.06		-	-	6.00	8.00	-2.00	**	-	-
# of Authors on Paper (Auth)	68	71	2.06	2.27	-0.21		-	-/+	2.00	2.00	0.00			-/+
Not in Top 50 Authors List (NTOP50)	68	71	0.85	0.90	-0.05		-	-/+	1.00	1.00	0.00			-/+
Not in Any Top Authors List (NPAL)	68	71	0.62	0.73	-0.11		-	-/+	1.00	1.00	0.00			-/+

* Significant at 10% level
** Significant at 5% level
*** Significant at 1% level

Table 2 Continued

This table reports the mean and median values of all the possible explanatory variables in equations (24) and (25) for both the anomaly observations and for the matched observations. The differences in the mean values between the anomaly and matched samples are tested using a simple pair-wise t-test, while the differences in the median values are tested using a simple non-parametric median two-sample test. The variables reported are defined in the first column of the table.

	N		Mean				Sign		Median				Sign	
Variable	Anom.	Matched	Anom.	Matched	Dif	Sig.	Actual	Expected	Anom.	Matched	Dif.	Sig.	Actual	Expected
PP x NTOP50	68	71	4.54	6.00	-1.46		-	-	1.00	2.00	-1.00	*	-	-
PP x NPAL	68	71	2.65	3.42	-0.78		-	-	0.00	0.00	0.00			-
PPY x NTOP50	60	54	0.47	0.70	-0.22	*	-	-	0.29	0.67	-0.38	**	-	-
PPY x NPAL	60	54	0.29	0.44	-0.15		-	-	0.00	0.00	0.00			-
PNP x NTOP50	68	71	2.41	3.66	-1.25		-	-	0.00	1.00	-1.00		-	-
PNP x NPAL	68	71	1.71	2.41	-0.70		-	-	0.00	0.00	0.00			-
PNPY x NTOP50	60	54	0.24	0.38	-0.15	*	-	-	0.00	0.17	-0.17		-	-
PNPY x NPAL	60	54	0.17	0.28	-0.10		-	-	0.00	0.00	0.00			-
RPP x NTOP50	68	71	-0.57	0.46	-1.03		-	-	-1.13	-1.44	0.32		+	-
RPP x NPAL	68	71	-0.07	0.37	-0.44		-	-	0.00	-0.08	0.08		+	-
RPNPY x NTOP50	60	54	-0.07	0.04	-0.11		-	-	-0.10	-0.05	-0.04		-	-
RPNPY x NPAL	60	54	-0.02	0.04	-0.07		-	-	0.00	0.00	0.00			-
PTP x NTOP50	68	71	2.13	2.34	-0.21		-	-	0.00	1.00	-1.00		-	-
PTP x NPAL	68	71	0.94	1.01	-0.07		-	-	0.00	0.00	0.00			-
PTPY x NTOP50	60	54	0.23	0.31	-0.08		-	-	0.02	0.10	-0.07		-	-
PTPY x NPAL	60	54	0.12	0.16	-0.04		-	-	0.00	0.00	0.00			-

* Significant at 10% level
** Significant at 5% level
*** Significant at 1% level

Table 3 – Single-Variable Probit Analyses

This table reports the parameter estimates and significance levels from estimating 25 iterations of a single-variable probit model on three samples. The dependent variable takes the value of 1 if the observation relates to an anomaly and 0 otherwise. The probit analysis is estimated 25 times using a different explanatory variable in each iteration. The 25 explanatory variables are those in Table 2 for which the theoretical model of the paper offers predications regarding the signs. The 25 iterations are performed on three different datasets. The first sample (Full Sample) is the full sample. The second sample (Lower 95%) is truncated to exclude the top 5% of the observations based on the variable serving as the independent variable in the iteration. For example, if the independent variable is total previous publications, the Lower 95% sample excludes those observations in the top 5% of total previous publications. The third sample is truncated to exclude the top 10% of the observations based on the variable serving as the independent variable. All but two variables (NTOP50 and NPAL) are defined in the first column of the table. NTOP50 takes the value of one if the author is not on any of Cooley and Heck's (2005) top 50 most prolific authors lists and zero otherwise. NPAL takes the value of one if the author is not on any of their prolific author lists and zero otherwise.

	Expected	Full Sample				Lower 95%				Lower 90%			
Variable	Sign	N	Estimate	Sig.		N	Estimate	Sig.		N	Estimate	Sig.	
Previous Total Publications (PP)	-	139	-0.001	0.93		133	-0.014	0.35		126	-0.008	0.68	
Previous Total Publications per Year (PPY)	-	114	-0.218	0.16		109	-0.355	0.06	*	104	-0.507	0.02	**
Previous Non-Top Publications (PNP)	-	139	-0.009	0.60		134	-0.001	0.98		127	-0.022	0.53	
Previous Non-Top Publications per Year (PNPY)	-	114	-0.372	0.12		109	-0.238	0.42		103	-0.754	0.04	**
Residual Previous Total Publications (RPP)	-	139	-0.017	0.39		133	-0.008	0.80		127	0.015	0.72	
Residual Previous Non-Top Publications per Year (RPNPY)	-	114	-0.361	0.15		109	-0.155	0.63		103	-0.431	0.29	
Previous Top Publications (PTP)	-	139	0.011	0.60		133	-0.009	0.75		127	-0.019	0.59	
Previous Top Publications per Year (PTPY)	-	114	-0.181	0.50		109	-0.317	0.32		103	-0.676	0.08	*
Years Between Obtaining PhD and Publishing Paper (Years)	-	114	-0.001	0.96		109	-0.009	0.67		105	-0.022	0.35	
PP x NTOP50	-	139	-0.015	0.28		134	-0.004	0.84		126	-0.025	0.35	
PP x NPAL	-	139	-0.013	0.47		133	-0.035	0.29		127	-0.031	0.46	
PPY x NTOP50	-	114	-0.316	0.07	*	109	-0.461	0.04	**	103	-0.331	0.20	
PPY x NPAL	-	114	-0.317	0.15		109	-0.373	0.18		103	-0.549	0.12	
PNP x NTOP50	-	139	-0.024	0.23		133	-0.017	0.63		127	-0.031	0.53	
PNP x NPAL	-	139	0.017	0.44		133	-0.043	0.40		127	-0.152	0.05	**
PNPY x NTOP50	-	114	-0.435	0.09	*	109	-0.573	0.10	*	103	-0.981	0.04	**
PNPY x NPAL	-	114	-0.377	0.19		109	-0.439	0.31		104	-0.560	0.33	
RPP x NTOP50	-	139	-0.022	0.29		133	-0.001	0.98		126	-0.005	0.93	
RPP x NPAL	-	139	-0.012	0.60		133	-0.055	0.32		126	-0.005	0.95	
RPNPY x NTOP50	-	114	-0.352	0.20		109	-0.331	0.37		103	-0.514	0.29	
RPNPY x NPAL	-	114	-0.278	0.37		109	-0.122	0.79		103	-0.127	0.83	
PTP x NTOP50	-	139	-0.010	0.73		134	-0.007	0.85		131	0.031	0.48	
PTP x NPAL	-	193	-0.012	0.83		134	-0.006	0.92		129	-0.069	0.52	
PTPY x NTOP50	-	114	-0.343	0.27		109	-0.670	0.11		103	-0.627	0.22	
PTPY x NPAL	-	114	-0.394	0.38		109	-1.041	0.12		103	-0.378	0.68	

* Significant at 10% level
** Significant at 5% level
*** Significant at 1% level

Table 4 – Full Specification Probit Analyses

This table presents the results from estimating equation (24) using three versions of the independent variables: (1) raw versions, (2) per year versions, and (3) orthogonalized versions. The estimation is performed on three samples: (1) the full sample (Full Sample), (2) the sample truncated by eliminating the observations with previous non-top publications or previous top publications in the highest five percent of the sample (Lower 95%), and (3) the sample truncated by eliminating the observations with previous non-top publications or previous top publications in the highest ten percent of previous publications (Lower 90%). A_i takes the value of one if article/author combination i introduces a market anomaly and zero if article/author combination i represents a benchmark observation. PNP_i and PTP_i are the number of non-top publications and top publications, respectively, the author had previous to the article representing the observation. $PNPY_i$ and $PTPY_i$ are the per-year definitions of these two variables, respectively. RPNPYi is the residual from regressing non-top publications per year on top publications per year. $YEARS_i$ is the years between the year author i received his Ph.D. and the year he published the article associated with the observation. $AUTH_i$ is the number of authors who wrote the article representing the observation. $NTOP50_i$ takes the value of one if the author is not on any of the top 50 most prolific authors lists presented by Cooley and Heck (2005). SNP_i and STP_i are the number of non-top publications and top publications, respectively, the author had subsequent to the article representing the observation. SNPYi and STPYi are the per year versions of these two variables, respectively. $RSNPY_i$ is the residual from regressing subsequent non-top publications per year on top publications per year. Panel A reports the results from estimations using the raw definitions of the variables, Panel B reports results using the per year definitions of the variables, Panel C reports results using the orthogonalized versions of the independent variables, and Panel D reports the correlation matrix of the independent variables using the raw definitions of the varibles.

$$A_i = \alpha + \beta_1 PNP_i + \beta_2 PTP_i + \beta_3 YEARS_i + \beta_4 AUTH_i + \beta_5 NTOP50_i + \beta_6 PNP_i \bullet NTOP50_i + \beta_7 PTP_i \bullet NTOP50_i + \beta_8 SNP_i + \beta_9 STP_i + \varepsilon_i \quad (24)$$

Panel A: Aggregate Values of Independent Variables

		Full Sample			Lower 95%			Lower 90%		
	Expected	(N = 114)			(N = 109)			(N = 104)		
Parameter	Sign	Estimate	p		Estimate	p		Estimate	p	
Intercept	-/+	-0.507	0.56		0.439	0.67		0.406	0.69	
PNP	-	0.032	0.67		-0.036	0.75		-0.037	0.66	
PTP	-	-0.039	0.64		-0.090	0.53		-0.075	0.43	
Years	-	0.034	0.27		0.018	0.63		0.014	0.71	
Auth	-/+	-0.090	0.61		-0.210	0.26		-0.173	0.34	
NTOP50	-/+	0.697	0.34		0.012	0.99		-0.045	0.96	
PNP x NTOP50	-	-0.057	0.48		0.095	0.45		0.089	0.37	
PTP x NTOP50	-	-0.003	0.97		0.003	0.98		0.015	0.87	
SNP	-/+	-0.013	0.24		-0.025	0.04	**	-0.022	0.06	*
STP	-/+	0.052	0.09	*	0.077	0.03	**	0.070	0.04	**

Panel B: Per Year Values of Independent Variables

		Full Sample			Lower 95%			Lower 90%		
	Expected	(N = 114)			(N = 109)			(N = 104)		
Parameter	Sign	Estimate	p		Estimate	p		Estimate	p	
Intercept	-/+	-0.010	0.99		-0.078	0.94		1.111	0.50	
PNPY	-	-0.397	0.63		0.780	0.54		2.699	0.25	
PTPY	-	-0.067	0.95		-1.516	0.30		-5.869	0.06	*
Years	-	0.014	0.48		0.021	0.46		0.038	0.29	
Auth	-/+	-0.119	0.47		-0.094	0.58		-0.047	0.80	
NTOP50	-/+	0.326	0.69		0.260	0.77		-1.051	0.51	
PNP x NTOP50	-	0.293	0.74		-0.782	0.57		-3.264	0.18	
PTP x NTOP50	-	-0.387	0.71		0.688	0.64		4.786	0.13	
SNPY	-/+	-0.242	0.27		-0.092	0.74		-0.010	0.97	
STPY	-/+	0.937	0.07	*	1.083	0.06	*	1.086	0.09	*

* Significant at 10% level
** Significant at 5% level
*** Significant at 1% level

Table 4 Continued

This table presents the results from estimating equation (24) using three versions of the independent variables: (1) raw versions, (2) per year versions, and (3) orthogonalized versions. The estimation is performed on three samples: (1) the full sample (Full Sample), (2) the sample truncated by eliminating the observations with previous non-top publications or previous top publications in the highest five percent of the sample (Lower 95%), and (3) the sample truncated by eliminating the observations with previous non-top publications or previous top publications in the highest ten percent of previous publications (Lower 90%). A_i takes the value of one if article/author combination i introduces a market anomaly and zero if article/author combination i represents a benchmark observation. PNP_i and PTP_i are the number of non-top publications and top publications, respectively, the author had previous to the article representing the observation. $PNPY_i$ and $PTPY_i$ are the per-year definitions of these two variables, respectively. RPNPYi is the residual from regressing non-top publications per year on top publications per year. $YEARS_i$ is the years between the year author i received his Ph.D. and the year he published the article associated with the observation. $AUTH_i$ is the number of authors who wrote the article representing the observation. $NTOP50_i$ takes the value of one if the author is not on any of the top 50 most prolific authors lists presented by Cooley and Heck (2005). SNP_i and STP_i are the number of non-top publications and top publications, respectively, the author had subsequent to the article representing the observation. SNPYi and STPYi are the per year versions of these two variables, respectively. $RSNPY_i$ is the residual from regressing subsequent non-top publications per year on top publications per year. Panel A reports the results from estimations using the raw definitions of the variables, Panel B reports results using the per year definitions of the variables, Panel C reports results using the orthogonalized versions of the independent variables, and Panel D reports the correlation matrix of the independent variables using the raw definitions of the varibles.

$$\begin{aligned} A_i = \alpha + \beta_1 PNP_i + \beta_2 PTP_i + \beta_3 YEARS_i + \beta_4 AUTH_i + \beta_5 NTOP50_i + \\ \beta_6 PNP_i \bullet NTOP50_i + \beta_7 PTP_i \bullet NTOP50_i + \\ \beta_8 SNP_i + \beta_9 STP_i + \varepsilon_i \end{aligned} \qquad (24)$$

Panel C: Per Year Orthogonalized Values of Independent Variables

		Full Sample (N = 114)			Lower 95% (N = 109)			Lower 90% (N = 104)		
Parameter	Expected Sign	Estimate	p		Estimate	p		Estimate	p	
Intercept	-/+	-0.205	0.81		0.057	0.95		1.780	0.31	
RPNPY	-	-0.397	0.63		0.836	0.51		2.773	0.24	
PTPY	-	-0.218	0.80		-1.283	0.27		-4.902	0.06	*
Years	-	0.014	0.48		0.029	0.33		0.039	0.28	
Auth	-/+	-0.119	0.47		-0.090	0.59		-0.019	0.92	
NTOP50	-/+	0.403	0.63		0.007	0.99		-1.967	0.26	
PNP x NTOP50	-	0.293	0.74		-1.131	0.42		-3.470	0.16	
PTP x NTOP50	-	-0.276	0.76		0.401	0.73		3.558	0.16	
RSNPY	-/+	-0.242	0.27		0.000	1.00		-0.025	0.94	
STPY	-/+	0.828	0.10	*	1.017	0.06	*	1.109	0.07	*

* Significant at 10% level
** Significant at 5% level
*** Significant at 1% level

Panel D: Correlation Matrix (Raw Definition of Independent Variables)

	PNP	PTP	Years	Auth	NTOP50	PNP x NTOP50	PTP x NTOP50	SNP	STP
PNP	1.00	0.46	0.63	0.15	-0.27	0.82	0.18	0.27	0.13
PTP	0.46	1.00	0.63	0.17	-0.53	0.09	0.55	-0.05	0.36
Years	0.63	0.63	1.00	0.17	-0.18	0.50	0.46	-0.02	-0.02
Auth	0.15	0.17	0.17	1.00	0.24	0.25	0.35	-0.25	-0.32
NTOP50	-0.27	-0.53	-0.18	0.24	1.00	0.19	0.24	-0.23	-0.76
PNP x NTOP50	0.82	0.09	0.50	0.25	0.19	1.00	0.32	0.23	-0.22
PTP x NTOP50	0.18	0.55	0.46	0.35	0.24	0.32	1.00	-0.20	-0.21
SNP	0.27	-0.05	-0.02	-0.25	-0.23	0.23	-0.20	1.00	0.34
STP	0.13	0.36	-0.02	-0.32	-0.76	-0.22	-0.21	0.34	1.00

Table 5 – Multicollinearity Mitigated Probit Analyses

This table presents the results from estimating equation (24), exclusive of strongly correlated variables, using the per year and orthogonalized definitions of the independent variables from two samples: (1) the sample truncated by eliminating the observations with explanatory variables of interest in the highest five percent of the sample (Lower 95%), and (3) the sample truncated by eliminating the observations with explanatory variables of interest in the highest ten percent of the sample (Lower 90%). The dependent variable takes the value of one if the article/author combination introduces a market anomaly and zero if the article/author combination represents a benchmark observation. $PNPY_i$ and $PTPY_i$ are the number of non-top publications and top publications per year, respectively, the author had previous to the article representing the observation. $RPNPY_i$ is the number of residual non-top publications per year (non-top publications per year in excess of non-top publications per year expected given the number of top publications per year) the author had previous to the article representing the observation. $YEARS_i$ is the years between the year author i received his Ph.D. and the year he published the article associated with the observation. $AUTH_i$ is the number of authors who wrote the article representing the observation. $NTOP50_i$ takes the value of one if the author is not on any of the top 50 most prolific authors lists presented by Cooley and Heck (2005). $SNPY_i$ and $STPY_i$ are the number of non-top publications and top publications per year, respectively, the author had subsequent to the article representing the observation. RSNPYi is the number of residual non-top publications per year (non-top publications per year in excess of the non-top publications per year expected given the number of top publications per year) the author had subsequent to the article representing the observation.

Panel A: Per Year Definition of Independent Variables

		Lower 95%				Lower 90%			
Parameter	Expected Sign	Estimate N = 105	Estimate N = 105	Estimate N = 101	Estimate N = 101	Estimate N = 94	Estimate N = 94	Estimate N = 89	Estimate N = 87
Intercept		0.052	-0.624	-0.077	-0.873	0.200	-0.787	-0.074	-1.163
Years	-			0.017	0.021			0.021	0.007
Auth	-/+	-0.076	-0.019	-0.111	-0.057	-0.095	-0.051	-0.084	-0.061
NTOP50	-/+	0.209	0.793	0.311	0.994 *	0.229	1.083	0.292	1.335 **
PNPY	-	0.114		0.092		-0.272		-0.353	
PTPY	-	-0.721		-0.829 *		-0.966 *		-1.132 *	
PNPY x NTOP50	-		-0.033		-0.073		-0.320		-0.453
PTPY x NTOP50	-		-0.938 *		-1.069 **		-1.293 *		-1.372 *
SNPY	-/+	-0.123	-0.094	-0.115	-0.077	-0.104	-0.191	-0.029	-0.076
STPY	-/+	1.051 *	1.125 **	1.069 *	1.154 **	0.947	1.473 ***	1.069 *	1.579 ***

Panel B: Orthogonalized Definition of Independent Variables

		Lower 95%				Lower 90%			
Parameter	Expected Sign	Estimate N = 104	Estimate N = 105	Estimate N = 100	Estimate N = 102	Estimate N = 93	Estimate N = 93	Estimate N = 87	Estimate N = 86
Intercept		0.052	-0.659	-0.111	-0.902	0.069	-0.879	-0.210	-1.241
Years	-			0.022	0.021			0.021	0.011
Auth	-/+	-0.079	-0.019	-0.114	-0.057	-0.066	-0.051	-0.058	-0.068
NTOP50	-/+	0.171	0.785	0.275	0.975 *	0.154	1.067 *	0.253	1.317 **
RPNPY	-	-0.037		-0.112		-0.170		-0.424	
PTPY	-	-0.646		-0.802 *		-1.074 **		-1.295 **	
PNP x NTOP50	-		-0.033		-0.073		-0.147		-0.271
PTP x NTOP50	-		-0.950 **		-1.097 **		-1.448 **		-1.606 **
RSNPY	-/+	-0.067	-0.094	-0.050	-0.077	-0.158	-0.154	-0.040	-0.039
STPY	-/+	0.970 *	1.082 **	0.993 *	1.119 **	1.062 *	1.410 ***	1.072 *	1.567 ***

* Significant at 10% level
** Significant at 5% level
*** Significant at 1% level

Table 6 – Preliminary Regression Analyses

This table reports the parameter estimates and significance levels from estimating 25 iterations of a simple regression model on the sample including an observation for each author who published an anomaly in the sample. The dependent variable in all iterations is the annualized profitability of the anomaly as reported in the paper. The regression is estimated 25 times. Four binary variables are included in every iteration to control for the risk adjustment procedure used by the authors of the anomaly paper. Matched takes the value of one if the author(s) use a matched firm approach and zero otherwise. APM takes the value of one if the author(s) use an asset pricing model to risk adjust and zero otherwise. CAR takes the vale of one if the author(s) use an event study approach to risk adjust and zero otherwise. LS takes the value of one if he authors use a long-short strategy and zero otherwise. In addition to the four binary variables, I add one explanatory variable of interest in each iteration. The explanatory variables of interest are those in Table 2 for which the theoretical model of the paper offers predications regarding the signs.

	Expected			Ind. Var		Risk-Adjustmet Dummies					
Independent Variable of Interest	Sign	Intercept		of Interest		Matched	APM	CAR	LS	N	R^2
Previous Total Publications (PP)	-	0.086	***	-0.001	*	0.023	0.010	-0.041	0.029	52	0.17
Previous Total Publications per Year (PPY)	-	0.090	***	-0.021	*	0.017	0.004	-0.036	0.034	48	0.17
Previous Non-Top Publications (PNP)	-	0.086	***	-0.003	*	0.021	0.010	-0.039	0.029	52	0.17
Previous Non-Top Publications per Year (PNPY)	-	0.086	***	-0.044	**	0.019	0.009	-0.030	0.038	48	0.20
Residual Previous Total Publications (RPP)	-	0.075	***	-0.003		0.015	0.010	-0.034	0.027	52	0.14
Residual Previous Non-Top Publications per Year (RPNPY)	-	0.065	***	-0.055	**	0.020	0.013	-0.024	0.040	48	0.20
Previous Top Publications (PTP)	-	0.085	***	-0.002		0.023	0.009	-0.041	0.030	52	0.16
Previous Top Publications per Year (PTPY)	-	0.087	***	-0.025		0.015	0.002	-0.036	0.030	48	0.13
Years Between Obtaining PhD and Publishing Paper (Years)	-	0.090	***	-0.001		0.020	0.005	-0.033	0.029	48	0.14
PP x NTOP50	-	0.087	***	-0.002	*	0.015	0.003	-0.041	0.032	52	0.18
PP x NPAL	-	0.078	***	0.000		0.014	0.008	-0.035	0.027	52	0.12
PPY x NTOP50	-	0.087	***	-0.025	*	0.014	0.000	-0.032	0.037	48	0.16
PPY x NPAL	-	0.080	***	-0.021		0.017	0.007	-0.026	0.033	48	0.12
PNP x NTOP50	-	0.084	***	-0.003		0.013	0.006	-0.037	0.030	52	0.15
PNP x NPAL	-	0.078	***	-0.001		0.014	0.008	-0.034	0.027	52	0.12
PNPY x NTOP50	-	0.082	***	-0.046	*	0.016	0.005	-0.025	0.042	48	0.17
PNPY x NPAL	-	0.080	***	-0.037		0.015	0.007	-0.025	0.034	48	0.12
RPP x NTOP50	-	0.076	***	-0.002		0.012	0.008	-0.035	0.027	52	0.13
RPP x NPAL	-	0.077	***	-0.001		0.012	0.008	-0.035	0.027	52	0.12
RPNPY x NTOP50	-	0.066	***	-0.053	*	0.016	0.010	-0.022	0.040	48	0.17
RPNPY x NPAL	-	0.074	***	-0.055		0.009	0.006	-0.028	0.032	48	0.14
PTP x NTOP50	-	0.087	***	-0.005	*	0.017	0.003	-0.043	0.032	52	0.18
PTP x NPAL	-	0.078	***	-0.001		0.015	0.008	-0.035	0.027	52	0.12
PTPY x NTOP50	-	0.086	***	-0.030		0.012	-0.001	-0.034	0.031	48	0.13
PTPY x NPAL	-	0.078	***	-0.016		0.016	0.006	-0.027	0.031	48	0.10

* Significant at 10% level
** Significant at 5% level
*** Significant at 1% level

Table 7 – Multicollinearity Mitigated Regression Analyses

This table presents the results from estimating equation (25), exclusive of highly correlated variables, using the per year and orthogonalized definitions of the independent variables from two samples: (1) the full sample and (2) the sample in which the dependent variables, with the exception of the binary variables, have been log transformed. The dependent variable is the annualized profitability of the anomaly as reported in the original journal article introducing the anomaly. $PNPY_i$ and $PTPY_i$ are the number of non-top publications and top publications per year, respectively, the author had previous to the article representing the observation. $RPNPY_i$ is the number of residual non-top publications per year (non-top publications per year in excess of non-top publications per year expected given the number of top publications per year) the author had previous to the article representing the observation. $YEARS_i$ is the years between the year author i received his Ph.D. and the year he published the article associated with the observation. $AUTH_i$ is the number of authors who wrote the article representing the observation. $NTOP50_i$ takes the value of one if the author is not on any of the top 50 most prolific authors lists presented by Cooley and Heck (2005). $SNPY_i$ and $STPY_i$ are the number of non-top publications and top publications per year, respectively, the author had subsequent to the article representing the observation. RSNPYi is the number of residual non-top publications per year (non-top publications per year in excess of the non-top publications per year expected given the number of top publications per year) the author had subsequent to the article representing the observation. Four binary variables are included in every iteration to control for the risk adjustment procedure used by the authors of the anomaly paper. Matched takes the value of one if the author(s) use a matched firm approach and zero otherwise. APM takes the value of one if the author(s) use an asset pricing model to risk adjust and zero otherwise. CAR takes the vale of one if the author(s) use an event study approach to risk adjust and zero otherwise. LS takes the value of one if he authors use a long-short strategy and zero otherwise.

Panel A: Per Year Definition of Independent Variables

		Full Sample (Raw Variables)				Full Sample (Log Transformed Variables)			
Parameter	Expected Sign	Estimate N = 44	Estimate N = 44	Estimate N = 48	Estimate N = 48	Estimate N = 44	Estimate N = 44	Estimate N = 48	Estimate N = 48
Intercept		0.205 ***	0.192 ***	0.199 ***	0.183 ***	0.189 ***	0.170 ***	0.193 ***	0.180 ***
Years	-	-0.001	-0.001			-0.006	-0.003		
Auth	-/+	-0.051 ***	-0.053 ***	-0.051 ***	-0.053 ***	-0.050 **	-0.050 **	-0.050 ***	-0.052 ***
NTOP50	-/+	-0.042	-0.022	-0.043	-0.017	-0.025	-0.004	-0.036	-0.013
PNPY	-	-0.039		-0.043		-0.053		-0.064	
PTPY	-	0.014		0.011		0.028		0.019	
PNPY x NTOP50	-		-0.035		-0.039		-0.058		-0.061
PTPY x NTOP50	-		-0.006		-0.008		-0.003		-0.003
SNPY	-/+	-0.014	-0.013	-0.014	-0.012	-0.015	-0.012	-0.022	-0.020
STPY	-/+	-0.052	-0.049	-0.051	-0.048	-0.063	-0.058	-0.068	-0.067
Matched	-/+	0.078 **	0.075 **	0.075 **	0.072 **	0.077 **	0.075 **	0.075 **	0.073 **
APM	-/+	0.041	0.034	0.041	0.033	0.042	0.036	0.040	0.034
CAR	-/+	0.028	0.025	0.029	0.026	0.022	0.019	0.024	0.024
LS	-/+	0.124 ***	0.124 ***	0.125 ***	0.126 ***	0.111 **	0.113 **	0.120 ***	0.122 ***

* Significant at 10% level
** Significant at 5% level
*** Significant at 1% level

Table 7 Continued

This table presents the results from estimating equation (25), exclusive of highly correlated variables, using the per year and orthogonalized definitions of the independent variables from two samples: (1) the full sample and (2) the sample in which the dependent variables, with the exception of the binary variables, have been log transformed. The dependent variable is the annualized profitability of the anomaly as reported in the original journal article introducing the anomaly. $PNPY_i$ and $PTPY_i$ are the number of non-top publications and top publications per year, respectively, the author had previous to the article representing the observation. $RPNPY_i$ is the number of residual non-top publications per year (non-top publications per year in excess of non-top publications per year expected given the number of top publications per year) the author had previous to the article representing the observation. $YEARS_i$ is the years between the year author i received his Ph.D. and the year he published the article associated with the observation. $AUTH_i$ is the number of authors who wrote the article representing the observation. $NTOP50_i$ takes the value of one if the author is not on any of the top 50 most prolific authors lists presented by Cooley and Heck (2005). $SNPY_i$ and $STPY_i$ are the number of non-top publications and top publications per year, respectively, the author had subsequent to the article representing the observation. RSNPYi is the number of residual non-top publications per year (non-top publications per year in excess of the non-top publications per year expected given the number of top publications per year) the author had subsequent to the article representing the observation. Four binary variables are included in every iteration to control for the risk adjustment procedure used by the authors of the anomaly paper. Matched takes the value of one if the author(s) use a matched firm approach and zero otherwise. APM takes the value of one if the author(s) use an asset pricing model to risk adjust and zero otherwise. CAR takes the vale of one if the author(s) use an event study approach to risk adjust and zero otherwise. LS takes the value of one if he authors use a long-short strategy and zero otherwise.

Panel B: Orthogonalized Variables

		Full Sample (Raw Variables)				Full Sample (Log Transformed Variables)			
Parameter	Expected Sign	Estimate N = 44	Estimate N = 44	Estimate N = 48	Estimate N = 48	Estimate N = 44	Estimate N = 44	Estimate N = 48	Estimate N = 48
Intercept	-	0.189 ***	0.187 ***	0.182 ***	0.178 ***	0.177 ***	0.167 ***	0.178 ***	0.175 ***
Years	-/+	-0.001	-0.001			-0.006	-0.003		
Auth	-/+	-0.051 ***	-0.053 ***	-0.051 ***	-0.053 ***	-0.050 **	-0.050 **	-0.050 ***	-0.052 ***
NTOP50	-	-0.042	-0.031	-0.043	-0.028	-0.025	-0.013	-0.036	-0.023
RPNPY	-	-0.039		-0.043		-0.053		-0.064	
PTPY	-	-0.001		-0.005		0.004		-0.009	
PNP x NTOP50	-		-0.035		-0.039		-0.058		-0.061
PTP x NTOP50	-/+		-0.020		-0.023		-0.029		-0.030
RSNPY	-/+	-0.014	-0.013	-0.014	-0.012	-0.015	-0.012	-0.022	-0.020
STPY	-/+	-0.059 *	-0.055 *	-0.057 *	-0.054 *	-0.070	-0.063	-0.078	-0.076
matched	-/+	0.078 **	0.075 **	0.075 **	0.072 **	0.077 **	0.075 **	0.075 **	0.073 **
apm	-/+	0.041	0.034	0.041	0.033	0.042	0.036	0.040	0.034
car	-/+	0.028	0.025	0.029	0.026	0.022	0.019	0.024	0.024
ls	-/+	0.124 ***	0.124 ***	0.125 ***	0.126 ***	0.111 **	0.113 **	0.120 ***	0.122 ***

* Significant at 10% level
** Significant at 5% level
*** Significant at 1% level

Table 8 – Principal Components

All previous publication variables, along with the years since an author received his Ph.D., are intended to proxy for a single factor – reputation. Similarly, all subsequent publication variables, along with the NTOP50 variable are intended to proxy for a single control variable – the proportional utility an author derives from reputation. This table contains the factor loadings and eigen values of the first principal component of various combinations of the explanatory (previous publications variables and years since an author received his Ph.D.) variables and various combinations of the control variables (subsequent publications variables and NTOP50).

	Raw Prev Pubs Factor Loadings			Per Year Prev Pubs Factor Loadings			Orth Prev Pubs Factor Loadings		
Variable	Factor	Interaction Factor	Control Factor	Factor	Interaction Factor	Control Factor	Factor	Interaction Factor	Control Factor
Previous Non-Top Publications (PNP)	0.886								
Previous Non-Top Publications per Year (PNPY)				0.846					
Residual Previous Non-Top Publications per Year (RPNPY)							0.553		
Previous Top Publications (PTP)	0.873								
Previous Top Publications per Year (PTPY)				0.793			0.636		
Subsequent Non-Top Publications (SNP)			0.681						
Subsequent Non-Top Publications per Year (SNPY)						0.605			
Subsequent Top Publications (STP)			0.98						
Subsequent Top Publications per Year (STPY)						0.938			0.864
Residual Subsequent Non-Top Publications per Year (RSNPY)									0.305
Years Between Obtaining PhD and Publishing Paper (Years)	0.68	0.669		0.442	0.307		0.547	0.576	
Not in Top 50 Authors List (NTOP50)			-0.82			-0.791			-0.858
PNP x NTOP50		0.791							
PNPY x NTOP50					0.838				
RPNPY x NTOP50								0.424	
PTP x NTOP50		0.793							
PTPY x NTOP50					0.671			0.35	
Eigen Value of 1st Principle Component	2.009	1.702	2.099	1.541	1.247	1.872	1.01	0.634	1.577
Eigen Value of 2nd Principle Component	0.001	0.001	0.139	0.002	0.004	0.001	0.001	0.001	0.001

Table 9 – Principal Components Regression Analyses

This table presents the results from estimating equation (25), replacing the previous publications and years variables with the first principal component obtained using those variables and replacing the subsequent publications and not in any of the top 50 authors lists variables with the first principal component obtained using those variables. The dependent variable is the annualized profitability of the anomaly as reported in the original journal article introducing the anomaly. Raw Previous Pubs Factor is the first principal component from the previous non-top publications, previous top publications, and years variables. Raw Previous Pubs Interaction Factor is the first principal component from the years variable and the previous non-top publications and previous top publications variables interacted on the not in any of the top 50 authors lists variable. Raw Control Factor is the first principal component from subsequent non-top publications, subsequent top publications, and the not in any of the top 50 authors binary variable. Per Year Previous Pubs Factor, Per Year Previous Pubs Interaction Factor, and Per Year Control Factor are similar to the Raw Previous Pubs Factor, Raw Previous Pubs Interaction Factor, and Raw Control Factor, respectively, except the publications are per year, instead of aggregate values. Orthogonalized Previous Pubs Factor, Orthogonalized Previous Pubs Interaction Factor, and Orthogonalized Control Factor are similar to the Raw Previous Pubs Factor, Raw Previous Pubs Interaction Factor, and Raw Control Factor, respectively, except the non-top publications and top publications have been orthogonalized. Matched takes the value of one if the author(s) use a matched firm approach and zero otherwise. APM takes the value of one if the author(s) use an asset pricing model to risk adjust and zero otherwise. CAR takes the vale of one if the author(s) use an event study approach to risk adjust and zero otherwise. LS takes the value of one if he authors use a long-short strategy and zero otherwise.

Panel A: Raw Definition of Variables (N = 48 for all specifications)

Parameter	Estimate		Estimate		Estimate		Estimate	
Intercept	0.074	***	0.080	***	0.135	***	0.138	***
Raw Previous Pubs Factor	-0.019	*			-0.009			
Raw Previous Pubs Interaction Factor			-0.021	**			-0.015	*
Auth					-0.046	***	-0.046	***
Raw Control Factor	-0.005		0.009		0.004		0.012	
Matched	0.027		0.014		0.067	**	0.061	**
APM	0.008		-0.001		0.026		0.020	
CAR	-0.034		-0.039		0.002		-0.003	
LS	0.036		0.032		0.104	***	0.102	***
	R^2 = .1687		R^2 = .1901		R^2 = .3669		R^2 = .3955	

Panel B: Per Year Definition of Variables (N = 48 for all specifications)

Parameter	Estimate		Estimate		Estimate		Estimate	
Intercept	0.077	***	0.076	***	0.139	***	0.140	***
Per Year Previous Pubs Factor	-0.020	**			-0.011			
Per Year Previous Pubs Interaction Factor			-0.024	**			-0.019	**
Auth					-0.049	***	-0.050	***
Per Year Control Factor	0.000		-0.011		-0.010		-0.018	**
Matched	0.019		0.014		0.068	**	0.067	**
APM	0.005		0.002		0.028		0.027	
CAR	-0.036		-0.027		0.008		0.013	
LS	0.034		0.038		0.110	***	0.116	***
	R^2 = .1855		R^2 = .2028		R^2 = .4004		R^2 = .4419	

Panel C: Orthogonalized Variables (N = 48 for all specfications)

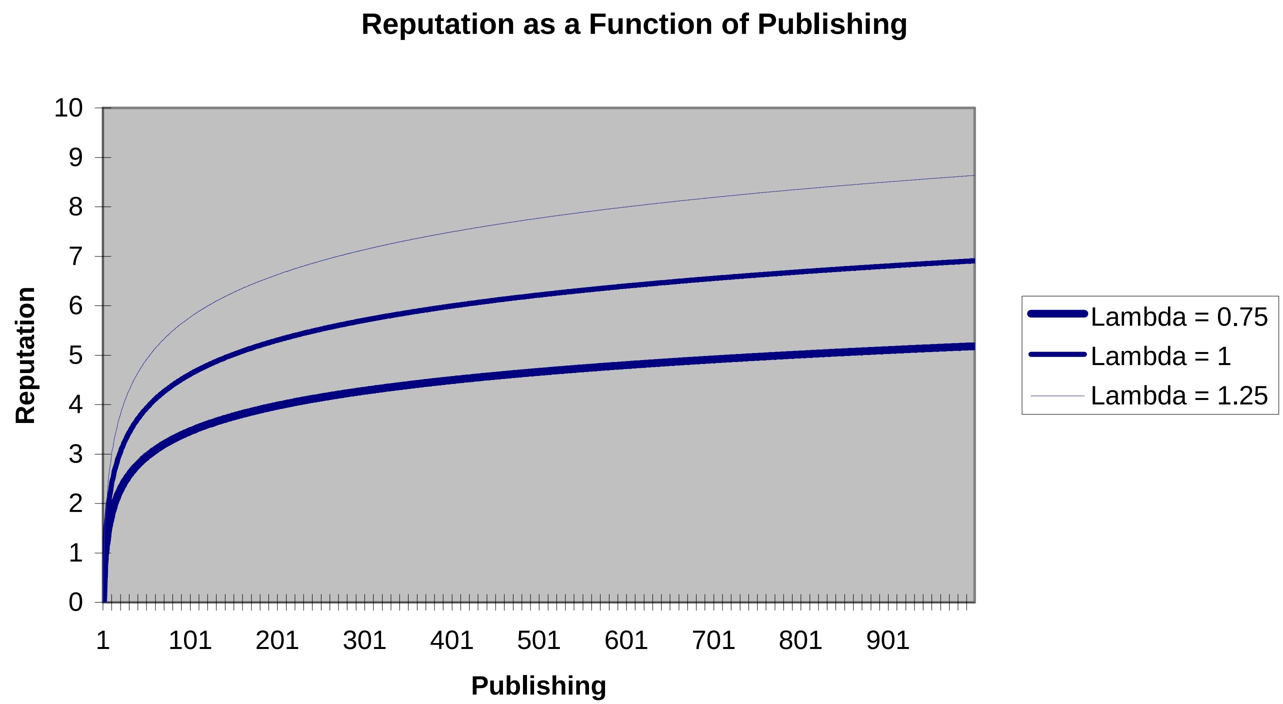
Parameter	Estimate		Estimate		Estimate		Estimate	
Intercept	0.077	***	0.077	***	0.137	***	0.138	***
Orthogonalized Previous Pubs Factor	-0.024	**			-0.014			
Orthogonalized Previous Pubs Interaction Factor			-0.027	**			-0.020	*
Auth					-0.047	***	-0.048	***
Orthogonalized Control Factor	0.000		-0.006		-0.008		-0.012	
Matched	0.021		0.019		0.067	**	0.068	**
APM	0.005		0.004		0.027		0.026	
CAR	-0.037		-0.033		0.003		0.005	
LS	0.033		0.032		0.106	***	0.107	***
	R^2 = .1907		R^2 = .1968		R^2 = .397		R^2 = .4179	

* Significant at 10% level
** Significant at 5% level
*** Significant at 1% level

Appendix A
Graphical Representation of Reputation as a Function of Publishing

Appendix A contains a graphical representation of the assumed relationship between reputation (R) and publishing (P) with three different values of the constant parameter λ_R (0.75, 1, 1.25). The graph depicts a positive but decreasing marginal relationship where the lower values of P add much more to R than do the higher values of P. I.e., the first few high quality publications increase reputation much more than the 30th high quality publication does. λ_R influences the magnitude of the effect of a given level of P on R.

$$R(P) = \ln(P^{\lambda_R}) \quad (2)$$



Appendix B
Partial Derivatives of Utility Function

Begin with the utility function:

$$U(W,R) = A^{\alpha} R^{\alpha+\beta} \tag{11}$$

$$\text{where A} = [\delta_S + \delta_O \ln(\pi^{\lambda_O})] \tag{12}$$

$$\text{and } R = \ln(P^{\lambda_R}) \tag{2}$$

We eventually need the first derivative of A with respect to π and the first derivative of R with respect to P.

$$\frac{dA}{d\pi} = \frac{\delta_O \lambda_O}{\pi} \tag{12.1}$$

$$\frac{dR}{dP} = \frac{\lambda_R}{P} \tag{2.1}$$

We next calculate the partial derivative of utility with respect to P. Note R is a function of P, but A is not. Using the chain rule and calling upon equation (2.1) above the partial derivative is calculated thusly:

$$\frac{\partial U}{\partial P} = A^{\alpha}\left[\frac{d\left(R^{\alpha+\beta}\right)}{dR}\right]\left[\frac{d(R)}{dP}\right] \tag{11.1A}$$

$$\frac{\partial U}{\partial P} = A^{\alpha}\left[(\alpha+\beta)R^{\alpha+\beta-1}\right]\left[\frac{\lambda_R}{P}\right] \tag{11.1B}$$

We next calculate the partial derivative of utility with respect to p. Note that A is f function of π, but R is not. Using the chain rule and calling upon equation (12.1) above the partial derivative is calculated thusly:

$$\frac{\partial U}{\partial \pi} = \left(\frac{dA^{\alpha}}{dA}\right)\left(\frac{dA}{d\pi}\right)R^{\alpha+\beta} \tag{11.2A}$$

$$\frac{\partial U}{\partial \pi} = \left(\alpha A^{\alpha-1}\right)\left(\frac{\delta_O \lambda_O}{\pi}\right)R^{\alpha+\beta} \tag{11.2B}$$