A Tangled Tale of Training and Talent: PhDs in Institutional Asset Management*

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Abstract

Performance of investment products managed by firms in which PhDs play a key role is superior to the performance of products managed by otherwise similar firms. This relation is not a result of endogenous matching between firms and PhDs. Performance is related to training (the field of study) because economics or finance PhDs outperform other PhDs. Performance is also related to talent because PhDs who published in top outlets outperform other PhDs. Field-specific training does not matter among the most talented PhDs because the performance gap between economics or finance PhDs and other PhDs completely disappears among published PhDs.

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This paper empirically examines whether educational attainment conveys field-specific training (acquired skill), talent (innate ability), or both. To address this longstanding question in economics (e.g., Becker (1962, 1964, 1993), Spence (1973), Arrow (1973)), we study investment performance records of investment professionals in the institutional asset management industry who hold PhDs in a variety of fields. Our deliberate choice of such a specific domain of human activity to address such a broad question is driven by two considerations.

First, institutional asset management entails a relatively homogeneous task of generating risk-adjusted portfolio returns. Investment performance can be measured relatively precisely by applying well-established performance measurement tools. Therefore, this setting alleviates concerns regarding both performance measurement imprecision and incomparability of the potentially highly variable tasks that may prevail in other settings. Second, two important facets of heterogeneity among the 531 PhDs from our sample enable us to provide a novel contribution to the literature by identifying and quantifying the relation between task performance and both acquisition of field-specific training and possession of talent. About one-half of the PhDs from our sample hold doctorates in economics, finance, or a closely related field, while others largely pursued STEM fields such as mathematics, physics, statistics, chemistry, and engineering disciplines.[1] Moreover, some have showcased their talent by publishing in the elite journals in their respective disciplines, while others have not.[2]

Our setting has substantial advantages in regard to performance measurement precision and task homogeneity. The extant literature focusing on intermediate levels of corporate structure typically resorts to measures reflecting success within the firm (e.g., promotion, salary, grade level, supervisor evaluations).[3] Such measures are not only inherently noisy and imprecise, but are also strongly tied to the organization itself, making broader comparison across organizations challenging because of the heterogeneity of both employee tasks and organizations. Another strand of the literature focuses on the leadership tier, often the relation between performance of corporate CEOs and their characteristics. A common firm performance metric is its stock return. However,

[1] A substantially smaller group, about 5% of the PhDs from our sample, earned their doctorates in liberal arts and humanities.
[2] In some specifications, we also exploit the fact that some of the PhDs from our sample hold doctorates from leading universities, while others hold doctorates from other institutions.
[3] In a seminal study of academic achievement and job performance of college graduates working in a large corporation, Wise (1975, p. 353) notes: "There seems to be no completely satisfactory way of measuring job performance, or even defining it."

measuring CEO performance by analyzing stock returns or other measures dependent on market valuations provided through the company's stock price is challenging.

Because firm market value typically reflects expectations of future profitability, an efficient market will realize that a firm has a more talented manager whose decisions are expected to generate greater profitability than that of the firm's peers and will swiftly incorporate this information into the firm's stock price. Therefore, the firm's subsequent returns or other valuation metrics that depend on this price dynamic will not necessarily reflect the actual level of the CEO's managerial talent. Instead, all expected risk-adjusted returns will be equal to zero in an efficient market. The use of other standard valuation metrics such as operating profitability (EBIT) is challenging, both because such metrics may have many different interpretations and because they are measured with low frequency, potentially reducing statistical power of the econometric tests employing them.[4]

By contrast, asset managers' performance measure is the performance of their portfolios, and that performance is not directly tied to the values of their asset management firms. Performance of an investment product is an agglomeration of many investment picks into a well-diversified instrument, rather than the performance of a single company (as is the case in the literature studying the relation between CEOs' performances and their characteristics). This circumstance enables not only more precise measurement of investment product performance by means of well-understood benchmarking techniques that control for exposures to systematic sources of risk, but it also, given the homogeneity of the task at hand, facilitates direct comparison across all investment products pursuing the same investment style. Moreover, unlike a more typical corporate finance setting, expectations of future performance are not immediately capitalized into the initial value of the investment product and subsequent product performance is not directly contaminated with expectations of skill.[5]

Therefore, it is not surprising that some of the most precise answers regarding the relation between performance and managerial characteristics come from the domains close to our own inquiry. Chevalier and Ellison (1999) find that mutual fund managers from higher average SAT undergraduate institutions tend to have higher raw and risk-adjusted returns, and Li, Xang, and Zhao

[4] The CEO literature has implicitly adjusted to these challenges by, instead of focusing directly on performance, often pursuing studies of top managements' traits such as risk aversion (e.g., Rotemberg and Saloner (1993, 1994, 2000) and Aggarwal and Samwick (2003, 2006)), overconfidence (e.g., Malmendier and Tate (2005, 2005, 2008) and Goel and Thakor (2008)), and managerial style (e.g., Bertrand and Schoar (2003) and Fee, Hadlock, and Pierce (2013)). A notable exception is Pérez-González (2006). It brings together studying top management performance and effects of educational attainment by finding wasteful nepotism—underperformance by family-appointed successor CEOs, but only in the instances without "selective" CEO education.

[5] Investment product size and firm size in the money management industry are both indirectly contaminated with expectations of managerial skill because money chases performance in the spirit of Berk and Green (2004). Because size lowers performance in an environment with decreasing returns to scale, we make sure to observe managerial performance conditional on size.

(2011) find the same for hedge-fund managers. Chevalier and Ellison (1999) also find that managers holding MBA degrees outperform their counterparts without an MBA in terms of raw returns, but that gap vanishes upon risk adjustment. However, absence of further information and lack of sufficient variation among asset managers' educational backgrounds result in the lack of evidence regarding the extent to which job performance varies with training (acquisition of task-specific background) and talent (innate ability). By contrast, the heterogeneity of the 531 PhDs from our sample in terms of the fields of doctoral study and publication records in top-tier journals enable us to overcome these limitations and identify and quantify the relation between task performance and both acquisition of field-specific training and possession of talent.

More than a thousand institutional asset management firms manage trillions of dollars for corporate retirement plans, government retirement plans, insurance companies, high net-worth individuals, endowments, foundations, and unions.[6] Among its investment professionals, 531 PhDs have been performing key roles related to the return-generating processes.[7] In the spirit of Grossman and Stiglitz (1980), a PhD performing a key role in an asset management firm can be viewed as an ongoing expenditure that increases information acquisition. Accordingly, our conjecture is that the human capital associated with a PhD degree is linked to the acquisition and utilization of information related to investments. We predict that institutional asset managers' skill is positively related to holding a PhD degree. We focus on actively-managed domestic equity products because they encompass more than one-half of the industry's assets under management and because their investment benchmarks are well-developed. We use various methods of risk-adjustment to remove many aspects of performance driven by several common strategies that may appear to outperform the market, but can be replicated with simple mechanical strategies.

We refer to the firms with one or more PhDs in key roles as PhD firms and to the products such firms manage as PhD products; accordingly, we refer to products managed by non-PhD firms as non-PhD products. In our baseline analyses, at the beginning of each sample year we match each PhD product-year observation with a corresponding non-PhD product-year observation along three dimensions. First, the two products should pursue the same investment objective. Second, the two products should belong to same quintile of the cross-sectional distribution of assets under

[6] According to Standard & Poor's (2007), at the end of 2006 (near the end of our sample period), more than 51,000 plan sponsors allocated more than seven trillion dollars in assets to about 1,200 institutional money management firms.

[7] Key roles in institutional money management, defined in accordance with the Nelson's Directory of Investment Managers classification, are enumerated in Section 1.1.

management for their investment objective.[8] Third, to align closely the characteristics of the respective firms in which the two products operate, the matched observation should be the closest to the PhD product-year observation in terms of their respective firms' PhD propensity scores.[9]

Differences between performances of PhD products and their matched non-PhD products are positive, statistically significant and economically meaningful for all five measures we employ. These performance differentials confirm our baseline hypothesis and are of inherent interest to institutional investors seeking superior performance. The key purpose of our study, however, is disentangling the roles of field-specific training and talent, an undertaking requiring further analyses.

We proceed by noting that the link between product performance and the presence of a PhD in a key role might stem from endogenous matching. For instance, better firms may choose to hire PhDs as an advertising tool to attract more money,[10] even without expectations of the PhDs' subsequent contributions to performance. Also, PhDs may be more capable than non-PhDs to determine which firms will do well and select employers accordingly. In both scenarios, PhDs in key roles might not provide any incremental contribution to product performance, yet an econometrician would observe a performance differential between PhD products and their matched non-PhD products.

We address these and other similar possibilities in two ways. First, we examine the products managed by the firms founded as PhD firms during our sample period, with PhDs performing key roles since inception. At the moment of founding, such firms had no history, and a PhD in a key role is an integral part of subsequent product performance from the outset. Finding a positive performance gap between PhD products and their matched non-PhD products in this subsample would suggest that performance differentials calculated for the full sample are not an artifact of endogenous matching in which PhDs do not have particular investment acumen, yet they somehow match with "good" firms. We indeed find performance gaps between PhD products and their matched non-PhD products in this subsample similar in magnitude to those obtained from the full sample. Conceivably, a PhD could be hired in a key role by newly founded firm without expectations regarding investment performance, and this hiring decision could be correlated with non-PhDs firm founders' innate ability. To address this possibility, we restrict the subsample of the firms founded by PhDs to those in which PhDs play increasingly more selective roles in the firm (it is implausible that PhDs would

[8] This matching requirement is in line with the extant mutual-fund literature that establishes a negative relation between performance and size (e.g., Berk and Green (2004), Chen, Hong, Huang, and Kubik (2004), Pollet and Wilson (2008)).
[9] The propensity score matching uses several observable firm characteristics to capture the likelihood that a product is managed by a PhD firm. Details are featured in Section 1.3 and in Appendix A.1.
[10] In Appendix A.2, we indeed report that PhD products attract more flows than their matched non-PhD products do.

occupy the most senior positions in the firm, but the firm's superior performance would be driven solely by other, non-PhD key personnel). If anything, we find that restricting the subsample first to the firms in which a PhD had played a key role of CEO, founder, president, or principal, and then to the firms in which a PhD had served as CEO at founding, only increases the performance gap.

Second, we implement an instrumental variables approach in a panel setting. Historically, the asset management industry has been strongly dominated by the firms with Anglo-Saxon and, to some extent, German roots (Davis and Gallman, 2001).[11] Each year, we match the investment professionals' last names with their ethnic origin and create a firm-year ethnic composition measure as the percentage of "outsiders" whose last names do not have Anglo-Saxon (or, alternatively, have neither Anglo-Saxon nor German) roots. The first stage of our instrumental variables analysis shows that the presence of a PhD in a key role is strongly positively related to the percentage of "outsiders," presumably reflecting the benefit of external validation embedded in hiring a PhD as a factor to offset the deviation from a traditional asset management firm's ethnic mix.

As in any instrumental variables setting, a key assumption is that the instrument satisfies the exclusion restriction. The firm's ethnic mix should only affect performance through the decision to hire a PhD. Whereas no instrument can be rigorously proven to satisfy this exclusion restriction, any challenges to this instrument would need to assert that there is a variation in the extent to which various ethnicities are capable of generating investment performance (i.e., that investment performance is caused by ethnicity), and we are comfortable not entertaining such challenges. The regression coefficients from the second stage of our instrumental variables approach indicate a statistically significant and economically large positive performance gap between PhD products and non-PhD products, with point estimates somewhat larger than those in the baseline matching and OLS panel approaches.

From the perspective of institutional asset management, pursuing a PhD may be viewed as a process of accumulating either directly relevant human capital (PhDs in economics or finance) or indirectly relevant human capital (PhDs in other fields). Accordingly, we estimate the performance gap between products managed by PhDs in economics or finance and products managed by PhDs in other, mostly STEM fields. The statistically significant and economically meaningful positive performance differential between PhD products managed by economics or finance PhDs and matched PhD products

[11] This domination evolved in the second half of the 19^{th} century, with a persistent effect that still affects the present. Indeed, to date, the names of many firms adhere to the naming conventions consistent with Anglo-Saxon and German roots.

managed by PhDs in other fields for three out of the five performance measures suggests that field-specific knowledge associated with a PhD degree is relevant in asset management.[12]

We proceed to focus on talent, measured as success in placing research in premier academic journals. Eighty-three of the PhDs in key roles from our sample have published in premier journals in their respective fields.[13] We show that the performance of PhD products managed by PhDs who published in top outlets exceeds the performance of matched PhD products managed by PhDs who did not publish in such outlets. This is true for the overall sample, for the subsample of PhDs with doctorates in economics or finance, as well as for the subsample of PhDs with doctorates in other fields. The robustness of the performance gap across the subsamples defined by the field of study indicates that talent contributes to performance regardless of the field of training.

We also compare the performance of economics or finance PhD products and the performance of other PhD products separately for published PhD products and unpublished PhD products. If the field of study leaves an equal differential imprint on performance across different levels of talent, the performance gap between economics or finance PhDs and other PhDs should prevail among both subsamples of published and unpublished PhD product-year observations. By contrast, it is also plausible that the field of training does not matter in the domain of the highest percentiles of talent. Our empirical results strongly confirm the latter. The aforementioned suggestive and moderately robust evidence of stronger performance delivered by economics or finance PhDs relative to other PhDs might be an agglomeration of different outcomes across the two subsamples. Indeed, our results show that, whereas the gap is very large and highly statistically significant among the unpublished—moderately talented—PhDs, the gap completely disappears among the published—highly talented—PhDs. This is a remarkable finding because it shows that the contribution of the specific field of training to performance is completely eclipsed by the sheer talent in its upper echelons.

Finally, among several other alternative specifications, we address the concern that viewing publication records as a measure of talent is instead not better interpreted as a byproduct of elite universities deploying some indeterminate combination of identifying superior talent during the

[12] We note that the field of study for each PhD is not randomly assigned and that a variety of selection issues might obscure the true magnitude of the importance of specific knowledge in finance. However, it would be difficult to argue that selection issues contaminate these results by leading to differential talent across disciplines. Indeed, ability-related admission criteria to doctoral programs in physics, mathematics, statistics, natural sciences, or engineering are unlikely to be less stringent than those pertaining to economics or finance.
[13] The list of top outlets in economics and finance comprises American Economic Review, Econometrica, Journal of Political Economy, Quarterly Journal of Economics, and Review of Economic Studies (economics), as well as Journal of Business, Journal of Finance, Journal of Financial Economics, and Review of Financial Studies (finance). Journals in other fields were taken to be of similar stature in the respective fields, as evinced by their impact factors and name recognition.

admission process, providing superior training during doctoral studies, and offering superior access to an influential alumni network thereafter to produce superior PhDs who, incidentally, are more likely to publish. We replicate the key results by means of an augmented matching strategy, matching PhD product-year observations along the usual dimensions and, also, by the elite university status of their PhDs. The results based on such an augmented matching diffuse this concern because they remain very similar to the respective results reported in the earlier analyses.

1. Data Sources, Sample Overview, and Matching Procedure

1.1. Data sources

Our unique data set covers the institutional asset management industry in the period from June 1993 to December 2007. In a manner similar to Berzins, Liu, and Trzcinka (2013), we obtained as a series of 59 quarterly snapshots from the Mobius Group and, toward the end of the sample period, from Informa Investment Solutions (IIS) PSN Data Select. The data snapshots were disseminated on disks, ensuring that the resulting data set is not affected by survivorship bias. The data set covers investment products that asset management firms offer to institutional clients. It consists of monthly product returns (net of trading costs, but gross of investment management fees) and a number of firm and product characteristics, including quarterly snapshots of products' firm affiliation and investment objectives, annual snapshots of products' assets under management, and, of particular importance for this study, quarterly snapshots of firms' personnel biographical data.[14]

Academic research concerning the institutional asset management industry considered determinants of clients' decisions to hire and terminate institutional asset management firms (Goyal and Wahal, 2008), persistence of their investment performance (Busse, Goyal, and Wahal, 2010), and connections between asset management and investment banking (Berzins, Liu, and Trzcinka, 2013), among other topics. At first glance, the paucity of research regarding the institutional asset management industry, especially compared to the substantially larger volume of research produced regarding the mutual fund industry, is striking. A key reason for

[14] Upon subsuming the Mobius Group in late 2006 and the subsequent expiration of one-year agreements with Mobius clients, Informa Investment Solutions began applying its own access and pricing model (data extractions charged by variable, for a severely limited number of products at a time), making continued subscription to the data substantially more onerous and prohibitively costly. Ultimately, December 2007 was the last installment IIS was willing to provide under the earlier pricing scheme and through dissemination of quarterly disks. Since that date, to our knowledge, there is no data set in existence that can recreate quarterly snapshots in a manner similar to the earlier dissemination from the 1993-2007 period (and also similar to the dissemination to the CRSP Survivor-Bias-Free US Mutual Fund Database).

this discrepancy is differential availability of detailed data. Whereas both industries fall within the purview of the Investment Advisers Act of 1940 (regulating virtually all investment advisers), only the mutual fund industry is regulated by the Investment Company Act of 1940. Consequently, compared to the mutual fund industry, institutional asset management firms are required to—and routinely choose to—disclose substantially less information.

Naturally, this circumstance places more constraints on what the econometrician may observe and analyze, thereby ruling out certain kinds of analyses routinely implementable in the mutual-fund research arena. For example, institutional asset management firms do not disclose daily performance (they may choose to do so for a specific client upon request) or the fees they charge to existing or new clients (nor their breakdown into equivalents of marketing costs, management fees, administrative fees, operating costs, and so on). Similarly, they do not disclose periodic product-level portfolio composition (they may choose to provide detailed portfolio composition and transaction history to specific clients upon request). Indeed, although institutional investment managers using U. S. mail or other means or instrumentality of interstate commerce and exercising investment discretion over $100 million or more in Section 13(f) securities must file Form 13F, their filings routinely contain holdings aggregated across all the investments they manage, rendering product-level disaggregation elusive.

However, particularly germane for the key purpose of this article—studying PhDs in asset management—is one distinct advantage of the institutional asset management industry. Specifically, unlike the mutual fund industry, the institutional asset management industry provides biographical descriptions for *all* of its investment professionals.[15] The biographical data contain personnel names, titles, and degrees for 21,313 distinct individuals. Their titles and the related descriptions provide the roles they play in their firms, but the vast majority of these individuals do not serve in key roles. There is considerable heterogeneity in the terminology the firms use to name the roles. We classified these various titles into 30 key roles (an individual could perform multiple roles, such as CEO *and* Chief Investment Officer),[16] as defined by the roles of "Key Personnel" in Nelson's Directory of Investment Managers.

[15] Whereas mutual-fund databases such as CRSP and Morningstar record some biographical data regarding mutual fund managers, they do not provide comparable information for other key personnel or other investment professionals.

[16] The thirty key roles are: Advisor; Analyst/Researcher; Associate; Assistant/Associate Director; Assistant Vice President; CEO; Chairman/Chairman of the Board; Chief Economist/Senior Economist; Chief Investment Officer/Chief Investment Strategist/Senior Investment Officer; Consultant; Chief Operating Officer; Chief Portfolio Manager/Senior Portfolio Manager/Lead Portfolio Manager; Director/Head/Leader; Director of Research; Economist; Executive Vice President; Executive Director; Founder; General Partner; Information Technology Specialist/Programmer; Managing Director; Managing Partner;

We focus on the 531 individuals holding a PhD degree and performing key roles in firms that manage domestic equity products.[17] In some instances, the indication of a PhD degree in the biographical data is accompanied by the field of study and the institution that awarded the degree. Because that coverage in the data is not comprehensive, we engaged in additional data collection through a variety of sources, including product prospectus information, biographical descriptions on firm web pages, profiles posted on LinkedIn, as well as other web sources. We succeeded in collecting the information regarding the field of PhDs' studies and the institutions that awarded their doctorates for practically all of the PhDs performing key roles in our sample.

The biographical data do not map personnel to specific products within firms. Indeed, unlike mutual fund companies, which disclose the managers for each mutual fund, institutional asset management firms do not reveal equivalent information for each product with the same degree of precision. Rather, they typically report their investment professionals' focus on particular asset classes.[18] Absent a precise mapping between managers and products, we define PhD firms as the firms in which a PhD performs a key role and PhD products as products managed by PhD firms; we define non-PhD firms and non-PhD products analogously. The potential imprecision associated with estimating gaps in performance between PhD products and non-PhD products, created in the absence of more precise information by labeling all domestic equity products managed by a PhD firm as PhD products, does not contaminate our findings for at least two reasons. First, investment philosophies and strategies typically are conceived at the asset-class level, permeating to the firm's individual domestic equity products. Second, assigning the PhD label to a product that had not been managed by PhDs (although the firm is a PhD firm) may only bias against finding performance gaps between PhD products and non-PhD products.

Our analyses employ standard investment benchmarks (objective- and size-adjusted annual returns, 4-factor Carhart (1997) alphas, Sharpe ratios, information ratios, and manipulation-free Goetzmann, Ingersoll, Spiegel, and Welch (2007) measure MPPM (rho = 3)).

Partner; Portfolio Manager/Investment Manager; President; Principal; Strategist; Senior Vice President/First Vice President; Vice Chairman; Vice President.

[17] Aside from the 531 individuals performing key roles, there are 166 other PhDs who perform other roles, typically related to sales and marketing (PhDs in marketing, psychology, and similar), and information technology (PhDs in information sciences, computer science, computer engineering, and similar), among others. Whereas these PhDs perform important roles in their respective firms, their activities are not regarded as central to the return-generating process.

[18] No regulation requires institutional money management firms to disclose which of their investment professionals managed specific products at specific times. If any information along these lines is reported, it typically provides no more than their investment professionals' focus on particular asset classes. Whereas such lack of specificity may benefit institutional money management firms by providing them with some latitude in allocating and shifting their investment professionals' effort and attention across multiple products over time, it makes the precise mapping unobservable for the econometrician.

The data for the domestic equity risk factors come from the data library made broadly available by Kenneth French.[19] Also, we classify products into twelve investment objectives: equity combined, equity growth, equity value, large cap, large growth, large value, mid cap, mid cap growth, mid cap value, small cap, small cap growth, and small cap value. Moreover, because analyses focus on actively managed products, we exclude index products.

The data set also contains some information about products' fee schedules. Because institutional asset management firms do not need to disclose them, fees were not reported for 36.7% of the sample observations. Moreover, unlike mutual funds, institutional asset management firms may charge different fees to different investors in the same product. Also, there are two additional reasons why the information contained in the data set does not enable us to calculate the actual fees charged for the product even when fee schedules are reported; both reasons are related to the fact that the data do not contain adequately detailed information about the clients. First, the data provide fee schedules by the ranges applying to client accounts' assets under management. Therefore, the fees the products charge cannot be computed for products with multiple client accounts because the information regarding their assets under management in the product is unavailable. Second, fees are negotiable and can be discounted, especially for larger clients with substantial bargaining power, and these discounts are not observable. With all these caveats, we calculate for each product-year observation its "expense ratio" by dividing the fees that the products state for the most commonly reported level of assets under management (25 million dollars) by 25 million dollars.[20]

To implement an instrumental variable strategy for some of the analyses that seek to address endogeneity concerns (Section 3), we match the last names of all the investment professionals in the firm with their ethnic origin.[21] The 21,313 investment professionals in the

[19] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[20] Results reported in the paper are very similar if we focus instead on 10-million dollar account or 50-million dollar accounts, but such calculations imply the loss of more observations because of the increased propensity not to report in those ranges. Moreover, 25 million dollars is close to 29 million dollars, the average median account size in the sample.

[21] The sources we used to identify last names' ethnic origin include Last Name Meanings and Origins (www.ancestry.com/learn/facts/), Behind the Name: Meaning of Surnames (surnames.behindthename.com/), Surname Origins - Ancestor Search (www.searchforancestors.com/surnames/origin/), Surname Finder | Free Ancestry Search Resource (www.surnamefinder.com/), Surname Database: Last Name Origins (www.surnamedb.com/), Family Tree Searcher: Family Trees Searched at Ten Sites (www.familytreesearcher.com/), World Family Names (worldnames.publicprofiler.org/), What Does My Last Name Mean, Surname Origins (genealogy.familyeducation.com/), By Origin - Last Name Meaning - Family Education (genealogy.familyeducation.com/browse/origin/), Last Name Meanings Dictionary (www.last-names.net/), Passenger Search - The Statue of Liberty & Ellis Island (libertyellisfoundation.org/passenger), Immigration Records (National Archives and Records Administration; https://www.archives.gov/), US Immigration Passenger Arrival Records – FamilySearch

database have 7,191 distinct last names. About 36.4% of those last names have Anglo-Saxon roots and 24.6% have German roots. Distant third are Italian last names (accounting for around 6.9% of all last names), followed by Russian (2.7%), Canadian (2.7%), Polish (2.3%), and French (2.2%) last names. We use the resulting matching between last names and their ethnic origin to develop a firm-year measure *%Outsiders*, defined as the percentage of the firm's investment professionals that year whose last names do not have Anglo-Saxon roots (and, as an alternative measure, the percentage of the investment professionals from the firm whose last names have neither Anglo-Saxon nor German roots).

The *%Outsiders* measure is motivated by the history of asset management in the United States. Initially, the industry was strongly dominated by the firms with Anglo-Saxon and, to some extent, German roots (Davis and Gallman, 2001). This domination evolved in the second half of the 19th century, with persistent effects stretching to the present. Indeed, to date, many firm names adhere to the naming conventions consistent with Anglo-Saxon and German roots. Therefore, *%Outsiders* captures the extent of the deviation of a firm's personnel ethnicity from the traditional ethnic mix of an asset management firm. Its median value across all firm-year observations is 54.6% (30%), its first quartile is 40.9% (17.7%), and its third quartile is 66.7% (40.9%) for the measure interpreted as the percentage of investment professionals whose last names do not have Anglo-Saxon (neither Anglo-Saxon nor German) roots.

The 531 PhDs in our sample have earned their doctorates in a variety of fields, ranging mainly from economics, finance, or a closely related field (246 PhDs) to various STEM fields such as natural sciences, engineering disciplines, mathematics, statistics (255 PhDs).[22] To capture this heterogeneity in specific knowledge acquired through field-specific training, we define for each PhD firm-year observation an indicator variable *EconFin*. It is set to one if the percentage of the firm's PhDs in key roles holding a PhD in economics, finance, or a closely related field is above median of its distribution (57.14%), and is set to zero otherwise. All PhD products associated with a given PhD firm that year share the value of this indicator variable. We also collect PhDs' publication records in leading outlets. Eighty-three of the 531 PhDs with doctoral degrees have had at least one publication in a top outlet in their respective fields.[23] We

(https://familysearch.org/learn/wiki/en/US_Immigration_Passenger_Arrival_Records), United States Emigration and Immigration – FamilySearch (https://familysearch.org/.../United_States_Emigration_and_...).

[22] The remaining 30 PhDs (5.6% of all PhDs from our sample) earned their doctorates in humanities.

[23] The economics journals we characterized as leading are American Economic Review, Econometrica, Journal of Political Economy, Quarterly Journal of Economics, and Review of Economic Studies. The finance journals we characterized as leading

define for each PhD firm-year observation an indicator variable *Published*. It is set to one if at least one of the firm's PhDs in key roles had published in a top outlet up to that point in time, and is set to zero otherwise. All PhD products associated with a given PhD firm that year share the value of this indicator variable.

Finally, in some additional specifications we consider the role of PhD granting institution selectivity. We define the elite status of a university as the university's overall ranking among the top twenty universities (based on the PhD-granting institutions' college rankings reported in U.S. News & World Report in 1992).[24] We further follow two approaches in characterizing a PhD firm in a given year (and, therefore, all of its product-year observations) as elite based on university selectivity. The first approach is captured by the variable *EliteOne*. It is set to 1 if that year *at least one* of the firm's PhDs in key roles holds a PhD degree from an elite university; otherwise, the PhD firm will be regarded as non-elite (*EliteOne* = 0). The second approach is captured by the variable *EliteAll*. It is set to 1 if that year *all* of the firm's PhDs in key roles hold PhD degrees from elite universities; otherwise, the PhD firm will be regarded as non-elite (*EliteAll* = 0).

1.2. Basic summary statistics

Table 1 provides a comparison between the 2000 year-end summary statistics for non-PhD and PhD institutional asset management firms and their products.[25] Panel A of Table 1 shows comparisons at the firm level. Among the 822 firms managing U.S. equity products, 688 (83.7%) were non-PhD firms and 134 (16.3%) were PhD firms. The overall 4.43 trillion dollars managed by domestic equity products were about evenly divided between these two categories, with 2.03 trillion (45.8%) managed by non-PhD firms and 2.40 trillion (54.2.7%) managed by PhD firms. Panel A of Table 1 further suggests that non-PhD firms were substantially smaller

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are Journal of Business, Journal of Finance, Journal of Financial Economics, and Review of Financial Studies. Given the diversity of fields and the associated notions of leading journals, we have characterized leading publications in other fields by their impact factors and name recognition.

[24] Detailed and encompassing rankings of doctoral programs over a broad range of disciplines were not available at the beginning of our sample period. Unlike present, very detailed rankings of graduate and professional programs, including doctoral programs, rankings of graduate and professional programs from the 1990s have been confined to but a few fields of graduate study (most notably professional programs offered by medical schools, law schools, and business schools), with hardly any coverage of doctoral programs. Under these circumstances, we opted to proxy for the rankings of doctoral programs by the rankings of undergraduate programs according to their overall ranking. We have also confirmed the results using the analogous ranking based only academic reputation and also using doctoral program rankings from 2013.

[25] Statistics reported for the year 2000 are similar for other years during the sample period from 1993 to 2007.

than PhD firms, with, on average, fewer domestic-equity products in the firm (2.6 versus 6.1), as well as both median and average non-PhD firm domestic equity asset sizes several times smaller than median and average PhD firm domestic equity asset sizes (360 million versus 3.88 billion dollars for medians, 2.95 billion versus 17.91 billion dollars for means).

Panel B of Table 1 shows product-level comparisons. Among the 2,607 domestic equity products, 1,773 (68.5%) were non-PhD products and 817 (31.5%) were PhD products. Similar to firm-level comparisons from Panel A, Panel B of Table 1 suggests that non-PhD products were substantially smaller than PhD products, with both median and average non-PhD domestic equity products' assets under management about three times smaller than median and average PhD domestic equity products' assets under management (198 million versus 572 million dollars for medians, 1.14 billion versus 2.94 billion dollars for means). Finally, Panel B of Table 1 also shows a comparison of fees, indicating that the average (median) annual fees stated by PhD products are 3.6 (6) basis points lower than those stated by non-PhD products.

TABLE 1 ABOUT HERE

1.3. Matching procedure

Panel B of Table 1 shows substantial differences in assets under management between PhD products and non-PhD products. In light of the documented negative relation between mutual-fund performance and size (e.g., Berk and Green (2004), Chen, Hong, Huang, and Kubik (2004), Pollet and Wilson (2008)), as well as the concern that products may be managed by a wide variety of heterogeneous firms, a direct comparison of product performance across these two categories may require additional care beyond the presence of controls for size. Therefore, we develop a matching procedure that, for each product managed by a PhD firm that year, identifies the product managed by a non-PhD firm that belongs to the same investment objective, is in the same product size quintile among the products pursuing the same investment objective, and, to capture the potential firm heterogeneity, is the closest in terms of its firm's PhD propensity score (key personnel information is available at the firm level only).[26]

[26] Our results are very robust to the choice of econometric approach. As shown in Section 3, the baseline results are unaffected if, instead of relying upon the matching procedure, estimation is performed in a panel setting. As shown in Section 6, our results are also unaffected in case of estimation using a calendar-time portfolio approach.

Specifically, the matching for a PhD product in year *t* requires that its matched, non-PhD product (1) pursues the same investment objective; (2) has similar assets under management (by virtue of belonging, at the end of year *t*–1, to the same quintile of the distribution of product assets under management); and (3) is the closest to the PhD product in terms of their respective firms' PhD propensity scores calculated for year *t*.[27] For each year *t*, propensity scores for a firm with a PhD in a key role are calculated by estimating a Logit model wherein the dependent variable set to one if a PhD performed a key role in the firm in year *t* and to zero otherwise, and independent variables log(firm domestic equity assets), its square, log(# of domestic equity products the firm offered), and log(# of unique domestic equity objectives the firm offered) are all measured at *t*–1. Each product-year observation in year *t* is assigned its firm's propensity score in year *t*, as calculated from the Logit model. The resulting matching aligns the PhD product-year observations and the matched non-PhD product-year observations very closely along the desired dimensions of assets under management and propensity matching scores. Further details regarding the closeness of the matching may be found in Appendix Table A.1.

2. Baseline Performance Analyses

In this section, we conduct baseline comparisons of the performance of PhD products and their matched non-PhD products along several performance metrics. The dependent variables studied in this section are all computed for each of the 6,723 resulting observations on the basis of the two twelve-month time series of returns for the PhD products and the matched PhD products. In the first regression analysis, the dependent variable is the difference in annual returns between the PhD product and the matching non-PhD product. The second analysis features the difference between their alphas, calculated from regressions of the respective 12-month return series on the four factors commonly employed in the analysis of risk-adjusted performance of U.S. equity portfolios (Carhart (1997)).[28] The dependent variable in the third

[27] Some analyses will require the matching to be extended to additional dimensions (including past product performance, pursuit of quantitative strategies, composition of the firm's PhDs across various fields of study, and composition of the firm's PhDs by the selectivity of their PhD-granting institution).

[28] A potential concern is that the calculations of alphas and information ratios rely upon twelve data points and, moreover, are carried out on the basis of risk-factor loadings calculated in-sample. To address this concern, we verify that the results persist when calculating factor loadings from the monthly returns over the previous 36-month period. The results for alphas and information ratios are 5.418 bp/month and 2.838, respectively, both statistically significant at the one-percent level. The requirement that there needs to be a 36-month track record preceding the period of measurement both induces survivorship bias and substantially lowers the number of observations to 4,284 (a 37% reduction in the number of observations relative to the full sample of 6,723 observations). Moreover, managed portfolios do not necessarily maintain factor loadings over a period of four years. For all these reasons, we continue to report the estimates for alphas and information ratios based on in-sample estimates.

analysis is difference between their Sharpe ratios. The dependent variable in the fourth analysis is the difference between their information ratios, based on the parameters obtained in the course of carrying out the regressions estimating Carhart alphas. The last analysis shows the difference between their manipulation-free performance measures MPPM, with rho = 3, as discussed in Goetzmann, Ingersoll, Spiegel, and Welch (2007). Regressions reported in this section control for assets under management for both products (in logarithmic form), as well as their respective firm assets under management (given the close and careful matching design, the point estimates for these variables are practically zero, and we do not report them). Standard errors are adjusted by clustering that accounts for heteroscedasticity and dependence of observations across the firm to which the PhD product belongs.[29]

Table 2, Panel A reports strong evidence that the gross performance realized by PhD products exceeds the performance realized by their matched non-PhD products. There are statistically significant and economically meaningful differences for all five performance measures: objective- and size-adjusted annual returns (72 basis points per year), Carhart alphas (6.48 basis points per month),[30] Sharpe ratios (1.43 percent), information ratios (5.43 percent),[31] and manipulation-free Goetzmann, Ingersoll, Spiegel, and Welch (2007) measure MPPM (rho = 3) (1.43 percent per year). This performance gap would likely even increase once fees are considered because Panel B of Table 1 suggests that PhD products charge lower fees compared to non-PhD products, on average lower by about four basis points per year.[32]

TABLE 2 ABOUT HERE

[29] In light of the considerations discussed in Petersen (2008), we have adopted this clustering approach as the most appropriate for the current setting. Nonetheless, in Appendix A.2 we show that these results are robust to a number of alternative (if less appropriate) clustering approaches.

[30] Cumulating monthly alphas yields an annualized alpha of 77.8 basis points per year, corresponding closely to the gap in objective-adjusted annual returns of 71.6 basis points. Therefore, the performance differential in annual returns cannot be attributed to differential exposures to risk factors.

[31] Aside from a positive and statistically significant difference in alphas (the numerators of information ratios), in unreported analyses we also show that the difference between PhDs' and matched non-PhDs' idiosyncratic standard deviations (the denominators of information ratios) is negative (-8.5 basis points/month) and is statistically significant at the one-percent level. Thus, both larger alphas and lower idiosyncratic standard deviations contribute to higher information ratios.

[32] Aside from reporting these summary statistics in Panel B of Table 1, in unreported results we estimate the difference between the fees stated by PhD products and the fees stated by their matched non-PhD products in the presence of a rich set of covariates. We find that the regression-based fee differential estimate is 3.82 basis points, virtually the same as the difference between average fees from Panel B, Table 1.

3. Addressing Alternative Explanations

An institutional management's firm act of hiring a PhD might be endogenous, taking place for reasons other than the PhDs' potentially superior investment acumen. Better firms might hire PhDs not because of their investment talent, but as a means to use the allure of having a PhD on the team to attract future flows (in Appendix A.3, we show that PhD products attract more investment flows than their matched non-PhD products do). Another possibility is that PhDs, although not in possession of a particularly pronounced talent relative to non-PhDs for generating superior investment performance, are superior to their non-PhD counterparts in terms of their ability to identify good firms and pursue their career opportunities accordingly. Both of these scenarios could generate results from Section 2, the presence of a PhD in a key role might still positively predict subsequent performance, but the performance differential relative to non-PhDs would be unrelated to the PhDs' training or talent.

In this section, we report two analyses that address the possibility that endogenous matching might account for our results. The first analysis, presented in the remainder of Table 2, focuses on the performance of institutional asset management firms *founded* by PhDs during our sample period. By definition, firms founded by PhDs have had a PhD in a key role since inception (all of the sample firms founded by a PhD continued to have a PhD in a key role thereafter), and the mechanisms outlined above simply do not apply. A performance gap between PhD products in this subsample and their matched non-PhD products would affirm that the performance differentials reported in the previous section do not stem (only) from PhDs matching to good firms. Indeed, a PhD in a key role in a firm founded by a PhD had been involved in investment decision-making aimed at generating subsequent performance from the very start. Results of carrying out performance analyses on this subsample of PhD product-year observations are presented in the first column of Table 2, Panel B. A comparison with the corresponding coefficients from the baseline analyses carried out over the full sample (Table 2, Panel A), reveal that the coefficients in the two columns of Table 2 are of similar magnitude and levels of statistical significance.

Admittedly, it is conceivable, if unlikely, that a PhD could be hired for a key role in a newly founded firm even if the PhD is not intended to be essential for product investment performance, perhaps because the true masterminds of a newly founded firm, non-PhDs themselves, had decided to hire a PhD for non-performance related reasons, presumably to attract additional assets. If this decision to hire a PhD in a key role is related to the quality of the non-PhD management team actually responsible for performance, the presence of a PhD is a useful signal for, but not the causal mechanism of, differences in performance. We address this somewhat remote possibility by considering increasingly more selective choices of roles a PhD may have played at firms' founding. First, we look into firms that, at founding, had a PhD perform one of the roles of CEO, Founder, President, or Principal, leading to an even smaller subsample of 633 observations. It is very unlikely that, at founding (nor, indeed, at any other time), roles of utmost seniority in the firm would have been assigned to PhDs solely because of their perceived ability to attract flows, to the complete exclusion of a consideration of their ability to generate performance. Second, we further limit the scope of key roles performed by the PhDs at founding to the role of the CEO, further reducing the size of the subsample to 239 observations. The results of these analyses, presented in the second and third columns of Table 2, Panel B, show increasingly larger performance gaps.

Overall, the evidence presented in Panel B of Table 2 suggests that the performance differential between products managed by PhDs and products managed by non-PhDs does not stem (only) from the possibility that PhDs might somehow be endogenously matched to firms with "good" characteristics; rather, the contribution of PhDs is an important component of superior performance that may begin at the founding of the firm.

Next, we implement an instrumental variables approach. Before proceeding, we note that we do not regard the OLS panel approach as ideal for the present study because regression controls in such a setting do not capture potential firm heterogeneity as well as a careful matching approach does (particularly including, among other matching dimensions, the propensity score whether the firm has a PhD performing a key role). Nonetheless, this framework allows us to develop and implement a compelling instrumental variables approach, thus alleviating concerns about endogeneity and reverse causality in yet another convincing way. We commence with OLS panel estimations in which we regress each of the five product-year performance measures on the key independent variable *PhDKey* (set to one if a PhD performs a key role in the product's firm that year and to zero otherwise) and a range of controls and effects: product and firm assets under management, product age, as well as year and objective indicator variables. As before, all product-year performance measures are adjusted for objective and size effects by calculating for each product-year observation its performance measures net of the respective median performances of the products pursuing the same investment objective and in the same size quintile that year. Standard errors are adjusted by clustering that accounts for heteroscedasticity and dependence of observations across the firm to which the PhD product belongs.

We use *%Outsiders* (the percentage of the firm's investment professionals whose last names do not have Anglo-Saxon or, alternatively, Anglo-Saxon or German roots, as discussed in detail in Section 1.1) as an instrument for *PhDKey*. The firm-year measure *%Outsiders* captures the extent of the deviation of a firm's personnel ethnicity from the traditional ethnic mix of a asset management firm. We use this measure as the instrument for the presence of PhDs in key roles. As in any instrumental variables setting, a key assumption is that the instrument satisfies the exclusion restriction. The firm's ethnic mix should only affect performance through the decision to hire a PhD. Whereas no instrument can be proven rigorously to satisfy the exclusion restriction, a challenge to this instrument would need to contain an assertion that there is a variation in the extent to which various ethnicities are capable of generating investment performance, and we are comfortable not entertaining such challenges.

The first stage of our instrumental variable analysis, presented in Panel A of Table 3, reveals that *%Outsiders* has strong predictive power for the presence of a PhD in a key role. For example, the coefficients associated with *%Outsiders* and its interquartile range of 25.8% (=66.7% – 40.9%) for last names not of Anglo-Saxon origin suggest a change in probability of having a product's key role performed by a PhD, holding all else equal, of about 2% (25.8% x 0.079). This is a shift from the baseline of 28.6% (calculated as 6,723 PhD product-year observations divided by the total number of 23,384 product-year observations). This shift amounts to about 7% of the baseline. Moreover, the *%Outsiders* instrument is not weak, as evinced by the sizeable values of the Kleibergen-Paap statistic[33] (Kleibergen and Paap (2006)) and the associated *p*-value from the instrumental variables regression.

Panel B presents in its first column the OLS panel regression that corresponds, metric by metric, to the baseline results from Table 2. There is a very close alignment of results for all five performance measures with the results reported in Section 2, confirming the validity of our baseline matching approach. The results of the second stage of the instrumental-variables regressions are presented in the last two columns of Panel B, Table 3. They feature statistically

[33] The use of the Kleibergen-Paap statistic has the advantage over other commonly used approaches because it is adjusts correctly for the specific covariance estimation procedure assumed for the error term.

significant and economically large estimates of the performance gap between PhD products and non-PhD products, with point estimates somewhat larger than those in the baseline results reported in Table 2 and those in the OLS results from the first column of Panel B of Table 3.

TABLE 3 ABOUT HERE

4. Role of Field-Specific Training (Field of Study)

As discussed in the introduction, from the perspective of institutional asset management, pursuing a PhD may be viewed as a process of accumulating either directly relevant human capital (PhDs in economics or finance) or indirectly relevant human capital (PhDs in other fields). PhDs in our sample have earned their doctorates in a variety of fields. Nearly one-half of them hold PhD degrees in economics, finance, or a closely related field (246 of 531), and about as many (255 of 531) hold degrees in various natural sciences, engineering disciplines, mathematics, or statistics, with the balance of 30 PhDs holding degrees in humanities. Therefore, there is a considerable range of background knowledge specific to asset management the PhDs have had at the point of entry into the industry. We use an indicator variable *EconFin*, described in detail in Section 1.1, to capture this heterogeneity. *EconFin* is set to one if the percentage of the firm's PhDs in key roles holding a PhD in economics, finance, or a closely related field is above median of its distribution (57.14%), and is set to zero otherwise. All PhD products associated with a given PhD firm that year share the value of this indicator variable.

We evaluate the role of field-specific training by estimating the performance gap between products managed by PhDs in economics or finance (characterized by *EconFin* = 1) and products managed by PhDs in other, mostly STEM fields (characterized by *EconFin* = 0) for all five performance measures and present the results in Table 4. The first column features the key result—statistically significant and economically meaningful positive performance differentials between PhD products managed by economics or finance PhDs and matched PhD products managed by PhDs in other fields for three out of the five performance measures. This finding suggests that field-specific knowledge associated with a PhD degree is relevant in asset management. It should be interpreted with some caution, however, because the field of study for each PhD is not randomly assigned and a variety of selection issues might obscure the true magnitude of the importance of specific knowledge in finance. That noted, it would be difficult to argue that selection issues contaminate these results by leading to differential talent across disciplines. Indeed, ability-related admission criteria to doctoral programs in physics, mathematics, statistics, natural sciences, or engineering are unlikely to be less stringent than those pertaining to economics or finance.

The remaining two columns of Table 4 show that both Economics or Finance PhD products and other (mostly STEM) PhD products outperform their respective matched non-PhD products, indicating that performance is positively associated with higher levels of training both in the case of acquisition of directly relevant human capital (PhDs in economics or finance) and in the case of indirectly relevant human capital (PhDs in other fields).[34]

TABLE 4 ABOUT HERE

5. The Role of Talent (Publication Records)

We proceed to focus on talent, measured as success in placing research in premier academic journals.[35] The PhDs performing key roles in institutional asset management firms have varying publication records in top outlets in their respective fields. In fact, only 83 of the PhDs, or approximately 15.6% of our sample, have published in premier journals in their respective fields.[36] We evaluate the role of talent by estimating the performance gap between products managed by published PhDs (characterized by *Published* = 1) and unpublished PhDs (characterized by *Published* = 0) for all five performance measures and present the results in Panel A of Table 5. The first column features the key result, a statistically significant and economically meaningful positive performance differential between published PhD products and matched unpublished PhD products managed by PhDs in other fields for all five performance measures. This finding confirms that talent is relevant in asset management too. The remaining two columns of Panel A of Table 5 show that both unpublished PhD products (second column) and published PhD products outperform their respective matched

[34] The performance gap between (mostly) STEM PhD products and non-PhD products appears about as large as (and, in some instances even larger than) the performance gap between Economics or Finance PhD products. This circumstance seemingly makes it difficult to reconcile the regression coefficients from the second and third columns with those reported in the first column. However, these results are not inconsistent. Rather, discrepancies between the regression coefficients reported in the first column and the difference between the regression coefficients reported in the second and third columns arise because of different matching outcomes across the three analyses.

[35] Our interpretation of talent, as measured by publications, is associated with not only potentially a higher level of ability or intelligence, but also with the tenacity and perseverance to place a strong academic contribution into a premier academic outlet in the face of a tenuous and often challenging process.

[36] The list of top outlets in economics and finance comprises American Economic Review, Econometrica, Journal of Political Economy, Quarterly Journal of Economics, and Review of Economic Studies (economics), as well as Journal of Business, Journal of Finance, Journal of Financial Economics, and Review of Financial Studies (finance). Journals in other fields were taken to be of similar stature in the respective fields, as evinced by their impact factors and name recognition.

non-PhD products, indicating that performance is positively associated with higher levels of training acquired through the pursuit of PhD for both categories of PhDs.[37]

It is possible that the performance gap between published and unpublished PhD products is not equally pronounced across Economics or Finance PhD products and other PhD products, perhaps reflecting the notion that placing research successfully in top outlets in economics and finance is more directly relevant for the task at hand—managing money—because the cutting-edge research in these directly relevant fields uncovers and advanced methods and approaches to investment to a larger extent than the research associated with new developments in physics or mathematics, for example. We explore this possibility in Panels B and C of Table 5 by splitting the sample of published PhD products into the subsamples of published Economics or Finance PhD products and other (mostly STEM) published PhD products. The gaps, reported in the first columns of the two panels, hint at that possibility because, consistently across all five measures, the point estimates of the respective performance gaps are larger in Panel B than in Panel C. Still, the performance gap is positive, large, and statistically significant for four of the five performance measures in the first column of Panel C, Table 5, confirming the role of talent (as measured by publications) even among the PhDs trained in other (mostly STEM) fields.

TABLE 5 ABOUT HERE

Finally, we pursue another aspect of exploring the performance gap between Economics or Finance PhD products and other (mostly STEM) PhD products by performing the analysis reported previously in the first column of Table 4 (also reported as the first column of Table 6) while focusing on the possibility that the field-specific performance gap those results reveal may not be spread equally across exceptionally talented, published PhDs and other, unpublished PhDs. It is plausible that the importance of field-specific training may diminish, even disappear in the realm of truly talented individuals. If true, such a finding would shed a nuanced light on the interplay and relative importance of field-specific training and talent. Accordingly, we replicate the analysis from Table 4 over two subsamples characterized by the PhDs' publication status and report the results in the second and third columns of Table 6. The results confirm this intuition because the performance gap between Economics or Finance PhD products and other (mostly STEM) products completely disappears among published PhDs, and the higher and more statistically significant coefficients associated with

[37] Once again, discrepancies between the regression coefficients reported in the first column and the difference between the regression coefficients reported in the third and second columns arise because of different matching outcomes across the three analyses.

unpublished PhD products suggest that the importance of field-specific training is concentrated among those who, though very capable and very well trained, are not at the top of the distribution of talent.

TABLE 6 ABOUT HERE

6. Alternative specifications

6.1. Portfolio Approach

In this section, we present briefly the results of portfolio-based analyses that correspond to the matching-based analyses discussed in Section 5. Table 7 focuses on the role of talent, as evinced by publications in top outlets. It mimics Table 5 and, therefore, shows that the results reported on the basis of our matching strategy are not sensitive to the estimation approach. In particular, the covariance structure between individual products at a point in time and the estimation of factor loadings at the product level to calculate each product's risk-adjusted return do not drive the results. Table 7 reports portfolio performance analysis of long-short portfolio formation strategies that place published PhD products into the long portfolio and unpublished PhD products into the short portfolio, be it for the full sample of all PhD products (first column of Table 7) or the two subsamples defined by the field of study—published Economics or Finance PhD products (*EconFin* = 1; second column of Table 7) and other (mostly STEM) published PhD products (*EconFin* = 0; third column of Table 7). Portfolios are asset-weighted and are revised quarterly, for a total of 168 monthly observations. The table reports risk-adjusted, 4-factor alphas and the factor loadings for each portfolio (Carhart (1997)). Standard errors are calculated using the Newey-West (1987) approach with three lags to account for heteroscedasticity and covariance of errors over time.

The risk-adjusted 4-factor alphas reported in Table 7 correspond very closely to the results from Table 5. According to the first column of Table 7, published PhD products outperform unpublished PhD products by 5.74 bp/month. This point estimate is very similar to the estimate of alpha from Table 5 (5.15 bp/month), and both estimates are statistically significant in their respective analyses. Similarly, the 4-factor alphas reported for the performance differentials between published and unpublished PhD products separately for Economics or Finance PhDs (second column of Table 7) and other (mostly STEM) PhDs (third column of Table 7), are very similar in terms of magnitude and statistical significance to the corresponding alphas from Table 5.

These performance gaps are 7.64 pb/month for the subset of published Economics or Finance PhDs (the corresponding alpha from Table 5, reported in the first column of its Panel B, is 7.88 bp/month) and 5.02 bp/month for the subset of other published PhDs (the corresponding alpha from Table 5, reported in the first column of its Panel C, is 4.60 bp/month).

TABLE 7 ABOUT HERE

Next, in an analogous manner, Table 8 focuses on the more nuanced interplay between field-specific training and talent, previously explored in Table 6 (Section 5). Table 8 reports portfolio performance analysis of long-short portfolio formation strategies that place Economics or Finance PhD products (*EconFin* = 1) into the long portfolio and other (mostly STEM) PhD products (*EconFin* = 0) into the short portfolio, be it for the full sample of all PhD products (first column of Table 8) or the two subsamples defined by publication status—published PhD products (*Publication* = 1; second column of Table 8) and unpublished PhD products (*Publication* = 0; third column of Table 8). As in Table 7, portfolios are asset-weighted and are revised quarterly, for a total of 168 monthly observations. Table 8 reports risk-adjusted, 4-factor alphas and the factor loadings for each portfolio (Carhart (1997)). As before, standard errors are calculated using the Newey-West (1987) approach with three lags to account for heteroscedasticity and covariance of errors over time.

The risk-adjusted 4-factor alphas reported in Table 8 align very closely to the results from Table 6. According to the first column of Table 8, Economics or Finance PhD products outperform other (mostly STEM) PhD products by 3.21 bp/month. This point estimate is very similar to the estimate of alpha from Table 6 (3.73 bp/month), and both estimates are statistically significant in their respective analyses. Consistent with Table 6, the 4-factor alpha reported for the performance differential between published Economics or Finance PhD products and other (mostly STEM) published PhD products (second column of Table 8) is small in magnitude and is not statistically significant (2.15 bp/month, n.s.), confirming that, as in Table 6, the performance gap between Economics or Finance PhD products and other (mostly STEM) products disappears among published PhDs. Finally, according to the third column of Table 8, unpublished Economics or Finance PhD products outperform other (mostly STEM) unpublished PhD products by 5.08 bp/month. This point estimate is similar to the estimate of alpha from Table 6

(3.95 bp/month), and both estimates are statistically significant in their respective analyses. Overall, results from Table 8 confirm our key results from Table 6, including the finding that the importance of field-specific training is concentrated among those who, though very capable and very well trained, are not at the top of the distribution of talent.

TABLE 8 ABOUT HERE

6.2. University Selectivity

Many PhDs in our sample hold doctorates from elite, highly selective universities, and many hold doctorates from other institutions. In our final robustness check, we address the concern that, instead of serving as a measure of talent, publication records might be better interpreted as a byproduct of elite universities deploying some indeterminate combination of identifying superior talent during the admission process, providing superior training during doctoral studies, and opening up access to an influential alumni network thereafter to produce superior PhDs who, incidentally, are more likely to publish.

In exploring the role of university selectivity, we rely on the university selectivity criteria outlined in Section 1.1. We first contrast PhD product-year observations generated by PhDs graduating from elite universities and their matched PhD product-year observations generated by PhDs graduating from other universities. We report the results in Panel A of Table 9, with two columns reflecting two alternative approaches to characterizing elite products. Both columns show that PhD product performance is positively associated with the elite status of the university from which the PhDs had graduated. The result, though establishing this positive relation, shares the limitation plaguing similar results previously obtained for the elite status of undergraduate institutions or MBA programs in the domains of mutual-fund and hedge-fund managers (e.g., Chevalier and Ellison (1999), Li, Xang, and Zhao (2011)). Specifically, it is clear that elite university status captures some indeterminate combination of identifying superior talent during the admission process, providing superior training during doctoral studies, and perhaps offering access to an influential alumni network. However, it is not at all clear which of these features are at play (and to what extent). In that sense, the analyses from Panel A of Table 9, though illustrative and broadly useful, cannot serve to disentangle the roles of training and talent.

Finally, we reaffirm that publication records indeed reflect talent, rather than merely serve as a noisy measure of elite quality for the universities from which the PhDs in our sample had graduated. To accomplish this goal, we augment the matching procedure to capture the additional dimension—the elite status of the PhDs' universities. With this addition, the matched product (1) has the same elite status classification; (2) pursues the same investment objective; (3) has similar assets under management (by virtue of belonging, at the end of year t–1, to the same quintile of the distribution of product assets under management); (4) and is the closest to the high presence of economics and finance PhD product in terms of their respective firms' PhD propensity scores calculated for year t. The logic behind this augmentation is simple. If the performance gap between published and unpublished PhD products, as reported in the previous section (without additional dimension of matching along the university elite status), is driven by the university elite status, the additional dimension of matching should dimish or completely erradicate the performance gap. On the other hand, if publications truly reflect talent, the key findings from previous sections should persist.

We present the results of estimations based on augmented matching procedures in Panels B and C of Table 9. To be thorough, we begin by showing in Panel B that the additional matching dimension along the university elite status does not affect the results from Table 4 (and Table 6) regarding the role of training. The first column in Panel B reports the earlier result from the first column of Tables 4 and 6. The remaining two columns in Panel B show that the added dimension of matching did not diminish these results; if anything, in some instances, the point estimates are a little larger and more statistically significant. We complete the inquiry associated with university selectivity in Panel C. There, we show that the additional matching dimension along the university elite status does not change the publication-related results either. Following the same pattern as in Panel B, we report in the first column of Panel C the results indicating the performance gap between published and unpublished PhD products without the dimension of matching based on elite university status, as it appears in Table 5. We report in the remaining two columns of Panel C that the performance gap between published and unpublished PhDs for the two approaches to capturing elite status alters neither the statistical significance nor the magnitude of the performance gaps. Therefore, we conclude that, indeed, the use of publication records as a measure of talent survives a very high level of scrutiny imposed by the additional dimension of matching based on university elite status.

TABLE 9 ABOUT HERE

7. Conclusion

In this paper, we exploit the presence of PhDs in key roles in institutional asset management to study some of the fundamental questions related to the relation between firm performance and top management characteristics, as well as to disentangling the roles of talent and training. Focusing on actively-managed domestic equity products offered to institutional clients, our first inquiry is whether the performance of PhD products exceeds the performance of carefully matched non-PhD products for a variety of performance metrics. We document statistically significant and economically meaningful differences between gross performance of PhD products and their matched non-PhD products for five performance measures (annual returns, 4-factor alphas, Sharpe ratios, information ratios, and the MPPM (rho = 3) measure). We proceed by showing, in two separate analyses, that the link between product performance and the presence of a PhD in a key role is unlikely to stem solely from endogenous matching.

We next explore the tangled tale of training and talent. We exploit the fact that PhDs in our sample have earned their doctorates in a variety of fields, ranging from economics, finance, or a closely related field to various natural sciences, engineering disciplines, mathematics, statistics, and humanities. Given this heterogeneity of field-specific training, the role of training merits a nuanced interpretation, wherein training in some fields is more directly related to tasks associated with asset management than training in other fields. We uncover evidence of performance differentials between PhD products managed by PhD firms with economics or finance PhDs and matched PhD products managed by firms with PhDs in other fields. These results—novel findings concerning the role of training—indicate that the field-specific coursework and dissertation research associated with a PhD degree are relevant for performance in asset management.

Because the field of study for each PhD is not randomly assigned, a variety of selection issues might obscure the true magnitude of the importance of specific knowledge in finance (even controlling for university selectivity). Of primary concern in this context is whether any such selection issues are linked with talent. For example, interpretation of our findings might face a challenge if the selection issues were to lead to differential innate abilities across disciplines. However, controlling for university selectivity, ability-based admission criteria to doctoral programs in physics, mathematics, statistics, natural sciences, or engineering are very unlikely to be less stringent than those pertaining to economics or finance.

Next, using success in generating and placing research in premier academic journals as a measure of talent, we uncover a positive performance differential between published PhD products and matched unpublished PhD products managed by PhDs in other (mostly STEM) fields for all five performance measures. This finding confirms that talent is also relevant in asset management. We find this to be true not only for the full sample of our observations, but also separately for the subsamples of Economics and Finance published PhDs and other (mostly STEM) published PhDs too, indicating the role of talent orthogonal to the field of training.

Finally, we revisit the exploration of the importance of field-specific training by estimating the performance gap between Economics or Finance PhD products and other (mostly STEM) PhD products separately for the subsamples off published PhDs and unpublished PhDs. In doing so, we shed a nuanced light on the interplay and relative importance of field-specific training and talent because we find that the performance gap between Economics or Finance PhD products and other (mostly STEM) products completely disappears among published PhDs, and the gap is large and statistically significant among unpublished PhD products. Therefore, we show that the importance of field-specific training is concentrated among those who, though very capable and very well trained, are not at the top of the distribution of talent.

A natural topic for a future study might be exploring *how* PhDs achieve their superior performance. Although data limitations preclude the execution of such analyses with precision using this dataset, we end the paper by making two related points. First, all the results hold for MPPM, a measure designed to eliminate the role of manipulation in performance evaluation, suggesting that the performance gap between PhDs and non-PhDs is not an artifact of PhDs' higher propensity to engage in manipulative strategies.[38] Second, within the limitations of the data, we show in Appendix A.4 that the superior performance of PhDs does not stem (only) from greater success with advanced quantitative strategies.[39]

[38] Goetzmann, Ingersoll, Spiegel, and Welch (2007) provide examples of simple strategies that, though not contributing to the actual portfolio performance, artificially inflate performance measures such as the Sharpe ratio.

[39] Another line of inquiry to which we are unable to contribute is the link between the marginal product of employees and their compensation, be it specifically in the finance industry (e.g., Phillipon and Reshev, 2012), or for executives more generally (see Murphy, 2012, for a recent survey of the voluminous literature concerning executive compensation). Unfortunately, the data set does not contain information concerning compensation.

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Table 1
Sample Summary Statistics

This table provides a comparison between the 2000 year-end summary statistics for non-PhD and PhD institutional asset management firms and their products. The statistics are based on the data set compiled from 59 quarterly releases of data from the Mobius Group and, from September 2006 onward, Informa Investment Solutions (IIS) PSN Data Select, for the period from June 1993 to December 2007. Panel A provides a comparison at the firm level. Panel B provides a comparison at the product level. Product fees, tabulated in Panel B, are the "expense ratios" obtained by dividing the fees the products state for 25-million dollar accounts by 25 million dollars.

Panel A: Firm-level Comparison

	Non-PhD Firms	PhD Firms
Number of firms in sample	688	134
Total domestic-equity assets under management (*$ trillion*)	2.03	2.40
Average number of domestic-equity products in firm	2.6	6.1
Firm assets (*$ million*)		
Average	2,948	17,908
Standard deviation	13,743	44,533
Cross-sectional distribution		
25^{th} percentile	86	414
50^{th} percentile (median)	360	3,877
75^{th} percentile	1,574	15,285

Panel B: Product-level Comparison

	Non-PhD Products	PhD Products
Number of domestic-equity products in sample	1,773	817
Product assets (*$ million*)		
Average	1,144	2,937
Standard deviation	5,381	9,605
Cross-sectional distribution		
25^{th} percentile	45	110
50^{th} percentile (median)	198	572
75^{th} percentile	710	2,047
Product fees (*bp/year*)		
Average	70.2	73.8
Standard deviation	22.9	21.2
Cross-sectional distribution		
25^{th} percentile	55	60
50^{th} percentile (median)	66	72
75^{th} percentile	85	90

Table 2
Baseline Analyses and Analyses of a Subsample of Products Managed by Firms Founded by a PhD

The dependent variables in this table are differences between performance measures of products managed by PhDs from the sample of firms founded by PhDs and their respective matched products managed by non-PhDs. A firm is regarded to be founded by a PhD if the list of the firm's key personnel at the time of founding contained a PhD. A product is regarded to be managed by a PhD if a key role in the firm is performed by a PhD (key roles are listed in Section 1.1). The first performance measure is the difference between annual returns of products managed by PhDs and their respective matched products managed by non-PhDs, expressed in percentages per year. The second performance measure is the difference between one-year monthly Carhart alphas of products managed by PhDs and their respective matched product managed by non-PhDs (expressed in basis points per month). The third performance measure is the difference between one-year monthly Sharpe ratios of products managed by PhDs and their respective matched product managed by non-PhDs (expressed in percentages). The fourth performance measure is the difference between one-year monthly information ratios (based on Carhart alphas and idiosyncratic standard deviation) of products managed by PhDs and their respective matched product managed by non-PhDs. The fifth performance measure is the difference between one-year manipulation-free measures MPPM (rho = 3) of products managed by PhDs and their respective matched product managed by non-PhDs (expressed in percentages per year). For each PhD product-year observation, the matching process identifies the non-PhD product-year observation that (1) pursues the same investment objective; (2) has similar assets under management (by virtue of belonging, at the end of year t–1, to the same quintile of the distribution of product assets under management); (3) and is the closest to the PhD product in terms of their respective firms' PhD propensity scores calculated for year t. For each year t, propensity scores for a firm with a PhD in a key role are calculated by estimating a Logit model with the dependent variable set to one if the a PhD performed a key role in the firm in year t and to zero otherwise, and independent variables log(firm domestic equity assets$_{t-1}$), its square, log(# of domestic equity products the firm offered$_{t-1}$), and log(# of unique domestic equity objectives the firm offered$_{t-1}$). Each product-year observation in year t is assigned its firm's propensity score in year t, as calculated from the Logit model. The first column shows the estimation over the full sample (Panel A). The next three columns (Panel B) focus on subsamples of products managed by firms founded by a PhD. The second column focuses on the observations associated with products managed by firms that, at founding, have had a PhD perform one of the key roles. The third column focuses on the observations associated with products managed by firms that, at founding, have had a PhD perform one of the CEO, Founder, President, or Principal roles. The fourth column focuses on the observations associated with products managed by firms that, at founding, have had a PhD perform the CEO role. Controls include product and matched product assets and their corresponding firm assets. All specifications contain investment objective and year effects. The values of R-squared range from 0.001 to 0.035. Standard errors are adjusted by clustering that accounts for heteroscedasticity and dependence of observations across the firm to which the PhD product belongs. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 2 (continued)
Baseline Analyses and Analyses of a Subsample of Products Managed by Firms Founded by a PhD

	Panel A: Full sample	**Panel B:** Subsamples of products managed by firms founded by a PhD		
		Sample of products managed by firms founded with a PhD in any key role listed in Section 1.1	Sample of products managed by firms founded with a PhD serving as CEO, founder, president, or principal	Sample of products managed by firms founded with a PhD serving as CEO
Annual return	0.72**	0.97**	1.53**	3.46***
(percent/year)	(0.29)	(0.47)	(0.74)	(1.43)
Alpha	6.48***	6.40**	14.87***	21.20***
(bp/month)	(1.92)	(3.09)	(4.83)	(8.86)
Sharpe ratio	1.43**	1.65**	2.38**	5.43**
	(0.57)	(0.74)	(1.18)	(2.17)
Information ratio	5.43***	5.78***	8.62***	13.42***
	(1.22)	(1.70)	(2.40)	(4.26)
MPPM (rho = 3)	1.43***	1.30***	1.74**	4.50***
(percent/year)	(0.30)	(0.46)	(0.70)	(1.30)
Number of obs.	6,723	1,329	633	239

Table 3
Panel Estimation: OLS Specifications and IV Specifications

This table presents results of panel regressions of product-year performance measures on indicator variables capturing the PhD status of the products' firms that year, controls variables, and effects. The dependent variables are the five product performance measures described in Section 1.1 and in the caption to Table 2. All product-year performance measures are adjusted for objective and size effects by calculating for each product-year observation its performance measures net of the respective median performances of the products pursuing the same investment objective and in the same size quintile that year. The key independent variable is the indicator variable *PhDKey*, set to one if a PhD performs a key role in the product's firm (key roles are listed in Section 1.1) that year, and to zero otherwise. Controls in both panels include product and firm sizes, product age, year, and objective indicator variables. The values of R-squared in all regressions range from 0.01 to 0.02. The number of observations in all regressions is N = 23,384. The table presents three sets of results. The first column of Panel B features panel regressions without instrumental variables. The next two columns of Panel B presents results of instrumental variables regressions that rely on two alternative definitions of the instrument *%Outsiders*. The first stage, in which *%Outsiders* is used as the instrument for *PhDKey*, is presented in Panel A. Standard errors are adjusted by clustering that accounts for heteroscedasticity and dependence of observations across the firm to which the PhD product belongs. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: First stage

	Dependent variable: *PhDKey*	
	(% not Anglo-Saxon)	(% not Anglo-Saxon or German)
%Outsiders	0.079***	0.100***
	(0.023)	(0.034)
Controls, effects	Yes	Yes
Kleibergen-Paap LM statistic	11.92	14.84
p-value from IV regression	(0.0006)	(0.0001)

Panel B: Second stage

	Baseline (OLS) panel regression	Instrument: %Outsiders (not Anglo-Saxon)	Instrument: %Outsiders (not Anglo-Saxon or German)
Annual return	0.80***	2.29**	2.31**
(percent/year)	(0.21)	(1.10)	(1.14)
Alpha	6.86***	14.60**	12.81*
(bp/month)	(1.51)	(7.16)	(7.09)
Sharpe ratio	1.19***	2.72*	2.63**
	(0.35)	(1.43)	(1.27)
Information ratio	4.10***	8.92**	7.83**
	(0.88)	(4.09)	(3.71)
MPPM (rho = 3)	0.90***	2.20**	2.05**
(percent/year)	(0.19)	(0.99)	(0.94)

Table 4
Performance of PhD Products by Field of Study

The dependent variables in this table are performance measure differentials between subgroups of PhD products and their respective control groups. A product is a PhD product if a key role in the firm is performed by a PhD (key roles are listed in Section 1.1). The five performance measures reported in the table are described in Section 1.1 and in the caption to Table 2. The first column features a comparison between Economics or Finance PhD products (products managed by PhDs in firms in which the percentage of managers with doctorates in Economics or Finance is above median; the products for which *EconFin* = 1) and their matched (mostly) STEM PhD products (products managed by PhDs with doctorates in other, mostly STEM fields; the products for which *EconFin* = 0). The second column shows the comparison between Economics or Finance PhD products and their matched non-PhD products. The third column shows the comparison between (mostly) STEM PhD products and their matched non-PhD products. For each product-year observation in a subgroup, the matching process identifies the PhD product-year observation from its respective control group that (1) pursues the same investment objective; (2) has similar assets under management (at the end of year t–1, it belongs to the same quintile of the distribution of product assets under management); and (3) is the closest to the initial product in terms of their respective firms' PhD propensity scores calculated for year t. Propensity score calculation is described in Section 1.3. The values of R-squared range from 0.001 to 0.003. Standard errors are adjusted by clustering that accounts for heteroscedasticity and dependence of observations across the firm to which the PhD product belongs. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	Economics or Finance PhD Products versus **(Mostly) STEM PhD Products**	**Economics or Finance PhD Products** versus **Non-PhD Products**	**(Mostly) STEM PhD Products** versus **Non-PhD Products**
Annual return	0.63**	0.92***	0.96***
(percent/year)	(0.31)	(0.28)	(0.35)
Alpha	3.73*	6.39***	7.46***
(bp/month)	(2.03)	(1.68)	(2.26)
Sharpe ratio	0.26	1.44***	3.55***
	(0.52)	(0.44)	(0.52)
Information ratio	0.84	5.97***	7.89***
	(1.28)	(1.01)	(1.35)
MPPM (Rho = 3)	0.82***	1.79***	1.58***
(percent/year)	(0.31)	(0.27)	(0.33)
Number of obs.	4,533	4,533	2,190

Table 5
Performance of PhD Products by Publication Records in Top Outlets

The dependent variables in this table are performance measure differentials between subgroups of PhD products and their respective control groups. A product is a PhD product if a key role in the firm is performed by a PhD (key roles are listed in Section 1.1). The five performance measures reported in the table are described in Section 1.1 and in the caption to Table 2. Panel A focuses on all PhD product-year observations, Panel B focuses on Economics or Finance PhD product-year observations (the observations for which *EconFin* = 1), and Panel C focuses on other (mostly STEM) PhD product-year observations (the observations for which *EconFin* = 0). The first column in each panel shows the comparison between published PhD products (products managed by PhDs who had published in a top outlet) and their matched non-PhD products. The second column in each panel shows the comparison between unpublished PhD products (products managed by PhDs who had not published in a top outlet) and their matched non-PhD products. The third column features a comparison between published PhD products and their matched unpublished PhD products. For each product-year observation in a subgroup, the matching process identifies the PhD product-year observation from its respective control group that (1) pursues the same investment objective; (2) has similar assets under management (at the end of year t–1, it belongs to the same quintile of the distribution of product assets under management); and (3) is the closest to the initial product in terms of their respective firms' PhD propensity scores calculated for year t. Propensity score calculation is described in Section 1.3. The values of R-squared range from 0.001 to 0.003. Standard errors are adjusted by clustering that accounts for heteroscedasticity and dependence of observations across the firm to which the PhD product belongs. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5 (continued)
Performance of PhD Products by Publication Records in Top Outlets

	Published PhD Products versus **Unpublished PhD Products**	**Unpublished PhD Products** versus **Non-PhD Products**	**Published PhD Products** versus **Non-PhD Products**
	Panel A: All PhD Products		
Annual return	0.91***	0.63**	1.32***
(percent/year)	(0.36)	(0.26)	(0.43)
Alpha	5.15**	5.08***	6.13***
(bp/month)	(2.27)	(1.59)	(2.37)
Sharpe ratio	1.59***	1.12**	2.74***
	(0.65)	(0.55)	(1.05)
Information ratio	5.91***	4.89***	6.68***
	(1.57)	(0.92)	(1.55)
MPPM (Rho = 3)	0.88**	1.21***	2.22***
(percent/year)	(0.35)	(0.24)	(0.40)
Number of obs.	2,662	4,061	2,662
	Panel B: Economics or Finance PhD Products (*EconFin* = 1)		
Annual return	1.50***	0.86***	1.71***
(percent/year)	(0.55)	(0.33)	(0.57)
Alpha	7.88**	5.98***	8.97***
(bp/month)	(3.39)	(2.14)	(3.39)
Sharpe ratio	3.23***	1.23**	3.93***
	(1.01)	(0.52)	(0.76)
Information ratio	6.03***	5.15***	8.14***
	(2.24)	(1.21)	(2.11)
MPPM (Rho = 3)	1.27**	1.32***	2.43***
(percent/year)	(0.54)	(0.34)	(0.56)
Number of obs.	1,318	3,215	1,318
	Panel C: (Mostly) STEM PhD Products (*EconFin* = 0)		
Annual return	0.86**	0.49*	1.12***
(percent/year)	(0.39)	(0.28)	(0.42)
Alpha	4.60*	2.96*	5.05*
(bp/month)	(2.47)	(1.65)	(2.93)
Sharpe ratio	0.93	0.98**	2.07***
	(0.72)	(0.39)	(0.75)
Information ratio	4.33**	2.47**	5.64***
	(1.82)	(0.97)	(1.88)
MPPM (Rho = 3)	0.68*	0.98***	1.90***
(percent/year)	(0.41)	(0.25)	(0.50)
Number of obs.	1,344	846	1,344

Table 6
Performance Differentials between Economics or Finance PhD Products and Other (mostly STEM) PhD Products by Publication Status

The dependent variables in this table are performance measure differentials between subgroups of PhD products and their respective control groups. A product is a PhD product if a key role in the firm is performed by a PhD (key roles are listed in Section 1.1). The five performance measures reported in the table are described in Section 1.1 and in the caption to Table 2. The first column features a comparison between Economics or Finance PhD products (products managed by PhDs in firms in which the percentage of managers with doctorates in Economics or Finance is above median; the products for which *EconFin* = 1) and their matched (mostly) STEM PhD products (products managed by PhDs with doctorates in other, mostly STEM fields; the products for which *EconFin* = 0). The second column shows the comparison between Economics or Finance PhD products and their matched non-PhD products. The third column shows the comparison between (mostly) STEM PhD products and their matched non-PhD products. For each product-year observation in a subgroup, the matching process identifies the PhD product-year observation from its respective control group that (1) pursues the same investment objective; (2) has similar assets under management (at the end of year t–1, it belongs to the same quintile of the distribution of product assets under management); and (3) is the closest to the initial product in terms of their respective firms' PhD propensity scores calculated for year t. Propensity score calculation is described in Section 1.3. The values of R-squared range from 0.001 to 0.003. Standard errors are adjusted by clustering that accounts for heteroscedasticity and dependence of observations across the firm to which the PhD product belongs. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	Economics or Finance PhD Products versus **(Mostly) STEM PhD Products**		
	All PhD Products (also Table 4, Column (1))	**Published PhD Products**	**Unpublished PhD Products**
Annual return	0.63^{**}	0.48	0.84^{**}
(percent/year)	(0.31)	(0.64)	(0.36)
Alpha	3.73^{*}	-0.54	3.95^{**}
(bp/month)	(2.03)	(4.82)	(2.02)
Sharpe ratio	0.26	0.23	1.86^{***}
	(0.52)	(1.29)	(0.63)
Information ratio	0.84	0.50	1.72^{*}
	(1.28)	(0.49)	(1.04)
MPPM (Rho = 3)	0.82^{***}	0.07	0.59^{**}
(percent/year)	(0.31)	(0.74)	(0.28)
Number of obs.	4,533	1,318	3,215

Table 7
Performance Differentials between PhD Products by Publication Status, Portfolio Approach

This table presents Carhart (1997) performance evaluation for zero-cost portfolio strategies formed by PhD product publication status. A product is managed by a PhD if a key role in the firm is performed by a PhD (key roles are listed in Section 1.1). The portfolio of Published PhD Products contains products from PhD firms in which at least one of the PhDs had published a paper in a top outlet at the time of portfolio formation. The portfolio of Unpublished PhD Products contains products from PhD firms in which none of the PhDs had published a paper in a top outlet at the time of portfolio formation. Portfolios are asset-weighted and are revised quarterly. The first column (corresponding to the first column of Table 5, Panel A) focuses on all PhD product-year observations, The second column (corresponding to the first column of Table 5, Panel B) focuses on PhD product-year observations for firms with Economics or Finance PhDs (the observations for which *EconFin* = 1), and the third column (corresponding to the first column of Table 5, Panel C) focuses on PhD product-year observations for firms with PhDs from other fields (the observations for which *EconFin* = 0). Each of the regressions is based upon 168 monthly observations. Standard errors are calculated using the Newey-West (1987) approach with three lags to account for heteroscedasticity and covariance of errors over time. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) All PhD Products	**(2) Economics or Finance PhD Products (*EconFin* = 1)**	**(3) (Mostly) STEM PhD Products (*EconFin* = 0)**
Matched Product Analysis Equivalent from Table 5	Panel A, column (1)	Panel B, column (1)	Panel C, column (1)
Long:	Published PhD Products	Published PhD Products	Published PhD Products
Short:	Unpublished PhD Products	Unpublished PhD Products	Unpublished PhD Products
Alpha (bp/month)	**5.74**** **(2.64)**	**7.64**** **(3.53)**	**5.02*** **(2.87)**
RMRF	-0.027*** (0.007)	-0.028** (0.010)	-0.046*** (0.012)
SMB	-0.001 (0.007)	0.019 (0.010)*	-0.052*** (0.012)
HML	0.019** (0.008)	0.037*** (0.013)	0.097*** (0.016)
UMD	0.001 (0.005)	0.009 (0.007)	-0.028*** (0.009)
R-squared	0.22	0.19	0.60

Table 8
Performance Differentials between PhD Products by Field of Study, Portfolio Approach

This table presents Carhart (1997) performance evaluation for zero-cost portfolio strategies formed by PhD product field of doctoral study. A product is managed by a PhD if a key role in the firm is performed by a PhD (key roles are listed in Section 1.1). The portfolio of Unpublished PhD Products contains products from PhD firms in which none of the PhDs had published a paper in a top outlet at the time of portfolio formation. The portfolio of Economics or Finance PhD Products contains products from PhD firms in which the percentage of managers with doctorates in Economics or Finance is above median (*EconFin* = 1). The portfolio of other (mostly STEM) PhD Products contains products from PhD firms in which none of the PhDs had earned their doctorates in Economics or Finance (*EconFin* = 0). Portfolios are asset-weighted and are revised quarterly. The first column (corresponding to the first column of Table 6) focuses on all PhD product-year observations. The second column (corresponding to the second column of Table 6) focuses on published PhD product-year observations (the observations for which *Publications* = 1). The third column (corresponding to the third column of Table 6) focuses on unpublished PhD product-year observations (the observations for which *Publications* = 0). Each of the regressions is based upon 168 monthly observations. Standard errors are calculated using the Newey-West (1987) approach with three lags to account for heteroscedasticity and covariance of errors over time. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) All PhD Products	**(2) Published PhD Products (*Publications* = 1)**	**(3) Unpublished PhD Products (*Publications* = 0)**
Matched Product Analysis Equivalent from Table 6	column (1) (also Table 4, column (1))	column (2)	column (3)
Long:	Economics or Finance PhD Products	Economics or Finance PhD Products	Economics or Finance PhD Products
Short:	(Mostly) STEM PhD Products	(Mostly) STEM PhD Products	(Mostly) STEM PhD Products
Alpha	**3.21***	**2.15**	**5.08****
(bp/month)	**(1.86)**	**(5.02)**	**(2.36)**
RMRF	-0.011**	-0.013	-0.016**
	(0.005)	(0.014)	(0.006)
SMB	-0.020***	0.038***	0.004
	(0.005)	(0.014)	(0.007)
HML	-0.002	-0.082***	0.016**
	(0.007)	(0.018)	(0.008)
UMD	0.005	0.027***	-0.004
	(0.004)	(0.009)	(0.005)
R-squared	0.16	0.34	0.13

Table 9
University Selectivity, Field of Doctoral Study, and Publication Record

This table documents performance differentials among PhD products along the dimension of university selectivity in Panel A, along the dimension of the PhDs' field of doctoral study (while controlling for the elite status of their PhD-granting institutions) in Panel B, and along the dimension of the PhDs' publication status (while controlling for the elite status of their PhD-granting institutions) in Panel C. A product is regarded to be managed by a PhD if a key role in the firm is performed by a PhD (key roles are listed in Section 1.1). The five performance measures reported in the table are described in Section 1.1 and in the caption to Table 2. For each product-year observation in Panel A, university selectivity is captured by two indicator variables, *EliteOne* and *EliteAll*. These indicator variables are based on two definitions of elite status, obtained from the PhD-granting institutions' college rankings reported in U.S. News & World Report in 1992. Elite status of the university is determined by the university's overall ranking among the top twenty universities. For *EliteOne*, each year a PhD firm (and, therefore, all of its domestic-equity products) will be regarded as elite (*EliteOne* = 1) if at least one of the firm's PhDs in a key role holds a PhD degree from an elite university, and zero otherwise. For *EliteAll*, each year a PhD firm (and, therefore, all of its domestic-equity products) will be regarded as elite (*EliteAll* = 1) if all of the firm's PhDs in key roles hold a PhD degree from an elite university, and to zero otherwise. Dependent variables in Panel A are differences between performance measures of PhD products managed by firms with a high presence of PhDs from elite universities and the corresponding performance measures of their respective matched PhD products managed by firms with a low presence of PhDs from elite universities. Dependent variables in Panel B are differences between performance measures of products managed by PhDs from firms with above median economics or finance PhDs (*EconFin* = 1) and their respective matched products managed by PhDs from other (mostly STEM) fields (*EconFin* = 0). Dependent variables in Panel C are differences between performance measures of products managed by PhDs who had published in top outlets and their respective matched products managed by PhDs who had not published in top outlets. In Panel A, for each PhD product-year observation with elite status, the matching process identifies the non-elite PhD product-year observation that (1) pursues the same investment objective; (2) has similar assets under management (by virtue of belonging, at the end of year t–1, to the same quintile of the distribution of product assets under management); (3) and is the closest to the elite PhD product in terms of their respective firms' PhD propensity scores calculated for year t. In Panels B and C, for each PhD product-year observation, the matching process identifies the PhD product-year observation such that the matched product (1) has the same elite status classification; (2) pursues the same investment objective; (3) has similar assets under management (at the end of year t–1, it belongs to the same quintile of the distribution of product assets under management); (4) and is the closest to the economics and finance PhD product in terms of their respective firms' PhD propensity scores calculated for year t. Propensity score calculation is described in Section 1.3. Controls in all regressions include product and firm sizes of the original PhD product-year observations and their matched PhD product-year observations. The values of R-squared in all regressions range from 0.001 to 0.005. Standard errors are adjusted by clustering that accounts for heteroscedasticity and dependence of observations across the firm to which the PhD product belongs. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9 (continued)
University Selectivity and Field of Doctoral Study Analyses

	Panel A: PhD Firm University Selectivity: Top 20 Overall University Ranking versus the Rest		***Panel B:*** PhD Field of Study: Economics or Finance (*EconFin* = 1) versus Other (mostly STEM) (*EconFin* = 0)			***Panel C:*** PhD Firm Publications: Published (*Published* = 1) versus Unpublished (*Published* = 0)		
	EliteOne=1 versus *EliteOne*=0	*EliteAll*=1 versus *EliteAll*=0	No matching by university selectivity (Table 4, Column (1); also, Table 6, Column (1))	Matched by university selectivity using *EliteOne*	Matched by university selectivity using *EliteAll*	No matching by University Selectivity (Table 5, Panel A, Column (1))	Matched by university selectivity using *EliteOne*	Matched by university selectivity using *EliteAll*
Annual return (percent/year)	0.92*** (0.29)	1.28*** (0.34)	0.63** (0.31)	0.61** (0.27)	0.82*** (0.29)	0.91*** (0.36)	0.83** (0.39)	0.70*** (0.39)
Alpha (bp/month)	4.08** (1.72)	4.63** (2.21)	3.73* (2.03)	3.24* (1.68)	4.40** (1.79)	5.15** (2.27)	4.64* (2.41)	4.12* (2.41)
Sharpe ratio	1.05** (0.48)	1.71*** (0.60)	0.26 (0.52)	0.93* (0.50)	0.89* (0.47)	1.59*** (0.65)	1.50** (0.73)	1.27* (0.72)
Information ratio	2.11* (1.16)	2.81* (1.52)	0.84 (1.28)	2.43** (1.17)	2.99** (1.21)	5.91*** (1.57)	7.74*** (1.68)	6.23*** (1.69)
MPPM (Rho = 3) (percent/year)	0.81*** (0.28)	1.33*** (0.32)	0.82*** (0.31)	0.55** (0.24)	0.79*** (0.26)	0.88** (0.35)	0.67* (0.37)	0.62* (0.37)
Number of obs.	4,022	2,005	4,533	4,533	4,533	2,662	2,662	2,662

Appendix A.1 Propensity score matching

Table A.1
Distributions of assets under management and propensity matching scores for PhD products and matched non-PhD products

This table documents the closeness of the matching between PhD product-year observations and their matched non-PhD product-year observations. The matching for a PhD product in year t requires that its matched non-PhD product (1) pursues the same investment objective; (2) has similar assets under management (by virtue of belonging, at the end of year t–1, to the same quintile of the distribution of product assets under management); and (3) is the closest to the PhD product in terms of their respective firm PhD propensity scores calculated for year t (key personnel information is available at the firm level only). For each year t, propensity scores for a firm with a PhD in a key role are calculated by estimating a Logit model with the dependent variable set to one if the a PhD performed a key role in the firm in year t and to zero otherwise, and independent variables log(firm domestic equity assets$_{t-1}$), its square, log(# of domestic equity products the firm offered$_{t-1}$), and log(# of unique domestic equity objectives the firm offered$_{t-1}$). Each product-year observation in year t is assigned its firm's propensity score in year t, calculated from the Logit model. Panel A presents the comparison of the distributions of assets under management for the PhD product-year observations and the matched non-PhD product-year observations. Panel B presents the comparison of the distributions of propensity matching scores for the PhD product-year observations and the matched non-PhD product-year observations. The two panels demonstrate the closeness of the matching, with closely aligned values at the corresponding distribution percentiles.

	Panel A: Assets under management				
	10th Pctl	25th Pctl	Median	75th Pctl	90th Pctl
PhD products	34	147	620	2,166	6,091
Matched non-PhD products	33	147	619	2,068	5,988
	Panel B: Propensity matching scores				
	10th Pctl	25th Pctl	Median	75th Pctl	90th Pctl
PhD products	0.155	0.290	0.450	0.572	0.661
Matched non-PhD products	0.153	0.284	0.438	0.577	0.650

Appendix A.2 Standard error estimation: Various clustering approaches

Table A.2
Baseline estimation with various standard error clustering approaches

This table replicates the baseline performance differential analyses from Panel A of Table 2 with various approaches to standard error clustering. The first approach, reported in the body of the paper, is clustering by firm. The next two alternatives are clustering by the investment objective, and double clustering by firm and year. All the details regarding estimation are presented in the caption to Table 2.

	Differential (intercept)	Controls	R-squared	Number of obs.
Annual Return (percent/year)	**0.72**	Yes	0.001	6,723
SE clustered by…				
PhD Firm	(0.29)**			
Investment Objective	(0.27)***			
PhD Firm and Year	(0.67)			
Alpha (bp/month)	**6.48**	Yes	0.003	6,723
SE clustered by…				
PhD Firm	(1.92)***			
Investment Objective	(1.31)***			
PhD Firm and Year	(2.22)***			
Sharpe Ratio	**1.43**	Yes	0.001	6,723
SE clustered by…				
PhD Firm	(0.57)**			
Investment Objective	(0.42)***			
PhD Firm and Year	(0.78)*			
Information Ratio	**5.43**	Yes	0.001	6,723
SE clustered by…				
PhD Firm	(1.22)***			
Investment Objective	(1.12)***			
PhD Firm and Year	(1.58)***			
MPPM (rho = 3) (percent/year)	**1.43**	Yes	0.001	6,723
SE clustered by…				
PhD Firm	(0.30)***			
Investment Objective	(0.37)***			
PhD Firm and Year	(0.81)*			

Appendix A.3 Net Flows

This appendix documents the patterns of differential flow-performance relations prevailing for PhD products and non-PhD products. The dependent variable in these analyses is the difference between annual net flows to PhD products and the matched, non-PhD products, expressed in percentages.[40] Given the strong, positive relation between flows and recent past performance (e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998), DelGuercio and Tkac (2002)), the matching we employ in this section augments the baseline matching by considering an additional, performance-related criterion.

For each PhD product-year observation, the matching process identifies the non-PhD product-year observation that (1) pursues the same investment objective, (2) has similar assets under management (by virtue of belonging, at the end of year t–1, to the same quintile of the distribution of product assets under management), (3) is closest in terms of its propensity score (as described in Section 1.3), and (4) has recent performance at the end of year t–1 in the same quintile of objective-adjusted returns. Controls, as in other analyses, are total assets under management for both products and for both firms (in logarithmic form). Also once again, given this matching design, the point estimates associated with these controls are practically zero, and we suppress them from the table for readability. As elsewhere, we adjust standard errors by clustering that accounts for heteroscedasticity and dependence of observations across the firm to which the PhD product belongs.

Panel A of Table A.3 reports estimates over the full set of observations. The gap between PhD product flows and their matched non-PhD product flows is large, 12 percent per year, and is statistically significant at the one-percent level. The interpretation of this results is that, whatever the flow into the matched non-PhD product (be it negative, slightly positive, or very large), the flow to its corresponding PhD product is 12 percent larger on average. The third column shows the results for the PhD product-year observations from firms with some economics and finance PhDs in which at least one of the PhDs from the firm had published a paper in a top outlet in economics or finance through year t. The flow gap between these PhD products and the matched counterparts increases to 16 percent.

[40] The distribution of annual net flows in the institutional money management industry is highly leptokurtic (even more so than in the mutual fund industry). To minimize the influence of outliers, we have undertaken standard steps. Specifically, we exclude products managing fewer than five million dollars in assets under management, and we winsorize flows at the 2.5th and 97.5th percentiles.

Panel B of Table A.3 reports results estimated for five subsamples defined by products' performance quintiles of objective- and size-adjusted past one-year performance. The flow gap is the largest for the top past performance quintile (19.1 percent), and is declining monotonically toward the flow gap for the bottom past performance quintile (4.7 percent). The flow gaps are statistically significant for all five past performance quintiles. Finally, Panel C shows that this proportional flow differential is the most pronounced among the products with assets under management smaller than 250 million dollars (25 percent), less pronounced among the products with assets under management in the range from 250 million to one billion dollars (10 percent), and still less pronounced among the products with assets under management in excess of one billion dollars (4 percent).[41]

Results presented in this Appendix suggest investors' belief that a given level of past performance by PhD products signals better future performance than the comparable level of past performance by the matched non-PhD products. The increased size of the flow gap for highest levels of past performance suggests that such a belief is particularly strong when applied to past winners. One interpretation of this finding is that investor appear more likely to ascribe past strong performance to skill (rather than luck) if it had been posted by PhD products, for which there is an external validation signal embedded in the PhD degree.

[41] Despite this coefficient pattern for the differential in relative flows, the differential in dollar flows is the greatest for the products in the large product category, in excess of one billion dollars in assets under management.

Table A.3
Net-flow Differentials between PhD-managed and Non-PhD Managed Products

The dependent variable is the difference between annual net flows to products managed by PhDs and their respective matched products managed by non-PhDs in year t+1, expressed in percentages. Product i's net flow during year t, $Flow_{i,t}$, is calculated as the ratio of the change in product i's assets under management from year t–1 to t and product i's assets under management at the end of year t–1, $Flow_{i,t} = (Assets_{i,t} - (1 + R_{i,t}) \times Assets_{i,t-1})/Assets_{i,t-1}$. We further adjust this net flow by subtracting from it the median net flow to a product pursuing the same objective in the same year, in the same asset-size quintile. A product is regarded to be managed by a PhD if a key role in the firm is performed by a PhD (key roles are listed in Section 1.1). For each PhD product-year observation, the matching process identifies the non-PhD product-year observation that (1) pursues the same investment objective, (2) has similar assets under management (by virtue of belonging, at the end of year t–1, to the same quintile of the distribution of product assets under management), (3) is closest in terms of its propensity score (calculated as described in Section 1.3), and (4) has similar recent performance (by virtue of belonging, at the end of year t, to the same quintile of objective-adjusted returns in year t). Panel A reports results estimated for all product-year observations in the sample. Panel B reports results estimated for subsamples determined by the objective- and size-adjusted product annual return quintile in year t. Panel C reports results determined by assets under management for each product in year t. Controls in the regressions are product and firm sizes of the PhD product and its matched non-PhD product. Standard errors are adjusted by clustering that accounts for heteroscedasticity and dependence of observations across the firm to which the PhD product belongs. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	Differential (intercept) (percent/year)	Controls	R-Squared	Number of obs.
Panel A: All products				
All products	12.4*** (1.3)	Yes	0.01	6,723
Panel B: Products by objective- and size-adjusted performance quintile in year t				
Performance in Top Quintile	19.1*** (3.8)	Yes	0.03	1,312
Performance in Quintile 4	18.2*** (3.0)	Yes	0.02	1,374
Performance in Quintile 3	11.6*** (2.5)	Yes	0.02	1,384
Performance in Quintile 2	6.8*** (2.5)	Yes	0.04	1,369
Performance in Bottom Quintile	4.7* (2.5)	Yes	0.01	1,284
Panel C: Products by assets under management in year t				
$Assets_{i,t}$ < 250 million	25.4*** (3.7)	Yes	0.02	2,235
$Assets_{i,t}$ 250 million to 1 billion	9.6*** (4.9)	Yes	0.02	1,928
$Assets_{i,t}$ > 1 billion	4.5*** (1.5)	Yes	0.01	2,560

Appendix A.4 Potential sources of superior performance

One plausible benefit of earning a PhD degree could be greater facility with the more sophisticated, quantitative techniques and strategies. Performance differential we identified in our baseline analyses could stem primarily from a potential gap between the successes of more quantitative strategies over less quantitative (presumably, more fundamental) strategies. In other words, the results we associate with the PhD degree might be primarily driven by the potential gap between types of strategies. Of course, if the ability to implement more exotic quantitative strategies is related to product performance, the presence of a PhD in a key role is an important factor anyway.

It is very difficult to ascertain precisely which products employ quantitative approaches (even a characterization of what constitutes a quantitative approach is not defined precisely). The amount of information an econometrician would need to differentiate objectively between various strategies with any degree of precision far exceeds the available data. Therefore, providing a very precise answer to this question is challenging. Our data set allows us to take a step in that direction because it enables us to develop an indicator variable proxy *Quantitative*, defined as the inclusive disjunction of an indicator variable for the products' use of derivatives and an indicator variable based on the categorical variable for self-reported use of other quantitative strategies recorded as "1" or "2" (out of four categories: 1 = Very accurate; 2 = Accurate; 3 = Applicable; 4 = Inapplicable, viewing products that report "1" or "2" as those pursuing other quantitative strategies).

Equipped with this proxy, we replicate the baseline analysis with the addition of *Quantitative* to the list of matching variables and report the results in the first column of Panel A in Table A.4.[42] We then proceed with analogous analyses for the two subsamples of more quantitative strategies (the observations for which *Quantitative* = 1) and less quantitative strategies (the observations for which *Quantitative* = 0). The results suggest that the performance gap among the PhD and non-PhD products likely pursuing more quantitative strategies appears somewhat larger than the performance gap between the PhD and non-PhD products likely pursuing less quantitative strategies across all five performance measures. Though suggestive of PhDs' particular advantage in the domain of the more quantitatively oriented strategies, the differentials are not statistically significant from each other. Moreover, these analyses confirm that our results are not driven by the potential superiority of quantitative strategies.

[42] The results reported in column 1 of Table A.4 are slightly different from those from Table 2 because of a change in the propensity matching approach driven by the inclusion of the matching criterion based on *Quantitative* in the present analyses.

The PhD products in our sample outperform their matched non-PhD counterparts both in the domain of more quantitative strategies and in the domain of less quantitative strategies. In general, we find that the performance gap among the PhD and non-PhD products likely pursuing quantitative strategies is only modestly larger than the performance gap between the PhD and non-PhD products less likely to pursue quantitative strategies. The differences in performance between the two subsamples are not statistically significant. Thus, these analyses show that the performance differentials in our baseline analyses do not stem primarily from the potential superiority of the more quantitatively oriented strategies.

We also analyze whether the performance differentials vary with market conditions. Our sample period, from 1993 to 2007, does not encapsulate the recent financial crisis. However, splitting the 15-year period into quintiles based on performance of the S&P 500, a broad market index, reveals that the quintile associated with the worst S&P 500 annual returns features some crisis-like negative returns (-22.1% in 2002; -11.9% in 2001; -9.1% in 2000). On the other side of the spectrum are very large positive S&P 500 annual returns from the top quintile (37.6% in 1995; 33.4% in 1997; 28.7% in 2003).

We perform analyses for the subsamples of observations associated with the worst-return quintile, the best-return quintile, and the middle three quintiles, and report the results in the respective columns of Panel B in Table A.4. Separate consideration of the worst-return quintile, the best-return quintile, and the middle three quintiles suggests that the PhDs have been the most successful during the worst market returns,[43] and nearly as successful during the best market returns. By contrast, though noticeable in magnitude and largely statistically significant, evidence of their superior performance during relatively tame market conditions is not as pronounced as it is during the more turbulent times.

The finding that better performance during turbulent times lends itself to several plausible interpretations. These include the possibilities that the superior performance might stem from factor timing of some form, that more effort might be exerted during turbulent times, and that, relative to non-PhD managers, the PhDs in our sample might be less prone to behavioral biases associated with the disposition effect (e.g., Odean (1998), Frazzini (2006)). Unfortunately, unavailability of portfolio holdings data at the product level precludes a careful attempt to identify the source of superior performance during turbulent times.

[43] The difference between performance measure estimates from the bottom quintile and the respective performance measure estimates from the middle three quintiles is statistically significant for some, but not all performance measures.

Table A.4
Performance differentials between PhD products and non-PhD products by their likely pursuit of quantitative strategies and by market conditions (S&P 500 annual returns)

The dependent variables in this table are differences between performance measures of products managed by PhDs and their respective matched products managed by non-PhDs. A product is regarded to be managed by a PhD if a key role in the firm (key roles are listed in Section 1.1) is performed by a PhD. The five performance measures reported in the table are described in Section 1.1 and in the caption to Table 2. Panel A addresses the likely pursuit of quantitative strategies. It is captured by defining *Quantitative* as the inclusive disjunction of an indicator variable for the use of derivatives and an indicator variable based on the categorical variable for self-reported use of other quantitative strategies recorded as "1" or "2" (out of four categories: 1 = Very accurate; 2 = Accurate; 3 = Applicable; 4 = Inapplicable). For each PhD product-year observation, the matching process identifies the non-PhD product-year observation that (1) pursues the same investment objective, (2) has similar assets under management (by virtue of belonging, at the end of year t–1, to the same quintile of the distribution of product assets under management), (3) is closest in terms of its propensity score, and (4) has the same value of the indicator variable *Quantitative* in year t. The first column of Panel A shows the estimation over the entire sample of observations (6,723 observations). The second column of Panel A focuses on the observations associated with a more likely pursuit of quantitative strategies (products that use derivatives or report "1" or "2" for pursuit of other quantitative strategies; 2,066 observations), and the third column focuses on the remaining observations, associated with a less likely pursuit of quantitative strategies (4,657 observations). Panel B addresses the variation in performance by market conditions. The matching process and propensity score calculation employed in Panel B are described in Section 1.3 and the caption to Table 2. The first column of Panel B features the estimation over the subsample of observations (N = 1,916) associated with the worst three years of S&P 500 returns during the sample period (the bottom quintile). The second column of Panel B shows the estimation over the subsample of observations (N = 1,219) associated with the best three years of S&P 500 returns during the sample period (the top quintile). Finally, the third column of Panel B features the estimation over the subsample of observations (N = 3,588) associated with the middle three quintiles of S&P 500 annual returns during the sample period. Controls in all regressions include product and matched product assets and their corresponding firm assets. All specifications contain investment objective and year effects. The values of R-squared in all regressions range from 0.001 to 0.005. Standard errors are adjusted by clustering that accounts for heteroscedasticity and dependence of observations across the firm to which the PhD product belongs. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.4 (continued)
Performance differentials between PhD products and non-PhD products by their likely pursuit of quantitative strategies and by market conditions (S&P 500 annual returns)

		Panel A: Quantitative Orientation		*Panel B*: Market Conditions		
		More quantitative orientation (*Quantitative* = 1)	Less quantitative orientation (*Quantitative* = 0)	Worst three years	Best three years	Other years
	Full sample (N = 6,723)	Product uses derivatives or applies other quantitative strategies	Product neither uses derivatives nor applies other quantitative strategies	Bottom quintile of annual S&P 500 returns	Top quintile of annual S&P 500 returns	Middle three quintiles of annual S&P 500 returns
		(N = 2,066)	(N = 4,657)	(N = 1,916)	(N = 1,219)	(N = 3,588)
Annual return	0.76***	0.82***	0.61**	1.42***	0.80**	0. 06
(percent/year)	(0.22)	(0.29)	(0.31)	(0.47)	(0.41)	(0.49)
Alpha	6.46***	6.95***	5.21***	11.96***	6.41*	4.69**
(bp/month)	(1.37)	(1.91)	(1.88)	(3.57)	(3.35)	(2.19)
Sharpe ratio	1.82***	1.97***	1.40***	1.74**	1.54**	1.08*
	(0.34)	(0.44)	(0.54)	(0.85)	(0.76)	(0.58)
Information ratio	6.05***	6.73***	5.18***	7.89***	5.74***	3.34**
	(0.81)	(1.30)	(1.03)	(1.93)	(2.15)	(1.71)
MPPM (rho = 3)	1.46***	1.69***	1.21***	2.30***	1.04**	0.98***
(percent/year)	(0.22)	(0.30)	(0.30)	(0.56)	(0.43)	(0.34)