ESSAYS IN ASSET MANAGEMENT AND CORPORATE CREDIT MARKETS

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Abstract

In the first chapter of this dissertation I investigate the extent to which firm cash holdings are affected by credit default swap (CDS) coverage of their product market peers. Using a sample of firms incorporated in the US, and defining peer groups using the text-based industry classification of Hoberg and Phillips (2016), I find that firm cash-to-asset ratios and relative-to-peer cash ratios are positively related to peer CDS coverage. The marginal effects are meaningful at approximately 2 and 9 percent of the sample medians respectively. Decomposing peer firm CDS coverage by relative financial constraints suggests that the effects are due to predatory motives.

In chapter two, I examine whether obtaining a foreign presence through sub-advisors affects fund performance and management behaviours of international equity mutual funds sold in the US. I find no evidence that international sub-advisors exploit information in a way that improves fund performance. Moreover, funds that hire outsourced international sub-advisors are found to underperform on a risk-adjusted basis by up to 126 basis points (bps) annually. The underperformance of outsourced international sub-advisors is concentrated in their local holdings and can be partly explained by lower activeness and greater risk shifting. These effects are alleviated in funds with multiple sub-advisors as they are more likely to be terminated following poor performance.

In the final chapter, I investigate the extent to which competition from low-cost index funds affects fees, performance, and survival rates of actively managed funds. I measure the intensity of competition using the market value of holdings overlap between the portfolios of index entrants and active incumbents. Disentangling the competitive effects of traditional index funds (market index) from smart-beta index funds (factor index), I find that future changes in actively managed net fees are negatively related to factor index fund entry but unrelated to market index fund entry. Additionally, I find that both factor and market index entry are negatively related to active incumbent survival rates and that this effect is most pronounced for relatively expensive active incumbents. Lastly, I find evidence that factor index entry has had an attenuating effect on active incumbent future performance.

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Chapter I

Corporate Liquidity Management in Response to Peer CDS Initiation

Michael Densmore[1]

1 Introduction

Although only a small proportion of firms are referenced by credit default swaps (CDS) – 503 (14.5%) of my sample firms in 2008 – they have been a subject of hot debate since they were first engineered. The collapse of major banks and insurance companies like Bear Sterns and Lehman Brothers, and the government takeover of AIG at the onset of the US subprime crisis in 2007-2008 were, for the most part, due to large positions in credit derivative markets.[2] More recently, lawsuits have been filed against major US banks regarding profiting from anti-competitive price setting in the CDS market.[3] Regulatory bodies have attempted to address various deficiencies by implementing regulations surrounding CDS trading (e.g., Dodd-Frank, Basel Accord and the Big Bang Protocol). Given that only a small proportion of firms are referenced by CDS, it is natural to question whether they influence management decisions of firms that are not themselves referenced by CDS. In this paper, I empirically investigate whether cash holdings decisions of non-referenced firms are affected by CDS coverage of their closest peers.

I concentrate on the impact on cash holdings for several reasons. CDS contracts

[1] I am grateful for the comments of Melanie Cao, Ambrus Kresckes, Fabio Moneta, Aleksandra Rzeźnik, Ben Sand, Pauline Shum Nolan and participants at the Schulich School of Business research seminar.

[2] AIG for example, had a net short position in CDS valued around \$546 billion in 2007 (Augustin et al., 2015), and failed to meet its obligations by late 2008 and required a bailout.

[3] https://www.bloomberg.com/news/articles/2015-10-01/jpmorgan-said-to-pay-most-as-banks-settle-1-86-billion-cds-suit

provide a simple means for lenders to transfer credit risk and have been shown to alter renegotiation policies and credit availability for the underlying firm. Bolton and Oehmke (2011) and Morrison (2005) provide theoretical evidence that the introduction of CDS trading increases the cost of debt, particularly when the referenced firm is financially constrained. The rationale being that creditors who have hedged their position are tougher during debt renegotiation processes and more likely to reject out-of-court restructuring. Indeed, if the CDS payoff is sufficiently high then over-insured lenders, often referred to as *empty creditors* (Black and Hu, 2008), will have incentive to induce bankruptcy.[4] The empirical evidence generally supports these theories. For example, CDS coverage is positively related to credit and loan spreads (Ashcraft and Santos, 2009), reductions in credit quality (Subrahmanyam et al., 2014) and increased default probabilities (Peristiani and Savino, 2011; Subrahmanyam et al., 2014; Arentsen et al., 2015), particularly for financially distressed firms. In sum, a large body of theoretical and empirical research stipulates that firms experience credit rationing or other financial constraints following CDS initiation, and that the effect is most pronounced for firms that are ex-ante financially constrained.

Next, extensive literature has shown that corporate liquidity management policies, and ultimately the success of a firm, can be influenced by the actions, and characteristics, of its immediate peers. In particular, firms facing financial frictions or credit constraints can be the target of predatory pricing or advertising strategies from unconstrained peers (Bolton and Scharfstein, 1990; Campello, 2006). This predatory pressure can lead constrained firms to suffer diminished cash flow due to reduced sales, which can further lead to under-investment and ultimately a loss of market share (Benoit, 1984). At the extreme, the constrained firm may be driven out of the market. As documented by Fresard (2010), cash reserves, and particularly industry adjusted cash reserves, are a plausible vehicle for predation. That is, firms can strategically use large relative-to-peer cash reserves to increase their market share at the expense of their peers as they are better situated to engage in predatory strategies. Given the evidence of credit rationing or other financial constraints associated with CDS coverage, I conjecture that CDS coverage signals that the referenced firm is a prime target for predation. Formally, under the predatory hypothesis I expect that non-referenced firm cash hold-

[4]The term empty creditor highlights the fact that the lender has hedged its credit risk while retaining control rights.

ings are positively related to the portion peer firms referenced by CDS. Moreover, this relationship should be restricted to CDS coverage peers that are relatively financially constrained as they are the firms most likely to experience a deterioration in credit availability following CDS coverage.

Alternatively, intra-industry credit contagion (Jorion and Zhang, 2007) and spillover effects from CDS trading (Darst and Refayet, 2018) might lead to increased borrowing costs for firms without traded CDS. Under this alternative firms are expected to increase cash holdings following peer CDS coverage due to contagion concerns rather than for predatory reasons. This alternative hypothesis follows Subrahmanyam et al. (2016) who show that firms respond to the increased bankruptcy risk of CDS coverage by increasing cash holdings. The rationale is based on the precautionary motive which posits that firms facing borrowing constraints can use cash reserves to smooth investment during market downturns (Kenneth Froot and Stein, 1993; Haushalter et al., 2007). As with the predatory hypothesis, the relationship between cash holdings of non-referenced firms and peer CDS coverage is positive; however, under the precautionary motive non-referenced firms are expected to be relatively financially constrained.

Lastly, lenders may use CDS to shed credit risk in an effort to reduce exposure, or to improve their capital ratio which can enable them to extend additional credit to referenced firms (Guest et al., 2016; Shan et al., 2014). Similarly, creditors who transfer credit risk may expend less resources on monitoring their borrowers, which can also lead to a reduction in financing constraints and increased debt capacities for CDS referenced firms (Guest et al., 2016; Che and Sethi, 2015). In this case, the relationship between firm cash holdings and peer CDS coverage is unclear.

In order to examine how cash holdings are affected by peer CDS coverage, an appropriate set of peer firms must be determined. Fixed industry classifications (e.g., SIC, NAICS or GICS) provide a simple, and easy to implement, approach. The drawback is that mangers tend to focus on only a small number of their most relevant peers (Kaustia and Rantala, 2015). Thus, groups formed using standard fixed industry classification codes lack the precision necessary to properly examine peer effects. In addition, the product market in which a firm operates evolves over time, and in some cases, innovation can lead to newly created product markets. Fixed industry classifications are slow to re-classify firms and fail to capture these important features of product market competition. I circumvent these issues by constructing peer groups using the text-based industry classification (TNIC) data from Hoberg and Phillips (2016) (HP). The structure of HP's product market data allows for a more more precise identification of the set of most relevant peers relative to common industry classification codes. Moreover, it provides a measure of the degree to which pairs of firms compete via their product market. Put differently, the TNIC data provides information regarding the economic distance between two firms product market and therefore allows one to concentrate on, and/or overweight, the more important peers rather than treating all peers equally.

In line with prior literature (e.g., Ashcraft and Santos, 2009; Saretto and Tookes, 2013; Subrahmanyam et al., 2014, 2016) I consider a firm to be referenced by CDS once Markit data services (my source of CDS data) reports a non-missing CDS price. In particular, I define a CDS coverage dummy variable that is equal to one if a firm is referenced by CDS and zero otherwise. Next, I utilize HP's similarity scores to construct measures of peer CDS coverage, as well as to control for peer characteristics. I consider a variety of methods for selecting the subset of the most relevant peers, but report results using the 5, 20 or 50 most similar peers in the bulk of my empirical tests. In particular, firm i's peer group contains the 5, 20 or 50 firms that are most similar to firm i in terms of product market (i.e., the 5, 20 or 50 peer firms have the highest pairwise TNIC similarity score). I then compute peer CDS coverage, and peer characteristics, using similarity score weighted averages. That is, peer CDS coverage is equal to the TNIC similarity score weighted proportion of peers that are referenced by CDS. Unlike an equally weighted measure, the similarity score weighted measure ensures that the most relevant peers receive higher weights than the least relevant peers.

Regressing firm cash-to-assets on the similarity score weighted peer CDS coverage variable shows that firm cash ratios are significantly higher when a larger proportion of its closest peers are referenced by CDS. The magnitude is also meaningful – the marginal effect is approximately 2.23% of the sample median. Replacing cash-to-asset ratios with relative-to-peer cash ratios yields similar results. In particular, a one-standard deviation increase in peer CDS coverage is associated with relative-to-peer cash ratios that are approximately 0.05 higher, which is about 9% of the sample median. Subrahmanyam et al. (2016) find that cash-to-asset ratios are about 10%

higher following the introduction of own-firm CDS trading which suggest that the effects of peer CDS coverage on firm cash ratios are meaningful. The fact that firm cash ratios, and particularly relative-to-peer cash ratios, are positively related to peer firm CDS coverage also offers initial support of a competitive, and likely predatory, channel.

The literature examining peer group effects shows that certain peer firm characteristics and actions are likely to influence corporate decisions.[5] Although prior research indicates that CDS markets provide information not captured by other observable metrics, I include an exhaustive list of peer controls to alleviate concerns that CDS coverage is indeed proxying for other observable peer characteristics. The marginal effects are numerically similar and continue to be statistically significant. Importantly, the effects of peer CDS coverage are not diminished when controlling for other observable measures of peer firm credit constraints such as Altman's Z-Score or S&P credit ratings.

Next, I show that the results are robust to alternative specifications. In particular, replacing the weighted average peer CDS coverage variable with individual CDS coverage dummy variables does not substantially alter the results. Additionally, I find that the positive effect on cash, and relative-to-peer cash, is generally subsumed by CDS coverage of a firms two closest peers. CDS trading on a firm is arguably an exogenous event to its peers, which typically do not trade CDS. Moreover, it is unlikely that firms select their product market space based on the number of peers that are covered by CDS. Nonetheless, I address the potential selection bias by confirming that the positive relationship between peer CDS coverage and firm cash holdings remains significant when using a propensity score-matched sample.

Having established a robust, positive relationship between peer CDS coverage and both firm cash ratios and relative-to-peer cash, I investigate potential mechanisms. In particular, I decompose peer CDS coverage variables based on Altman Z scores in an effort to separate the effects of CDS coverage of financially constrained from coverage of financially unconstrained peers. This is important since the impact of CDS coverage on the reference firm has been shown to differ based on ex-ante financial constraints. My evidence is consistent with a predatory motive: the positive effect of peer CDS coverage

[5]For example: Bizjak et al. (2008) study how benchmarking in CEO compensation affects pay levels, Kaustia and Rantala (2015) show that a firm is more likely to split it's stock if it's peer have recently done so, and Leary and Roberts (2014) examine how peer behaviour affects firm financing decisions.

on firm cash holdings is confined to peers who are already financially constrained, and is insignificant for CDS coverage of firms that are financially unconstrained. Decomposing peer CDS coverage by relative financial constraints offers additional support – the positive relationship is restricted to firms that are less financially constrained than their CDS covered peers.

Lastly, I test whether the presence of empty creditors impacts the results. Empty creditors will prefer that their borrowers declare bankruptcy and reject any out-of-court restructuring when the payout offered by the CDS is greater than the payoff from restructuring. This situation is most likely to arise under ex-restructuring (XR) CDS contracts since debt-restructuring does not trigger a payout. In contrast, debt restructuring qualifies as a credit event under cum-restructuring (CR), modified restructuring (MR) and modified-modified restructuring (MM) contracts. Naturally, creditors have greater incentives to induce bankruptcy and to fight debt-restructuring when they insure their positions with XR CDS contracts as they are only triggered by bankruptcy. My evidence offers some support that empty creditors are driving the results. Cash ratios are significantly higher for firms that have peers covered by XR CDS relative to firms whose peers are covered by CR, MM or MR CDS. However, the results for relative-to-peer cash ratios are inconclusive.

This paper contributes to three broad fields. First, I contribute to the sparse literature on the spillover effects of CDS trading. To the best of my knowledge, the only research directly examining spillover effects of CDS initiation is by Li and Tang (2015), who examine how CDS coverage of customers impacts supplier leverage. The perspective in my paper differs in that I investigate spillover effects through product market peers rather than through a customer supplier channel.

I also supplement the vast literature on the determinants, and use, of cash reserves. Most relevant to this paper is the research on the strategic use of cash reserves. For instance, firm cash holdings have been shown to be positively related to industry cash flow volatility (Opler et al., 1999), which has led to the theories about the precautionary motive for corporate cash holdings (Han and Qui, 2007). Similarly, firms facing high levels of competition have been shown to hold more cash (Morellec et al., 2014) while firms with large relative-to-rival cash reserves tend to gain future market share at the expense of their cash poor rivals (Fresard, 2010). I contribute to this debate in that I offer a new angle through which firms obtain relevant information regarding peer credit constraints. In particular, my evidence suggests that peer CDS coverage provides a signal of credit constraints not provided by standard measures and that firms act on this information by holding higher levels of cash reserves. Importantly, these findings hold when replacing cash-ratios with relative-to-peer cash, and the latter have been shown to influence product market outcomes.

Lastly, I contribute to the ever growing research on peer effects. For example, firm decisions have been shown to be influenced by peer firm decisions and characteristics. For instance, firm financing decisions and stocks splits are positively related to peer financing decisions (Leary and Roberts, 2014; Harvey and Harvey, 2001) and peer stock splits (Kaustia and Rantala, 2015), respectively. Similarly, firms have been shown to use peer firm compensation in setting executive pay (Bizjak et al., 2008) and peer firm valuations in making investment decisions (Foucault and Fresard, 2016). Most similar to my research is YiWen Chen and Chang (2019) who find that firm cash holdings decision are influenced by peer firm cash holdings decisions. My research differs in that I focus on the extent to which outside information about peer firm credit constraints, rather than peer characteristics or actions, affects firm cash management decisions. Importantly, I show that the effects hold when controlling for peer characteristics found to be relevant in predicting firm cash holding, e.g., peer cash holdings. In addition, my methodological approach differs in that I explicitly account for the fact that managers pay attention a relatively small number of their most relevant peers.

The remainder of this paper is organized as follows: the next section describes the methodology, data selection and variable construction. The results are presented in Section 3 and Section 4 offers a conclusion.

2 Methodology and data

2.1 Defining peer groups

The issue of empirically identifying the most relevant set of peers has been thoroughly discussed in both the finance and economics literature.[6] Classifications in the finance literature typically involve fixed industry classification codes: SIC, GICS and NAICS. For example, Leary and Roberts (2014) define peer groups using 3-digit SIC industries, Seo (2020) uses 6-digit GICS industries, and YiWen Chen and Chang (2019) restrict their analysis to firms classified as manufacturing firms – SIC codes between 2000 and 3999.

Unfortunately, fixed industry classifications (FICs) suffer from a number of deficiencies. First, a firm's product market evolves over time. Since FICs are slow to re-classify firms they do not necessarily capture this important feature of product market competition. Similarly, innovation can lead to new product markets being formed, which FICs fail to incorporate. Moreover, the broad nature of FICs does not allow one to directly identify the most suitable set of peers. This subtle, yet important shortfall is highlighted by evidence showing that managers pay attention to only their most relevant peers (Kaustia and Rantala, 2015). Kaustia and Rantala (2015) addresses this issue by identifying peers using the number of common analysts covering a pair of firms given sell-side analysts tend to concentrate on a specific industry. Although novel, this approach suffers from a selection bias as it explicitly removes firms that have insufficient analyst coverage. Moreover, firms with negligible analyst coverage are typically defined as opaque and CDS coverage of opaque firms will provide more information than coverage of transparent firms.

I overcome these issues by identifying competitors through HP's text-based network industry classification (TNIC) (see Hoberg and Phillips, 2010, 2016). Hoberg and Phillips (2016) describe the methodology in detail, so here I provide only a brief description and concentrate on arguing why their data, and methodology, is most ap-

[6] Examples in the economics literature include Xu and Lin 2010 who examine how peer groups using friends to study the impact on school achievement and Ioannides and Zabel (2003) who use neighborhood characteristics to study housing demand and consumption decisions.

propriate in my empirical setting in comparison to other proposed methodologies.

The text-based industry classification from HP provides pairwise scores that measures how similar two firms are with respect to their product market space. Scores are constructed from the text in the business description section of firm's annual 10-K reports filed with the SEC, which as they note, provides details on the products that a firm offers. In specific, HP compute similarity scores for each pair of firms, and for each fiscal year, based on the number of words shared by the pair of firms when describing their product market. Scores are bounded between 0 and 1 with higher values indicating a higher level of similarity in the product market space. HP choose a minimum similarity threshold such that they produce the same fraction of industry pairs as the three-digit Standard Industrial Classification (SIC) industries.

Importantly, HP's methodology for identifying firm peers alleviates many of the deficiencies that arise from using fixed industry classifications. For example, HP's measure is updated on an annual basis and therefore accounts for the fact that firm product markets evolve over time. Along the same vein, their methodology allows for newly created product markets that arise from innovation. Since similarity scores provide a measure of economic distance between two firms product market space, they allow for over-weighting CDS coverage of peers that are most relevant and under-weighting of less relevant peers. Fixed industry codes explicitly treat all peers as equally important which fails to account for the fact that managers concentrate on only a small number of their most relevant peers. Lastly, peer groups formed using HP's similarity score data produce substantial cross-sectional and time-series variation in peer group sizes as well as heterogeneous groups.

My empirical approach for measuring peer CDS coverage, and characteristics, is similar to that of Foucault and Fresard (2016) but differs along two levels. First, I restrict my attention to the most relevant set of peer firms. I examine various cutoffs but find generally similar results when using between 5 and 50 of the most similar firms (highest TNIC similarity scores). In cases where the number of related firms is less than the cutoff, I include all related firms.[7] Next, I exploit the fact that higher pairwise scores indicate higher levels of product market similarity by weighing peer CDS coverage, and

[7]The main results are numerically similar if I instead include only peers that surpass a minimum similarity score threshold.

characteristics, by the associated similarity score. In specific, individual peer weights are calculated by dividing each peer's similarity score by the sum of similarity scores across firm i's peers. My results are generally similar if I instead use equal weights, as in Foucault and Fresard (2016); however, the ability to over-weight the most relevant peers while under-weighting the least relevant peers is one of the primary benefits of using HP's data over fixed industry classification codes.

2.2 Data

I start by collecting annual firm characteristic data collected from Compustat from 2000 to 2015. Since my focus is on US firms, I remove firms that are incorporated outside of the US. In addition, I exclude observations where cash holdings are missing or greater than total assets. In the bulk of my tests I include firms in the financial and utility industries, but replicate all tests with the sub-sample of firms that excludes these two industries. I obtain equity data from CRSP, which I merge to Compustat using *CUSIP* identifiers.

The daily CDS data is from Markit data services. Markit provides daily data on CDS pricing starting in 2001 and has been frequently used as a primary source of CDS coverage in prior literature (e.g., Guest et al., 2016; Kim et al., 2015; Peristiani and Savino, 2011; Subrahmanyam et al., 2014). In line with prior literature, I identify the initial date of CDS coverage using the first date that Markit reports a CDS price for each firm eventually covered by CDS. Due to Markit's stringent data cleaning tests, a small number of firms covered by CDS do not appear on this database. While this does introduce noise as some firms with CDS coverage may enter my sample as uncovered, this bias works against finding significant results. I proceed by collecting all single name corporate CDS traded on US firms and include all types of restructuring clauses: CR, MM, MR and XR. I do not differentiate between restructuring clause in the bulk of my empirical tests since many firms are covered by multiple types of CDS contracts simultaneously and because my objective is to identify peer firm CDS coverage. The CDS data is merged to the CRSP-Compustat dataset by *CUSIP* number, which results in 959 CDS referenced firms.

The TNIC data is downloaded from HP's website[8] and is merged to the Compustat/CRSP/Markit dataset by firm *GVKEY*. The size of peer groups can be quite large as HP impose a minimum product market similarity threshold that generates industries with the same fraction of membership pairs as the 3-digit SIC industries. For the majority of my empirical tests I restrict my focus to CDS coverage of the 5, 20 or 50 most similar set of peers since these are the peers that managers are most likely to pay attention to. After merging all datasets, and removing firms that have missing outcome or control variables, I obtain a dataset that contains 5495 unique firms, 574 of which are covered by CDS at some point between 2001 and 2015.

2.3 Outcome variables

I employ two measures of firm cash holdings. The first, $Cash_{i,t}$, is equal to total cash and marketable securities scaled by total assets, as of fiscal year t. As argued by Fresard (2010) and Mackay and Phillips (2005), a firm's cash position relative to its peers is more important than a firm's raw cash-to-asset ratio in the context of competition. For this reason, I also consider firm cash ratios that are standardized within a firm's peer group-year. In specific, I compute relative-to-peer cash ($zCash_{i,t}$) by subtracting the average cash-to-asset ratio of firm i's TNIC peers and then divide this difference by the standard deviation of cash-to-asset ratios within the peer group-year:

$$zCash_{i,t} = \frac{Cash_{i,t} - Cash_{-i,t}}{Std.Dev.(Cash_{-i^*,t})} \tag{I.1}$$

where $Cash_{i,t}$ denotes firm i's cash-to-asset ratio in year t, $Cash_{-i,t}$ denotes the average cash-to-asset ratio of firm i's peers (excluding firm i) in year t and $Std.Dev.(Cash_{-i^*,t})$ equals the standard deviation of cash holdings in firm i's peer group (including firm i) in year t.

[8] Hoberg and Phillips provide free access to their data at https://hobergphillips.tuck.dartmouth.edu

2.4 Methodology

To avoid the process of disentangling the effects of own firm CDS coverage from peer firm CDS coverage, I follow Li and Tang (2015) and focus on the sample of firms that are not referenced by CDS. This ensures that own-firm CDS coverage does not contaminate any effects of peer firm CDS coverage. In the appendix, I show that the main results are robust to relaxing this restriction and controlling for own firm CDS coverage with a binary variable that is equal to one if a firm is covered by CDS and zero otherwise. I estimate the effect of peer firm CDS coverage on firm cash reserves using the following panel regression:

$$Cash_{i,t} = \alpha_i + \beta CDS_{-i(m),t-1} + \gamma X_{i,t-1} + \theta \bar{X}_{-i,t-1} + \nu_i + \mu_t + \epsilon_{i,t} \tag{I.2}$$

where $X_{i,t-1}$ is a vector of firm level control variables and $\bar{X}_{-i,t-1}$ is a vector of similarity score weighted average peer group characteristics. The $-i$ is used to emphasize the fact that these calculations exclude firm i. The variable of interest, peer CDS coverage ($CDS_{-i(m),t-1}$) is defined as the similarity score weighted average number of peers that are referenced by CDS at time $t-1$. The subscript m is used to denote the number of peer firms used in the calculation. Measuring the effects of own firm CDS coverage vis-à-vis a dummy variable is common in the literature[9] while literature examining the spillover effects of CDS coverage has used the proportion of related firms covered by CDS.[10] Rather than using a simple average, I exploit the nature of HP's similarity score data by weighting CDS coverage of each peer firm by its similarity score. I let m vary from 5 to 50 but report results using the 5, 20 and 50 most similar peers for brevity. ν_i captures firm level fixed effects while μ_t captures time trends. Firm fixed effects are necessary to control for fundamental information relevant to optimal levels of the cash reserves. Time fixed effects capture trends in average cash holdings over time.

The vectors of firm characteristics ($X_{i,t-1}$) and peer characteristics ($\bar{X}_{-i,t-1}$) contain variables deemed relevant for predicting cash holdings by prior literature (for example: Kim et al., 1998; Opler et al., 1999; Haushalter et al., 2007; Bates et al., 2009;

[9]For example see: Ashcraft and Santos (2009), Saretto and Tookes (2013), Subrahmanyam et al. (2014) and Subrahmanyam et al. (2016).

[10]For instance, Li and Tang (2015) use the proportion of customers covered by CDS to investigate spillover effects to suppliers.

Subrahmanyam et al., 2016). Firms with strong investment opportunities can avoid giving up profitable projects by holding sufficient cash reserves which I proxy for using market-to-book ratios. Next, firms who have poor access to capital markets have incentives to hold more cash which I proxy for using an indicator variable that is equal to one if a firm has a credit rating and zero otherwise. I include firm size, defined as the logarithm of total assets, since larger firms may hold less cash if economies of scale exist with liquid assets. Profitable firms are better able to finance investments internally which reduces the need to hold excess cash. In contrast, managers of profitable firms have more of an opportunity to hoard excess cash. The expected relationship between firm profitability and cash holdings is therefore ambiguous. Nonetheless, I control for firm profitability using operating income after depreciation. I control for firm payout policies using a binary variable that equals 1 if a firm paid dividends over the previous year and zero otherwise since firms who pay out a large portion of profits in the form of dividends (low retention ratio) reduce the pool of funds available for holding and therefore are expected to have lower cash reserves. Cash shortfalls can lead to a contraction in firm investment activities, thus, one might expect that firms with higher levels of capital expenditures and R&D hold more cash reserves. Similarly, certain industries require more (or less) cash holdings by design; I therefore include the average industry cash volatility and the weighted average of lagged peer cash holdings. With the exception of market-to-book ratios, indicator variables and size, all balance sheet items are scaled by total assets. Formal definitions of the variables used throughout this paper are provided in Table A1 in the Appendix.

3 Peer CDS coverage and firm cash holdings

3.1 Summary statistics

Table 1 provides a breakdown of CDS coverage by year and restructuring clause. The four types restructuring clauses: cum-restructuring (CR), no restructuring (XR), modified restructuring (MR) and modified-modified restructuring (MM), differ based on the type of credit event that triggers CDS payment and the type of debt obligation that can be used for delivery. For example, CR, MR and MM CDS are triggered by any type of credit event (bankruptcy, failure to pay and debt restructuring) and differ only by the type of debt obligations available for physical delivery. In contrast, debt-restructuring is not considered a credit event under XR CDS contracts. The "modified modified restructuring" clause (MM) was introduced in June 2003 which is why it there is no value for 2002. Table A.5 in the appendix provides additional details about the differences in deliverable obligations under different restructuring clauses. Consistent with previous literature, the total number of firms is decreasing over time. Furthermore, CDS coverage peaks around 2007-2008 and subsequently declines following the Financial Crisis.

[Table 1]

Table 2 summarizes the variables used throughout this paper. I present statistics for the sub-sample of firms that are not themselves referenced by CDS since this is the sample used in the bulk of my empirical tests. All balance sheet items are winsorized at the 1st and 99th percentiles. The outcome variables, cash-to-assets ($Cash$) and relative-to-peer cash-to-assets ($zCash$), are shown in the first panel. The median firm holds approximately 15% of it's net assets in cash[11] and has a median relative-to-peer cash ($zCash$) equal to approximately -0.5.

The mean of the CDS coverage variable is approximately 0.09, regardless of the number of peers included in the calculation. The medians are closer to zero highlighting the positive skewness of these variables. Importantly, there is both substantial cross-sectional variation (as can be seen in Table A4 in the Appendix) in the number of peers covered by CDS but also substantial time-series variation (highlighted by Table 1). In addition, due to the time-varying nature of HP's TNIC data, a firm's peer group can evolve over time. Put differently, the relevance of a given peer, and the set of most relevant peers, varies over time which further adds to variation in peer CDS coverage.

[Table 2]

The typical firm has an Altman's Z-Score of about 4.4 indicating a relatively low probability of financial distress. That said, there is substantial variability – more than

[11] Consistent with prior literature, this value is significantly lower for firms that are referenced by CDS at about 6%.

25% of firm-year observations would be deemed to be financially constrained. The average S&P credit rating of BB (11) seems to contradict the Altman's Z-Scores; however, a large portion of firm-year observations (approximately 75%) have no S&P credit rating. This number is significantly lower for firms eventually referenced by CDS at around 6%. The statistics for the remaining firm characteristics are comparable to those in prior literature (e.g., Li and Tang, 2015; Chi and Su, 2016). The average firm has a market-to-book ratio close to 2, book leverage of approximately 0.18, annualized returns of approximately 12% and only 26% of firms pay dividends. Peer group characteristics, calculated as the similarity score weighted average across the most similar 50 peers, are generally comparable to the corresponding firm characteristics.

3.2 Empirical results

In this section I investigate how peer CDS coverage affects firm cash holding decisions by estimating Equation I.2. The results, displayed in Table 3, include fund and year fixed effects with standards errors that are corrected for clustering at the firm level. I present regressions using the sample of firms who are not referenced by CDS but obtain numerically similar results when including these firms and controlling for own-firm CDS coverage. Additionally, Table 3 includes financial firms and utility firms since they make up a significant portion (149) of CDS covered firms (see Table A3 in the Appendix). Nonetheless, my results are robust to excluding these firms.

The impact of peer firm CDS coverage on firm cash-to-asset ratios is provided in columns (1), (2) and (3). The results show that firm cash ratios are positively related to peer firm CDS coverage and that the effect is robust to the number of peers used in constructing the peer CDS coverage variable. For example, the estimated coefficients on $CDS_{-i(5),t-1}$ and $CDS_{-i(20),t-1}$ are 0.0167 and 0.0229 respectively, both of which are both significant at the one-percent level. The effects are also economically meaningful – the effect of a one-standard deviation increase in $CDS_{-i(5),t-1}$ ($CDS_{-i(20),t-1}$) on cash-to-asset ratios is approximately 1.9% (2.23%) of the sample median or about 2.65% and 3.09% of difference between the 25th and 50th percentiles.

[Table 3]

Columns (4), (5) and (6) display the effects of peer firm CDS initiation on relative-to-peer cash holdings. As with cash-to-asset ratios, the effect of peer CDS coverage on relative-to-peer cash is positive and significant. The estimated coefficients on $CDS_{-i,(5),t-1}$, $CDS_{-i,(20),t-1}$ and $CDS_{-i,(50),t-1}$ are positive and significant. In terms of economic magnitude, a one-standard deviation increase in peer CDS coverage is associated with relative-to-peer cash holdings that are between 0.044 and 0.069 higher. $zCash_{i,t}$ is highly skewed – the mean is close to zero while the median is approximately -0.5 – I therefore discuss various measures of economic magnitude. A effect of one-standard deviation change in peer firm CDS coverage on $zCash_{i,t}$ is about 8.84% and 13.8% of the sample median. Alternatively, this represents between 3.88% and 6.09% of the difference between the 25^{th} and 50^{th} percentiles of z-scored cash. Panel A of Table A5 in the Appendix shows that effects are robust to including firms referenced by CDS while controlling for own-firm CDS coverage ($\text{CDS}_{i,t-1}$).[12] Panel B in Table A5 shows that the effects are robust to excluding firms operating in the financial or utility sectors.

3.3 Robustness

The spillover effects documented in the previous sub-section are consistent with CDS coverage providing a negative signal with respect to peer credit constraints, and the conjecture that firms act on this information by strategically increasing cash holdings. One potential concern is that peer CDS initiation might reflect information available from other observable measures of credit risk. For instance, a widely used metric of firm credit risk is its credit rating, which incorporates both the probability of bankruptcy and restructuring (Subrahmanyam et al., 2014). Firms referenced by CDS – who by definition have outstanding debt and typically in the form of corporate bonds – tend to have their corporate debt rated by one of the major rating agencies. Indeed, 97.2% of the firms covered by CDS in my sample also have a long-term credit rating issued by Standard and Poor's (S&P). In contrast, the proportion of unreferenced firms that have a credit rating is significantly lower, at around 25%. Thus, I control for peer credit

[12] The effect of own-firm CDS coverage is positive and significant at the one-percent level. The magnitude is smaller than reported in Subrahmanyam et al. (2016) at approximately 4%. Possibly reasons for this difference include differences in sampling periods and the data sources used to define CDS coverage.

ratings to ensure CDS initiation is not simply capturing information contained in credit ratings. In particular, *Credit Rating*$_{-i,t-1}$ is equal to the average S&P credit rating of firm i's peers at $t-1$.

The results, displayed in Panel A of Table 4, suggest that the positive effect of peer CDS initiation on firm cash holdings is not explained by peer firm credit ratings. As with prior regressions, I adjust standard errors for clustering along the firm dimension and include both year and firm fixed effects. The magnitudes, and significance, of the peer firm CDS coverage variables are slightly larger relative to the baseline results from Table 3.

[Table 4]

Credit ratings are updated rather infrequently; therefore, I also draw from the large literature showing that Altman's Z-Score (AZ-Score) performs quite well as a measure of a financial distress and bankruptcy predictor (Edward Altman and Laitinen, 2017 provide a comprehensive review). In particular, I control for the average AZ-Score of firm i's peer group at time $t-1$, denoted by $AZ_{-i,t-1}$. That is, I first compute AZ, as defined in Equation I.3, for each of firm i's peers. $AZ_{-i,t-1}$ is then equal to the TNIC similarity score weighted average AZ score across firm i's m closest peers.

$$AZ = 1.2 \times \frac{WCAP}{AT} + 1.4 \times \frac{RE}{AT} + 3.3 \times \frac{EBIT}{AT} + 0.6 \times \frac{CSHO \times PRCC}{AT} + \frac{SALE}{AT} \tag{I.3}$$

where: AT equals total assets, $WCAP$ denotes working capital, RE is retained earnings, $EBIT$ equals earnings before interest and taxes, $SALES$ denotes sales, $CHSO$ is the number of shares outstanding and $PRCC$ is the associated share price.

The results, provided in Panel B of Table 4, confirm that the positive relationship between cash reserves and peer firm CDS coverage is not explained by peer AZ scores. The marginal effect on firm cash-to-asset ratios, shown in columns (1) and (2), is larger than the baseline effect. In contrast, the marginal effect on z-scored cash, columns (3) and (4), is nearly identical to the baseline effect.

As a further test of robustness, I re-estimate Equation I.2 using an alternate specification of rival coverage. In specific, I collect firm i's 20 most similar peers in each year based on ranked TNIC scores. Next, I compute an indicator for each of the 20 most similar peer firms that is equal to one if it is covered by CDS and zero otherwise. I then regress firm i cash, and z-scored cash, on the CDS indicators for the most similar 1, 5, 10, and 20 peers.

The results, reported in Panel C of Table 4, show that the effect of peer CDS coverage is robust to this alternate specification. To preserve space, I report results using the closest 1 or 5 peers but note that the results are numerically similar when extending the analysis to the 10 or 20 most similar peers. Unsurprisingly, the positive effect is, for the most part, absorbed by the two most similar peers, $CDS_{(1),t-1}$ and $CDS_{(2),t-1}$. For example, the effect of CDS coverage of a firm's closest peer is associated with an increase in cash-to-assets, Columns (1) and (2), of between 0.0062 and 0.0071 and is significant at the one-percent level. The economic magnitudes are also quite large as they amount to 4.1% and 4.7% of the median cash-to-asset ratio respectively. Columns (3) and (4) of Table 4 show that the effect on z-scored cash-to-assets confirms that: i) the effects are robust to this alternative specification and ii) the effects appear to be largely driven by CDS coverage the two most similar peers.

CDS trading on a firm is most likely an exogenous event to its unreferenced peers. Moreover, firms presumably do not select their product market based on the number of potential peers that are referenced by CDS. Put differently, it is improbable that the proportion of peers covered by CDS is jointly determined with a firm's cash holdings. In any event, I address potential selection issues using a propensity score matching methodology. While this will not solve a fundamental endogeneity problem, it does offer a convenient, and simple, robustness test (Roberts and Whited, 2013; Subrahmanyam et al., 2014).

I estimate the probability of having CDS referenced peers as a function of lagged size, sales, cash, 2-digit SIC code, leverage and peer group AZ-score. For each firm that has a CDS referenced peer, I select one firm that has no peers referenced by CDS using the nearest propensity score. I re-estimate Equation I.2 using the matched sample in Panel D of Table 4. The coefficient estimates for peer CDS coverage are positive and significant at the one-percent level in both the cash ($Cash_{i,t}$), and relative-to-peer cash (z$Cash_{i,t}$) regressions.

3.4 Mechanisms

3.4.1 Financially distressed peers

Prior CDS literature suggests that the borrowing conditions of opaque and financially constrained firms deteriorate following CDS coverage (e.g., Ashcraft and Santos, 2009; Subrahmanyam et al., 2014). Thus, under a predatory motive, the positive relationship between firm cash holdings and CDS coverage of its peers is expected to be largely restricted to CDS coverage of peers that are financially constrained prior to the initiation of CDS coverage. In contrast, CDS coverage of unconstrained peers is likely to be indicative of a lender shedding credit risk for reasons other than firm credit worthiness[13] and can lead to improved borrowing conditions for the referenced firm (Ashcraft and Santos, 2009; Shan et al., 2014; Guest et al., 2016).In this case, the relationship between firm cash holdings and peer CDS coverage is ambiguous. A firm might be subject to increased predation risk if its peers experience improved borrowing conditions. As documented by Haushalter et al. (2007) firms may strategically benefit from using cash holdings to manage predation risk. Alternatively, unreferenced firms may also experience improved borrowing conditions from spillover effects of CDS trading on their most relevant peers (Darst and Refayet, 2018) which would reduce the need to hold additional cash.

To test these conjectures, I re-calculate peer CDS coverage variables separately for the subset of the 20 (50) most similar peers that are financially constrained and for the subset that are not. I proxy for financial constraints using the AZ-Score. In particular, I consider a firm to be financially constrained if it has an AZ-Score that is less than or equal to 1.8 in the year prior to CDS initiation. The remaining firms, who have a Z-Score greater than 1.8, are defined as financially unconstrained. I then re-calculate the peer CDS coverage variables separately for these two sub-samples. In specific, Constrained $CDS_{-i(20),t-1}$ is the weighted proportion of peer firms that are covered by CDS in year $t-1$ conditional on having an AZ-Score that is less than or equal to 1.8. Unconstrained $CDS_{-i(20),t-1}$, is calculated analogously but for the subset of peer firms that have an AZ-Score that is above 1.8.

[13] For example, Subrahmanyam et al. (2014) show that CDS coverage is positively associated to lender's tier 1 capital ratio and foreign exchange hedging.

The results from re-estimating Equation I.2 with peer CDS coverage decomposed by financial constraints are shown in Panel A of Table 5. To conserve space, I report only the coefficient estimates on the peer CDS coverage variables, but include the full set of firm and peer controls used in Table 3. I also include year and firm fixed effects and estimate standard errors that correct for heteroskedasticity and within-firm error clustering. The results generally support the predatory motive. The estimated coefficients on CDS coverage of financially constrained peers (Constrained $\text{CDS}_{-i(20),t-1}$ and Constrained $\text{CDS}_{-i(50),t-1}$) are positive and significant while the estimated coefficients on CDS coverage of unconstrained peers are positive but only marginally significant. The difference between these coefficients is also statistically significant for relative-to-peer cash.

[Table 5]

As a further test of the predatory motive, I investigate the role of relative financial constraints. My conjecture is that, under the predatory hypothesis, the effects will be strongest for firms that are less financially constrained relative to their CDS referenced peers. Alternatively, if the effects are strongest for firms that are more financially constrained than their CDS referenced peers, then the results are likely explained by precautionary savings due to industry credit contagion.

I proceed by decomposing the peer CDS coverage variables by relative AZ-Scores. In particular, *High Relative AZ* $CDS_{-i(20),t-1}$ is the peer CDS coverage variable calculated from the subset of the 20 closest peers that have an AZ-Score below that of firm i. *Low Relative AZ* $CDS_{-i(20),t-1}$ is computed using the remaining subset of peers – i.e., the subset of peers that have an AZ-Score greater than firm i's. In computing High and Low Relative AZ CDS coverage variables, I recompute the TNIC similarity weights within each subset of peers which I use to recompute the peer CDS coverage variables. As in Panel A, I report only the coefficient estimates on the peer CDS coverage variables but include the full set of firm and peer controls used in Table 3 as well as year and firm fixed effects.

The results, shown in Panel B of Table 5, are consistent with the predatory motive. The positive relationship between peer CDS coverage and cash is, for the most part, restricted to firms that are less financially constrained than their CDS referenced peers. The effect of CDS coverage of relatively constrained peers on both cash and relative-to-peer cash ratios is positive and significant at the one-percent level. In contrast, CDS coverage of relatively unconstrained peers is insignificantly related to cash and relative-to-peer cash. Moreover, the difference between the estimated coefficients, *High Relative AZ – Low Relative AZ*, is positive and significant at the five-percent level.

Next, I investigate whether relative sales interact with the relationship between firm cash holdings and peer CDS coverage. If my findings are in fact due to a predatory motive, then I expect the results to be largely restricted to firms that have relatively high relative to their CDS referenced peers. In contrast, the findings in Leary and Roberts (2014) indicate that smaller, less profitable firms mimic the financial policies of their more successful peers, but that the policies of industry leaders are not influenced by their less successful peers. Given that own-firm CDS coverage is positively related to cash holdings (as shown in Table A6 of this paper and in Subrahmanyam et al., 2016) it is possible that rather than a predatory motive, my findings are explained by less successful following their peer group leaders.

I test these conjectures in Panel C of Table 5 by decomposing peer CDS coverage into the subset of peers that have higher sales than firm i and the subset that do not. Consistent with the predatory motive, the positive effect of peer CDS coverage on firm cash holdings is restricted to coverage of the subset of firms that have higher sales than their CDS referenced peers.

The results in this sub-section support the hypothesis that the positive relationship between firm cash reserves and peer firm CDS coverage is due to a predatory motive. The positive relationship between cash-to-assets and relative-to-peer cash is generally restricted to firms that are less financially constrained than their CDS referenced peers. Not only are financially constrained firms prime targets for predation, but they have also been shown to experience the most severe deterioration in credit quality and availability following CDS initiation (Subrahmanyam et al., 2014), further supporting the predatory hypothesis.

3.4.2 Industry characteristics

In this section, I investigate the extent to which strategic interactions between firms within a peer group impact the relationship between firm cash holdings and peer firm CDS coverage. As shown by Haushalter et al. (2007), predation risk is most relevant when a firm's investment opportunities are similar to its peers. Thus, under the predatory motive, I expect the positive relationship between firm cash holdings and peer firm CDS coverage to be most pronounced for firms where strategic interaction amongst peers is strongest. I proxy for the degree to which firms interact within their peer group using two approaches.

The first is the Herfindahl-Hirschman Index (HHI). For each firm i in my sample, the HHI is equal to the sum of squared sales share across all firms located in firm i's peer group (including firm i) in year t. I select the size of the peer group to coincide with the number of peers used in the peer CDS coverage variables. Thus, the standard interpretation applies: firms with lower HHI index values reside in industries that are more competitive relative to firms with a higher HHI index values. However, the actual values will be inflated relative to HHI calculated at broader industry levels, e.g., 3-digit SIC codes. With this in mind, I use the distribution of the computed HHI variables to differentiate between concentrated and competitive peer groups. In particular, I consider a firm to operate in a competitive peer group (Low HHI) if it's HHI index lies below the sample median. Moderately (Mid HHI) and highly concentrated (High HHI) peer groups are those that lie between the 50th and 75th percentile and above the 75th percentile respectively.[14]

Regardless of cash measure, Panel A of Table 6 confirms that CDS coverage of peers has a differential impact on firm cash holdings depending on the level of competition. In particular, the estimated coefficients on peer CDS coverage variables are positive and significant at the one- and five-percent level for cash-to-assets and relative-to-peer cash respectively for firms operating in the most competitive peer groups (Low HHI) but insignificant for firms operating in less competitive peer groups. These findings are consistent with the predatory motive since, as shown by Fresard (2010), firms that

[14] The results are robust to alternate cutoffs. In particular, the effects are strongest for firms operating in the first two HHI quartiles, i.e., in the more competitive peer groups.

hold more cash than their peers outperform in the product market, and that the effect is most pronounced for firms that operate in more competitive industries.

[Table 6]

The second approach is meant to capture the degree of similarity between a firm's products and its closest peers. I incorporate this feature using two approaches. First, I use the operating similarity measure from Mackay and Phillips (2005), Haushalter et al. (2007) and Fresard (2010) which is defined as the absolute difference between a firm's ratio of net plant and equipment per employee and the median ratio of its peer group. Lower values indicate that a firm operates near the technological core of it's industry. Thus, high similarity is defined by relatively smaller values. The second measure is simply equal to the average TNIC similarity score across a firm's peer group. Higher values indicate that a firm operates in product market that is more similar to that of its typical peer relative to lower values. I compute both measures using the number of peers that coincides with the peer CDS coverage variable. In specific, I use the 20 most similar peers when regressing cash on $\text{CDS}_{-i(20),t-1}$ and the 50 most similar peers in regressions using $\text{CDS}_{-i(50),t-1}$.

The results, displayed in Panel B of Table 6, are somewhat unexpected. The positive relationship between cash and peer CDS coverage is generally strongest for firms that are less similar to their peers. In particular, the relationship is most pronounced for firms that operate furthest from the technological core of their industry (low operating similarity) for both cash-to-assets and relative-to-peer cash. Similarly the effect on relative-to-peer cash holdings is restricted to firms that are less similar to their typical peer (low average TNIC similarity score). These results seem to suggest that firms operating in a more unique corner of their product market space expend more resources to "defend their turf."

3.4.3 Empty creditors

In this subsection I investigate whether the existence of empty creditors interacts with the relationship between peer CDS coverage and firm cash reserves. Empty creditors have incentives to fight restructuring only if the CDS payoff is greater under bankruptcy than under debt restructuring. This scenario arises naturally under the XR (no-restructuring) clause where bankruptcy triggers CDS payment but debt-restructuring does not. That is to say, lenders will have relatively stronger incentives to induce borrower bankruptcy when restructuring is not covered by CDS in comparison to CDS that are triggered by restructuring.

I investigate the impact of empty creditors by decomposing peer firm CDS coverage by restructuring clauses. In particular, I re-compute CDS$_{-i(20),t-1}$ separately for peers referenced by CDS contracts that exclude restructuring (XR CDS$_{-i(20),t-1}$) and for peers referenced by CDS that include restructuring clauses (AR CDS$_{-i(20),t-1}$). The latter group contains three types of contracts: cum-restructuring (CR), modified restructuring (MM) and modified-modified restructuring (MMR). Table A2 in the appendix provides detailed descriptions of the differences between restructuring clauses.

[Table 7]

I display the results from re-estimating Equation I.2 with peer CDS decomposed by CDS contract type in Table 7. As with prior regressions, I include the full set of firm and industry controls from Table 3 and cluster standard errors along the firm dimension. Columns (1), (2), (3) and (4) in Panel A suggest that the positive relation between cash-to-asset ratios and peer CDS coverage is unrelated to the type of restructuring clause. Examining the impact simultaneously, shown in Columns (5) and (6), supports the conjecture that empty creditors are driving the relationship. In particular, XR CDS$_{-i(20),t-1}$ is significantly positive while AR CDS$_{-i(20),t-1}$ is now insignificant.

In contrast, the results for relative-to-peer cash, displayed in Panel B, suggest that the positive relation between cash-to-asset ratios and peer CDS coverage is unrelated to the type of restructuring clause. In particular, Columns (1), (2), (3) and (4) show that the individual effects of either type of restructuring clause has a positive and significant effect on relative-to-peer cash holdings. However, neither type of restructuring clause dominates when examining the joint effects in Columns (5) and (6).

4 Conclusion

Although the notional size of CDS markets is relatively small, and they cover only a small proportion of all firms, the results documented in this paper indicate that cash holding decisions of unreferenced firms are indeed affected by CDS coverage of their most relevant peers. Defining peers using HP's TNIC data, I find that firm cash holdings, and relative-to-peer cash, are positively related to the introduction of CDS trading on its peers. Importantly, the effects are robust to controlling for other common measures of peer credit worthiness and financial constraints and to alternative specifications of peer CDS coverage.

Next, I investigate whether the increase in cash holdings are due to predatory or precautionary motives. Under a predatory motive, the positive relationship between firm cash holdings and peer CDS coverage should be predominately due to coverage of financially constrained peers, and particularly peers that are more constrained than the firm in question. Indeed, I find evidence in support of a predatory motive. In particular, the positive relationship between cash holdings and peer firm CDS coverage is generally restricted to firms that are less financially constrained than their CDS referenced peers. Importantly, the effect is strongest for firms operating in the most competitive peer groups. This is consistent with a predatory motive as the strategic value of relative-to-peer cash holdings have been shown to be most relevant for firms operating in highly competitive markets.

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6 Tables

Table 1: CDS Coverage by Year and Type

For each year in my sample period, this table presents the distribution of firms that are covered by CDS as well as the distribution across restructuring type. CDS includes all firms that are covered by any type of CDS contract, Non-CDS include all firms that are not covered by CDS. CR shows the number of firms that are covered by contracts with a cum-restructuring clause, MM includes firms covered by CDS with a modified-modified restructuring clause, MR presents the number of firms covered by CDS with a modified restructuring clause and XR shows the number of firms covered by a CDS with an ex-restructuring clause. Full definitions of each restructuring clause is given in Table A.6 in the appendix.

Year	Non-CDS Firm	CDS	CR	XR	MR	MM
2002	4482	239	225	193	239	
2003	4139	324	304	267	324	224
2004	3836	437	383	344	432	297
2005	3649	497	403	401	492	335
2006	3619	489	427	431	483	344
2007	3600	497	433	445	489	345
2008	3450	503	434	457	496	344
2009	3335	473	428	447	468	331
2010	3135	446	409	444	440	317
2011	2991	409	153	407	386	111
2012	2980	406	179	406	379	122
2013	3010	402	178	402	381	85
2014	3060	389	162	389	373	119

Table: 2 Summary Statistics

This table summarizes the main variables used throughout this paper. I present the mean, median (50th percentile) standard deviation and the 25th and 75th percentiles. The sample includes all firms with non-missing variables in the CRSP/COMPUSTAT/TNIC merged dataset and spans 2002 to 2015. Variable definitions are provided in Table A1 in the Appendix.

	Mean	Std. Dev.	25^{th} Percentile	50^{th} Percentile	75^{th} Percentile
Outcome Variables					
Cash	0.2371	0.2420	0.0417	0.1506	0.3643
zCash	-0.0088	2.4681	-1.6295	-0.4981	1.1660
Peer CDS Coverage					
$\text{CDS}_{-i(5)}$	0.0875	0.1726	0.0000	0.0000	0.1443
$\text{CDS}_{-i(20)}$	0.0894	0.1468	0.0000	0.0242	0.1218
$\text{CDS}_{-i(50)}$	0.0899	0.1430	0.0000	0.0321	0.1194
Firm Characteristics					
AZ-Score	4.4039	7.1809	1.5636	3.2782	5.8273
S&P Rating	11	3	9	10	13
	BB		B+	BB-	BBB-
Market-to-Book	2.0962	1.7075	1.0966	1.5172	2.3990
Book Leverage	0.1814	0.2051	0.0009	0.1153	0.3000
Annualized Return	0.1230	0.6134	-0.2497	0.0328	0.3507
Dividend Indicator	0.2686	0.4433	0.0000	0.0000	1.0000
Cap. Exp.	0.0493	0.0557	0.0145	0.0306	0.0614
Fixed Assets	0.2416	0.2310	0.0642	0.1577	0.3481
R&D	0.0665	0.1218	0.0000	0.0049	0.0843
Size	5.4625	1.7176	4.2229	5.4672	6.6357
NWC	0.0607	0.1838	-0.0482	0.0474	0.1736
Sales	1.0726	0.7968	0.5081	0.9016	1.4444
Peer Characteristics					
Cash Volatility	0.0789	0.0430	0.0435	0.0711	0.1126
Cash Holdings	0.2457	0.1907	0.0854	0.1843	0.3784
Market-to-Book	2.0503	1.0246	1.3472	1.7541	2.4428
Book Leverage	0.2001	0.1204	0.1060	0.1800	0.2718
Returns	0.1235	0.3271	-0.0541	0.1072	0.2669
Cap. Exp.	0.0501	0.0399	0.0252	0.0368	0.0608
Fixed Assets	0.2440	0.1959	0.0981	0.1658	0.3260
R&D	0.0785	0.1050	0.0005	0.0224	0.1300
Size	6.0626	1.1865	5.1157	5.9976	6.8772
NWC	0.0350	0.1172	-0.0503	0.0251	0.1198

Table 3: The Impact of Peer Firm CDS Coverage on Cash Holdings (Baseline Estimation)

This table presents the results from regressing firm cash holdings, and z-scored cash holdings, on peer firm CDS coverage, a set of firm level controls, peer group controls and year and firm fixed effects. The sample consists of all firms who have non-negative cash holdings that are less than total assets and that are in both CRSP and Compustat databases between 2002 and 2014. The dependent variables are the ratio of firm cash holdings to total assets ($Cash_{i,t}$) and cash-to-assets z-scored by peer group ($zCash_{i,t}$). Explanatory variable definitions are given in Table A.1. The $-i$ subscript indicates peer group weighted averages whereas the i subscript denotes firm level variables. $\text{CDS}_{-i(5),t-1}$, $\text{CDS}_{-i(20),t-1}$ and $\text{CDS}_{-i(50),t-1}$ are the weighted proportion of firm i's most similar 5, 20 and 50 peers that are referenced by CDS at time $t-1$. Standard errors are calculated to be robust to clustering at the firm level. Test statistics are presented in parentheses with ***/**/* denoting significance at the 1/5/10 percent levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome Variable:		$\text{Cash}_{i,t}$			$\text{zCash}_{i,t}$	
Peer CDS Coverage						
$\text{CDS}_{-i(5),t-1}$	0.0167***			0.5053***		
	(3.20)			(2.86)		
$\text{CDS}_{-i(20),t-1}$		0.0229***			0.7254***	
		(3.33)			(2.74)	
$\text{CDS}_{-i(50),t-1}$			0.0246***			0.7771***
			(3.46)			(2.77)
Firm Characteristics						
$\text{Earnings}_{i,t-1}$	0.0056	0.0056	0.0056	0.0380	0.0390	0.0391
	(1.39)	(1.40)	(1.40)	(0.69)	(0.71)	(0.71)
$\text{Earnings Vol.}_{i,t-1}$	0.0138	0.0138	0.0138	-0.0591	-0.0603	-0.0608
	(1.59)	(1.59)	(1.59)	(0.53)	(0.54)	(0.54)
$\text{Book Leverage}_{i,t-1}$	-0.1196***	-0.1196***	-0.1196***	-1.7264***	-1.7270***	-1.7262***
	(11.47)	(11.47)	(11.47)	(9.21)	(9.22)	(9.22)
$\text{Cap. Exp.}_{i,t-1}$	-0.2746***	-0.2746***	-0.2746***	-4.3839***	-4.3844***	-4.3834***
	(11.33)	(11.33)	(11.33)	(8.78)	(8.78)	(8.78)
$\text{Market-to-Book}_{i,t-1}$	0.0112***	0.0112***	0.0112***	0.1258***	0.1258***	0.1258***
	(9.31)	(9.31)	(9.31)	(6.10)	(6.10)	(6.10)
$\text{R\&D}_{i,t-1}$	-0.0409	-0.0407	-0.0407	-1.3463***	-1.3398***	-1.3396***
	(1.42)	(1.41)	(1.41)	(2.72)	(2.71)	(2.71)
$\text{Size}_{i,t-1}$	-0.0146***	-0.0145***	-0.0145***	-0.3536***	-0.3509***	-0.3508***
	(4.18)	(4.16)	(4.16)	(4.26)	(4.23)	(4.23)
$\text{NWC}_{i,t-1}$	-0.0971***	-0.0973***	-0.0973***	-0.8308***	-0.8389***	-0.8407***
	(7.95)	(7.96)	(7.97)	(3.48)	(3.51)	(3.52)
$\text{Return}_{i,t-1}$	0.0151***	0.0151***	0.0151***	0.1991***	0.1991***	0.1989***
	(11.39)	(11.39)	(11.39)	(7.53)	(7.53)	(7.52)
$\text{Dividend Indicator}_{i,t-1}$	0.0055	0.0055	0.0055	0.1042	0.1045	0.1054
	(1.38)	(1.38)	(1.39)	(0.97)	(0.98)	(0.99)
$\text{Rated}_{i,t-1}$	-0.0049	-0.0050	-0.0050	0.0044	0.0002	-0.0003
	(0.91)	(0.93)	(0.93)	(0.04)	(0.00)	(0.00)
Peer Characteristics						
$\text{Industry Cash Vol.}_{i,t-1}$	0.2086***	0.2074***	0.2072***	-1.8646	-1.9075	-1.9133
	(4.31)	(4.28)	(4.28)	(1.38)	(1.41)	(1.41)
$\text{Cash Holdings}_{-i,t-1}$	0.0267	0.0270	0.0270	-3.7661***	-3.7578***	-3.7577***
	(1.49)	(1.50)	(1.50)	(5.66)	(5.64)	(5.64)
$\text{Book Leverage}_{-i,t-1}$	-0.0004	-0.0004	-0.0004	0.5873	0.5877	0.5872
	(0.03)	(0.03)	(0.03)	(1.43)	(1.43)	(1.43)
$\text{Cap. Exp.}_{-i,t-1}$	0.1051**	0.1053**	0.1053**	2.9801**	2.9904**	2.9894**
	(2.46)	(2.46)	(2.46)	(1.97)	(1.97)	(1.97)
$\text{Market-to-Book}_{-i,t-1}$	-0.0026*	-0.0027*	-0.0027*	-0.0833**	-0.0851**	-0.0855**
	(1.69)	(1.73)	(1.73)	(2.14)	(2.18)	(2.19)
Peer R&D	0.1004***	0.0997***	0.0995***	-2.8977**	-2.9269**	-2.9333**
	(2.83)	(2.81)	(2.80)	(2.06)	(2.08)	(2.08)
$\text{Size}_{-i,t-1}$	-0.0025	-0.0029	-0.0030*	-0.1670**	-0.1799**	-0.1829**
	(1.47)	(1.64)	(1.69)	(2.08)	(2.19)	(2.22)
$\text{NWC}_{-i,t-1}$	0.0083	0.0082	0.0083	-0.9666*	-0.9705*	-0.9694*
	(0.50)	(0.49)	(0.49)	(1.75)	(1.76)	(1.76)
$\text{Return}_{-i,t-1}$	-0.0065***	-0.0065***	-0.0064***	-0.3018***	-0.3017***	-0.3014***
	(2.68)	(2.68)	(2.67)	(4.33)	(4.32)	(4.32)
Observations	32,836	32,836	32,836	32,823	32,823	32,823
R-squared	0.84	0.84	0.84	0.52	0.52	0.52

Table 4: The Impact of Peer Firm CDS Coverage on Cash Holdings (Robustness)

This table presents the results from regressing firm cash holdings, and z-scored cash holdings, on peer firm CDS coverage, a set of firm level controls and peer group controls. The sample consists of all firms who have non-negative cash holdings that are less than total assets and that are in both CRSP and Compustat databases between 2002 and 2014. The dependent variables are the ratio of firm cash holdings to total assets ($Cash_{i,t}$) and cash-to-assets z-scored by peer group ($zCash_{i,t}$). Explanatory variable definitions are given in Table A.1. Each regression includes the full set of firm and peer group control variables used in Table 3. The explanatory variables of interest in panels A, B and D are CDS$_{-i(20),t-1}$ and CDS$_{-i(50),t-1}$, and are equal to the weighted proportion of firm i's 20 and 50 most similar peers that are referenced by CDS at time $t-1$ respectively. In Panel B I re-define peer CDS coverage by constructing a dummy variable for each of the 5 most similar peers that is equal to one if the peer is covered by a CDS at time $t-1$ and zero otherwise. Standard errors are calculated to be robust to clustering at the firm level. t-statistics are presented in parentheses with ***/**/* denoting significance at the 1/5/10 percent levels.

	(1)	(2)	(3)	(4)
Panel A: Peer Credit Quality: S&P Rating				
	$\text{Cash}_{i,t}$		$\text{zCash}_{i,t}$	
$\text{CDS}_{-i(20),t-1}$	0.0258***		0.7129***	
	(3.62)		(2.81)	
$\text{CDS}_{-i(50),t-1}$		0.0281***		0.7763***
		(3.81)		(2.86)
$\text{Rating}_{-i,t-1}$	-0.0008**	-0.0008**	-0.0365***	-0.0364***
	(2.28)	(2.28)	(3.74)	(3.73)
Observations	29,694	29,694	29,693	29,693
R-squared	0.85	0.85	0.58	0.58
Panel B: Peer Financial Constraints: Altman's Z				
	$\text{Cash}_{i,t}$		$\text{zCash}_{i,t}$	
$\text{CDS}_{-i(20),t-1}$	0.0227***		0.7232***	
	(3.31)		(2.73)	
$\text{CDS}_{-i(50),t-1}$		0.0245***		0.7752***
		(3.44)		(2.76)
$AZ_{-i,t-1}$	0.0008**	0.0008**	0.0114	0.0114
Observations	32,836	32,836	32,823	32,823
R-squared	0.84	0.84	0.52	0.52
Panel C: Alternate Specification				
	$\text{Cash}_{i,t}$		$\text{zCash}_{i,t}$	
$\text{CDS}_{-(1),t-1}$	0.0064***	0.0072***	0.2634***	0.2753***
	(2.67)	(2.89)	(3.00)	(3.12)
$\text{CDS}_{-(2),t-1}$		0.0038*		0.1551**
		(1.79)		(2.26)
$\text{CDS}_{-(3),t-1}$		0.0011		-0.0272
		(0.60)		(-0.43)
$\text{CDS}_{-(4),t-1}$		0.0021		0.0341
		(1.05)		(0.67)
$\text{CDS}_{-(5),t-1}$		0.0051**		-0.0086
		(2.49)		(-0.16)
Observations	32,819	32,819	32,819	32,819
R-squared	0.85	0.85	0.53	0.53
Panel D: Matched Sample				
	$\text{Cash}_{i,t}$		$\text{zCash}_{i,t}$	
$\text{CDS}_{-i(20),t-1}$	0.0219***		0.9020***	
	(2.77)		(2.90)	
$\text{CDS}_{-i(50),t-1}$		0.0242***		0.9780***
		(2.94)		(2.98)
Observations	18,339	18,339	18,333	18,333
R-squared	0.83	0.83	0.50	0.50

Table 5: The Impact of Peer Firm CDS Coverage on Cash Holdings: Constrained versus Unconstrained Peers

This table presents the results from regressing firm cash holdings ($Cash_{i,t}$), and z-scored cash holdings ($zCash_{i,t}$) on a set of firm level controls, peer group controls and peer firm CDS coverage variables. Regressions include the full set of firm and peer group control variables used in Table 3. Peer CDS coverage variables are decomposed by peer credit constraints in Panel A and by relative credit constraints in Panels B and C. In particular, I group the 20 most similar peers into a *Constrained* group and a *High Z-Score* group. The *Low Z-Score* group contains peer firms that have an Altman Z-Score that is less than or equal to 1.8, the *Unconstrained* group includes peer firms that have an Altman Z-Score that is greater than 1.8. I then recalculate the peer CDS coverage variables separately for these two peer groups. For instance, $\text{CDS}_{-i(20),t-1}(Z_{-i,t-1} \leq 1.8)$ is the weighted average peer CDS coverage calculated using the set of the 20 most similar peers that have an Altman's Z-Score less than or equal to 1.8. Standard errors are calculated to be robust to clustering at the firm level. Test statistics are presented in parentheses with ***/**/* denoting significance at the 1/5/10 percent levels.

	(1)	(2)	(3)	(4)
Panel A: Peer Financial Constraints – Altman's Z				
	$\text{Cash}_{i,t}$		$\text{zCash}_{i,t}$	
Constrained $\text{CDS}_{-i(20),t-1}$	0.0392***		1.5272***	
	(3.32)		(2.98)	
Unconstrained $\text{CDS}_{-i(20),t-1}$	0.0206***		0.5669*	
	(2.80)		(1.87)	
Constrained $\text{CDS}_{-i(50),t-1}$		0.0363***		1.3762***
		(3.19)		(2.83)
Unconstrained $\text{CDS}_{-i(50),t-1}$		0.0193***		0.5052*
		(2.61)		(1.67)
Cons. Peer CDS – Uncons. Peer CDS	0.0186	0.0171	0.9603*	0.8710*
	(1.59)	(1.51)	(1.75)	(1.66)
Observations	32,869	32,869	32,855	32,855
R-squared	0.84	0.84	0.60	0.60
Panel B: Relative Financial Constraints – Altman's Z				
	$\text{Cash}_{i,t}$		$\text{zCash}_{i,t}$	
High Relative AZ $\text{CDS}_{-i(20),t-1}$	0.0340***		1.1587***	
	(4.02)		(3.38)	
Low Relative AZ $\text{CDS}_{-i(20),t-1}$	0.0138		0.3646	
	(1.55)		(1.11)	
High Relative AZ $\text{CDS}_{-i(50),t-1}$		0.0334***		1.0887***
		(3.98)		(3.24)
Low Relative AZ $\text{CDS}_{-i(50),t-1}$		0.0104		0.2692
		(1.17)		(0.83)
High Relative AZ – Low Relative AZ	0.0203**	0.0230***	0.7941**	0.8195**
	(2.04)	(2.31)	(2.11)	(2.23)
Observations	30,773	30,773	30,767	30,767
R-squared	0.84	0.84	0.61	0.61
Panel C: Relative Sales				
	$\text{Cash}_{i,t}$		$\text{zCash}_{i,t}$	
High Relative Sales $\text{CDS}_{-i(20),t-1}$	0.0340***		0.7526***	
	(4.09)		(2.87)	
Low Relative Sales $\text{CDS}_{-i(20),t-1}$	0.0115		0.2424	
	(1.24)		(0.88)	
High Relative Sales $\text{CDS}_{-i(50),t-1}$		0.0328***		0.7027***
		(3.96)		(2.73)
Low Relative Sales $\text{CDS}_{-i(20),t-1}$		0.0117		0.1986
		(1.27)		(0.73)
High Relative Sales – Low Relative Sales	0.0225**	0.0211**	0.5102*	0.5041*
	(2.13)	(2.01)	(1.65)	(1.67)
Observations	32,832	32,832	32,818	32,818
R-squared	0.84	0.84	0.59	0.59

Table 6: Industry Characteristics and the Impact of Peer CDS Coverage on Cash Holdings

This table presents the results from regressing firm cash-to-asset ratios ($Cash_{i,t}$), and z-scored cash ($zCash_{i,t}$) on a set of firm level controls, peer group controls and peer firm CDS coverage variables interacted with industry characteristics. Each regression includes the full set of firm and peer group control variables used in Table 3. In Panel A, I decompose the sample by Herfindahl-Hirschman Index (HHI) constructed where the number of peers included coincides with the peer CDS coverage variable. In Panel B, I decompose the sample based on industry similarity measures. The first, operating similarity, follows Mackay and Phillips (2005) and Fresard (2010) and captures the degree to which a firm operates at the technological core of its industry. The second is the average TNIC similarity score across a firms peers. Standard errors are calculated to be robust to clustering at the firm level. t-statistics are presented in parentheses with ***/**/* denoting significance at the 1/5/10 percent levels.

Panel A: Industry Concentration (HHI)

	(1)	(2)	(3)	(4)	(5)	(6)
		$\text{Cash}_{i,t}$			$\text{zCash}_{i,t}$	
	Low HHI	Mid HHI	High HHI	Low HHI	Mid HHI	High HHI
$\text{CDS}_{-i(20),t-1}$	0.0355***	0.0054	0.0008	0.4381**	0.2759	0.4992
	(2.92)	(0.33)	(0.11)	(2.00)	(0.48)	(1.37)
$\text{CDS}_{-i(50),t-1}$	0.0456***	0.0078	0.0008	0.5622**	0.2895	0.5088
	(3.34)	(0.47)	(0.11)	(2.21)	(0.49)	(1.40)

Panel B: Industry Similarity Measures

	(1)	(2)	(3)	(4)
	$\text{Cash}_{i,t}$		$\text{zCash}_{i,t}$	
	Low	High	Low	High
Operating Similarity				
$\text{CDS}_{-i(20),t-1}$	0.0298***	0.0096	0.9625***	0.3371
	(3.83)	(1.32)	(3.12)	(0.83)
$\text{CDS}_{-i(50),t-1}$	0.0294***	0.0109	1.0149***	0.3452
	(4.12)	(1.24)	(3.17)	(0.78)
Average TNIC Similarity Score				
$\text{CDS}_{-i(20),t-1}$	0.0161**	0.0253**	0.7229**	0.0032
	(2.80)	(2.28)	(2.54)	(0.02)
$\text{CDS}_{-i(50),t-1}$	0.0173***	0.0370**	0.7431**	0.0772
	(3.00)	(2.20)	(2.64)	(0.29)

Table 7 : The Effects of Empty Creditors on the Relation Between Cash Holdings and Peer CDS Coverage

This table presents the results from regressing firm cash holdings ($Cash_{i,t}$), and z-scored cash holdings ($zCash_{i,t}$) on a set of firm level controls, peer group controls and peer firm CDS coverage variables decomposed by restructuring clause. In particular, XR CDS$_{-i(20),t-1}$ is the similarity score weighted average number of firm i's most similar 20 peers that are referenced by CDS that are not triggered by debt restructuring in year $t-1$. AR CDS$_{-i(20),t-1}$ is calculated analogously, but for peers that are referenced by CDS that are triggered by debt restructuring (MM, MR and CR restructuring clauses in Table A2). Regressions include the full set of firm and peer control variables used in Table 3 with standard errors estimated to be robust to clustering at the firm level. t-statistics are in parentheses, with ***/**/* denoting significance at the 1/5/10 percent levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Dependent Variable = Cash$_{i,t}$						
XR CDS$_{-i(20),t-1}$	0.0382***				0.0365**	
	(4.01)				(2.01)	
XR CDS$_{-i(50),t-1}$		0.0429***				0.0430**
		(4.33)				(2.28)
AR CDS$_{-i(20),t-1}$			0.0355***		0.0017	
			(3.86)		(0.10)	
AR CDS$_{-i(50),t-1}$				0.0396***		-0.0000
				(4.16)		(-0.00)
Observations	32,671	32,671	32,671	32,671	32,671	32,671
R-squared	0.85	0.85	0.85	0.85	0.85	0.85
Panel B: Dependent Variable = zCash$_{i,t}$						
XR CDS$_{-i(20),t-1}$	1.0420**				0.4995	
	(2.41)				(0.73)	
XR CDS$_{-i(50),t-1}$		1.1536**				0.6036
		(2.51)				(0.80)
AR CDS$_{-i(20),t-1}$			1.0255**		0.5644	
			(2.47)		(0.90)	
AR CDS$_{-i(20),t-1}$				1.1276**		0.5702
				(2.57)		(0.84)
Observations	32,660	32,660	32,660	32,660	32,660	32,660
R-squared	0.54	0.54	0.54	0.54	0.54	0.54

7 Appendix

Table A1: Variable Definitions

CDS Coverage	
$\text{CDS}_{-i(m),t-1}$	The TNIC score weighted average number of peers that are covered by CDS in year $t-1$. m denotes the maximum number of peers included in the calculation. For example, $CDS_{-i(20),t-1}$ is calculated using the 20 firms that are most similar to firm i as measured by HP's TNIC similarity score.
$\text{CDS}_{i,t-1}$	Binary variable equal to one if firm i is referenced by a CDS contract during year $t-1$ and zero otherwise.
Outcome Variables	
$\text{Cash}_{i,t}$	Firm i's cash-to-asset ratio as of year t given by cash and marketable securities scaled by total assets.
$\text{zCash}_{i,t}$	Firm i's industry-adjusted cash-to-asset ratio as of year t. $\text{zCash}_{i,t} = \frac{Cash_{i,t}-Cash_{-i,t}}{Std.Dev.(Cash_{-i,t})}$
Control Variables	
Z-Score	$1.2\times\frac{WCAP}{AT}+1.4\times\frac{RE}{AT}+3.3\times\frac{EBIT}{AT}+0.6\times\frac{CSHO\times PRCC}{AT}+\frac{SALE}{AT}$
Earnings	Earnings before interest and taxes, scaled by total assets.
Earnings Volatility	The standard deviation of earnings over the prior 5 years.
Book Leverage	The sum of long-term debt and debt in current liabilities scaled by total assets.
Cap. Ex	Additions to a firm's property, plant and equipment, scaled by total assets.
Dividend Indicator	Takes a value of 1 if the firm issued cash dividends over the current year.
Fixed Assets	The proportion of fixed assets (measure by net property, plant and equipment) relative total assets.
Market Leverage	The sum of long-term debt and debt in current liabilities as a percentage of market value of assets.
Market-to-Book	The ratio of market value of assets to book value of assets.
NWC	The difference between total current assets minus total current liabilities scaled by total assets.
R&D	Research and development expenses scaled by total assets.
Rated	Variable equal to one if the firm has a S&P issuer credit rating and zero otherwise.
Sales	Gross sales less cash discounts, trade discounts and returned sales, scaled by total assets.
Size	The natural logarithm of the total value of balance sheet assets.

Table A2: Restructuring Clause Definitions

This table displays definitions of the four types of restructuring clauses, including the type of credit events that qualify as a trigger and the types of obligations available for physical delivery. As of April 2009 – the implementation date of The Big Bang Protocol – new contracts are typically issued with no restructuring clause.

Clause	Definition
CR – Cum-Restructuring (Full Restructuring)	Any type of credit event qualifies as a trigger. Credit events include bankruptcy, failure to pay and debt restructuring. Any debt obligation with a maturity of up to 30 years can be used for physical delivery.
MM – Modified Modifed Restructuring	Any type of credit event qualifies as a trigger for delivery. Only obligations with maturities within 60 months of the CDS contract maturity are available for physical delivery.
MR – Modified Restructuring	Any type of credit event qualifies as a trigger for delivery. Only obligations with maturities within 30 months of the CDS contract maturity are available for physical delivery.
XR – Ex-Restructuring	Restructuring is not considered a credit event – only bankruptcy or failure to pay debt obligations qualify as credit events.

Table A3: Industry Classifications of CDS Sample Firms

This table provides the distribution of CDS coverage across industries. The distribution is calculated from the merged COMPUSTAT/CRSP/Markit/S&P Ratings dataset and spans 2002 to 2015.

Industry	**Number of CDS Sample Firms**
Agriculture, Forest & Fishing	2
Mining	50
Construction	17
Manufacturing	309
Transportation & Public Utilities	141
Wholesale Trade	23
Retail Trade	54
Fin. Insurance and Real Estate	149
Services	94
Unclassified	5

Table A4: Distribution of Group Sizes

The table presents the distribution of peer group sizes for the full sample period. The only filter applied is that firm cash holdings must be less than total assets, obviously neither variable can be missing. Summation (average) group scores are calculated by adding (averaging) all peer similarity scores for firm i in year t. Higher summations indicate a large number of peers, more similar peers, or both. High average peer group score indicates that peers are highly similar, regardless of peer group size.

	Peer Group Size	Sum(Peer Group Scores)	Average Peer Group Score
50 Most Similar Peers			
Mean	22	2.74	0.1
Std Dev	20	3.44	0.06
P5	1	0.06	0.05
P25	3	0.26	0.07
P50	14	1.07	0.08
P75	50	4.17	0.11
P99	50	13.65	0.3
Largest 50 Peers in Terms of Sales			
Mean	22	2.01	0.09
Std Dev	20	2.08	0.05
P5	1	0.06	0.05
P25	3	0.26	0.07
P50	14	1.06	0.08
P75	50	3.72	0.09
P99	50	7.49	0.23

Table A5: The Impact of Peer Firm CDS Coverage on Cash Holdings: Additional Robustness Tests

This Table presents the results from re-estimating Equation I.2 using the sample of firms that have non-negative cash holdings that are less than total assets between 2002 and 2015. Panel A includes the subset of firms that are covered by CDS at some point throughout the sampling period while in Panel B firms that operate in the financial or utility sector (and firms eventually referenced by CDS) are excluded. The dependent variables are the ratio of firm cash holdings to total assets ($Cash_{i,t}$) and relative-to-peer cash ($zCash_{i,t}$). The $-i$ subscript indicates peer group weighted averages whereas the i subscript denotes firm level variables. $\text{CDS}_{-i(5),t-1}$, $\text{CDS}_{-i(20),t-1}$ and $\text{CDS}_{-i(50),t-1}$ are the similarity score weighted proportion of firm i's most similar 5, 20 and 50 peers that are referenced by CDS at time $t-1$. $\text{CDS}_{i,t-1}$ is a dummy variable that is equal to one if firm i is referenced by CDS in year $t-1$ and zero otherwise. Each regression includes the full set of firm and peer control variables from Table 3 as well as year and firm fixed effects. Standard errors are robust to clustering at the firm level. t-statistics are presented in parentheses with ***/**/* denoting significance at the 1/5/10 percent levels. All control variables (other than book leverage) are scaled by total assets.

	(1)	(2)	(3)	(4)	(5)	(6)
		Cash			zCash	
Panel A: Own-Firm CDS Coverage						
$\text{CDS}_{-i(5),t-1}$	0.0131***			0.3276**		
	(3.07)			(2.33)		
$\text{CDS}_{-i(20),t-1}$		0.0169***			0.4698**	
		(2.88)			(2.11)	
$\text{CDS}_{-i(50),t-1}$			0.0184***			0.4914**
			(2.99)			(2.06)
$\text{CDS}_{i,t-1}$	0.0075**	0.0076**	0.0075**	0.1482	0.1464	0.1470
	(2.21)	(2.24)	(2.23)	(1.37)	(1.36)	(1.36)
Observations	32,787	32,787	32,787	32,787	32,787	32,787
R-squared	0.85	0.85	0.85	0.56	0.56	0.56
Panel B: Excluding Financial and Utility Sectors						
$\text{CDS}_{-i(5),t-1}$	0.0161***			0.4995**		
	(2.82)			(2.56)		
$\text{CDS}_{-i(20),t-1}$		0.0208***			0.7510***	
		(2.87)			(2.62)	
$\text{CDS}_{-i(50),t-1}$			0.0227***			0.8051***
			(3.06)			(2.67)
Observations	27,291	27,291	27,291	27,282	27,282	27,282
R-squared	0.85	0.85	0.85	0.53	0.53	0.53

Chapter II

The Geography of Sub-advisors and its Impact on International Equity Mutual Funds

Markus Broman, Michael Densmore and Pauline Shum Nolan[1]

1 Introduction

Since the mid 2000s, the U.S. mutual fund industry has seen a significant increase in demand from investors seeking international exposure. According to the 2017 *Investment Company Institute (ICI) Factbook*, net outflows from U.S. equity mutual funds totaled $834 billion between 2006 and 2015, while international equity funds experienced net inflows of $643 billion over the same period. More importantly, the rise in international mandates has led to an increase in the hiring of portfolio managers overseas. Indeed, many fund managers boast about having an international presence in their marketing materials.[2]

A U.S. mutual fund family that wants to tap into local expertise aboard has several options. First, the fund can retain in-house (i.e., belonging to the same parent organization) subadvisors overseas, which we will refer to as an *international in-house sub-advised* fund. For example, according to the SEC's N-SAR filings, Fidelity U.S. sub-

[1]We are grateful for the comments of Kelley Bergsma, Melanie Cao, Raymond Kan, Fabio Moneta, Aleksandra Rzeźnik, Ben Sand and seminar participants at York University. We also benefited from comments received during presentations at the 2019 Financial Management Association, the 2019 CFA Society Toronto and Hillsdale Canadian Investment Research Award Reception and the 2020 Midwestern Finance Association. Lastly, we would like to thank Valeriya Kolobashkina for her excellent assistance in collecting data for an earlier version.

[2]For example, Wilmington Multi-Manager International Fund claims that their sub-advisory team provides investors with "global brand name association" and "access to local investment teams."

advises its international equity funds to Fidelity offices around the world. Second, the fund can outsource to unaffiliated sub-advisors overseas, which we will refer to as an *international outsourced* fund. For example, BBH International Equity currently sub-advises its international equity fund to unaffiliated investment advisors in the U.K..[3]

In this paper, we study the extent to which hiring an international sub-advisor(s) – in-house or outsourced – impacts fund performance, conditioned on a fund's sub-advising decision. Importantly, we focus not only on the sub-advising relationship, but also on the geography of the sub-advisors. Using the geography of the sub-advisors, we decompose a fund into its local (country or region) and non-local holdings, from the perspective of its sub-advisors. Further, this decomposition helps us isolate and identify evidence of local expertise (if any), and allows us to better understand the channels through which the overall fund-level abnormal performance can arise. To the best of our knowledge, this perspective is new to the literature.

Our sample consists of international and global equity funds registered for sale in the U.S.. Therefore, all fund advisors, who either manage the fund themselves or hire sub-advisors, are U.S. based. International funds provide worldwide exposure to stock markets outside the U.S., while global funds provide exposure to both U.S. and international markets. The bulk of our empirical tests focus on international funds. This is because they represent the majority of the sample (73 percent), and importantly, they allow for a cleaner test: since all of their holdings are foreign, there is potentially an incentive to seek local expertise abroad.

Local investors may have a local information advantage as a consequence of specialization that is facilitated by physical proximity (Van Nieuwerburgh and Veldkamp (2009)), as well as by language and cultural similarities (Hau (2001), Grinblatt and Keloharju (2001)). Important channels of local information diffusion include local social networks and local media outlets (Bernile, Kumar and Sulaeman (2015)). However, hiring outsourced, as opposed to in-house, sub-advisors abroad presents a trade-off, as agency conflicts from outsourcing, such as excessive risk taking and less preferential treatment compared to the sub-advisors' own brand of funds, may negatively

[3] It is also possible, but not tested in the current paper, that a fund hires a U.S. sub-advisor that originated in a foreign country.

impact fund performance (Chen, Hong, Jiang, and Kubik (2013), Churprinin, Massa and, Schumacher (2015)).

That said, the negative impact of agency costs should apply to the entire fund managed by the outsourced sub-advisor(s). Therefore, irrespective of agency costs, portfolio managers with a local information advantage would be expected to perform better in their local, compared to their non-local, holdings. By decomposing overall fund performance into local- and non-local holdings-based performance, we provide a better understanding of whether internationally sub-advised funds in-house or outsourced are able to exploit their local expertise, and to shed light on the root cause of any abnormal performance. This perspective stands in contrast to Chen et al. (2013) and Churprinin et al. (2015), both of which focus exclusively on fund-level performance. The former compares outsourced funds to in-house funds, while the latter compares a sub-advisor's own brand of funds to outsourced funds that they manage in parallel (side-by-side management).[4]

Following Debaere and Evans (2017), we use the SEC's N-SAR filings to obtain a complete list of a fund's sub-advisors and their headquarter locations over time. This allows us to cleanly identify all locations where a fund has access to local expertise, and to partition a fund's holdings into local versus non-local, from the sub-advisors' perspective. (See Figure 1 for an illustration of the various relationships.) Approximately two-thirds of the internationally sub-advised funds in our sample have more than one sub-advisor and about 45 percent have more than two. Therefore, the N-SAR data is well suited to studying the geography of the sub-advisors compared to the Factset database used by Chuprinin et al. (2015), which only identifies one sub-advisor, and to the Thomson Mutual Fund database used by Chen et al. (2013), which only identifies up to two.

[Figure 1]

At the fund level, we find that the attempt to tap into local expertise via an interna-

[4]Chen, Hong, Jiang and Kubik (2013) examine a broad sample of U.S. equity mutual funds and show that outsourced funds underperform in-house funds by around 50 bps per year and are more likely to be closed following poor performance. Chuprinin, Massa and Schumacher (2015) examine a sample of asset management firms that manage both in-house and outsourced funds. They find that in-house funds outperform outsourced funds by approximately 85 bps per year.

tional sub-advisory relationship in-house or outsourced does not improve fund performance. Further, funds that hire international outsourced sub-advisors significantly underperform relative to both international in-house sub-advised funds and non-sub-advised funds. The magnitude of this underperformance is economically meaningful. For example, using the Fama-French-Carhart (FFC4) alpha, the underperformance is 122 basis points per year compared to non-sub-advised funds. Moreover, we show that internationally outsourced funds underperform U.S. outsourced funds, which suggests that the former do not (or are unable to) exploit their local expertise in a way that compensates for the agency costs of outsourcing. Even international in-house sub-advised funds, which do not suffer from agency conflicts between the advisor and the sub-advisor, do not outperform.

In order to examine how sub-advisors perform in their local versus non-local holdings, we split a fund's holdings into three mutually exclusive sub-portfolios: i) local country, ii) local region and iii) non-local. The local country sub-portfolio contains securities that are headquartered in the same country as the fund's sub-advisor(s), and this is the sub-set of securities that local sub-advisors should have relative expertise.[5] The local region sub-portfolio includes all securities headquartered in the same region (U.S., Europe, or Asia-Pacific), but outside the sub-advisor's local country. A fund's non-local sub-portfolio contains the holdings in regions where the fund has no physical presence. In this construct, we expect agency costs to affect overall fund performance in the case of outsourced funds, but not variations in sub-portfolio performance.

We find that internationally sub-advised funds, whether in-house or outsourced, significantly underperform in their local country and local region sub-portfolios relative to that of non-sub-advised funds. Interestingly, we continue to find strong evidence of underperformance when we focus on within-fund variations by controlling for fund fixed effects. For example, internationally outsourced funds underperform in their local country sub-portfolio by 140 bps per year based on DGTW-adjusted returns and by 200 bps per year based on FFC4 alphas, relative to their non-local sub-portfolio. These magnitudes are large enough to explain the overall fund-level results, since these funds allocate a substantial fraction of their assets to local country and local region holdings – on average 26 and 39 percent, respectively.

[5]For funds with sub-advisors in multiple countries (e.g., in the U.K. and in Hong Kong), the local country sub-portfolio includes holdings in all those countries.

To shed light on the underperformance in international sub-advisors' local holdings, we investigate two aspects of fund management: portfolio activeness and risk taking, across and within funds. An important line of inquiry in the mutual fund literature is whether actions by fund managers reveal skill. Existing literature has shown that a number of actively managed funds are closet indexers as they have similar holdings to their passive benchmark, and that these funds tend to underperform (e.g., Cremers and Petajisto (2009), Cremers and Pareek (2016)). A related stream of literature examines a manager's incentive to engage in risk shifting due to agency issues in delegating fund management (e.g., Brown, Harlow and Starks (1996), Goetzmann et al (2007), Lee, Trzcinka and Venkatesan (2019), and Ma, Tang, and Gomez (2019)). In particular, Huang, Sialm and Zhang (2011) document a negative relation between risk shifting and performance, and suggest that risk shifting is either an indication of unskilled managers or agency conflicts.

At the overall fund level, we document a new source for the underperformance of outsourced funds: we find that internationally outsourced funds, and to a lesser extent U.S. outsourced funds, have significantly lower active share and greater risk shifting. This appears consistent with the higher agency costs associated with outsourcing. However, these fund-level results hide significant within-fund variations. Specifically, we find that internationally outsourced funds have lower active share and higher risk shifting in their local, compared to their non-local, holdings. In fact, lower active share is also found among international in-house sub-advised funds.

Taking advantage of our data where 40% of funds have multiple sub-advisors (57% when there is at least one international outsourced sub-advisor), we investigate whether fund underperformance is related to entrenchment (in single sub-advised funds) or coordination problems (in multiple sub-advised funds). We find evidence of the former: funds outsourced to a single international sub-advisor underperform but at the same time, they are less likely to be terminated following poor performance compared to multiple sub-advised funds.

The decision by a fund family to outsource fund management to a third party is endogenous. One possibility for the continued use of international sub-advisors, particularly outsourced ones, is that the U.S. based fund could not have obtained better outcomes by managing the fund itself (Debaere and Evans (2017) and Massa and Schumacher (2019)). Endogenizing the sub-advising decision is beyond the scope of this paper, except for a reversal causality test to see whether poor past performance leads to international outsourcing (it does not).

To summarize, we make the following contributions to the existing literature. First, we focus on the geography of the sub-advisors of international/global equity mutual funds and how it impacts fund performance. In order to do so properly, we collect the full list of sub-advisors (if any) and their locations for each fund, as well as the changes in the sub-advising relationships over time. Second, by taking the geography of the sub-advisors into account, we show that funds that outsource to international sub-advisors underperform funds that outsource to U.S. sub-advisors. Third, using the location data, we decompose a fund into its sub-advisor(s)' local and non-local holdings. We provide insights into the relative performance of and manager behaviours in these sub-portfolios, both within a fund and against non-sub-advised funds. Fourth, we document a new channel of underperformance for outsourced funds in terms of their activeness and risk-shifting. In fact, some of these behaviours are also found amongst international in-house sub-advisors. Taken together, these within-fund differences in performance and behaviours are difficult to reconcile with agency costs alone, as long as the sub-advisors are responsible for the whole portfolio. Finally, our results on single versus multiple sub-advised funds suggest that the incentive mechanism inherent in multiple sub-advised funds can alleviate some of the agency costs of outsourcing by reducing entrenchment, which is new to the literature.

2 Data and variable definitions

Our sample consists of equity mutual funds with an international or global investment mandate that are sold in the U.S., as identified by Morningstar Direct. We include funds that belong to one of the following Morningstar categories: foreign large-value, foreign large-blend, foreign large-growth and world large stock. Funds in the foreign/world small cap categories are eliminated, since we do not have benchmark holdings for these funds (they represent 11 percent of the raw sample). In the asset management industry, international/foreign refers to funds that invest across developed markets outside of the U.S., whereas global/world refers to funds that invest worldwide including the U.S..

Thus, our sample does not include any single-country or regional funds. We further screen for and delete sector funds, balanced funds, long-short funds, fund-of-funds and funds that primarily use ETFs/futures contracts. Our sample period is from January 2000 to December 2014.

We collect data on fund returns and characteristics from Morningstar Direct and the CRSP Survivor-Bias-Free U.S. Mutual Fund database (henceforth CRSP MFDB). We link the two databases by CUSIP and TICKER. To verify the accuracy of the matches, we compare fund names and inception dates (and liquidation dates, if applicable) between the two databases. Following Berk and Van Binsbergen (2014) and Pastor, Stambaugh and Taylor (2015), we reconcile the data on fund returns and assets under management (AUM) between Morningstar Direct and CRSP MFDB.[6] Data on expense ratios are obtained from CRSP MFDB.

Following Kacperczyk Nieuwerburgh and Veldkamp (2014), we address the potential bias resulting from a fund's incubation period by removing observations prior to its inception date, and we only include a fund in our final sample once it passes the $15 million in AUM. Further, we exclude any fund that holds less than 70 percent of its assets in equities (Amihud and Goyenko (2013)). The average fund in our sample holds more than 95 percent in equities at any given point in time.

2.1 Defining sub-advisory relationships

We use the form N-SAR filed with the SEC to obtain each fund's complete list of sub-advisors and their locations through time. This form is a semi-annual report filed by registered investment companies, and it includes comprehensive details on fund management and sub-advisory relationships. For each fund in our sample, we extract the reporting period, registrant name (Q1), the full list of sub-advisor names (Q8A) and their locations (Q8D). If no sub-advisory contract exists, then the advisor is solely responsible for managing the fund.[7] For sub-advised funds, the advisor typically acts as a manager of the managers and is responsible for determining how the fund's assets are spread among the sub-advisors.

[6] Additional details are provided in the Internet Appendix, Sections IA-1 and IA-2.

[7] In all but two cases, the advisor is the asset management arm of the registrant in our sample.

By definition, a sub-advisor's responsibilities include research and asset management. As such, we use the sub-advisor's headquarters location to measure international presence. We classify each fund as either outsourced or in-house using Bloomberg, supplemented with web queries. We check historical affiliations between the advisor and the sub-advisors, carefully tracing a firm's parent (or subsidiaries) all the way up (or down) the corporate ladder. Similar to Chen et al. (2013), we classify a fund as outsourced if at least one sub-advisor is unrelated to the fund complex.

2.2 Performance measures

We measure fund performance relative to factor models and style benchmarks. First, for factor models, we include the CAPM, the 3-factor Fama and French (FF3), and the 4-factor Fama-French-Carhart (FFC4). We use a rolling 36-month window to estimate the factor loadings. To construct appropriate factors for our international/global equity funds, we use country-level factors provided by AQR and weigh each country by each fund's actual country weight based on its reported holdings at $t-1$.[8] This methodology is consistent with Fama and French (2012, 2017) and Hollstein (2020), who show that local factors are superior to global factors that weigh each country by its market capitalization at $t-1$. Our results remain robust to using global factors.

Second, we evaluate fund performance relative to style benchmarks, since the average retail investor has been shown to rely on Morningstar style benchmarks to indirectly adjust for risk (Evans and Sun (2018), Chakraborty et al. (2020)). Fund managers themselves are often evaluated against style benchmarks (Evans et al. (2020)), which gives them an incentive to maximize this measure. We define the benchmark-adjusted return as the fund's gross return minus the style benchmark return. This effectively assumes that the beta on the benchmark is equal to one. We also consider benchmark-adjusted alphas, where the beta with respect to the benchmark is estimated using the prior 36 months of data.

[8] Said differently, local factors are assigned to each stock in a fund's portfolio. The stock-level factors are then aggregated to the fund-level by taking a weighted average across the stocks in a fund's portfolio based on the weight invested at $t-1$. AQR's risk factors are only available for developed markets. For emerging markets (tax havens) we use the corresponding regional (global) factors. The median proportion invested in emerging markets and tax havens is relatively low, at around 4 percent.

2.3 Fund benchmarks and underlying portfolio holdings

To select the style benchmark for each fund, we use the following procedure. First, we classify each fund into one of four broad categories: i) All Country World Index (MSCI ACWI) (developed and emerging markets), ii) MSCI WORLD (developed markets), iii) MSCI ACWI ex. U.S., or iv) MSCI WORLD ex. U.S.. We select the primary benchmark with the lowest median active share (i.e., with the closest portfolio overlap) as suggested by Cremers and Petajisto (2009). Primary benchmarks are time-invariant for most funds. The only exception is if a fund has changed its strategy from global to international, or vice-versa. To identify these cases, we look for changes in the Morningstar Category variable and manually confirm these changes by checking the fund's historical prospectus. We then select the benchmark with the lowest active share.

Second, we determine a fund's style. We use Morningstar style box classifications, which are updated monthly based on the prior three years of fund holdings and account for style tilts (value, blend, or growth). We use the four broad benchmarks above together with the Morningstar style tilts to select the style benchmark for each fund. In total we have twelve style benchmarks corresponding to twelve MSCI indices.[9] Their returns are used in the fund-level performance analysis.

Many of our empirical tests require data on a fund's benchmark holdings. Unfortunately, we do not have MSCI index constituent data, and there are no corresponding index funds or ETFs with sufficiently long histories. Thus, we use Vanguard index funds[10] tracking the four broad benchmarks above for the holdings. We collect this data from Morningstar Direct because it provides reliable and complete holdings data on a quarterly basis. Specifically, for international equity funds (i.e., ex. U.S.), we use the Vanguard Total International Stock Index Fund (developed and emerging markets) and the Vanguard Developed Markets Index Fund (exclude emerging markets). For global equity funds, we use the Vanguard Total World Stock Index Fund. This fund is, however, only available after July 2008. Prior to this date, we construct the index using three constituent funds that cover developed (Vanguard Developed Markets Index

[9]The twelve (4×3) indices we use for style benchmark returns are: MSCI ACWI Value, MSCI ACWI Growth, MSCI ACWI Blend, MSCI WORLD Value, MSCI WORLD Growth, MSCI WORLD Blend, MSCI ACWI ex. U.S. Value, MSCI ACWI ex. U.S. Growth, MSCI ACWI ex. U.S. Blend, MSCI WORLD ex. U.S. Value, MSCI WORLD ex. U.S. Growth and MSCI WORLD ex. U.S. Blend.

[10]We use Vanguard funds since they have the longest time-series of historical holdings.

Fund), emerging (Vanguard Emerging Markets Stock Index Fund) and the U.S. equity markets (Vanguards Total Stock Market Index Fund). To combine the three funds into one global benchmark, we start by computing the weights in July 2008 based on Vanguard Total World Stock Index Fund. We then back-fill the weights by assuming that any changes over time are solely driven by return differences. This gives us a complete time-series of holdings for the ACWI benchmark from January 2000 to December 2014. The benchmark for WORLD is the same, except that we exclude all stocks that are headquartered in emerging markets.

We obtain the data on underlying stock returns and characteristics from CRSP (US firms), Compustat/North America (Canadian firms) and Compustat/Global (non-US firms).[11] We convert international stock prices to U.S. dollars using the exchange rates from the U.S. Federal Reserve Board's H.10 release.[12] Our final sample consists of 489 distinct funds holding 13,558 unique securities. The benchmark funds hold 12,526 unique securities. The total number of unique securities held by our sample funds and/or their benchmark funds is 16,340.

2.4 Measures of active fund management

Our first measure is active share (Cremers and Petajisto (2009)), which is based on deviations of a fund's actual portfolio weights from those of its benchmark. Since the Vanguard funds that serve as our benchmarks have no style tilt, we include style fixed effects in the analysis to help account for the influence of style. The results remain robust when we compute active share relative to a subset of the benchmark holdings with similar style characteristics. Our second measure of activeness is tracking error, which is the standard deviation of the difference between the fund's gross return and its benchmark return, estimated over a rolling 24-month window.

We use risk shifting based on tracking error as another predictor of fund performance. Following Huang, Sialm and Zhang (2011) and Lee, Trzcinka and Venkatesan (2019), we define risk shifting as the difference between the tracking error on a hy-

[11]As shown by Chaieb, Langlois and Scaillet (2020), the data quality in Compustat Global is superior to Datastream. We follow the data cleaning steps provided in their Appendix B.

[12]For exchange-rates not covered by H.10, we use WM/Reuters closing mid-quote rates from Datastream.

pothetical portfolio consisting of the securities currently held and the actual tracking error based on realized returns. The hypothetical holdings-based tracking error uses the most recently disclosed portfolio weights (e.g., as of December 2010) with returns measured over the preceding 24 months (e.g. from January 2009 to December 2010). As shown by Huang, Sialm and Zhang (2011), this measure of risk shifting is the strongest predictor of future performance.

2.5 Descriptive statistics

In Table 1, we report for each year the number of funds, the proportion of funds that are managed by international sub-advisors and the proportion of funds that are in-house or outsourced. The total number of global/international funds has steadily increased over our sample period. The fraction of funds that are sub-advised increases until around 2009, after which it remains relatively stable at around 52 percent. Similarly, the proportion of funds that outsource sub-advisory duties peaks in 2009 at just under 37 percent, followed by a modest decline to about 32 percent by the end of 2014. Although our sample of funds is significantly different from those used in Chen et al. (2013) and Chuprinin et al. (2015) in terms of the investment mandate (global/international) and investor clientele (U.S. investors), the overall proportion of outsourced funds remains comparable.

[Table 1]

Table 2 reports univariate differences amongst different sub-advisory arrangements. Columns (1) and (2) show that funds that hire international sub-advisors tend to be older, smaller, more expensive and have a lower proportion of AUM in institutional share classes, compared to non-sub-advised funds. Moreover, internationally sub-advised funds are significantly less active based on both active share and tracking error. In terms of fund performance, there are no statistically significant differences in the unconditional means.

Comparing column (3) to column (4), shows that internationally outsourced funds underperform significantly on all performance metrics relative to funds with in-house international sub-advisors. They also have significantly lower active share but significantly lower risk shifting. These results offer provisional support of the higher agency costs associated with outsourcing.

If international-based sub-advisors possess a local information advantage, and if the performance benefit of this advantage exceeds the agency costs associated with outsourcing, then internationally outsourced funds should outperform funds that outsource to U.S. sub-advisors. However, the results in column (8) provide some tentative evidence that internationally outsourced funds actually underperform U.S. outsourced funds, although the difference is only marginally significant. Chen et al. (2013) finds that outsourced funds tend to be smaller and come from smaller fund families. Our findings indicate that internationally outsourced funds are in fact significantly larger (by a factor of three), older, less expensive and they tend to come from larger fund families, relative to funds outsourced to U.S. sub-advisors.

[Table 2]

3 Empirical results

Here we investigate the consequences of international sub-advising for fund performance and activeness first at the fund-level, and then separately for the fund's local and non-local holdings.

3.1 Fund-level performance

To study the impact of sub-advisor locations and affiliations on fund performance, we regress fund i's risk-adjusted return in month t on lagged sub-advisory dummies, control variables and fixed effects:

$$\textsc{Perf}_{i,t} = \beta_0 \textsc{Int'l SA}_{i,t-1} + \gamma_0 \text{US SA}_{i,t-1} + c_0 \text{Controls}_{i,t-1} + \alpha_t + \alpha_{s,t-1} + \epsilon_{i,t} \qquad \text{(II.1)}$$

$$\text{Perf}_{i,t} = \beta_1 \text{Int'l In-H}_{i,t-1} + \beta_2 \text{Int'l Outs.}_{i,t-1} + \gamma_1 \text{US In-H}_{i,t-1} + \gamma_2 \text{US Outs.}_{i,t-1} + c_1 \text{Controls}_{i,t-1} + \alpha_t + \alpha_{s,t-1} + \epsilon_{i,t} \quad \text{(II.2)}$$

where Int'l $\text{Outs}_{i,t-1}$ is equal to one if fund i has at least one outsourced sub-advisor headquartered abroad at $t-1$ and zero otherwise, Int'l $\text{In-H}_{i,t-1}$ is equal to one if the fund has at least one in-house sub-advisor headquartered abroad and zero otherwise. US $\text{Outs}_{i,t-1}$ and US $\text{In-H}_{i,t-1}$ are constructed to be mutually exclusive from the international sub-advisor dummies. All specifications include time fixed effects (α_t) to account for time trends in fund performance, and Morningstar style fixed effects ($\alpha_{s,t-1}$) to account for style-specific differences in performance.

Our conjecture is that funds managed by international sub-advisors have a local information advantage $\beta > 0$, $\beta_1 > 0$ and $\beta_2 > 0$). If the costs of outsourcing exceed the potential benefits of having access to local information, then internationally outsourced funds are expected to underperform international in-house sub-advised funds $\beta_1 - \beta_2 > 0$). Moreover, if the benefits of a local information advantage exceed outsourcing costs, then internationally outsourced funds are expected to outperform relative to U.S. outsourced funds $\beta_2 - \gamma_2 > 0$).

We include a standard set of lagged control variables: the net expense ratio from CRSP, the cumulative gross return over the preceding 12-months, and net fund flows over the preceding 12-months and the natural logarithm of fund size. In addition, we include the percentage of assets in institutional share-classes to control for the possibility that more sophisticated investors are better at monitoring the fund manager. We also control for the liquidity of fund holdings relative to its benchmark, as measured by the natural log of the dollar-weighted monthly Amihud's illiquidity for the fund's holdings minus the corresponding weighted average for the fund's benchmark holdings. Additional details on variable construction can be found in Table A-1 in the Appendix.

Standard errors are clustered by style × time to account for any residual dependence among funds in the same style at a given point in time. To minimize the impact of outliers, we winsorize all control variables at the 1^{st} and 99^{th} percentiles on an annual basis.

3.1.1 Results

We focus our discussion on the results from the sample of funds with an international (i.e., ex. U.S.) mandate. This is arguably the more interesting subset of funds and accounts for the majority of the sample (73 percent). They are more popular than globally mandated funds because fund companies already offer a wide array of U.S. equity funds. Importantly, they present a cleaner test of the local information advantage hypothesis. Since the U.S. equities make up roughly half of the global stock market by capitalization, global funds that are managed by a U.S.-based firm may have a home advantage in the U.S. market. Nonetheless, our main findings are robust to using the full sample of international and global funds.

The regression results for Equation II.1 in Table 3 – columns (1), (3), (5), (7) and (9) – provide no evidence that internationally sub-advised funds outperform non-sub-advised funds. This contradicts the idea that local sub-advisors exploit local information in a manner that boosts fund performance.

[Table 3]

The results from estimating Equation (2) are provided in columns (2), (4), (6), (8) and (10). Here, we find that internationally outsourced funds underperform funds that are managed by international in-house sub-advisors. This difference is statistically significant and ranges from 77 and 131 bps per year (6.4 and 10.9 bps per month). Moreover, this difference is entirely driven by the poor performance of internationally outsourced funds: they underperform non-sub-advised funds by between 74 bps (CAPM alpha) and 124 bps per year (FF3 alpha), while international in-house sub-advised funds do not have significantly different performance relative to non-sub-advised funds.

Using the geography of the sub-advisors, we show that within the context of the international equity mandate, funds with international outsourced sub-advisors do not outperform funds with U.S. outsourced sub-advisors, despite the possibility of a local information advantage. The performance differential is negative in all cases (between 0.23 and 0.60 percent annualized) and significant at the 10 percent significance level for three out of five measures. This finding is new to the mutual fund outsourcing literature.[13]

3.2 Sub-portfolio performance

3.2.1 Decomposing fund performance

The existing literature on outsourcing in fund management suggests that the poor performance of outsourced funds is to a large extent explained by agency costs (Chen et al. (2013) and Chuprinin (2015)). To the extent that the sub-advisor (or the sub-advisors together, if there is more than one) manage the entire portfolio, agency costs should affect the entire portfolio.[14] Irrespective of agency costs, managers that have a local information advantage are expected to perform better in their local holdings relative to their non-local holdings.

To explore this hypothesis, we decompose the fund-level portfolio into three mutually exclusive sub-portfolios: i) local own country, ii) local own region (excluding own country), and iii) non-local holdings. A fund's local own country sub-portfolio contains all securities that are headquartered in the same country as its sub-advisors. For funds with sub-advisors in multiple countries, the local country sub-portfolio includes holdings in all those countries. For instance, if a fund has one sub-advisor in the U.K. and another in Hong Kong, then its local country portfolio includes the U.K. and Hong Kong. Sub-advisors may also have a regional information advantage. A sub-advisor in the U.K. (Hong Kong) might be more informed about European (Asian) securities than a sub-advisor in the U.S.. We take this into account by constructing a local region sub-portfolio that includes all securities headquartered in the same region (North America, Europe, Asia-Pacific), but outside the countries where the sub-advisors are located. Lastly, a fund's non-local sub-portfolio contains all securities located in regions where it has no physical sub-advisory presence. Funds without international sub-advisors have only non-local holdings by definition, since the advisors/sub-advisors are all U.S. based.

[13]In unreported results, we find that the performance differences are in fact negative and significant at the 5 percent level for all five measures if we use instead the full sample of international and global funds. Although not the focus of our study, this difference is largely explained by the outperformance of U.S. outsourced funds with a global mandate.

[14]Although there may be instances where the international sub-advisors only manage their local holdings, and the fund advisor or its U.S. sub-advisors manage the non-local holdings. Unfortunately, the N-SAR filings do not provide this level of information.

We use quarterly fund holdings from Morningstar Direct to construct buy-and-hold portfolio returns. For the three types of sub-portfolios, we compute international risk factors using the same procedure as before. That is, we use country-level Fama-French-Carhart factors provided by AQR and weigh each country in the sub-portfolio of a given fund i by its actual country weight based on its reported holdings at $t-1$. Our country-weighted methodology extends the standard models in the prior literature, where the performance of U.S. equity funds is adjusted for risk exposure to U.S. risk factors. As an example, for a U.K. sub-advisor, the local region includes other European stocks. We therefore weigh each of the 14 developed markets in Europe (ex. U.K.) by the fund's actual weight in each market at $t-1$.

Although the sub-portfolio risk-adjusted returns provide a clean decomposition of the fund-level abnormal returns, a potential drawback is that we are restricting the factor loadings for each sub-portfolio to be the same as their fund-level counterparts. It is possible that managers take more (or less) systematic risk in their local holdings compared to their non-local holdings. To address this concern, we turn to the characteristic-based benchmarks by Daniel, Grindblatt, Titman, and Wermers (1997). We extend their benchmarking approach to international markets, with a few modifications. Specifically, our benchmarks are defined by region to maintain consistency with the existing literature on international asset pricing (e.g., Asness, Moskowitz and Pedersen (2013), Fama and French (2017)).[15] The DGTW-adjusted sub-portfolio returns are then computed as the dollar-weighted average of the difference between the actual holdings returns and the characteristic-benchmark returns.

3.2.2 Results

We estimate Equations II.1 and II.2 at the fund (i)-sub-portfolio (k)-month (t) level. For each fund-month, there are up to three observations, one for each sub-portfolio. To

[15] We make a few additional modifications. First, we use the Fama-French 48 industries for computing industry-adjusted B/M ratios. Second, for international markets we compute breakpoints for large stocks based on the 55th percentile by region (roughly equivalent to using NYSE stocks), similar to Fama and French (2017). Third, for the benchmark portfolios, we only include primary issues and stocks traded on the main exchanges in each country (see e.g., Chaieb, Langlois, and Scaillet (2020); Bessembinder et al. (2020)). Fourth, to ensure that we have a similar number of stocks in the benchmark portfolios across regions, we construct 5×5×5 = 125 benchmark portfolios on size, B/M and momentum for North America and Developed Europe; for Asia-Pacific ex Japan and Japan we use instead 4×4×4 = 64 benchmark portfolios.

disentangle the performance of local from non-local holdings, we focus on two types of comparisons. First, we compare the local sub-portfolio performance of internationally sub-advised funds with the non-local performance of non-sub-advised funds (the omitted group). Second, we compare the local sub-portfolio with the non-local sub-portfolio among internationally sub-advised funds by controlling for fund fixed effects. In this case, each fund has its own omitted group which corresponds to the average performance across all its sub-portfolios. To account for the correlation in residuals across the sub-portfolios of a given fund, we cluster standard errors by fund.

The results in Table 4, columns (1) and (4), show that internationally sub-advised funds underperform in their local country sub-portfolios, suggesting that they are unable to exploit their most immediate local information. Next, in columns (2), (3), (5) and (6), we decompose these results further based on sub-advisor affiliation (outsourced vs. in-house). Whether we consider the DGTW-adjusted returns or the FFC4 alphas, we find very strong evidence of underperformance in the local country holdings of both international outsourced and in-house funds. For example, the local country sub-portfolios underperform by 158 bps per year using the DGTW measure for international outsourced sub-advisors, and by 150 bps per year for international in-house sub-advisors, relative to non-sub-advised funds (the omitted group, where the advisor is based in the U.S.). The results remain strong, particularly for internationally outsourced funds, if we control for fund fixed effects in order to focus on within fund variations, as shown in columns (3) and (6). In column (3), internationally outsourced funds underperform by 138 bps per year in their local country sub-portfolios relative to their non-local counterparts. The results in column (6) based on the FFC4 alphas are even stronger, at 204 bps per year.[16]

[Table 4]

Our evidence clearly indicates that internationally sub-advised funds – in-house or outsourced – do not outperform in their local holdings. Further, the magnitudes are large enough to explain the overall fund-level underperformance of internationally outsourced funds since these funds allocate a substantial fraction of their assets to local

[16]Similar results are obtained for the full sample of funds (global and international), see Table IA-1 in the Internet Appendix.

own country or own region holdings – 26 and 39 percent on average, respectively. Funds managed by international in-house sub-advisors also show no evidence of outperformance in local holdings. These results run counter to the hypothesis that local investors should outperform in their local holdings relative to their non-local holdings due to an information advantage, irrespective of agency costs. In the next section, we show that the underperformance can, at least in part, be explained by differences in sub-portfolio activeness and risk shifting.

3.3 Active fund management

An active line of inquiry in the mutual fund literature is whether actions by managers reveal the existence of skilled asset management. Cremers and Petajisto (2009) document that active share and tracking error are positively related to future risk-adjusted fund performance. Huang, Sialm and Zhang (2011) show that the funds that engage in positive risk shifting perform abnormally poorly in the future.

We explore differences in active fund management ”activeness” and risk shifting between funds that should have a local information advantage and those that do not. Our conjecture is that funds with such an advantage are more active and are less likely to engage in significant risk shifting, particularly in their local holdings, a necessary condition for obtaining higher risk-adjusted performance.

3.3.1 Fund-level activeness and risk shifting

We start by confirming the existence of a positive (negative) and significant relationship between active share (risk shifting) and future fund performance in our sample. We do not want to take these relationships for granted, because recent evidence by Jones and Mo (2019) suggests that the out-of-sample performance of mutual fund predictors has declined substantially in the U.S., which they link to the increase in arbitrage capital and the size of the mutual fund industry.

The regression specification is the same as Equation II.1, except that we drop the sub-advisory dummies and we include either style or fund fixed effects. Results, reported in Table IA-2 in the Internet Appendix, show that active share and tracking error both positively predict future performance at the one percent level in the cross-section (when controlling for style and time fixed). Moreover, within fund variations in future performance are also significantly negatively predicted by risk shifting at the one percent level. Next, we investigate whether the degree of activeness or risk shifting varies across sub-advising status. We use Equation (2) and replace fund performance with a measure of activeness or risk shifting. To account for the persistence in some of these measures over time (e.g., active share), we cluster standard errors by fund. The results indicate that relative to non-sub-advised funds, active share is significantly lower for both internationally outsourced and U.S. outsourced funds by 4.6 percent and 2.7 percent, respectively. Similarly, risk shifting is significantly higher for internationally outsourced funds by about 0.11 percent, corresponding to almost twice the unconditional mean. Tracking error is insignificantly related to sub-advising status.

Overall, these results appear consistent with the hypothesis of higher agency costs associated with outsourcing documented in previous studies. However, these fund-level results hide significant within-fund variations that cannot be fully explained by standard agency cost arguments, as we explain below.

[Table 5]

3.3.2 Sub-portfolio activeness and risk shifting

In this section, we compute active share separately for each sub-portfolio (local country, local region and non-local), with weights summing to 100 percent at the fund (i)-sub-portfolio (k)-month (t) level. Sub-portfolio tracking error is defined as the standard deviation of the return differences between the buy-and-hold sub-portfolio return and the buy-and-hold benchmark return.

To measure risk shifting at the sub-portfolio level, we use the difference between the hypothetical sub-portfolio tracking error with the end-of-quarter portfolio weights and the actual sub-portfolio tracking error based on buy-and-hold returns. The hypothetical tracking error uses the most recently disclosed portfolio weights with returns measured over the preceding 24-month window as suggested by Huang, Sialm and Zhang (2011).

We estimate Equations II.1 and II.2 with active share, tracking error, or risk shifting as the dependent variable. We include time fixed effects in all specifications, and either style or fund fixed effects. To account for the correlation in residuals within a fund, we cluster standard errors by fund.

We hypothesize that internationally sub-advised funds with a local information advantage should be more active and less prone to risk shifting in their local holdings. Our results, for the most part, do not support this conjecture. Columns (1), (4), (7) and (10) in Table 6 show that local country active share of internationally sub-advised funds are both significantly lower than non-local active share of non-sub-advised funds, while tracking error and risk shifting are significantly higher.[17]

[Table 6]

Next, we explore the differences among sub-advised funds based on their affiliation: in-house vs. outsourced. Both international in-house and outsourced funds are significantly less active in their local country and region sub-portfolios relative to non-sub-advised funds (the omitted group of ”No SA”). For example, for internationally outsourced funds, active share is lower by 14.3 and 9.5 percent points (unconditional mean = 75.9 percent), and risk shifting is higher by 0.30 percent and 0.40 percent points (unconditional mean = 0.17 percent), respectively. If we focus on within-fund variations by including fund fixed effects, we continue to find that internationally outsourced funds have significantly lower active share (by 12.6) and significantly higher risk shifting (by 0.32 percent) in their local country sub-portfolio compared to their non-local sub-portfolio. Similar results are obtained for the local region sub-portfolio.[18]

For international in-house sub-advised funds, the main difference is that risk shifting is not significantly different for their local versus non-local holdings in terms of within-fund variations. This may help explain why only internationally outsourced funds underperform at the fund level, but international in-house sub-advised funds do not.

[17] Cremers and Petajisto (2009) suggest that funds with lower than average active share and higher than average tracking errors focus on factor bets.

[18] This set of results is not sensitive to the inclusion of funds with a global mandate. See Table IA-3 in the Internet Appendix.

Overall, the lower activeness and greater risk shifting of internationally outsourced funds offer some explanation for their relatively poor performance. Importantly, to the extent that sub-advisors manage the entire portfolio, our findings are not explained by agency costs alone because we would expect lower activeness and risk-shifting across the entire portfolio.

3.4 Multiple sub-advised funds: Peer incentives

Roughly 40 percent of our sample of sub-advised funds have multiple sub-advisors. This proportion rises to 57 percent on average for internationally outsourced funds. Peer monitoring and joint monetary incentives in team-based managerial structures can, in theory, be an effective tool for mitigating agency costs; see for example, Ma et al. (1988), Kandel and Lazear (1992), and Acemoglu et al. (2008). Multi-manager fund structures can also be an effective tool for reducing the likelihood of extreme and risky decisions through diversification of opinions (Bar, Kempf, and Ruenzi (2011)), for offsetting an individual manager's overconfidence (Fedyk, Patel and Sarkissian (2020)) and for improving overall fund performance (Patel and Sarkissian (2017)). We contend that the underperformance of internationally outsourced funds is explained by single sub-advised (single SA) funds having an entrenched sub-advisor, resulting in higher agency costs. In contrast, we expect multiple sub-advised (multi SA) funds to have lower agency costs due to better effort coordination through peer pressure and monitoring, and a higher likelihood of termination in the event of poor performance.

To test this hypothesis, we start by re-estimating the fund-level performance regressions (Equation (2)) for two specifications. In the first, we drop multi SA funds from the sample. In the second, we drop single SA funds. The results, found in Table 7, indicate that the underperformance of internationally outsourced funds is worse among single SA funds compared to multi SA funds. We also confirm that outsourced funds with a single international sub-advisor underperform in their local holdings, are generally less active, and more likely to engage in risk shifting (see Tables IA-4 and IA-5 in the Internet Appendix).

[Table 7]

The lack of underperformance among multi SA funds could be explained by single SA funds having an entrenched sub-advisor leading to higher agency costs. An important implication of entrenchment is that sub-advisors in single SA funds are less likely to be fired for poor performance compared to their counterparts in multi SA funds. We investigate this hypothesis by estimating logistic regressions of sub-advisor termination on prior performance and fixed effects:

$$\begin{aligned} Pr(T_{j,i,t} = 1) = F(a_0 + b_1 Perf^{\geq 0}_{j,i,[t-1,t-36]} SingleSA_{i,t} + b_2 Perf^{<0}_{j,i,[t-1,t-36]} SingleSA_{i,t} \\ + b_3 Perf^{\geq 0}_{j,i,[t-1,t-36]} MultiSA_{i,t} + b_4 Perf j,i,[t-1,t-36]^{<0} MultiSA_{i,t} \\ + \alpha_t + \alpha_{s,t-1}) \end{aligned} \tag{II.3}$$

where $T_{j,i,t}$ equals one if sub-advisor j employed by fund i is terminated at time t, and $F(.)$ is the logistic function. We infer a termination event as the last observation when a given sub-advisor appears on the semi-annual N-SAR filing.[19] Our sample consists of 601 unique termination events, out of which 50 are for international outsourced sub-advisors, 417 are for U.S. outsourced sub-advisors and the remaining cases are for the termination of in-house sub-advisors.

The explanatory variable of interest is past performance, $Perf$, which corresponds to the average monthly performance over the prior 36 months. This measure is sub-advisor specific in the sense that we only include time-periods during which a sub-advisor has been employed by fund i. Evans et al. (2020) document that fund managers are evaluated based on their performance relative to pure (index) benchmarks, peer (funds in a similar style) benchmarks, or both. We therefore assess past performance using benchmark-adjusted returns or the equal-weighted peer benchmark-adjusted returns. We define the set of peers based on Morningstar categories.[20] We

[19]To qualify as a termination event, we impose the following three requirements. First, the last observation of a sub-advisor must be at least 12 months before the fund's termination (liquidation/merger) date (if applicable), or the end date of the sample period (December 2014). This is to minimize the possibility that we are picking up events related to fund closures. Second, the sub-advisor must have been employed by the fund for at least 12 months before termination. Third, we include interim terminations (i.e., termination followed by a re-hiring) if the sub-advisor is dropped from the N-SAR filings, but it reappears at least 18 months later.

[20]We require a minimum of 30 funds per category, which is the typical size of peer group for U.S.

include category fixed effects to account for category-specific differences in termination probabilities, and cluster standard errors by fund.

To ease the interpretation of results, we report average marginal effects and their associated t-stats instead of the raw coefficient estimates in Table 8. The results confirm our conjecture: poor performance is more likely to lead to termination in multi SA funds than it is in single SA funds. This is especially true for international outsourced sub-advisors (column (2)), where the average marginal effect of a one std. dev. decrease in performance – when performance is negative – is associated with a 7.2 to 7.8 percentage point increase in the termination probability for multi SA funds. In contrast, poor performance is insignificantly related to the termination probability for internationally outsourced sub-advisors in single SA funds. A similar pattern is evident for U.S. outsourced funds, but not among in-house funds where termination seems to be unaffected by past performance.[21]

[Table 8]

In summary, these results are consistent with the conjecture that single SA funds with an outsourced sub-advisor suffer from significant entrenchment effects and offers an additional explanation for the fund level underperformance of internationally outsourced funds. Importantly, our results indicate that the incentive mechanism inherent in multiple sub-advised funds can help alleviate the agency costs of outsourcing, which is entirely new to the literature.

3.5 Alternative explanations

In this section, we add to the literature by considering several possible reasons for the underperformance of international outsourced funds beside agency cost.

equity funds (Evans et al. (2020)). For categories with fewer than 30 funds, we use benchmark-adjusted returns.

[21] In Table IA-6 of the Internet Appendix, we provide additional results on the unconditional differences in termination probability between different sub-advising types. The results suggest that internationally outsourced sub-advisors in single-SA funds are more likely to be terminated compared to multi-SA funds. Similar, albeit weaker, results are also obtained for U.S. outsourced sub-advisors.

3.5.1 Reverse causality

The decision by a fund family to hire a sub-advisor (or not) is clearly endogenous. The analysis in this paper, however, is conditioned on a firm's sub-advising decision, and the goal is to evaluate the performance consequences of sub-advising from an investor's perspective. That said, it is possible that our fund-level results are driven by underperforming funds trying to tap into outside expertise. To test this hypothesis, we estimate the impact of prior performance on the propensity to outsource. The dependent variables, Int'l Outs. SA, is equal to equal to one if the fund has at least one outsourced sub-advisor headquartered abroad and zero otherwise. We keep only the first semi-annual observation during which a fund is reported to have an outsourced subadvisor. Any subsequent observations are removed from the sample. The results in Table IA-7 in the Internet Appendix indicate that performance is not significantly related to the propensity to outsource internationally.

3.5.2 Distribution channel

Bergstresser, Chalmers and Tufano (2009) and Del Guercio and Reuter (2015) suggest that funds sold through brokers have less incentive to generate alpha than those sold directly to investors. It is therefore possible that the underperformance of internationally outsourced funds is concentrated in broker-sold funds. This is, however, not the case. Using the definition of broker-sold funds from Christoffersen, Evans and Musto (2013), we find that internationally outsourced funds are significantly less likely to be broker-sold compared to funds managed by international in-house sub-advisors (see Table IA-8 in the Internet Appendix). If anything, the underperformance is worse among direct-sold funds. Similar results are also obtained using the Sun (2014) definition of broker-sold funds.

Using the definition of broker-sold funds from Christoffersen, Evans and Musto (2013), we find that internationally outsourced funds are significantly less likely to be broker-sold compared to funds managed by international in-house sub-advisors (see Table I.A.8). If anything, the underperformance is worse among direct-sold funds. Similar results are also obtained using the Sun (2014) definition of broker-sold funds.

Additional details on defining broker sold funds are provided in the Internet Appendix, section 1.3.

3.5.3 Quantitative funds

By definition, quantitativeas opposed to fundamentalinvestment strategies are less reliant on local information. Therefore, we should expect the negative effects of outsourcing to outweigh the potentially positive effects of local information for quant funds. We conjecture that funds that have higher regression R2 from the FFC4 model, funds with more holdings, and funds that voluntarily report holdings more frequently than is required are more likely to follow quantitative strategies. Our findings, provided in Table IA-9 in the Internet Appendix, show that the underperformance of internationally outsourced funds is actually stronger among non-quant funds, which runs counter to the argument that quantitative funds are driving the results.

4 Summary and Conclusions

We extend the literature on mutual fund sub-advising to the international setting by focusing on i) international/global mandates and ii) the geography of the sub-advisors. We analyze whether and how local information obtained through sub-advising abroad impact fund performance. Taking the geography of sub-advisors into account allows us to decompose a fund into its local versus non-local holdings from the perspective of its advisors/sub-advisors. Importantly, this decomposition helps us test for evidence of local expertise by comparing the performance of funds with different sub-advising arrangements in their local versus non-local sub-portfolios We also study the extent to which active management and risk shifting behaviours differ across these sub-portfolios. Lastly, our design allows us to provide new evidence on the incentive mechanism and consequences inherent in multiple versus single sub-advised funds.

We document that sub-advising abroad does not improve fund performance, whether the international sub-advisors are in-house or outsourced. Funds that hire outsourced international sub-advisors, in particular, underperform on a risk-adjusted basis by up to

126 bps annually. Further, we find that internationally outsourced funds underperform U.S. outsourced funds. Diving deeper to identify the source of the underperformance, we find that it is concentrated in the outsourced international sub-advisors' local stock picks. Surprisingly, we also find that international in-house sub-advisors underperform in their local sub-portfolios, leading to the conclusion that even if a local information advantage exists, it does not translate into risk-adjusted returns for investors.

We also explore several possible reasons. First, we show that international sub-advisors – in-house or outsourced – are significantly less active in managing holdings in countries/regions where they are located, compared to the rest of the fund. In addition, we provide evidence that international outsourced sub-advisors engage in higher risk shifting in those same local holdings. Prior studies have shown that these behaviours are not conducive to producing superior fund performance. While we do not rule out agency costs as a contributing factor to the relative underperformance, these within-fund variations suggest that there is more to the story. Second, we document that the incentive mechanism in multiple sub-advised funds can alleviate some of the agency costs of outsourcing by reducing entrenchment. Finally, we rule out the reverse causality explanation; that is, poorly performing funds try to boost performance by tapping into outside, international expertise.

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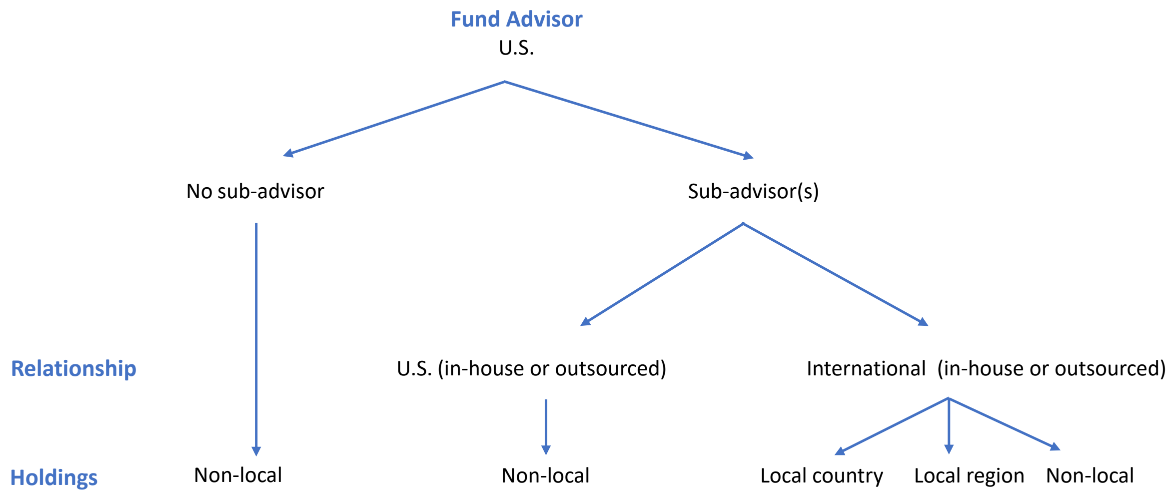
6 Figures

Figure 1: Sub-Advisory Relationship and Portfolio Holding Definitions

International Equity Funds (ex. U.S.)



7 Tables

Table 1: Sub-Advisory Status of International/Global Mutual Funds

This table summarizes the sub-advisory status for the full sample of funds over time. For each year we provide: the total number of distinct funds (aggregated by share class), the average fraction of funds i) that are sub-advised (i.e., having a U.S. or International sub-advisor whether in-house or outsourced), ii) with international sub-advisor(s), whether in-house or outsourced (Int'l SA), iii) with U.S. based sub-advisors, whether in-house our outsourced (U.S. SA), and iv) with an outsourced sub-advisor, whether U.S. or international (Outs. SA). Annual averages are calculated from fund-month observations since sub-advisory status can change throughout the year.

		Proportion of Funds per SA Category			
Year	Number of Funds	Sub-advised	Int'l SA	U.S. SA	Outs. SA
2000	200	27.39	11.44	15.95	17.5
2001	210	32.13	11.39	20.74	20.57
2002	236	32.77	11.37	21.4	20.07
2003	251	40.51	14.67	25.84	24.31
2004	273	44.05	15.3	28.75	25.51
2005	292	45.89	16.66	29.23	27.7
2006	316	47.81	17.51	30.3	30.13
2007	364	47.7	16.36	31.34	30.42
2008	388	48.83	16.16	32.67	30.87
2009	409	51.1	19.97	31.13	32.01
2010	416	51.23	21.04	30.19	30.8
2011	432	51.53	21.02	30.51	30.18
2012	407	50.69	19.59	31.1	27.75
2013	394	49.8	19.06	30.74	26.91
2014	384	50.98	20.27	30.71	25.56

Table 2: Descriptive Statistics by Sub-Advisory Status

This table reports univariate tests for differences between sub-advising categories. Performance measures and net flows are reported in percentages per month, while expense ratios are annual. AUM is reported in $millions. Sub-sample means are reported in Columns (1), (2), (3), (4) and (5). For example, the column labeled Int'l SA presents statistics using the sub-sample of funds that have at least one international sub-advisor, whether in-house or outsourced. Cochran and Cox t-statistics associated with testing for differences in sub-sample means are in columns (6), (7) and (8). Statistics are calculated using the full sample of observations (2000-2014). A full list of variable descriptions is given in the Table A-1 in the appendix.

	No SA	Int'l SA	Int'l Outs.	Int'l In-H	US Outs.	(2) - (1)	(4) - (3)	(5) - (3)
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
%Performance (p.m.)								
CAPM Alpha	0.04	0.01	-0.05	0.05	-0.01	1.75	3.00	1.33
FF3 Alpha	0.00	-0.02	-0.09	0.03	-0.05	0.97	3.77	1.43
FF4 Alpha	-0.05	-0.09	-0.16	-0.04	-0.10	1.87	3.57	1.80
BMK-Adj. Return	0.16	0.13	0.05	0.18	0.11	1.66	3.92	2.13
BMK Alpha	0.16	0.13	0.07	0.18	0.11	1.3	3.63	1.55
%Activeness and risk taking								
Active Share	76.85	71.45	69.96	72.52	74.74	28.02	7.60	17.10
Risk Shifting	0.09	0.09	0.08	0.1	0.12	-0.89	2.08	4.18
Tracking Error	1.45	1.27	1.27	1.28	1.36	21.15	0.36	7.08
Fund characteristics								
ln(Illiq. Dev.)	-146.00	-139.65	-136.10	-142.21	-134.54	-2.01	-1.13	0.33
Age	11.98	13.30	14.69	12.30	10.27	-10.96	-10.38	-21.86
Family AUM	11545	33318	14735	46861	3746	-32.64	26.43	-12.21
Fund AUM	2738	2478	1646	3085	708	2.82	11.87	-13.38
%Expense Ratio	1.19	1.24	1.22	1.25	1.37	-7.96	2.50	17.72
%Net Flow	0.58	0.48	0.36	0.57	0.63	1.53	1.80	2.66
%Inst. Share Class	55.6	48.39	62.57	38.01	51.35	12.36	-25.06	-12.86

Table 3: Baseline Performance Regression

This table reports estimates from panel regressions of risk-adjusted fund performance on sub-advisory variables (Equations (III.1) and (III.2)) for the sample of funds with international (ex-US) mandates. The sample period is from January 2000 to December 2014. Odd numbered columns use broad sub-advisory dummies measuring local presence: Int'l SA is equal to one if a fund has an international sub-advisor at time $t-1$ and zero otherwise; US SA is equal to one if a fund has a US sub-advisor and zero otherwise. In even numbered columns we further differentiate sub-advisors by affiliation: Int'l Outs. SA is equal to one if a fund has an internationally outsourced sub-advisor at time $t-1$ and zero otherwise, Intl In-H SA is equal to one if a fund has at least one in-house international sub-advisor. US In-H SA is equal to one if a fund has at least one in-house sub-advisor located in the US and no international in-house sub-advisors, US Outs. SA is equal to one if a fund has at least one outsourced US sub-advisor and no internationally outsourced sub-advisors. A full description of additional explanatory variables is given in Table A-1 in the Appendix. The t-statistics (in parentheses) are calculated from standard errors that are robust to clustering by style × time. */**/*** denotes statistical significance at the 10, 5 and 1 percent levels.

	CAPM Alpha		FF3 Alpha		FF4 Alpha		BMK-adj Return		BMK Alpha	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Int'l SA	-0.0070		-0.0216		-0.0177		-0.0067		-0.0090	
	(0.41)		(1.22)		(1.00)		(0.35)		(0.46)	
US SA	-0.0367***		-0.0387***		-0.0541***		-0.0241*		-0.0310**	
	(3.01)		(3.16)		(4.29)		(1.88)		(2.28)	
US In-H SA		-0.0256		-0.0049		-0.0246		-0.0244		-0.0201
		(1.20)		(0.22)		(1.09)		(1.03)		(0.82)
US Outs. SA		-0.0457***		-0.0572***		-0.0588***		-0.0299**		-0.0426***
		(3.11)		(3.88)		(3.90)		(1.98)		(2.74)
Int'l In-H SA		0.0024		0.0059		0.0066		0.0185		0.0042
		(0.11)		(0.27)		(0.30)		(0.78)		(0.17)
Int'l Outs. SA		-0.0618***		-0.1035***		-0.1007***		-0.0739***		-0.0657***
		(2.59)		(4.17)		(3.68)		(3.10)		(2.65)
Past Performance	0.0065*	0.0064*	0.0063**	0.0062**	0.0076***	0.0075***	0.0071***	0.0070***	0.0097***	0.0096***
	(1.82)	(1.80)	(2.33)	(2.29)	(3.31)	(3.27)	(2.90)	(2.85)	(3.78)	(3.75)
Inst. Share Class (%AUM)	-0.0002	-0.0002	-0.0005***	-0.0004**	-0.0004**	-0.0004**	-0.0001	-0.0000	-0.0003	-0.0002
	(1.16)	(0.93)	(2.74)	(2.39)	(2.38)	(2.02)	(0.40)	(0.08)	(1.45)	(1.23)
Ln(Illiq.)	0.0001**	0.0001**	0.0001**	0.0001**	0.0001***	0.0001**	0.0002***	0.0002***	0.0001***	0.0001***
	(2.45)	(2.41)	(2.28)	(2.24)	(2.66)	(2.58)	(3.51)	(3.52)	(3.41)	(3.39)
Netflow	0.0001	0.0001	0.0003***	0.0003***	0.0002*	0.0002*	-0.0000	-0.0000	0.0001	0.0001
	(0.89)	(0.92)	(2.91)	(2.93)	(1.85)	(1.91)	(0.38)	(0.31)	(1.13)	(1.17)
Expense Ratio	0.0177	0.0174	0.0729***	0.0712***	0.0342	0.0313	-0.0054	-0.0051	0.0335	0.0334
	(0.78)	(0.76)	(3.19)	(3.12)	(1.56)	(1.43)	(0.22)	(0.21)	(1.43)	(1.43)
Ln(AUM)	0.0018	0.0009	0.0026	0.0016	0.0047	0.0036	-0.0034	-0.0045	0.0029	0.0020
	(0.32)	(0.17)	(0.44)	(0.27)	(0.82)	(0.64)	(0.58)	(0.76)	(0.50)	(0.34)
Ln(Family AUM)	0.0023	0.0008	0.0064*	0.0038	0.0019	-0.0007	0.0067*	0.0052	0.0080**	0.0065*
	(0.68)	(0.24)	(1.77)	(1.03)	(0.53)	(0.18)	(1.75)	(1.34)	(2.16)	(1.72)
Ln(Age)	-0.0124	-0.0105	-0.0136	-0.0100	-0.0224*	-0.0182	-0.0129	-0.0091	-0.0152	-0.0130
	(1.08)	(0.89)	(1.17)	(0.84)	(1.96)	(1.54)	(1.04)	(0.72)	(1.24)	(1.06)
Int'l In-H SA - Int'l Outs. SA		0.0642**		0.1094***		0.1073***		0.0924***		0.0699**
		(2.19)		(3.66)		(3.20)		(3.25)		(2.31)
Fund FE	No	No	No	No	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.26	0.26	0.26	0.26	0.29	0.29	0.22	0.22	0.23	0.23
Observations	37,369	37,369	37,369	37,369	37,369	37,369	37,408	37,408	37,408	37,408

Table 4: Decomposing fund performance

This table reports the results for regressions of sub-portfolio risk-adjusted performance on sub-advisory (SA) dummies and control variables for the sample of funds with international (ex-US) mandates. For each fund i and month t, there are up to three sub-portfolios. The three mutually exclusive sub-portfolios are: i) local own country, ii) local own region (excl. own country) and iii) non-local. A fund's local own country sub-portfolio contains all stocks that are headquartered in the same country as the fund's sub-advisor(s). The local own region sub-portfolio includes all stocks headquartered in the same region, but outside the country where the funds sub-advisor(s) is (are) located. A fund's non-local sub-portfolio contains all stocks located in regions where the fund's sub-advisor(s) has (have) no physical presence. The omitted group consists of funds without sub-advisors. The sample period is from January 2000 to December 2014. A full description of the control variables is given in Table A-1 in the Appendix. The t-statistics (in parentheses) are calculated from standard errors that are robust to clustering by fund. */**/*** denotes statistical significance at the 10, 5 and 1 percent levels.

	DGTW-adj. Returns			FFC4 Alpha		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Local Country × Int'l SA	-0.1319***			-0.1302***		
	(4.79)			(4.88)		
Local Region × Int'l SA	0.0081			-0.0316		
	(0.37)			(1.29)		
Non-Local × US SA	-0.0339			-0.0497***		
	(1.39)			(2.62)		
Non-Local × Int'l SA	-0.0853***			-0.0305		
	(2.73)			(0.97)		
Local Country × Int'l In-H SA		-0.1246***	-0.0873*		-0.0875***	-0.0239
		(4.20)	(1.78)		(2.60)	(0.50)
Local Country × Int'l Outs. SA		-0.1318***	-0.1149***		-0.1916***	-0.1711***
		(3.57)	(2.62)		(5.26)	(3.64)
Local Region × Int'l In-H SA		-0.0176	0.0198		0.004	0.0676
		(0.67)	(0.42)		(0.13)	(1.38)
Local Region × Int'l Outs. SA		0.0524**	0.0695**		-0.0837***	-0.0632*
		(2.22)	(1.98)		(2.98)	(1.76)
Non-Local × US In-H SA		0.0010			-0.0255	
		(0.04)			(1.21)	
Non-Local × US Outs. SA		-0.0356			-0.0515**	
		(1.59)			(2.57)	
Non-Local × Int'l In-H SA		-0.0679*			-0.0067	
		(1.85)			(0.15)	
Non-Local × Int'l Outs. SA		-0.0742**			-0.0425	
		(1.98)			(1.07)	
Omitted group: Non-local portf.	× No SA	× No SA	Within-fund	× No SA	× No SA	Within-fund
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	Yes	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	No	Yes	Yes	No
R-squared	0.08	0.09	0.1	0.12	0.16	0.17
Observations	51,986	46,816	46,814	52,094	46,927	46,925

Table 5: Fund Activeness and Sub-Advisory Status

This table reports the results for regressions of fund activeness on sub-advisory variables for the sample of international and global equity funds. Tracking Error is the standard deviation of the fund return in excess of the benchmark return from time t to $t+35$. Active Share is the sum of the absolute differences between the fund's portfolio weight and its benchmark weight divided by two at time t. The independent variables include the sub-advisory dummies and control variables at $t-1$. The sample includes funds with international (ex-US) mandates. The t-statistics (in parentheses) are calculated from standard errors that are clustered by fund. */**/*** denotes statistical significance at the 10, 5 and 1 percent levels.

	Active Share	Tracking Error	Risk Shifting
Variables	(1)	(2)	(3)
Int'l In-H SA	-2.0876*	-0.0527	0.0378
	(-1.71)	(-1.28)	(1.64)
Int'l Outs. SA	-4.5343***	-0.0658	0.1081***
	(-2.89)	(-1.13)	(3.07)
US In-H SA	-0.5542	0.0193	0.0596*
	(-0.40)	(0.40)	(1.80)
US Outs. SA	-2.7828***	0.0071	0.0330
	(-2.80)	(0.17)	(1.50)
Past Performance	0.1005***	0.0031***	-0.0001
	(5.29)	(3.31)	(-0.17)
Inst. Share Class (%AUM)	-0.0229*	-0.0004	-0.0002
	(-1.88)	(-0.95)	(-0.56)
Ln(Illiq.)	0.0011	0.0001*	-0.0001*
	(0.99)	(1.87)	(-1.80)
Netflow	0.0073***	0.0002**	-0.0002**
	(3.08)	(2.23)	(-2.07)
Expense Ratio	4.1468***	0.1208***	-0.0066
	(3.10)	(2.62)	(-0.25)
ln(AUM)	0.0425	0.0178	-0.0026
	(0.15)	(1.55)	(-0.36)
ln(Family AUM)	-0.7780***	-0.0155**	0.0026
	(-4.81)	(-2.31)	(0.68)
ln(Age)	-0.8328	-0.0827***	0.0051
	(-1.14)	(-3.22)	(0.31)
Fund FE	No	No	No
Time FE	Yes	Yes	Yes
Style FE	Yes	Yes	Yes
R-squared	0.34	0.39	0.07
Observations	50,585	40,367	39,804

Table 6: Decomposing Fund Activeness

This table reports the results for regressions of sub-portfolio activeness (active share or tracking error) or risk shifting on sub-advisory dummies and control variables for the sample of funds with international (ex-US) mandates. For each fund i and month t, there are up to three observations, one for each sub-portfolio. The three mutually exclusive sub-portfolios are: i) the local own country, ii) the local own region (excl. the own country) and iii) the non-local. A funds local own country sub-portfolio contains all stocks that are headquartered in the same country as its sub-advisors. The local region sub-portfolio includes all stocks headquartered in the same region, but outside the countries where the sub-advisors are located. A funds non-local sub-portfolio contains all stocks located in countries where it has no physical presence through sub-advisors. The sample period is from January 2000 to December 2014. A full description of additional explanatory variables is given in Table A-1 in the appendix. The t-statistics (in parentheses) are calculated from standard errors that are robust to clustering by fund. */**/*** denotes statistical significance at the 10, 5 and 1 percent levels.

	Active Share			Tracking Error			Risk Shifting		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Local Country × Int'l SA	-13.6249***			0.2339***			0.1400***		
	(8.71)			(3.74)			(2.94)		
Local Region × Int'l SA	-10.1905***			0.0653			0.2309***		
	(6.61)			(1.10)			(3.74)		
Non-Local × US SA	-5.4603***			-0.0318			0.0044		
	(4.65)			(0.75)			(0.19)		
Non-Local × Int'l SA	1.1229			0.3855***			0.0550		
	(0.70)			(5.39)			(1.46)		
Local Country × Int'l In-H SA		-9.2727***	-8.7555***		0.2803***	0.0000		0.0315	-0.1042
		(5.13)	(7.41)		(3.59)	(0.00)		(0.79)	(1.35)
Local Country × Int'l Outs. SA		-14.3355***	-12.0604***		0.1626**	-0.0472		0.2957***	0.3155***
		(7.11)	(10.17)		(2.07)	(0.89)		(3.00)	(2.87)
Local Region × Int'l In-H SA		-6.7583***	-6.2411***		0.1282*	-0.1547**		0.1138**	-0.0241
		(3.87)	(6.84)		(0.87)	(2.17)		(2.01)	(0.27)
Local Region × Int'l Outs. SA		-9.4940***	-7.2190***		-0.0296	-0.2457***		0.3975***	0.4111***
		(4.67)	(6.30)		(0.34)	(4.57)		(3.11)	(3.03)
Non-Local × US In-H SA		-1.9614			-0.0458			0.0457	
		(1.20)			(0.81)			(1.18)	
Non-Local × US Outs. SA		-3.5516***			-0.0211			-0.0401*	
		(2.79)			(0.46)			(1.66)	
Non-Local × Int'l In-H SA		6.2272***			0.4123***			0.0400	
		(3.20)			(4.41)			(0.83)	
Non-Local × Int'l Outs. SA		1.0807			0.3672***			0.0567	
		(0.53)			(3.77)			(1.12)	
Omitted group: Non-local portf.	× No SA	× No SA	Within-fund	× No SA	× No SA	Within-fund	× No SA	× No SA	Within-fund
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	Yes	No	No	Yes	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
R-squared	0.28	0.3	0.8	0.36	0.36	0.69	0.07	0.08	0.19
Observations	49,424	46,608	46,607	35,974	35,957	35,955	35,492	35,475	35,473

Table 7: Single vs. Multi Sub-Advised Funds

This table reports the results for regressions of risk-adjusted fund performance on sub-advisory variables for two sub-samples. First, we compare funds with a single sub-advisor to non-sub-advised funds by dropping funds with multiple sub-advisors from the sampleresults are in columns denoted by Single. Second, we drop funds with a single sub-advisor to compare multi sub-advised funds to non-sub-advised fundsresults are in columns denoted by Multi. The sample includes funds with international (ex US) investment mandates and the sample period is from January 2000 to December 2014. The t-statistics (in parentheses) are calculated from standard errors that allow for clustering by style and time. */**/*** denotes statistical significance at the 10, 5 and 1 percent levels.

	CAPM Alpha		FF3 Alpha		FF4 Alpha		BMK-adj. Return		BMK Alpha	
	Single	Multi	Single	Multi	Single	Multi	Single	Multi	Single	Multi
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Int'l In-H SA	-0.0312	0.0294	-0.0035	0.0017	0.0107	-0.0158	-0.0534	0.0560*	-0.0251	0.0182
	(-0.99)	(1.08)	(-0.11)	(0.06)	(0.31)	(-0.57)	(-1.52)	(1.85)	(-0.73)	(0.61)
Int'l Outs. SA	-0.0977***	-0.0305	-0.1495***	-0.0643**	-0.1486***	-0.0546**	-0.1260***	-0.0389	-0.1114***	-0.0297
	(-2.63)	(-1.19)	(-3.96)	(-2.44)	(-3.62)	(-1.99)	(-3.14)	(-1.53)	(-2.73)	(-1.13)
US In-H SA	-0.0182	-0.0684*	0.0065	-0.0557	-0.0273	-0.0669*	-0.0211	-0.0751**	-0.0030	-0.0942**
	(-0.69)	(-1.81)	(0.24)	(-1.45)	(-0.98)	(-1.71)	(-0.72)	(-1.97)	(-0.10)	(-2.39)
US Outs. SA	-0.0559***	-0.0186	-0.0519***	-0.0611***	-0.0733***	-0.0362	-0.0531***	0.0110	-0.0493***	-0.0127
	(-3.09)	(-0.80)	(-2.84)	(-2.74)	(-3.96)	(-1.55)	(-2.99)	(0.46)	(-2.69)	(-0.53)
Past Performance	0.0061	0.0068	0.0064**	0.0054*	0.0079***	0.0086***	0.0067**	0.0074***	0.0095***	0.0084***
	(1.60)	(1.50)	(2.26)	(1.78)	(3.30)	(3.47)	(2.48)	(2.64)	(3.48)	(3.12)
Inst. Share Class (%AUM)	-0.0002	-0.0002	-0.0005**	-0.0006**	-0.0005**	-0.0003	-0.0001	-0.0000	-0.0004*	-0.0003
	(-0.81)	(-0.71)	(-2.57)	(-2.48)	(-2.26)	(-1.37)	(-0.34)	(-0.03)	(-1.74)	(-1.09)
Ln(Illiq.)	0.0001***	0.0001**	0.0001**	0.0001**	0.0001***	0.0001**	0.0002***	0.0002***	0.0002***	0.0002***
	(2.60)	(2.04)	(2.20)	(2.13)	(2.59)	(2.46)	(3.22)	(3.84)	(3.25)	(3.35)
Netflow	0.0001	0.0001	0.0003***	0.0002	0.0001	-0.0000	-0.0000	-0.0001	0.0001	0.0001
	(0.99)	(0.47)	(2.89)	(1.49)	(1.41)	(-0.32)	(-0.16)	(-0.81)	(1.11)	(0.53)
Expense Ratio	0.0142	0.0081	0.0771***	0.0749***	0.0304	0.0292	-0.0094	-0.0164	0.0348	0.0282
	(0.54)	(0.30)	(2.91)	(2.71)	(1.21)	(1.09)	(-0.34)	(-0.54)	(1.30)	(0.96)
ln(AUM)	0.0018	0.0014	0.0027	0.0059	0.0047	0.0039	-0.0056	-0.0041	0.0025	0.0054
	(0.29)	(0.23)	(0.41)	(0.93)	(0.76)	(0.63)	(-0.88)	(-0.64)	(0.40)	(0.87)
ln(Family AUM)	-0.0003	-0.0033	0.0026	0.0010	-0.0010	-0.0002	0.0028	0.0028	0.0061	0.0038
	(-0.07)	(-0.81)	(0.62)	(0.22)	(-0.25)	(-0.06)	(0.67)	(0.65)	(1.47)	(0.92)
ln(Age)	-0.0106	-0.0186	-0.0063	-0.0318**	-0.0223*	-0.0406***	-0.0135	-0.0131	-0.0143	-0.0252*
	(-0.84)	(-1.28)	(-0.49)	(-2.14)	(-1.75)	(-2.74)	(-1.02)	(-0.84)	(-1.08)	(-1.67)
Firm FE	No	No	No	No	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.24	0.26	0.24	0.26	0.27	0.29	0.21	0.23	0.22	0.24
Observations	30,043	26,228	30,043	26,228	30,043	26,228	30,076	26,258	30,076	26,258

Table 8: Sub-Advisor Termination and Performance

This table reports the results for logistic regressions of sub-advisor termination on the average fund performance over the prior 36 months and style and year fixed effects. Performance is measured either by the benchmark-adjusted return (relative to style benchmarks), or by the equal-weighted peer-adjusted return (of other funds in the same Morningstar Category). We estimate separate coefficients for negative and positive performance. Past performance is then interacted with a dummy for single or multi sub-advised funds. The t-statistics (in parentheses) are calculated from standard errors that allow for clustering by fund. */**/*** denotes statistical significance at the 10, 5 and 1 percent levels.

		Sub-sample results			
Variables	Full Sample	Intl. Outs.	U.S. Outs.	Intl. In-House	U.S. In-House
Panel A: Benchmark-adjusted return					
$\text{Perf}_{\geq 0}$ × Single	0.0130***	0.0008	0.0123	-0.0309	0.0184**
	(3.83)	(0.03)	(1.48)	(0.66)	(2.24)
$\text{Perf}_{<0}$ × Single	-0.0176***	-0.0151	-0.0305**	-0.0086	-0.0062
	(3.20)	(0.74)	(2.24)	(0.57)	(0.82)
$\text{Perf}_{\geq 0}$ × Multi	-0.0003	0.0242	0.0028	-0.0055	-0.0035
	(0.05)	(1.50)	(0.36)	(0.42)	(0.35)
$\text{Perf}_{<0}$ × Multi	-0.0401***	-0.0721***	-0.0805***	0.0109	-0.0226***
	(4.73)	(2.71)	(6.08)	(0.86)	(2.63)
Year FE	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.103	0.24	0.111	0.167	0.099
Observations	7,065	423	2,688	1,303	1,498
Panel B: Peer benchmark-adjusted return					
$\text{Perf}_{\geq 0}$ × Single	0.0091***	0.0015	0.0117**	-0.0186	0.0075**
	(3.68)	(0.09)	(1.96)	(0.48)	(2.09)
$\text{Perf}_{<0}$ × Single	-0.0199***	-0.0254	-0.0344***	-0.0193	-0.0012
	(4.62)	(1.34)	(3.16)	(1.38)	(0.18)
$\text{Perf}_{\geq 0}$ × Multi	0.0052	0.0254*	0.0113*	-0.0021	-0.0069
	(1.37)	(1.72)	(1.91)	(0.22)	(0.55)
$\text{Perf}_{<0}$ × Multi	-0.0427***	-0.0775***	-0.0846***	0.0037	-0.0183**
	(5.11)	(2.79)	(7.13)	(0.37)	(2.23)
Year FE	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.107	0.241	0.129	0.131	0.095
Observations	7,643	445	2,990	1,404	1,595

8 Internet Appendix

https://sites.google.com/view/geography-sa-internet-appendix/home

9 Appendix

Table A.1

Variable Definitions

Performance Measures	
CAPM Alpha	1-Factor alpha relative to the market portfolio.
FF3 Alpha	3-Factor alpha relative to the Fama and French 3-factor model.
FF4 Alpha	4-Factor alpha relative to the Fama-French-Carhart 4-factor model.
BMK-Adj. Returns	Gross fund returns in excess of the fund's benchmark return. We classify each fund into one of four primary benchmarks: i) All Country World Index (ACWI) (developed and emerging markets), ii) WORLD (developed markets), iii) ACWI ex. U.S., or iv) WORLD ex. U.S.. Furthermore, we use the Morningstar Category at $t-1$ to assign a value/blend/growth tilt to each fund. We then use the corresponding MSCI index return (e.g., MSCI ACWI ex US Value).
BMK Alpha	1-Factor alpha relative to the benchmark return. All factor-models are estimated with 36 months of data for funds with at least 24 months of valid returns. For funds with less than 24 months of return data, we use instead the median factor loadings of other funds with the same benchmark and style classification as of $t-1$.
Sub-Advisory Variables	
Int'l SA	Binary variable equal to one if a fund has an internationally headquartered sub-advisor and zero otherwise.
Int'l In-H SA	Binary variable equal to one if a fund has an affiliated sub-advisor located in an international country (ex-U.S.) and zero otherwise.
Int'l Outs. SA	Binary variable equal to one if a fund has an unaffiliated sub-advisor located in an international country (ex-U.S.) and zero otherwise.
U.S. SA	Binary variable equal to one if a fund has a sub-advisor headquartered in the United States and zero otherwise.
U.S. In-H SA	Binary variable equal to one if a fund has an affiliated sub-advisor headquartered in the United States and zero otherwise.
U.S. Outs. SA	Binary variable equal to one if a fund has an unaffiliated sub-advisor headquartered in the United States and zero otherwise.
Activeness and Risk Taking	
Active Share	$\text{Active Share}_{i,t} = \frac{\sum_{j=1}^{N} \lvert w_{i,j,t} - w_{benchmark,j,t} \rvert}{2}$
Tracking Error	The standard deviation of the difference between a fund's returns and its benchmark returns (calculated using 24 month rolling windows with a minimum of 12 months).
Risk Shifting	The difference between a hypothetical holdings-based tracking error of the fund and the actual tracking error based on realized returns. The hypothetical holdings-based tracking error uses the most recently disclosed portfolio weights (e.g., as of December, 2010) with returns measured over the preceding 24-month window (in this case from January, 2009 to December, 2010).
Fund Characteristics	
Expense Ratio	The percentage of fund assets used to pay for operating expenses and management fees.
AUM	Fund assets under management.
Net Flow	$\text{Net Flow}_{i,t} = 100 \times \left(\frac{AUM_{i,t} - (1+R_{i,t}) \times AUM_{i,t-1}}{AUM_{i,t-1} \times (1+R_{i,t})} \right)$.
%Inst. Share Class	The proportion of a fund's assets held by institutional investors.
Ln(Ill. Dev)	The natural log of the fund's deviation from it's benchmarks illiquidity measure - the illiquidity measure is as defined in Amihud (2002).

Chapter III

The growth of passive indexing and smart-beta: Competitive effects on actively managed funds

Michael Densmore[1]

1 Introduction

Over the past decade the US mutual fund industry has seen a dramatic shift from active management towards explicitly indexed funds, including both exchange traded funds (ETFs) and open-ended index funds. Historically, index fund assets have been concentrated in funds that provide investors with diversified exposure to the market portfolio. For example, the SPDR trust (ticker: SPY) and the NASDAQ 100 trust (ticker: QQQ) provide investors with exposure to the total return of the US stock market by passively replicating the performance of the S&P 500 and NASDAQ 100 indexes respectively. For the remainder of this paper, these types of funds are referred to as *market index* funds. More recently, there has been a proliferation of index funds that strategically select stocks based on metrics other than market capitalization (e.g., smart-beta funds). Common examples of these metrics include risk factors such as momentum and volatility or firm fundamentals such as earnings growth or profitability. For instance, Invesco's DWA Momentum ETF (Ticker:PDP) tracks the Dorsey Wright Technical Leaders Index which selects stocks based on security and industry performance. Hereafter, I refer to these types of index funds as *factor index* funds. As show in Figure 1, the recent growth in both market and factor US equity index funds has been accompanied by a significant

[1] I am grateful for the comments of Markus Broman, Melanie Cao, Fabio Moneta, Aleksandra Rzeźnik, Ben Sand, Pauline Shum Nolan and seminar participants at the Schulich School of Business, York University.

decline in flows to actively managed US equity funds.[2]

[Figure 1]

The increased popularity in index investing can be attributed to, at least partially, the low cost and comparable performance relative to actively managed funds. Indeed, the debate on active versus passive management tends to focus on the relative value, or performance net of fees.[3] In this paper, I investigate the degree to which increased competition from index funds has affected actively managed mutual fund fees, survival, and future performance. Factor index funds provide investors with active risk exposure whereas market index funds deliver diversified exposure to the broad market. Thus, investors seeking active risk strategies are likely to substitute actively managed mutual funds with factor index funds rather than market index funds. By the same token, active funds are more likely to respond to competitive threats from factor index funds than to competitive threats from market index funds. Thus, my conjecture is that factor index funds are more of a competitive threat to actively managed funds than market index funds.

The question of whether competitive forces from open-ended index funds and ETFs has affected actively managed mutual funds is important for several reasons. The existing evidence on the competitiveness of the money management industry is mixed. For example, research showing relatively stable average, or aggregate, expense ratios during periods of rapid industry growth (Barber, Odean and Zheng, 2005; Wahal and Wang, 2011; Khorana and Servaes, 2012; Sun, 2020) has raised questions about whether sufficient price competition exists. Along the same vein, net expense ratios have been shown to be unrelated to market share growth (Sirri and Tufano, 1993) or fund inflows (Barber, Odean and Zheng, 2005) and are higher for funds that operate in more competitive regions (Ellis and Underwood, 2018). On the other hand, competition between actively managed funds has been shown to attenuate management

[2] According to the 2020 ICI Factbook, US equity index funds and ETFs received $1.8 trillion in new cash and reinvested dividends, whereas actively managed US equity funds experienced a net outflow of $1.7 trillion from 2010 to 2019.

[3] Research in agreement with the implications of Sharpe (1991)'s arithmetic of active management, active investing is a negative sum game at the aggregate level (French, 2008) and on average, include: Carhart (1997), Edelen (1999), Gruber (1996), Fama and French (2010), Jensen (1968), Malkiel (1995) and Wermers (2000).

fees (Wahal and Wang, 2011; Ellis and Underwood, 2018; Hoberg, Kumar and Prabhala, 2018), and relative family level fees have been found to predict family market share (Khorana and Servaes, 2012). With the exceptions of Cremers, Ferreira, Matos and Starks (2016) and Sun (2020), very little has been said about the consequences of index fund competition on active management.

Determining an appropriate measure of competition is not an easy task. I follow Wahal and Wang (2011) and measure the intensity of index fund competition using the overlap between entrant and incumbent portfolio holdings. This measure is calculated by multiplying the ratio of the market value of each overlapping security in each incumbent's and entrant's portfolio by the weight of the security in the incumbent's portfolio. Wahal and Wang (2011) use this measure to examine competition between actively managed funds whereas my focus is on investigating the consequences of index fund competition on actively managed mutual funds, and whether the competitive effects differ based on index fund strategy. I therefore calculate overlap measures for three types of entrants: factor index overlap, market index overlap and active overlap. I include the latter group to control for direct competition from active entrants.

There are several reasons why this measure is appropriate in my empirical setting. First, a new fund must enter for an incumbent to experience a change in competition. Aside from being intuitive, this ensures that the variation over time is influenced by the number of new entrants. There is also considerable variation in the degree to which incumbents are affected by new entry. Importantly, this variation is a function of the similarity between the portfolios (products) of the incumbent and entrant which is reflected by the number of overlapping stocks in their portfolios. This is important since investors holding an actively managed incumbent fund that has a high factor or market index overlap can obtain exposure to a similar set of stocks, and pay lower fees, by switching to the index entrant. Moreover, concentrating on overlapping stocks speaks to competition in security selection, which can have implications for performance and costs. A second source of incumbent level variation is the weight of each overlapping security in each incumbent's portfolio. This ensures that entrants who hold the most important stocks in an incumbent's portfolio are treated as a greater competitive threat than entrants who hold stocks that are less important to the incumbent's portfolio.

Using the entrant-incumbent overlap measure as a proxy for competition, I first investigate the consequences of index fund entry on active incumbent fee decisions. Standard theory on competition suggests that active incumbent fees should decline following the entry of relatively inexpensive index funds that offer exposure to a similar portfolio. In contrast, investor search costs, and increased product diversity can lead to substantial fee dispersion (Gârleanu and Pedersen, 2018; Hortaçsu and Syverson, 2004). On the one hand, factor index funds offer active risk exposure at a relative discount to active mutual funds. On the other hand, the advent of active risk exposure packaged into an index fund increases the diversity of products available to investors and therefore could result in increased search costs. The effect of factor index fund entry on active mutual fund fees is therefore unclear. The objective of market index funds is distinctly different – to provide diversified exposure to the market portfolio. Actively managed funds presumably differentiate themselves from market index funds by delivering active risk exposure. Nonetheless, questions regarding the relative performance suggest that actively managed fees most likely decline with increased market index fund entry.

I test these hypotheses by regressing post entry changes in net fees (and their various components) on the index overlap measures. My findings indicate that index fund competition has had significant effects on actively managed net fees, but that the effect depends on the type of index fund. In particular, there is no significant relationship between market index overlap and changes in net fees. In contrast, active funds reduce net fees by approximately 1.1 basis points following a one standard deviation increase in factor index overlap. The effect is largest for funds that charge above the median of their actively managed peers at approximately 1.52 basis points. While the magnitude may seem marginal, it represents roughly 6.3% of the total reduction in the average net fee charged by active funds over my sampling period. Thus, competitive pressure from relatively low-cost index funds that offer active risk exposure (factor index funds) has directly contributed to a reduction in the net cost of actively managed US equity mutual funds.

Next, I investigate the source of net fee changes by examining the impact on the three largest components: management fees, operating fees, and distribution fees. Management fees provide the cleanest price of a fund's investment performance and increased competition should reduce the ability of funds to extract profit through management fees. Ex-ante, index fund competition is expected to be positively related to distribution fees as they are generally used to generate investor attention. The expected effect on operating fees is ambiguous as it is unclear how index competition effects the supply and demand for the types of services they include.

My findings indicate that both factor and market index fund competition are positively related to future changes in active management fees, negatively related to changes in operating fees and insignificantly related to changes in distribution fees. With market index fund competition, the increase in management funds is offset by the decrease in operating fees, resulting in no significant change in net fees. In contrast, the increase in management fees associated with factor index fund competition is more than offset by a reduction in operating fees which is not surprising given the negative effect on net fees.

It may seem counter-intuitive that management fees are positively related to index overlap, however, my results indicate that this effect is driven by funds that: 1) outperform their peers and 2) charge relatively low management fees to begin with. A similar observation can be made for operating fees – reductions are restricted to funds with relatively high operating costs and who have outperformed their peers. The implication is that entry of low-cost alternatives has helped to drive fee components towards their peer group median. These findings are important as prior criticisms against sufficient competition in the mutual fund industry point to the considerable dispersion in fees charged by similar funds (Cooper, Halling and Yang, 2020).

Importantly, the observed relationships between changes in active fund fees and index fund competition are, for the most part, consistent with funds optimizing future net flow. Funds that reduce net fees or operating fees over the prior two years experience significantly positive net flows over the subsequent year relative to funds that either increase these fees or leave them unchanged. For example, reducing net (operating) fees is associated with an increase in annual net flows of about 3.42% (3.28%) relative to increasing or maintaining current net (operating) fee levels. Increases in management fees do not predict positive future net flow, however, they also do not predict negative net flow. Thus, the changes in active incumbent fees associated with increased index fund entry appear to be rewarded by the typical investor through increased net flow.

Although my findings show a direct relationship between active fund net fees and factor index fund competition, casual inspection of Figure 1 might lead one to hypothesize that factor index competition has also had an indirect effect on actively managed net fees through increased exit rates. I test this conjecture by analyzing the relationship between active incumbent survival rates and the index entry overlap measures. I find that liquidation rates of actively managed funds are positively related to both factor and market index overlap measures. In line with my conjecture, the negative effect on liquidation rates is most prevalent for active funds that charge net fees above the median of their actively managed peers. These findings are, to the best of my knowledge, new to the literature.

In the final section I examine the performance implications. If markets are complete and frictionless, then composite assets (i.e., mutual funds and ETFs) are redundant and do not impact the prices of their constituent securities. Nonetheless, theoretical and empirical evidence suggests otherwise. [4] Moreover, Hoberg, Kumar and Prabhala (2018) and Wahal and Wang (2011) find that competition amongst active funds has a moderating effect on performance. Factor index funds seek active risk exposure which is, at least in some cases, similar to the active risk exposure offered by active mutual funds. Presumably, increases in the number of investors trading on a given risk factor reduces the associated profitability. I therefore expect that the increase in factor-based trading associated with factor index fund entry is detrimental to the performance of actively managed incumbents.

Ex-ante, the effect of market index fund entry on the performance of actively managed funds is not overly clear. On the one hand, buying and selling by passive market index funds is based solely on market-capitalization rather than fundamental values which may provide active managers with opportunities to capitalize on mis-priced securities. On the other hand, institutional investors have been shown to hold relatively large proportions of stocks held in common indices (Dannhauser, 2017) and to reduce information asymmetries and pricing inefficiencies in the stocks they hold (Bartov, Rad-

[4] Basak, and Pavlova (2013) provide theoretical evidence that institutional investors have incentive to tilt their portfolios toward benchmark constituents which amplifies prices, volatility and return correlation of constituent stocks and overall market volatility which are supported empirically by Dannhauser (2017) and Boone and White (2015). Additions (deletions) from large indices have been found to increase (decrease): prices, correlations and trading volume with other constituent stocks (Chen, Noronha and Singal , 2004; Greenwood and Sosner, 2007). ETF activity has been shown to have similar effects (Da and Shive, 2018; Ben-David, Franzoni and Moussawi, 2018).

hakrishnan and Krinsky, 2000; Boehmer and Kelley, 2009; Boone and White, 2015). In this case, it should be more difficult for active managers to identify mis-priced securities.

I find some evidence that index fund entry is detrimental to the future performance of actively managed mutual funds. For instance, a one-standard deviation increase in factor index overlap is associated with a reduction in performance over the next 24 months between 17 and 38 basis point. In contrast, while I find a negative relationship between market index overlap and active incumbent future performance, the effect is not robust. Given that I have shown that higher index fund competition is positively related to future attrition, future performance cannot be estimated for the worst performing funds since returns are unavailable. My estimates are therefore conservative.

The main contribution of the current paper is to investigate whether index fund strategy interacts with competition in determining actively managed fees, survival rates and performance. In this respect, my research complements the vast literature that explores competition within the actively managed space.[5] In contrast, research examining the effects of index fund competition on actively managed mutual funds is sparse.

Two notable exceptions include Cremers, Ferreira, Matos and Starks (2016) and Sun (2020). The former performs a cross-country study on the relationship between index fund availability and active fund strategies and find that funds operating in countries with more explicit indexing have lower total shareholder costs and higher levels of active share. The latter finds that funds distributed through broker (direct) channels increase (decrease) total shareholder costs following entry of Vanguard index mutual funds launched between 1976 and 1998. My paper differs from these papers in a few distinct ways. First, my objective is to determine whether competition originating from factor index funds is distinct from competition arising from market index funds in the US equity market, which is not addressed by previous studies. Sun (2020) analyzes the first wave of open-ended index funds offered by the ”Walmart” of the index fund industry over a period in which: 1) the average actively managed net fee was stable and 2) ETFs were relatively non-existent. In contrast, I examine a period over which there was a proliferation of ETFs and more elaborate factor-based indexing, as well as

[5]Noteworthy studies on competition between actively managed funds include: Coates and Hubbard (2007), Gil-Bazo and Ruiz-Verdu (2009), Wahal and Wang (2011), Ellis and Underwood (2018), Hoberg, Kumar and Prabhala (2018), Khorana and Servaes (2012) and Hortaçsu and Syverson (2004).

an observable reduction in the average net fee charged by actively managed mutual funds. Thus, Sun's objective was to explain the lack of observable reduction in average actively managed net fees over sample period, while mine is to explain the recently observed reduction.

Other notable differences include the methodological approach and specific tests performed. For instance, I not only provide evidence that index fund competition has had a negative effect on total net fees, but show which components are responsible for the reduction. Moreover, I provide evidence on how index fund entry has impacted active fund exit rates and offer an indirect channel through which active net fees have been affected, neither of which were addressed in Cremers, Ferreira, Matos and Starks (2016) or Sun (2020). Lastly, I close by examining the performance implications whereas the prior two papers concentrate on investigating activeness.

The remainder of this paper is as follows. Section 2 describes the data and sample construction. Section 3, presents the results and Section 4 offers concluding remarks.

2 Data and variable construction

2.1 Data

The mutual fund data is from Morningstar Direct's Mutual Fund Database over the period 1998 to 2018. To avoid survivorship bias, I include live and defunct funds. The sample of actively managed funds is restricted to domestic equity-only funds sold in the US since this asset class has suffered more pronounced declines in assets under management relative to fixed income or international/global equity funds. Accordingly, I include only funds that fall into one of the following Morningstar classifications: small blend, small growth, small value, mid-cap blend, mid-cap growth, mid-cap value, large blend, large growth, and large value. This filter eliminates: bond funds, money market funds, international funds, funds of funds, sector funds, real estate funds and life-cycle funds. I use Morningstar identifiers to confirm that the sample of active funds is free from: index funds, leveraged funds, fund-of-funds, feeder funds and life cycle funds.

Mutual funds often offer multiple share classes of the same fund. Individual share classes of a given fund are managed by the same manager and provide claims to the same portfolio of assets. The primary difference between share classes is their fee structure. For example, institutional share classes generally charge lower fees than retail share classes. Therefore, I aggregate all share classes of the same fund. I compute fund assets under management (AUM) by summing the AUM across a fund's share classes and aggregate share class level characteristics using AUM weighted averages. I collect quarterly holdings data from Morningstar which includes all equity positions and their associated CUSIP, as well as other non-equity positions; including bond and option holdings. I link Morningstar holdings data to the CRSP stock database by security CUSIP.

Pastor, Stambaugh and Taylor (2015) find that instances of extreme reversal patterns exist in net asset data provided by Morningstar and that it is likely due to decimal-place mistakes. I follow their methodology to identify these observations and treat reversals as missing values.[6] As is standard in the mutual fund literature (e.g., Evans, 2010; Kacperczyk et al., 2014 among others), I address the potential bias that results from fund incubation periods being included in the mutual fund databases by eliminating observations prior to a fund's inception date.[7] In addition, a fund is included in the sample only after it's aggregate AUM across all share classes passes a threshold of $10 million. Funds that fall below $10 million are not subsequently deleted. The resulting data set contains 2914 actively managed US equity funds.

Evidence in Sun (2020) suggests that fund responses to changes in competition might differ based on distribution channel. I classify funds as either direct- or broker-sold following Christoffersen, Evans and Musto (2013). This methodology relies on data from fund semi-annual reports (form N-SAR) filed with the Securities and Exchange Commission (SEC). Christoffersen, Evans and Musto (2013) describes the N-SAR data in detail, so here I focus primarily on how I define broker-sold funds. The N-SAR form reports mutual fund data on combined share classes (i.e., at the aggregate fund level). Thus, the classification is at the fund level rather than the share class level.

[6] The precise methodology is described on page 10 of the online data appendix for Pastor, Stambaugh and Taylor (2015).

[7] The inception date given in the Morningstar Direct database provides the first date that the fund was listed.

Fund i is defined as broker-sold if, over the prior fiscal year, it received loads through unaffiliated brokers/dealers (N-SAR Q32 > 0) or through captive broker/dealers (N-SAR Q33 > 0). I merge the N-SAR data to the aggregated Morningstar by fund name, and confirm imperfect name matches by checking the difference between net assets reported by each database.

2.1.1 Market and factor index funds

This sub-section describes how I construct the samples of market and factor index funds. Open-ended index funds and ETFs differ primarily by structure and, depending on the type account in which they are held, tax implications. Nevertheless, they offer exposure to similar, and often times the same, indexes, charge comparable fees, and have been shown to be substitutes (Agapova, 2011). I therefore do not explicitly differentiate between open-ended index funds and ETFs.

The sample of open-ended index funds and ETFs comes from Morningstar Direct and is selected in a manner that is consistent with the sample of active mutual funds with respect to asset class and end-investor. In specific, my objective is to select the sub-set of US equity index funds, both open-ended and exchanged traded, that are most likely to be considered as alternatives to the sample of actively managed mutual funds. I collect all live and defunct ETFs and open-ended funds flagged as index funds by Morningstar between 1998 and 2018. ETFs sold in the US over this period were required to disclose portfolio holdings on a daily basis which led to the vast majority being structured as index funds. In any case, I use Morningstar's actively managed flag to remove all actively managed ETFs. I also remove all ETFs that are not sold on a US exchange to keep the end investor consistent across samples. Similarly, I exclude all open-ended index funds that are not registered for sale in the US. Lastly, I remove leveraged funds, life-cycle funds, and funds that do not invest primarily in US equity.

Next, I classify funds as either a market index fund or a factor index fund. Market index funds track broad market indexes using market capitalization weighting schemes.[8] In contrast, factor index funds generally seek to enhance returns by tracking bench-

[8] Common examples of broad market indexes include: Russell 1000 and 3000, S&P 500, Wilshire 5000 total market, CRSP US Large Cap and CRSP US total market.

marks that provide active risk exposure, for example, momentum and volatility factors or firm fundamentals. I use Morningstar's strategic beta flag as a starting point – all index funds Morningstar flags as strategic beta are defined as factor index funds. As noted in Broman (2019), this filter fails to account for a number of factor-based index funds. I manually examine fund names, stated benchmarks and objectives to classify the remaining index funds as either market index or factor index.[9] Lastly, I remove any funds where the first reported holdings date is more than 18 months after the fund's reported inception date but note that my main results are robust to more stringent restrictions. Applying these filters results in 151 market index funds and 552 factor index funds.

2.2 Definition of variables

2.2.1 Measuring competition

Various methodologies for studying the effects of fund competition have been proposed in prior literature. Self-disclosed benchmarks provide a simple method for inferring a fund's investment universe but are not strictly regulated. Moreover, they are not suitable for identifying fund style since they do not necessarily coincide with holdings-based style metrics.[10] Morningstar institutional categories are intended to help institutional investors identify peer groups (Box, Davis and Fuller, 2018) but are static and therefore problematic since fund styles vary over time.

In this paper, I use a variation of the holdings overlap measure proposed by Wahal and Wang (2011). This measure is based on the ratio of the market value of overlapping securities in entrant's and incumbent's portfolios, with each ratio being multiplied by the weight of the overlapping security in the incumbent's portfolio. This provides a measure of the degree of competition between entrants and incumbents based on the substitutability of their products (portfolios), and effectively assumes that investors behave as if they observe fund holdings. The latter may seem problematic, however, prior evidence indicates that many investors are interested in fund holdings. For example,

[9] I am grateful to Markus Broman for providing me an initial list of manual classifications. I extend this list since our samples are not identical.

[10] For example, see Sensoy (2009) and Cremers and Petajisto (2009).

Solomon, Soltes and Sosyura (2014) find that flows are related to returns on individual holdings, particularly holdings with recent media coverage.[11] Furthermore, prior evidence indicates that managers engage in window dressing and that this behaviour can ultimately influence investor flows (Agarwal, Gay and Ling, 2014). Lastly, the most relevant portion of a fund's portfolio (i.e., the most heavily weighted stocks) is readily available to investors at no cost through public sources (e.g., Morningstar's website).[12]

The calculation and notation are as follows. $MVO_{i,t}$ denotes the average market value of overlapping securities between active incumbent i and new entrants $e = 1, 2, ..., N$ during quarter t. I calculate the measure separately for each type of entrant: factor index fund entrants ($Factor\ Index\ MVO_{i,t}$), market index fund entrants ($Market\ Index\ MVO_{i,t}$) and actively managed mutual fund entrants ($Active\ MVO_{i,t}$), but discuss only the general construction for concision. I include $Active\ MVO_{i,t}$ in my analysis to control for the competitive effects from actively managed entrants.

Let $s = 1, ..., M$ denote the subset of securities that exist in both the incumbent's and entrant's portfolio. Let $j = 1, ..., K$ denote the full set of securities in active incumbent i's portfolio. The overlap measure is then computed as:

$$w_{i,e,s,t} = \left(\frac{P_{e,s,t} S_{e,s,t}}{P_{i,s,t-1} S_{i,s,t-1}}\right)\left(\frac{P_{i,s,t-1} S_{i,s,t-1}}{\sum_{j=1}^{K} P_{i,j,t-1} S_{i,j,t-1}}\right) \tag{III.1}$$

$$MVO_{i,t} = \frac{1}{N} \sum_{e=1}^{N} \sum_{s=1}^{M} w_{i,e,s,t} \tag{III.2}$$

where $P_{i,s,t}$ ($P_{e,s,t}$) is equal to the price of overlapping security s at the beginning of quarter t. The subscripts e and i are used to denote the entrant and incumbent respectively. $S_{i,s,t}$ and $S_{e,s,t}$ denote the number of shares of stock s in incumbent i's and entrant e's portfolio at the beginning of quarter t respectively. The weight, $w_{i,e,s,t}$, is the ratio of the dollar value of overlapping security s, scaled by the weight of security s in the incumbent's portfolio. The first term in $w_{i,e,s,t}$ accounts for the relative market value of the overlapping security. The second term accounts for the relative importance of the overlapping security in the incumbent's portfolio. $MVO_{i,t}$ is calculated by

[11] Solomon, Soltes and Sosyura (2014) also note that Morningstar indicates that 42% of retail investors would prefer holdings to be disclosed more frequently.

[12] Page 44 in Wahal and Wang (2011) provides a similar discussion.

summing the weights ($w_{i,e,s,t}$) for all overlapping securities between incumbent i and entrant e and then averaging across all entrants. I remove entrants with zero holdings overlap from the calculation. This eliminates the impact of entrants that have zero overlap with an incumbent. Unlike, Wahal and Wang (2011) I define entry dates as 6 months after the entrant's reported inception date and include the subsequent two quarters in the calculation. This is important since a large portion of the index funds in my sample are ETFs, which, as shown by Broman and Shum (2018) take time to establish liquidity. Investors, and active incumbent's, are less likely to consider funds that are still establishing liquidity as a viable substitute and competitive threat respectively. Less importantly, I use the average overlap measure over the prior year when estimating annual regressions.[13]

Rather than treating all entrants within a certain group (e.g., investment category or region of sale) as equally important, the overlap approach measures the intensity of competition based on the similarity between entrant and incumbent portfolios. This is important since incumbents that have high portfolio overlap with entrants are more likely to face increased competitive pressure relative to incumbents that have more unique portfolios. By using market values, this approach also addresses an important element of competition – large entrants, and particularly the size of their overlapping holdings, are more of a competitive threat than small entrants.

2.2.2 Fund performance

When studying the impact of index fund entry of active incumbent future performance, I measure fund performance relative to factor models or style benchmark indices. For factor models, I use the capital asset pricing model (CAPM), and the 4-factor model (4F) from Carhart (1997). I estimate factor loadings with rolling 36 month windows and use the US equity factors provided on Fama and French's website.

Evans, Gomez, Ma and Tang (2020) document that fund managers are evaluated based on their performance relative to pure index benchmarks, peer group benchmarks, or both. I therefore include benchmark adjusted returns and the equal weighted

[13] My main results are numerically similar when using alternative constructions. For example, defining various entry windows and, to a lesser extent, restricting the calculation to incumbent-entrant pairs that are located in the same Morningstar style box.

peer benchmark adjusted returns in assessing fund performance. Peer benchmark adjusted returns are equal to the difference between fund i's gross return and the equally weighted gross return of its peer group based on Morningstar categories. Benchmark adjusted returns use traded style benchmarks provided by Morningstar. Morningstar classifies US equity funds into nine different categories based on style and assigns a benchmark portfolio to each category[14] that is defined based on actual fund holdings meaning it does not suffer from any self selection bias. Pastor, Stambaugh and Taylor (2015) and Zhu (2018) suggest the use of Morningstar benchmark portfolios over factor models (e.g. Fama-French factors) since the former are accessible to the typical investor while the latter are not. These benchmarks are also free from the "cherry-picking bias" associated with prospectus benchmarks (Sensoy, 2009) and, as argued by Cremers, Petajisto and Zitzewitz (2013) and Pastor, Stambaugh and Taylor (2015), index-based benchmarks are more likely to capture style and risk than the Fama-French factors.

2.3 Descriptive statistics

Table 1 presents the time series variation in: the number of existing funds, new entries, total net assets and the equally weighted net expense ratio. Statistics are grouped by three fund types: actively managed mutual funds (Active), factor index funds (Factor) and market index funds (Market). Entry dates are identified using the inception date of each fund's oldest share class. Statistics on the number of existing funds, total AUM and net expense ratios are calculated using all funds with non-missing net asset data. Note that some funds shown in this table are removed from my main analysis due to missing data. I present this broader sample to provide a more complete picture of the US equity fund industry.

Consistent with the aggregate flow statistics in Figure 1, the past two decades have seen a substantial increase in the number of index funds, reflected by both the number

[14] The categories are based on size and the book-to-market ratio of the stocks held. The specific benchmark indices and associated styles are: Russell 1000 Total Return for large blend, Russell 1000 Growth Total Return for large growth, Russell 1000 Value Total Return Index for large value, S&P 400 Mid Cap Total Return for mid blend, Russell Mid Cap Growth Total Return for mid growth, Russell Mid Cap Value Total Return for mid value, Russell 2000 Total Return for small blend, Russell 2000 Growth Total Return for small growth and Russell 2000 Value Total Return for small value.

of new entries and the number of existing funds. For example, the number of existing factor (market) index funds increases from 16 (46) in 1998 to 485 (152) in 2018. Similarly, the number of existing, and newly launched, active funds increases until around 2009, at which point it starts to decline.

[Table 1]

The size of each market segment, AUM (Billions USD), is also illuminating. As of the end of 1998, the total amount of net assets invested in market index funds was approximately 11 times the total net assets invested in factor index funds. By the end of 2018 this number was closer to 2. The equally weighted expense ratios (EW Net Expense) highlight the cost differential between active and passive management as well as the additional cost associated with factor indexing relative to market indexing. In addition, the decline in average active fund expense ratios from 1998 to 2018 is quite large at 24 basis points. In sum, the observed patterns in Table 1 roughly coincide with the concept that average actively managed net fees have declined with the growth of passive index investing.

Before proceeding to my empirical tests, I provide some basic summary statistics on the variables used in this paper. Table 2 presents the distributions over the full sample period. The median factor index MVO and market index MVO are 0.062 and 0.125 respectively, both of which are well below their means (0.306 and 0.724 respectively). As noted in Wahal and Wang (2011), this variation is important as funds with high overlap are expected to face stronger competitive pressure than incumbents with little overlap.

[Table 2]

The average annual net fee is approximately equal to 1.14% of fund net assets. Management fees make up the largest portion of net expenses at 0.69%, while operating fees and distribution fees are generally smaller at 0.20% and 0.25% per year respectively. Performance measures (benchmark adjusted returns and alphas) are stated as annual percentage returns gross of fees. The average benchmark adjusted return is approximately 0.74% per year while the mean 3- and 4-factor alphas are slightly lower at 0.637% and 0.412% per year respectively. Given the average net expense ratio is 1.14%, the average after fee performance is indeed negative. The equally weighted peer benchmark return (Peer Bmk. Adj. Ret.) is closer to zero at 0.024% per year. The average fund in my sample has about 1.6 billion in assets under management, 30% of which is in an institutional class, and is approximately 154 months old.

3 Empirical results

3.1 Strategic fee adjustment

In this section I investigate the consequences of index fund entry overlap on actively managed fee decisions. Factor index funds offer investors active risk exposure at a considerable discount relative to actively managed mutual funds. It is therefore reasonable to expect that factor index competition has put negative pressure on actively managed net fees. In contrast, the packaging of active risk exposure into a passive product is a relatively new concept which suggests an increase in product diversity and investor search costs. Thus, the expected relationship between factor index overlap and changes in active fund net fees is ambiguous. Market index funds are another low-cost alternative to active management but are distinct from actively managed funds in that they provide diversified exposure to market beta rather than active risk exposure. Despite these differences, questions regarding relative performance suggest that actively managed net fees are likely to be negatively related to market index fund overlap.

Fee changes require approval from the fund's board of trustees and typically occur on an annual basis. I therefore examine fees change over the two years following the entry of a new index fund competitor but reproduce the primary results for three- and four-year changes in Table A2 of the appendix. I proceed by regressing changes in active fund net fees over the next two years (t to $t+2$) on the average overlap measures over the prior year, control variables and fixed effects:

$$\Delta Fee_{i,t:t+2} = \alpha + \beta_1 FactorIndex\ MVO_{i,t} + \beta_2 MarketIndex\ MVO_{i,t} + \beta_3 Active\ MVO_{i,t} + \boldsymbol{\gamma} \times C_{i,t} + v_t + z_s + \epsilon_{i,t} \tag{III.3}$$

The dependent variable, $\Delta Fee_{i,t:t+2}$, is the change in fund i's fee from year t to year $t+2$. The control variables, $C_{i,t}$, include: turnover, the standard deviation of gross returns over the prior 24 months (std.(Gross Ret.)), fund size as measured by the natural log of net assets (ln(AUM)), the equally weighted peer benchmark adjusted return compounded over the prior year (Peer Bmk. Adj. Ret.), and the natural log of a fund's age in months (ln(Age)). The explanatory variables of interest, factor index overlap ($Factor\ Index\ MVO_{i,t}$) and market index overlap ($Market\ Index\ MVO_{i,t}$), are equal to the average overlap measures over the prior fiscal year ($t-1$ to t).

All specifications are estimated with year fixed effects (v_t) to control for unobserved heterogeneity in the cross-section of funds over time. Additionally, I control for fund (Panel A) and style fixed effects (Panel B) to account for fund and style specific differences in fee changes (z_s). I address the concern that errors might be correlated within funds or across time by estimating standard errors that allow for clustering along the fund and year dimensions (shown in parentheses). I employ two main specifications in my baseline regressions. First, I concentrate solely on index competition by analyzing the effects of the two index overlap measures. Next, I ensure that I am not picking up the direct effects of active competition by controlling for the active overlap measure.

Panel A of Table 3 reports the results from estimating Equation III.3 with fund and year fixed effects. To ease interpretation of the overlap measures, I report average marginal effects and their associated t-statistics instead of the raw coefficient estimates. The results suggest that the negative effect on fees arising from cheap, factor-based, alternatives outweighs any increase in investor search costs. In particular, factor index overlap has a significantly negative effect on two-year changes in net fees ($\Delta Net\ Fee_{i,t:t+2}$). A one-standard deviation change in factor index overlap is associated with a reduction in net fees of around 1.1 basis points. Although this represents only a fraction of the observed reduction in actively managed net fees over my sample period, evidence presented in later sections shows that this is only part of the story. In contrast, market index overlap is not significantly related to future changes in net fees.

[Table 3]

Net fees can be decomposed into management fees, distribution fees, and other operating fees. Management fees are the proportion of fund net assets used to compensate the portfolio manager(s) and, unlike net fees, provide a purer price of a fund's investment performance. Fund's facing increased competition should have a reduced ability to extract profit through management fees which suggests competition should negatively affect changes in management fees. That said, total manager revenue is equal to assets under management multiplied by the management fee. Thus, the large withdrawals from actively managed US equity funds, shown in Figure 1, indicate a considerable reduction in the compensation paid to active managers. Since managers require some base level of compensation, the relationship between management fees and index competition could instead be positive.

The other two fee components are distribution fees and operating expenses. Distribution fees are comprised of marketing and distributing costs and are often used as a commission to brokers for selling the fund. Operating fees include accounting, administrator, auditor, board of directors, custodial, legal, organizational, professional, registration, shareholder reporting, and transfer agency fees. Ex-ante, index fund competition is expected to be positively related to distribution fees as they are generally used to generate investor attention. The expected effect on operating fees is ambiguous as it is unclear how index competition effects the supply and demand for the types of services they include.

The results show that both factor and market index overlap are positively related to changes in active incumbent management fees ($\Delta Mgmt.Fee_{i,t:t+2}$), negatively related to future changes in operating fees ($\Delta OperatingFees_{i,t:t+2}$) and generally unrelated to changes in distribution fees ($\Delta Dist.Fee_{i,t:t+2}$). The magnitudes of the changes in management and operating fees are also quite large. For instance, a one-standard deviation increase in factor index MVO is associated with a 3.36 basis point increase in management fees which represents almost 5% of the sample average (68.7 basis points). Similarly, a one-standard deviation increase in factor index MVO is associated with a 4.57 basis point reduction in operating fees which is around 20% of the sample average. While the change in operating fees may seem excessive relative to the mean, results in the subsequent sub-section show that this effect is restricted to funds that incur relatively high operating expenses to begin with. In short, the reduction in net fees associated with factor index competition is due to reductions in operating fees.

In some cases, fund managers contractually agree to waive/reimburse expenses above and beyond a pre-specified threshold. Alternatively, fee waivers can be used as a discretionary tool by fund companies to temporarily improve their net performance (Christoffersen, 2001). While they are not meant to permanent, active funds may use waivers in response to increased index fund competition to improve net performance, thereby increasing expected fund flows. I estimate the probability that a fund uses a waiver in the next year with a logistic regression. The dependent variable, Prob.(Waiver$_{i,t+1}$), is an indicator that is equal to one if a fund uses an expense waivers in year $t + 1$ and zero otherwise. As with distribution fees, neither factor nor market index MVO are significantly related to active incumbent fee waivers.

In Panel B of Table 3, I replace fund fixed effects with style fixed effects. Although the t-statistics are generally smaller, the main results are still significant at the one percent level. In unreported results, I find that the main results are also robust to alternative clustering specifications. Moreover, separating the sample into broker- and direct-sold funds does not significantly alter my findings. I find that restricting the sample to the pre-2005 period yields results similar to Sun (2020) – factor index fund entry is associate with an increase in net expense ratios for broker-sold funds and no significant change for direct-sold funds. Differences in results could be due to variations in methodologies, sampling period and the type of index funds considered. For example, Sun (2020) concentrates solely on Vanguard index mutual funds whereas I include a broad sample of index mutual funds and ETFs investing in US equities that are sold in the US. Additionally, there is very little overlap in the entry dates of index funds between our samples.

3.1.1 Fee change explanations

In this sub-section I investigate explanations for the relationships between fee changes and index competition. Intuitively, the observed relationships should be a function of various fund characteristics. For example, investors have gravitated towards relatively cheap funds over the past two decades[15] which suggests that funds charging fees above the average (median) charged by their actively managed peers have the strong incen-

[15]By the end of 2019, actively managed funds in the lowest expense ratio quartile held 73 percent of actively managed fund assets (Investment Company Institute Factbook 2020, Chapter 6).

tives to reduce fees, particularly in response to entry of new low-cost index funds that offer exposure to similar stocks. Thus, I expect the positive (negative) relationship between index fund overlap and actively managed management (net and operating) fees from Panel A to be confined to funds that charge relatively low (high) fees to begin with. I test this conjecture by interacting index overlap measures with fee indicators, denoted by $High\ Fee_{i,t}$, that are equal to one if fund i charges a fee above the median fee charged by all other active funds in the same Morningstar style box, in year t, and zero otherwise. To be clear, the $High\ Fee_{i,t}$ indicators in Panels C and D of Table 3 coincide with the dependent variable under consideration.

The results from interacting high fee indicators with factor index overlap are shown in Panel C of Table 3. I include all control variables from Panel A, but report only the coefficients on the overlap measures and their interaction effects to conserve space. The results generally support my conjecture. The observed fee increases (decreases) associated with the factor index overlap measure are restricted to funds that charge below (above) the median fee charged by their active peers. For example, the coefficient estimate on $Factor\ Index\ MVO_{i,t} \times HighFee$ in the net fee regression is -0.0152 and is significant at the 1 percent level, while the coefficient on $Factor\ Index\ MVO_{i,t}$ is now positive but insignificant. The implication is that the relatively expensive active funds respond to increased factor index competition by reducing net fees while the least expensive funds do not make any significant changes. A 1.5 basis point may not seem overly meaningful; however, it represents approximately 6.3% of the total reduction in average net fees observed over my sampling period.

The results for the interactions between factor index overlap measures and the various fee components are largely similar to the net fee results. The increase (decrease) in management (operating) fees is restricted to funds that charge below (above) the median charged by their peers. Moreover, the interaction between $Factor\ Index\ MVO_{i,t}$ and the high distribution fee indicator is significantly negative while $Factor\ Index\ MVO_{i,t}$ is now significantly positive. This helps explain the somewhat puzzling finding of no significant relationship between distribution fees and index fund competition. An interesting implication of these results is that factor index competition appears to be driving net fees, and their various components, towards the peer group median.

Next, I investigate the role of past performance. My hypothesis is that the positive relationship between management fees and factor index fund competition should be related to prior performance. That is, the funds that increase management fees in response to index fund entry are expected to have outperformed their peers in the recent past. Gil-Bazo and Ruiz-Verdu (2009) document that funds with worse before-fee performance strategically charge higher fees. Their findings suggest that poorly performing charge higher fees due to relatively performance insensitive investors while better-performing funds have performance sensitive investors and therefore engage in price competition. This suggests that the effect of increased availability of low-cost factor index funds on net fees should be most pronounced for active funds that have sophisticated, performance sensitive investors and is therefore expected to exacerbate this puzzle. The effects on operating and distribution fees are less clear.

Evans, Gomez, Ma and Tang (2020) show that fund managers are evaluated based on their performance relative to peer funds in a similar style, pure index benchmarks, or both. I therefore measure performance using benchmark-adjusted returns or the equal-weighted peer benchmark-adjusted returns compounded over the prior 12 months. I present results using equal-weighted peer benchmark-adjusted returns ($Peer\ Bmk.\ Adj.\ Ret._{i,t}$) but note that the results are numerically similar, though statistically weaker, when using benchmark-adjusted returns.

The results are consistent with the conjecture that factor index competition does not alleviate the fee-performance puzzle identified in Gil-Bazo and Ruiz-Verdu (2009) – the negative relation between changes in net fee and factor index competition is most pronounced for better-performing funds. The influence of peer benchmark-adjusted performance on the relation between factor index overlap and changes in management fees is also in line with my predictions – the top performing funds increase their management fees the most. Lastly, reductions in operating fees are also most pronounced for funds that have performed well relative to their peers.

The interaction effects of market index overlap and high fee dummies, reported in Panel D of Table 3, are generally similar to those reported in Panel C for factor index overlap interactions. That is, market index overlap seems to drive fees towards their peer group median. In contrast, the interaction between index overlap and past performance does not significantly effect changes in fees.

The results in this section show that both market index fund competition and factor index fund competition are positively related to future changes in management funds, but negatively related to future changes in operating fees. With market index fund competition, the effects are offsetting which results in no significant change in net fees. In contrast, the increase in management fees associated with factor index fund competition is more than offset by a reduction in operating fees, resulting in a negative effect on net fees. Moreover, retaining talented managers is exceedingly important in the actively managed equity space. Active managers who have performed well in the face of increased competition from cheap alternatives are rewarded through increased management fees. When taking stock of the survivorship bias associated with looking at future changes in fees this finding is quite intuitive. Lastly, my findings indicate that competitive pressure from index funds has helped to drive active fees towards their peer group median. To the best of my knowledge, this finding is new to the literature.

3.1.2 Investor response to fee changes

In this sub-section I investigate how investors respond to the changes in fund fees associated with index entrant overlap in Section 3.1. The objective is to determine whether the observed relationships between fund fee changes and market/factor index overlap measures are consistent with flow optimizing behavior. To answer this question, I construct dummy variables based on changes in fees over the prior two years. The direction of the fee change is set to correspond to the relationship between the fee in question and the index overlap measures from Panel A in Table 3. For example, $Increase\ Mgmt.\ Fee_{i,t}$ is equal to one if fund i increased it's management fee over the prior two years and zero otherwise. I measure monthly dollar flow following the approach in Sirri and Tufano (1998) and obtain forward dollar flows by adding monthly flows over the next one, two and four quarters. Percentage flow is calculated by dividing forward dollar flows by the fund's current period net assets. I then regress forward percentage flow on the fee change indicators, a set of control variables and fixed effects:

$$Flow_{i,t:t+T} = \alpha + \beta_1 Reduce\ Net\ Fee_{i,t} + \gamma C_{i,t} + v_t + z_s + \epsilon_{i,t} \tag{III.4}$$

$$Flow_{i,t:t+T} = \alpha + \beta_1 Increase\ Mgmt.\ Fee_{i,t} + \beta_3 Reduce\ Operating\ Fee_{i,t} + \beta_3 Increase\ Dist.\ Fee_{i,t} + \gamma C_{i,t} + v_t + z_s + \epsilon_{i,t} \tag{III.5}$$

$Flow_{i,t:t+T}$ denotes cumulative flow (in percent) from quarter t to T, with T equal to t plus one, two or four quarters. The control variables, $C_{i,t}$, include variables shown to influence flows by prior literature: size, age, net fees, turnover, return volatility, performance and tracking error. I account for past performance using CAPM alpha compounded over the prior year as prior research has shown that CAPM outperforms other models in explaining investor capital allocation decision (Berk and Binsberger, 2015; Barber, Huang and Odean, 2016).[16] The remaining control variables are as defined in Section 3.1. I account for style and fund specific differences in net flow by including style or fund fixed funds, z_s, and allow for time specific differences by including time fixed effects, v_t. To address the concern that errors might be correlated within styles or time periods, I cluster standard errors by fund style and year-quarter. To minimize the impact of outliers, I winsorize all control variables at the 1st and 99th percentiles. I winsorize net flow at the 1st and 98th percentile since the positive side is extremely volatile. The results I present are robust to winsorizing net flow measures using other methods proposed in the literature, (e.g., winsorizing observations where the net fund flow percentage is larger than 300% in a year as in Sun, 2020).

The results in Panel A of Table 4 show that the relationships between fund fee changes and factor index fund entry are generally consistent with flow optimizing behavior. Reducing net fees, and particularly operating fees, is associated with positive net flow over the next year. For example, the estimated coefficient on $Decrease\ Net\ Fee_{i,t}$ is 1.0003 when predicting fund net flow over the next quarter ($Net\ Flow_{i,t:t+1}$) and 3.4241 when predicting fund net flow over the next year ($Net\ Flow_{i,t:t+4}$). These values translate to increases in net flow of about 1 and 3.4 percent over the next quarter and year respectively. The estimated coefficients on $Increase\ Mgmt.\ Fee_{i,t}$ are positive, but insignificant.

[16] I find numerically similar results when accounting the asymmetrical relationship between flows and past performance (Ippolito, 1992; Sirri and Tufano, 1998) when using Morningstar fund ratings which follows Del Guercio and Tkac (2008) who provide evidence that Morningstar fund ratings have a causal impact on fund flows.

[Table 4]

In Panel B of Table 4, I show that the results in Panel A are robust to replacing fund fixed effects with style fixed effects. The regression specifications are otherwise the same, but I omit control variable coefficient estimates for concision. In unreported results, I find that the results are also robust to clustering standard errors along alternate dimensions. Thus, the results in this sub-section suggest that the changes in fees made by active funds following entry of similar factor or market index funds are rational in the sense that they are consistent with optimizing net flow. That is, investors respond positively through increased net flow.

3.2 Active Incumbent attrition

In this section I study the impact of index fund entry on active fund attrition rates. Morningstar Direct identifies the exact date and reason for exit which allows me to study liquidations and mergers separately. Funds frequently merge or liquidate single share classes in which case the portfolio still exists. For this reason, I consider exits at the fund level rather than the share class level.

I start by sorting all active funds into quintiles based on the average factor index, market index and active overlap measures over the prior year. Sorts are performed on an annual basis and I examine attrition rates over the next one, two and five years. The results are reported in Panel A of Table 5. There is no apparent relationship between active fund merger rates and any of the three overlap measures. On the other hand, liquidation rates monotonically increase with all three overlap measures. For example, the two-year (five-year) liquidation rate for funds in factor index MVO quintile 5 is 6.53% (14.95%), compared to 3.77% (9.31%) for funds in factor index MVO quintile 1.

The sorting exercise suggests that active fund liquidations are correlated with the entry of index funds that have relatively high post-entry holdings overlap. However, it is well known that various fund characteristics influence a fund's probability of exiting which could explain the differences in attrition rates shown in Panel A. For example, performance, size and inflows have been shown to be negatively related to mergers while net fees and age have been shown to be positively predict mergers (Jayaraman, Khorana and Nelling, 2002; Zhao, 2005). I additionally control for return volatility and tracking error since risk and activeness might influence exit. I proceed by estimating a Cox proportional hazard model:

$$Exit_{i,t} = h_{0,i,t}e^{(\beta_1 FactorIndex\ MVO_{i,t}+\beta_2 MarketIndex\ MVO_{i,t}+\beta_1 Active\ MVO_{i,t}+\beta_2 Controls_{i,t})} \quad \text{(III.6)}$$

The baseline hazard function, $h_{0,i,t}$, is year and style specific. Funds that survive until the end of the sample period are included as censored observations. To ease the interpretation of results, I report average marginal effects and their associated z-scores instead of the raw coefficient estimates. I estimate the covariance using the "sandwich estimator" developed in Lin and Wei (1989).[17] The control variables, size, return volatility, tracking error, age and net fees are as defined in Section 3.1. I control for fund performance using benchmark-adjusted returns compounded over the prior two years and fund flow using percentage net flows over the prior 6 months. To minimize the impact of outliers, I winsorize all control variables at the 1st and 99th percentiles.

[Table 5]

Panel B of Table 5 presents the hazard ratios and z-scores (in parentheses) from estimating equation III.6. Consistent with the univariate results, the factor index overlap measure has a positive and significant effect on liquidation rates and no significant effect on merger rates. A one-standard deviation increase in factor index overlap increases the implied probability of liquidation by between 16 and 21 percent. In contrast, market index fund overlap has a positive effect on both merger and liquidation rates, although the effect on merger rates is marginally significant. The magnitude of the effect on liquidations is again quite large – a one-standard deviation increase in market index MVO is associated with about a 28 percent increase in the baseline hazard ratio.

Next, I investigate whether index fund overlap measures interact with active incumbent relative net fees, and past performance, in predicting future exit rates. I contend that part of the reduction in actively managed average net fees over my sample period

[17]Results are very similar when specifying a parametric survival model with a Weibull distribution. The Weibull distribution also fits the data better than other commonly used distributions.

can be explained by increased exit rates of the most expensive funds following an increase in competition from low-cost index fund alternatives. In addition, I expect that funds that have performed well are more likely to be insulated from the index fund entry and are therefore less likely to be liquidated. I test these hypotheses by interacting benchmark adjusted returns compounded over the prior 24 months and the high net fee dummy variable defined in Section 3.1.1 with the market and factor index overlap measures.

The results generally support my conjectures – the positive effect of factor and market index fund competition on active incumbent liquidation rates is most severe for the funds that charge relatively high net expense ratios. The coefficient estimates on the interactions between the high net fee indicator and both factor and market index overlap measures are positive and significant at the 1 percent level. In contrast, there is only marginal evidence that liquidation rates are less pronounced for funds that have performed well over the prior 24 months. These findings, combined with the findings in Section 3.1, suggest that increased index fund competition has put negative pressure on active fund net fees both directly, through actual fee reductions, and indirectly through increased liquidation rates of the funds charging the highest net fees. Furthermore, the average net fee charged by active funds that exit, either through a liquidation or merger, my sample subsequent to 2010 is 1.19%. In contrast, the average actively managed entrant over the same time period charges a net fee of 0.97%.

3.3 Future performance

This section investigates the performance implications. My expectation is that entry of factor index funds negatively affects the performance of actively managed incumbents with high overlap as both chase active risk. In contrast, market index funds deliver passive exposure to the market portfolio. On the one hand, increased overlap with passive investors might enhance manager's ability to capitalize on mis-priced securities. On the other hand, it may reduce informational asymmetries, thereby making it more difficult to identify mis-priced securities. To provide an answer to these questions, I first estimate cumulative performance over the 8-quarters ($t : t+8$) after a new fund enters. I define performance using the Fama, French and Carhart 4-factor alpha, peer adjusted benchmark returns or benchmark adjusted returns. Next, I regress estimated post-entry performance on the three overlap measures, a standard set of control variables, year-quarter fixed effects and style or fund fixed effects. I estimate standard errors that allow for clustering along year and fund dimensions to account for residual dependence in a given year and within funds.

The results are shown in Table 6 with column headings specifying the dependent variable. In Panel A I include fund and year-quarter fixed effects while in Panel B I replace fund fixed effects with style fixed effects. As with the prior regressions, I report average marginal effects of overlap measures and their associated t-statistics instead of the raw coefficient estimates. Whether considering alpha, peer benchmark adjusted returns or benchmark adjusted returns, I find significant evidence that active incumbents with high factor index overlap underperform over the next two years. For example, the underperformance associated with a one-standard deviation increase in factor index overlap ranges between 17 basis points (4-factor alpha and controlling for style fixed effects) and 38 basis points (using the 4-factor alpha and controlling for fund fixed effects).[18] In contrast, the effects of market index overlap on future performance is restricted to peer benchmark adjusted returns.

[Table 6]

Active incumbents that have high overlap with factor index entrants chase performance by investing in a largely similar set of stocks. Thus, a possible explanation for the negative effect on future performance is that the future profitability of these assets diminishes as more investors invest in them. In this case, underperformance might be reflected by increased trading costs as more funds invest in the same set of securities. I test this latter conjecture by regressing active incumbent return gaps (Kacperczyk et al. (2008)) compounded over the 2 years after entry on the entrant overlap measures. As noted in Kacperczyk et al. (2008), the return gap measures the costs, or benefits, of managers unobserved actions. A large portion of the costs consist trading costs, e.g., the price impact of trade execution and trading commissions. In unreported results I find some support of my conjecture – factor index overlap is negatively related to future return gaps, however, the statistical significance is marginal at best.

[18]In unreported results, I find some evidence of underperformance over the next year. Results are also similar when measuring performance with 3-factor alpha.

4 Conclusion

In this paper, I study the consequences of increased index fund competition on actively managed mutual fund fees, survival, and performance. While there is ample anecdotal evidence supporting the conjecture that index competition has significantly affected the actively managed industry, this paper provides a rigorous empirical investigation. Importantly, I find that the competitive effects of index competition varies depending on the type of exposure offered, namely exposure to active risk or broad market beta. Measuring the intensity of index competition using entry/incumbent holdings overlap, I show that future changes in net fees are negatively related to factor index overlap but insignificantly related to market index overlap.

Decomposing net fees into their various components suggests that the reduction in net fees associated with factor index overlap is due to a reduction in operating expenses. However, investors only realize approximately one-quarter of this reduction as the rest is diminished by an accompanied increase in management fees. The effects of market index overlap on changes in operating fees is negative, but is completely offset by a positive changes in management fees.

The direct effect on net fees, or lack there of in the case of market index funds, is only part of the story. Competitive pressure from index funds has also had an indirect effect on actively managed net fees through increased liquidation rates. In particular, active incumbents charging relatively high net fees are more likely to be liquidated following entry of both factor and market index funds compared to active incumbents charging relatively low net fees.

Lastly, critics have argued that the substantial fee dispersion for nearly identical mutual funds that has existed for some time does not reflect pricing in a competitive market. The evidence in this paper indicates that increased availability of index funds, and particularly factor index funds, has not only contributed to the reduction in average net fees but has also led to a reduction in fee dispersion by helping to drive fees towards their peer group medians.

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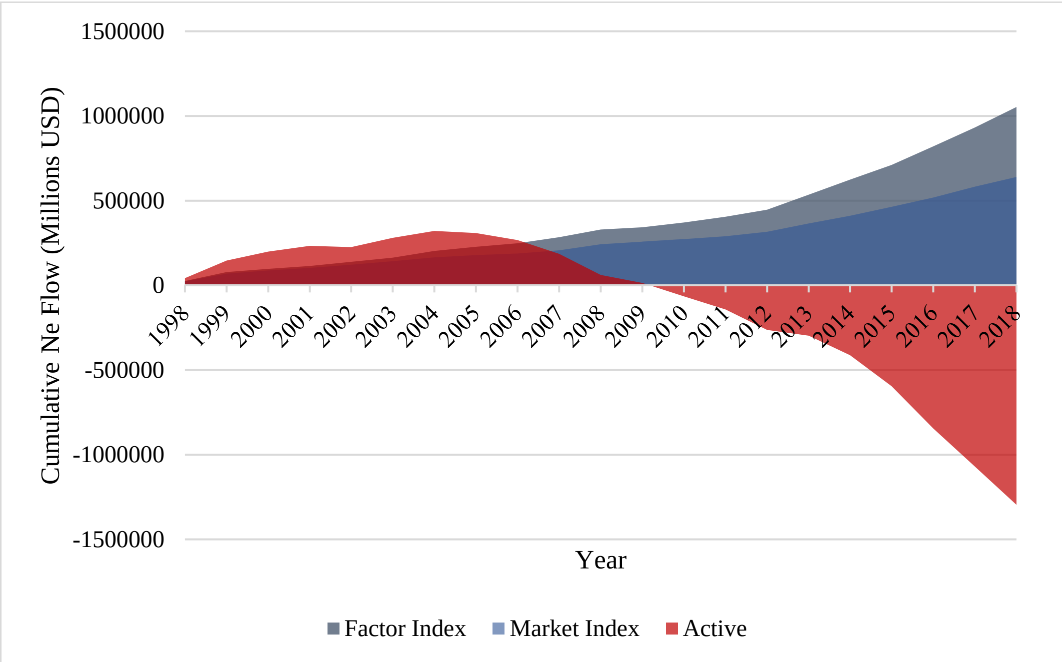
6 Figures

Figure 1: Cumulative Annual Flows by Fund Type

This figure presents cumulative dollar net flows, in millions of USD, from 1998 to 2018 for the three fund types used in this paper: actively managed mutual funds, market index funds and factor index funds. A complete description of how factor index funds differ from market index funds is provided in section 2.1.1.



7 Tables

Table 1: Sample Fund Entry Statistics

For each calendar year in my sample period, this table presents: 1) the number of new mutual funds created (entrants), 2) the number of existing funds (entrants plus incumbents), 3) the total AUM and iv) the equally weighted net expense ratio (EW Net Expense). Statistics are grouped by the three fund types: actively managed mutual funds, market index funds and factor index funds. Entry dates are defined as the inception date of a fund's oldest share class. A complete description of how factor index funds differ from market index funds is provided in section 2.1.1.

	Number of Existing Funds			Number of New Entries			AUM (Billions USD)			EW Net Expense (%)		
		Index			Index			Index			Index	
Year	Active	Factor	Market	Active	Factor	Market	Active	Factor	Market	Active	Factor	Market
1998	957	16	46	104	2	9	1505.9	16.9	190.7	1.28	0.55	0.42
1999	1059	17	59	102	2	13	1968.0	28.6	292.4	1.26	0.57	0.42
2000	1161	38	82	102	21	23	1937.6	29.7	312.4	1.30	0.40	0.43
2001	1308	49	95	147	10	11	1776.3	34.4	311.2	1.33	0.63	0.47
2002	1378	57	100	70	8	6	1398.4	34.2	264.1	1.31	0.64	0.47
2003	1464	68	106	86	11	5	1934.9	56.4	370.5	1.30	0.55	0.44
2004	1549	83	114	86	15	8	2268.1	89.5	435.6	1.27	0.57	0.43
2005	1673	102	117	125	19	4	2489.5	110.7	473.0	1.25	0.56	0.41
2006	1800	146	120	130	44	3	2829.4	149.3	549.3	1.21	0.55	0.41
2007	1906	190	124	107	45	5	2993.1	171.8	615.8	1.21	0.61	0.42
2008	1982	199	126	78	9	4	1737.5	124.1	435.3	1.27	0.58	0.40
2009	2018	207	137	51	12	11	2289.7	163.2	582.0	1.19	0.55	0.42
2010	2003	218	143	79	26	13	2537.9	215.4	697.4	1.17	0.53	0.37
2011	1972	257	148	74	46	8	2392.7	232.4	729.1	1.15	0.51	0.35
2012	1951	279	142	86	27	1	2597.5	286.4	868.3	1.12	0.51	0.34
2013	1948	274	132	105	25	3	3508.3	450.7	1178.4	1.09	0.50	0.32
2014	1938	297	130	77	28	4	3708.6	549.0	1389.7	1.08	0.50	0.32
2015	1953	352	139	62	58	12	3516.4	584.2	1444.8	1.07	0.48	0.31
2016	1950	396	142	63	48	6	3621.2	736.7	1690.1	1.05	0.44	0.32
2017	1922	464	146	61	87	10	4153.4	901.6	2100.9	1.02	0.42	0.30
2018	1894	485	152	44	34	12	3685.4	909.6	2054.7	1.04	0.42	0.30

Table 2: Descriptive Statistics

This table presents descriptive statistics on the annual sample of actively managed funds. The sampling period is from January 1998 to December 2018. Fees are reported as annual percentages of fund net assets. Benchmark adjusted returns (Bmk. Adj. Ret.), 3F alpha, 4F alpha and equal weighted peer benchmark adjusted returns (EW Peer Bmk. Adj. Ret.) are annualized returns expressed in %. Net flow is equal to annual percentage flows. AUM (Billions) is fund total net assets in billions of USD. % AUM Inst. Class is the proportion of fund assets that are in an institutional class. Age in months refers to a fund's oldest share class. Turnover is the lesser of the dollar value of purchases or sales divided by previous period assets under management. The standard deviation of gross returns (std.(Gross Ret.)) and tracking error are calculated using 24 months of return data.

	Mean	Std. Dev.	25th Pctl.	50th Pctl.	75th Pctl.
Overlap measures					
Factor Index MVO	0.306	0.519	0.012	0.062	0.323
Market Index MVO	0.724	1.258	0.022	0.125	0.732
Outcome variables					
Net Fee (%)	1.144	0.393	0.900	1.104	1.352
Mgmt. Fee (%)	0.687	0.341	0.556	0.728	0.888
Operating Fee (%)	0.199	0.399	0.001	0.165	0.327
Dist. Fee (%)	0.248	0.236	0	0.250	0.379
Bmk. Adj. Ret. (% p.a.)	0.743	18.004	-7.954	0.205	8.809
3F Alpha (% p.a.)	0.637	16.961	-7.724	0.219	8.134
4F Alpha (% p.a.)	0.412	15.271	-7.472	0.140	7.655
Peer Bmk. Adj. Ret. (% p.a.)	0.024	16.552	-7.805	0.076	7.961
Net Flow (% p.a.)	-0.446	13.353	-4.982	-1.855	2.193
Control variables					
AUM (Billions)	1.596	5.941	0.070	0.270	1.045
%AUM Inst. Class	0.296	0.381	0	0.039	0.634
Age (Months)	154	135	63	122	198
Turnover (%)	77	184	31	57	96
std.(Gross Ret.)	4.515	1.703	3.225	4.127	5.631
Tracking Error	1.514	0.963	0.892	1.274	1.820
Broker Sold	0.427	0.495	0	0	1

Table 3: Strategic Fee Adjustment

This table presents regressions of post-entry changes in active fund fees on the set of overlap measures and control variables. Dependent variables are given in column headers. Logistic regressions are used to predict the probability that fund i uses a fee waiver in the next period (Pr.(Waiver)), all other columns show pooled Ordinary Least Square (OLS) estimates. The dependent variables: ΔNet Fee$_{i,t:t+2}$, ΔMgmt. Fee$_{i,t:t+2}$, ΔOperating Fee$_{i,t:t+2}$ and ΔDistribution Fee$_{i,t:t+2}$ are changes in active incumbent fees from fiscal year t to $t+2$. Ln(AUM) is the natural log of fund net assets as of the end fiscal year $t-1$. Peer Bmk. Adj. Ret. is equal to the difference between fund i's gross return and the equally weighted gross return of it's peer group based on Morningstar categories, and is compounded over the prior fiscal year $(t-1:t)$. The standard deviation of gross returns (std(Gross Ret.)) and tracking error are calculated over the prior 24 months. All regressions include year fixed effects. Regressions in Panel A, C and D include fund fixed effects and regressions in Panel B include style fixed effects. Reported t-statistics, shown in parentheses, use heteroskedasticity-robust standard errors that cluster by style and year. ***/**/* denote statistical significance at the 1%/5%/10% level.

Panel A: Strategic Fee Adjustments

Dependent Variable:	ΔNet Fee$_{i,t:t+2}$		ΔMgmt. Fee$_{i,t:t+2}$		ΔOperating Fee$_{i,t:t+2}$		ΔDist. Fee$_{i,t:t+2}$		Pr.(Waiver)
Factor Index MVO$_{i,t}$	-0.0114***	-0.0113***	0.0303***	0.0335***	-0.0444***	-0.0474***	0.0027	0.0027	-0.0116
	(5.42)	(5.35)	(3.68)	(4.18)	(5.03)	(5.51)	(1.16)	(1.14)	(0.20)
Market Index MVO$_{i,t}$	0.0028*	0.0031	0.0219**	0.0275***	-0.0227**	-0.0280***	0.0036*	0.0036	0.0379
	(1.68)	(1.58)	(2.50)	(3.13)	(2.48)	(3.00)	(1.75)	(1.59)	(0.71)
Active MVO$_{i,t}$		-0.0006		-0.0144***		0.0137**		0.0001	0.1196**
		(0.32)		(2.69)		(2.16)		(0.03)	(2.07)
Turnover$_{i,t}$	0.0032	0.0032	-0.0009	-0.0010	0.0088	0.0089	-0.0047*	-0.0047*	0.0538
	(1.16)	(1.15)	(0.14)	(0.15)	(1.08)	(1.10)	(1.94)	(1.94)	(0.78)
std(Gross Ret.)$_{i,t}$	0.0033*	0.0033*	-0.0035	-0.0038	0.0116***	0.0119***	-0.0049***	-0.0049***	0.0461
	(1.86)	(1.86)	(1.14)	(1.23)	(2.86)	(2.92)	(3.50)	(3.50)	(0.91)
Peer Bmk. Adj. Ret.$_{i,t}$	-0.1362***	-0.1362***	0.1311***	0.1304***	-0.2348***	-0.2341***	-0.0325*	-0.0325*	0.3498
	(8.22)	(8.23)	(3.51)	(3.50)	(5.12)	(5.12)	(1.68)	(1.68)	(0.76)
ln(Age)$_{i,t}$	-0.0144***	-0.0144***	-0.0689***	-0.0697***	0.0403***	0.0410***	0.0143***	0.0143***	-0.2039*
	(3.13)	(3.14)	(7.44)	(7.53)	(3.65)	(3.73)	(3.09)	(3.08)	(1.89)
Tracking Error	-0.0018	-0.0019	0.0056	0.0045	-0.0122**	-0.0112**	0.0049**	0.0049**	-0.0276
	(0.76)	(0.78)	(1.33)	(1.08)	(2.12)	(1.98)	(2.12)	(2.13)	(0.43)
ln(AUM)$_{i,t}$	0.0083***	0.0083***	-0.0216***	-0.0221***	0.0270***	0.0274***	0.0029**	0.0029**	-0.1616***
	(8.45)	(8.33)	(6.44)	(6.58)	(7.30)	(7.41)	(2.40)	(2.38)	(5.48)
Observations	20,632	20,632	20,632	20,632	20,632	20,632	20,632	20,632	20,755
R-squared	0.25	0.25	0.18	0.18	0.18	0.18	0.10	0.10	0.04

Panel B: Robustness

Dependent Variable:	ΔNet Fee$_{i,t:t+2}$	ΔMgmt.$_{i,t:t+2}$	ΔOperating$_{i,t:t+2}$	ΔDist. Fee$_{i,t:t+2}$
Factor Index MVO$_{i,t}$	-0.0058***	0.0224***	-0.0309***	0.0027
	(3.05)	(3.03)	(3.90)	(1.27)
Market Index MVO$_{i,t}$	0.0060***	0.0220***	-0.0183**	0.0022
	(3.38)	(2.67)	(2.15)	(1.14)
Observations	23,092	22,414	20,751	21,219
R-squared	0.09	0.03	0.06	0.02

Panel C: Factor Index Interaction Effects

Dependent Variable:	ΔNet Fee$_{i,t:t+2}$	ΔMgmt. Fee$_{i,t:t+2}$	ΔOperating Fee$_{i,t:t+2}$	ΔDist. Fee$_{i,t:t+2}$
Factor Index MVO$_{i,t}$	0.0028	0.0608***	-0.0089	0.0070***
	(1.27)	(6.50)	(1.19)	(2.85)
Factor Index MVO$_{i,t}$ × High Fee$_{i,t}$	-0.0152***	-0.0594***	-0.0490***	-0.0145***
	(5.67)	(6.96)	(4.62)	(4.79)
Factor Index MVO$_{i,t}$	-0.0077***	0.0378***	-0.0481***	0.0015
	(4.24)	(4.82)	(5.56)	(0.64)
Factor Index MVO$_{i,t}$ × Peer Bmk. Adj. Ret.$_{i,t}$	-0.0498**	0.1691***	-0.1781**	-0.0002
	(2.40)	(2.70)	(2.23)	(0.01)

Panel D: Market Index Interaction Effects

Dependent Variable:	ΔNet Fee$_{i,t:t+2}$	ΔMgmt. Fee$_{i,t:t+2}$	ΔOperating Fee$_{i,t:t+2}$	ΔDist. Fee$_{i,t:t+2}$
Market Index MVO$_{i,t}$	0.0136***	0.0433***	0.0187**	0.0070**
	(6.49)	(3.93)	(2.32)	(2.52)
Market Index MVO$_{i,t}$ × High Fee$_{i,t}$	-0.0155***	-0.0484***	-0.0564***	-0.0029
	(6.00)	(4.61)	(5.18)	(0.93)
Market Index MVO$_{i,t}$	0.0043**	0.0226***	-0.0245***	0.0035
	(2.55)	(2.75)	(2.68)	(1.61)
Market Index MVO$_{i,t}$ × Peer Bmk. Adj. Ret.$_{i,t}$	-0.0379	0.1056**	-0.1021	-0.0171
	(1.42)	(2.04)	(1.56)	(1.26)

Table 4: Investor Response to Fee Changes

This table presents results from estimating pooled OLS regressions of active fund net flows on a set of dummy variables corresponding to fee changes over the prior two years. The unit of observation is fund-quarter. The dependent variables, shown in column headings, are net fund flow over the next quarter $(i, t : t + 1)$, 6 months $(i, t : t + 2)$ or year $(i, t : t + 4)$ scaled by the AUM at the beginning of the measurement period. The explanatory variables include the natural log of fund net assets (ln(AUM)), gross return volatility estimated over the prior 24 months (std(Gross Ret.)), fund turnover, and the natural log fund age in months (ln(Age)) and prior performance. Prior performance is measured by CAPM alpha compounded over the prior year. Fee change variables are measured over the prior two years. For example, Decrease Net Fee$_{i,t-8:t}$ is equal to the change in net fees over the prior two years (eight quarters). Regressions in Panel A include fund and year-quarter fixed effects. Panel B includes style and year-quarter fixed effects and the full set of control variables from Panel A. Reported t-statistics, shown in parentheses, use heteroskedasticity-robust standard errors that are clustered by fund style $\times$ year-quarter. ***/**/* denote statistical significance at the 1%/5%/10% level.

Panel A: Investor response to active fund fee changes

Dependent Variable:	Net Flow$_{i,t:t+1}$	Net Flow$_{i,t:t+2}$	Net Flow$_{i,t:t+4}$	Net Flow$_{i,t:t+1}$	Net Flow$_{i,t:t+2}$	Net Flow$_{i,t:t+4}$
Decrease Net Fee	0.6392*	1.3453**	1.9010**			
	(2.79)	(4.60)	(4.99)			
Increase Mgmt. Fee				0.2136	0.4947	0.6188
				(0.92)	(1.27)	(1.19)
Increase Dist. Fee				-0.1449	-0.3586	0.2295
				(1.12)	(1.43)	(0.55)
Decrease Operating Fee				0.7418*	1.3781**	2.0322*
				(2.95)	(3.68)	(3.04)
Turnover	-0.0095***	-0.0164***	-0.0198*	-0.0079**	-0.0161**	-0.0240*
	(8.83)	(6.82)	(2.86)	(4.21)	(3.30)	(3.10)
std(Gross Ret.)	-0.1838	-0.4391	-1.2556	-0.1445	-0.4502	-1.5927
	(0.81)	(1.37)	(1.10)	(0.61)	(1.22)	(1.34)
CAPM Alpha	0.2755***	0.5108***	0.7480***	0.2778***	0.5179***	0.7571***
	(10.82)	(6.95)	(6.78)	(7.46)	(6.21)	(6.29)
Tracking Error	0.6913**	1.5728**	2.9520**	0.6619*	1.5681**	3.0171**
	(3.88)	(4.09)	(3.99)	(3.07)	(4.00)	(3.76)
ln(Age)	-2.1102**	-4.7418**	-14.3292***	-1.3370	-3.2498*	-11.9595***
	(3.42)	(3.34)	(7.98)	(2.14)	(2.42)	(7.10)
ln(AUM)	-2.4685***	-6.4770***	-19.5219***	-2.5978***	-6.7525***	-20.1269***
	(10.95)	(11.55)	(15.12)	(10.94)	(11.18)	(14.14)
Net Flow	0.2096***	0.4015***	0.7520***	0.2109***	0.4029***	0.7617***
	(10.82)	(11.21)	(14.47)	(10.14)	(11.37)	(10.48)
Observations	101,364	101,496	101,792	91,540	91,656	91,873
R-squared	0.31	0.32	0.34	0.33	0.34	0.35

Panel B: Robustness

Dependent Variable:	Net Flow$_{i,t:t+1}$	Net Flow$_{i,t:t+2}$	Net Flow$_{i,t:t+4}$	Net Flow$_{i,t:t+1}$	Net Flow$_{i,t:t+2}$	Net Flow$_{i,t:t+4}$
Decrease Net Fee$_{i,t-8:t}$	0.7216**	1.5610**	2.7918***			
	(4.37)	(5.58)	(5.90)			
Increase Mgmt. Fee$_{i,t-8:t}$				0.3087	0.7382	1.5528**
				(1.58)	(2.19)	(4.00)
Increase Dist. Fee$_{i,t-8:t}$				-0.2049	-0.3988	0.3759
				(1.98)	(1.74)	(0.61)
Decrease Operating Fee$_{i,t-8:t}$				0.8970**	1.7315**	2.9555**
				(4.52)	(4.90)	(5.18)
Observations	99,879	100,010	100,297	90,333	90,446	90,657
R-squared	0.29	0.28	0.22	0.31	0.30	0.22

Table 5: Active Incumbent Attrition

Panel A of this table provides one, two and five year attrition rates of active mutual funds sorted by the factor index, market index and active overlap measures. Portfolios are updated annually with rankings based on the average overlap measure over the prior year. One, two and five year attrition rates are equal to the proportion of funds that are liquidated or merged over the one, two and five years after the sort. Panel B presents the results from estimating a Cox proportional hazard model:

$$Hazard_{i,t} = h_{0,i,t}e^{(\beta_1 FactorIndexMVO_{i,t}+\beta_2 MarketIndexMVO_{i,t}+\beta_3 ActiveMVO_{i,t}+\gamma C_{i,t})}$$

The unit of observation is fund-quarter. Active funds that exist for the entire sample are included as censored observations. Control variables include: benchmark adjusted returns compounded over the prior two years (Bmk. Adj. Ret.), turnover, percentage net flow over the prior 6 months (Net Flow), the natural log of fund net assets size (ln(AUM), gross return volatility calculated over the prior 24 months (std.(Gross Ret.), the natural log of fund age in months (ln(Age), tracking error and the net expense ratio (Net Fee). The covariance matrix is estimated using the "sandwich estimator" developed in Lin and Wei (1989). Hazard ratios are reported with z-scores in parentheses. ***/**/* denote statistical significance at the 1%/5%/10% level.

Panel A: Attrition rates based on univariate sorts by competition ranking

	Merged			Liquidated		
Factor Index MVO Quintile	1 Year	2 Year	5 Year	1 Year	2 Year	5 Year
1	2.02	3.33	7.78	1.94	3.77	9.31
2	1.70	3.22	8.43	2.07	4.38	10.64
3	1.42	3.16	8.57	2.61	4.75	11.32
4	1.49	3.52	8.67	2.31	4.70	11.60
5	1.65	3.20	7.25	3.28	6.53	14.95
Market Index MVO Quintile	1 Year	2 Year	5 Year	1 Year	2 Year	5 Year
1	1.75	2.79	7.02	2.26	4.06	9.60
2	1.51	3.31	8.58	1.71	3.67	9.71
3	1.52	3.49	8.66	2.43	4.81	11.27
4	1.57	3.39	9.02	2.40	5.02	12.26
5	1.94	3.45	7.47	3.41	6.58	14.99
Active MVO Quintile	1 Year	2 Year	5 Year	1 Year	2 Year	5 Year
1	1.33	2.43	6.68	1.86	3.66	8.96
2	1.48	3.40	8.98	1.94	3.87	9.88
3	1.76	3.49	8.38	2.27	4.62	11.43
4	1.65	3.48	8.80	2.74	5.34	12.76
5	2.05	3.63	7.91	3.41	6.65	14.80

Panel B: Cox proportional hazard model estimation

	Baseline Regressions				Interaction Effects			
Dependent Variable:	Merged		Liquidated		Merged		Liquidated	
Factor Index MVO$_{i,t}$	0.9801	1.0297	1.1692***	1.1916***	1.0865	1.0375	1.0685	1.2258***
	(0.24)	(0.40)	(3.44)	(3.96)	(1.11)	(0.48)	(1.22)	(4.57)
Market Index MVO$_{i,t}$	1.0405	1.0774	1.2383***	1.2457***	1.0817	1.1588	1.2770***	1.1077
	(0.50)	(1.04)	(4.80)	(5.04)	(1.13)	(1.64)	(5.49)	(1.60)
Active MVO$_{i,t}$		0.7764***		0.9382*	0.7734***	0.7738***	0.9452	0.9433
		(3.89)		(1.69)	(3.92)	(3.92)	(1.48)	(1.56)
Bmark Adj. Ret.$_{i,t}$	0.9803***	0.9810***	0.9882***	0.9887***	0.9829***	0.9814***	0.9939	0.9903**
	(3.16)	(3.06)	(2.69)	(2.59)	(2.63)	(2.98)	(1.30)	(2.19)
Turnover$_{i,t}$	1.0006***	1.0006***	1.0006***	1.0006***	1.0006***	1.0007***	1.0004***	1.0005***
	(3.29)	(3.30)	(4.71)	(4.77)	(2.95)	(3.46)	(2.79)	(4.30)
Net Flow$_{i,t-2:t}$	0.9793***	0.9801***	0.9771***	0.9775***	0.9800***	0.9800***	0.9776***	0.9776***
	(7.01)	(6.75)	(10.59)	(10.29)	(6.68)	(6.70)	(10.29)	(10.33)
ln(AUM)$_{i,t}$	0.9245***	0.8775***	0.9264***	0.9069***	0.8912***	0.8916***	0.8861***	0.8902***
	(2.70)	(4.07)	(3.56)	(3.95)	(3.66)	(3.64)	(5.02)	(4.80)
std(Gross Ret.)$_{i,t}$	1.2242**	1.2230**	1.0769	1.0724	1.2267**	1.2273**	1.0527	1.0558
	(2.49)	(2.45)	(1.46)	(1.38)	(2.47)	(2.49)	(0.99)	(1.03)
ln(Age)$_{i,t}$	1.5545***	1.5633***	0.7409***	0.7426***	1.5483***	1.5485***	0.7667***	0.7639***
	(6.82)	(6.88)	(6.95)	(6.95)	(6.70)	(6.70)	(6.29)	(6.43)
Tracking Error$_{i,t}$	0.7330***	0.7155***	0.9147*	0.9073*	0.7001***	0.7021***	0.9448	0.9461
	(3.75)	(4.00)	(1.74)	(1.88)	(4.36)	(4.33)	(1.12)	(1.08)
Net Fee$_{i,t}$	1.2633	1.2678*	1.5843***	1.5818***				
	(1.63)	(1.65)	(4.60)	(4.63)				
High Net Fee$_{i,t}$					1.4850***	1.4197***	1.1266*	1.2096***
					(3.91)	(3.60)	(1.71)	(2.86)
Factor Index MVO$_{i,t}$ × Bmk. Adj. Ret.$_{i,t}$					0.9951		0.9917*	
					(0.81)		(1.75)	
Factor Index MVO$_{i,t}$ × High Net$_{i,t}$					0.8955		1.1855***	
					(1.06)		(3.25)	
Market Index MVO$_{i,t}$ × Bmk. Adj. Ret.$_{i,t}$						1.0000		0.9963*
						(0.00)		(1.87)
Market Index MVO$_{i,t}$ × High Net$_{i,t}$						0.8950		1.1518***
						(1.32)		(3.00)
Observations	94,803	94,803	94,803	94,803	94,803	94,803	94,803	94,803
Pseudo R-squared	0.03	0.03	0.05	0.05	0.04	0.04	0.05	0.05

Table 6: Future Performance

This table presents pooled OLS regressions of active fund performance on the entry overlap measures, a standard set of control variables, year-quarter and fund or style fixed effects. The dependent variable is given by benchmark adjusted returns, peer benchmark adjusted returns or alpha compounded over the 24 months after entry. Turnover and expense ratio are annual values as of quarter t. Tracking error and the standard deviation of gross returns are calculated over the prior 24 months. ln(Age) is the natural log of the age, in months, of a fund's oldest share class and ln(AUM) is the natural log of a fund's total assets under management. Past performance is the compounded returns over the prior year and is calculated using the same performance measure as the dependent variable. Regressions in Panel A include fund fixed effects while regressions in Panel B include style fixed effects. Reported t-statistics, shown in parentheses, use heteroskedasticity-robust standard errors that are double clustered by fund and year. ***/**/* denote statistical significance at the 1%/5%/10% level.

Panel A: Future Performance

Dependent Variable:	Peer Bmk. Adj. Ret.$_{t:t+8}$		Bmk. Adj. Ret.$_{t:t+8}$		4F Alpha$_{t:t+8}$	
Factor Index MVO$_{i,t}$	-0.2930**	-0.2565**	-0.2908***	-0.2568**	-0.3750***	-0.3382***
	(2.52)	(2.45)	(2.89)	(2.82)	(4.16)	(4.71)
Market Index MVO$_{i,t}$	-0.3814***	-0.2845***	-0.3145***	-0.2258**	-0.2116**	-0.1188
	(4.46)	(3.46)	(3.39)	(2.60)	(2.86)	(1.64)
Active MVO$_{i,t}$		-0.3467***		-0.3184***		-0.3418***
		(3.30)		(3.41)		(3.74)
Past Performance$_{i,t}$	-0.1801**	-0.1798**	-0.1626***	-0.1623***	-0.0795**	-0.0796**
	(2.66)	(2.66)	(2.87)	(2.87)	(2.12)	(2.13)
Turnover$_{i,t}$	0.0014	0.0013	0.0004	0.0004	-0.0026	-0.0026
	(0.35)	(0.34)	(0.12)	(0.12)	(1.08)	(1.09)
ln(AUM)$_{i,t}$	-3.3545***	-3.3973***	-3.2610***	-3.3006***	-2.4605***	-2.5014***
	(7.78)	(7.77)	(8.06)	(8.06)	(11.32)	(11.09)
Tracking Error$_{i,t}$	0.7370**	0.7209**	1.0853**	1.0702**	0.0280	0.0130
	(2.56)	(2.52)	(2.23)	(2.22)	(0.15)	(0.07)
Net Fee$_{i,t}$	1.4366*	1.4267*	1.5841*	1.5744*	0.7720	0.7605
	(1.91)	(1.89)	(2.01)	(1.99)	(1.37)	(1.35)
%AUM Inst. Class$_{i,t}$	1.7994*	1.8180*	1.5917	1.6084	0.4579	0.4738
	(1.85)	(1.87)	(1.67)	(1.69)	(0.69)	(0.71)
Net Flow (%)$_{i,t}$	-0.0136**	-0.0131**	-0.0143*	-0.0138*	-0.0135*	-0.0129*
	(2.19)	(2.10)	(2.05)	(1.99)	(1.93)	(1.85)
Observations	96,865	96,865	97,302	97,302	93,839	93,839
R-squared	0.22	0.22	0.27	0.27	0.28	0.28

Panel B: Robustness

Dependent Variable:	Peer Bmk. Adj. Ret.$_{t:t+8}$		Bmk. Adj. Ret.$_{t:t+8}$		4F Alpha$_{t:t+8}$	
Factor Index MVO$_{i,t}$	-0.2439***	-0.2315***	-0.2569***	-0.2346***	-0.1720***	-0.1724***
	(2.95)	(2.78)	(3.14)	(2.83)	(2.69)	(2.69)
Market Index MVO$_{i,t}$	-0.2147***	-0.1716**	-0.1193*	-0.0448	0.0622	0.0607
	(2.91)	(2.36)	(1.65)	(0.63)	(1.15)	(1.14)
Active MVO$_{i,t}$		-0.1111**		-0.1937***		0.0040
		(2.40)		(4.07)		(0.13)
Past Performance$_{i,t}$	-0.0482***	-0.0481***	-0.0505***	-0.0500***	0.0795***	0.0795***
	(4.07)	(4.06)	(4.09)	(4.05)	(7.24)	(7.24)
Turnover$_{i,t}$	-0.0002	-0.0002	-0.0003	-0.0003	-0.0007	-0.0007
	(0.40)	(0.40)	(0.63)	(0.63)	(0.93)	(0.93)
ln(AUM)$_{i,t}$	-0.2801***	-0.2922***	-0.2255***	-0.2468***	-0.1861***	-0.1857***
	(5.14)	(5.27)	(4.14)	(4.47)	(4.50)	(4.40)
Tracking Error$_{i,t}$	0.3896***	0.3824**	0.2577*	0.2451	0.1843*	0.1846*
	(2.59)	(2.53)	(1.65)	(1.56)	(1.77)	(1.77)
Net Fee$_{i,t}$	-0.4536*	-0.4602*	-0.4861*	-0.4978*	-0.3988**	-0.3986**
	(1.75)	(1.78)	(1.84)	(1.89)	(2.14)	(2.14)
%AUM Inst. Class$_{i,t}$	-0.1355	-0.1378	-0.0860	-0.0897	-0.0704	-0.0703
	(0.72)	(0.74)	(0.46)	(0.48)	(0.48)	(0.48)
Net Flow (%)$_{i,t}$	-0.0204***	-0.0203***	-0.0182***	-0.0181***	-0.0119***	-0.0119***
	(4.91)	(4.89)	(4.30)	(4.27)	(3.89)	(3.89)
Observations	96,867	96,867	97,309	97,309	93,852	93,852
R-squared	0.01	0.01	0.14	0.14	0.15	0.15

8 Appendix

Table A1

Variable Definitions

Competition Measures	
Overlap Measure (MVO)	$\text{MVO}_{i,t} = \frac{1}{N}\sum_{e=1}^{N}\sum_{s=1}^{M} w_{i,e,s,t}$ $w_{i,e,s,t} = \left(\frac{P_{e,s,t}S_{e,s,t}}{P_{i,s,t-1}S_{i,s,t-1}}\right)\left(\frac{P_{i,s,t-1}S_{i,s,t-1}}{\sum_{j=1}^{K}P_{i,j,t-1}S_{i,j,t-1}}\right)$ i subscript denotes incumbent, e subscript denotes entrant, s denotes stocks held by both incumbent i and entrant e. $P_{i,s,t}$ ($P_{e,s,t}$) = the price of security s in quarter t. $S_{i,s,t}$ = number of shares of security s in incumbent i's portfolio in quarter t. $S_{e,s,t}$ = number of shares of security s in entrant e's portfolio in quarter t. M = the number of overlapping securities held by incumbent i and entrant e. N = the number of entrants in quarter t that have at least one overlapping security. K = the number of securities in incumbent i's portfolio in quarter t.
Factor Index $\text{MVO}_{i,t}$	Aggregate holdings overlap measure for fund i in quarter t. Computed for all factor index funds that enter in quarter $t-1$.
Market Index $\text{MVO}_{i,t}$	Aggregate holdings overlap measure for fund i in quarter t. Computed for all market index funds that enter in quarter $t-1$.
Performance Measures	
Bmk. Adj. Ret.	Gross fund returns in excess of the funds' benchmark return. I use the Morningstar US-equity Category benchmarks.
Peer Bmk. Adj. Ret.	Gross fund returns in excess of the funds' equally weighted peer group return. I use Morningstar US-equity Category to determine peer groups.
Alpha	CAPM, Fama and French 3-factor, Fama, French and Carhart 4-factor. Estimated using 36 months of gross return data.
Fund Characteristics	
ln(AUM)	The natural log of fund assets under management.
ln(Age)	The natural log of a fund's age in months.
Tracking Error	The standard deviation of the difference between gross fund returns and benchmark returns.
Turnover	The lesser of the dollar value of purchases or sales divided by previous period (year) assets under management.
Net Fee	The percentage of fund assets used to pay for operating and management fees. This includes 12b-1 fees, administrative fees and all other asset-based costs incurred by the fund, excluding brokerage costs.
Management Fee	The fee charged by manager(s) as given in the fund's annual report. Expressed as a % of fund net assets.
Distribution Fee	The % of fund net assets used for marketing and distribution.
Operating Fee	Net fees minus management fees minus distribution fees. Expressed as a % of fund net assets. These fees include: accounting, administration, auditing, compensating the board of directors, custodial, legal, organizational, professional, registration, shareholder reporting and transfer agency fees . Expressed as a % of fund net assets.
Expense Waiver	The difference between expenses incurred (gross expense ratio) and expenses charged to unit holders (net expense ratio).
High Fee	Indicator variables that measure relative: management fees, operating fees, distribution fees and and net fees. To be precise, high fee is equal to one if a fund charges a fee (as a % of net assets) that is above the median fee for all other actively managed mutual funds in the same style category, in the same year.

Table A2: Strategic Fee Adjustment: Three- and Four-Year Fee Changes

This table presents regressions of post-entry changes in active fund fees on the set of overlap measures and control variables. Dependent variables are given in column headers. Logistic regressions are used to predict the probability that fund i uses a fee waiver in the next period (Pr.(Waiver)), all other columns show pooled Ordinary Least Square (OLS) estimates. The dependent variables are changes in active incumbent fees over the three (t to $t+3$) and four years (t to $t+4$) after entry. The control variables are the same as those from Table 3. All regressions include year and fund fixed effects. The dependent variables in Panel A are three-year changes in fees and are four-year changes in Panel B. Reported t-statistics, shown in parentheses, use heteroskedasticity-robust standard errors that cluster by fund and year. ***/**/* denote statistical significance at the 1%/5%/10% level.

Panel A: Three-Year Fee Adjustments

Dependent Variable:	ΔNet Fee$_{i,t:t+3}$	ΔMgmt. Fee$_{i,t:t+3}$	ΔOperating Fee$_{i,t:t+3}$	ΔDist. Fee$_{i,t:t+3}$
Factor Index MVO$_{i,t}$	-0.0167***	0.0350***	-0.0525***	0.0015
	(6.30)	(4.23)	(5.88)	(0.59)
Market Index MVO$_{i,t}$	0.0019	0.0316***	-0.0350***	-0.0008
	(0.75)	(3.46)	(3.69)	(0.32)
Active MVO$_{i,t}$	0.0013	-0.0096*	0.0115*	0.0022
	(0.47)	(1.80)	(1.67)	(0.77)
Turnover$_{i,t}$	0.0084**	0.0028	0.0087	-0.0059**
	(2.55)	(0.44)	(1.07)	(2.31)
std(Gross Ret.)$_{i,t}$	0.0034	-0.0020	0.0106***	-0.0061***
	(1.53)	(0.66)	(2.77)	(3.32)
Peer Bmk. Adj. Ret.$_{i,t}$	-0.2029***	0.0501	-0.2249***	0.0094
	(8.46)	(1.11)	(4.14)	(0.46)
ln(Age)$_{i,t}$	-0.0237***	-0.0778***	0.0327**	0.0201***
	(4.12)	(7.66)	(2.60)	(3.82)
Tracking Error$_{i,t}$	-0.0017	0.0015	-0.0106*	0.0055**
	(0.57)	(0.37)	(1.81)	(2.48)
ln(AUM)$_{i,t}$	0.0139***	-0.0254***	0.0362***	0.0055***
	(11.58)	(6.66)	(8.58)	(4.55)
Observations	20,752	20,116	18,658	19,116
R-squared	0.29	0.23	0.25	0.16

Panel B: Four-Year Fee Adjustments

Dependent Variable:	ΔNet Fee$_{i,t:t+4}$	ΔMgmt. Fee$_{i,t:t+4}$	ΔOperating Fee$_{i,t:t+4}$	ΔDist. Fee$_{i,t:t+4}$
Factor Index MVO$_{i,t}$	-0.0182***	0.0325***	-0.0540***	0.0030
	(6.19)	(3.51)	(4.95)	(1.08)
Market Index MVO$_{i,t}$	-0.0030	0.0435***	-0.0461***	-0.0032
	(1.11)	(3.82)	(3.75)	(1.00)
Active MVO$_{i,t}$	0.0040	-0.0110	0.0187**	0.0009
	(1.21)	(1.64)	(2.40)	(0.31)
Turnover$_{i,t}$	0.0069*	0.0023	0.0112	-0.0078***
	(1.72)	(0.34)	(1.12)	(2.65)
std(Gross Ret.)$_{i,t}$	0.0024	-0.0001	0.0066	-0.0043*
	(0.86)	(0.03)	(1.32)	(1.85)
Peer Bmk. Adj. Ret.$_{i,t}$	-0.2007***	-0.0320	-0.1651***	0.0442*
	(7.83)	(0.66)	(2.91)	(1.85)
ln(Age)$_{i,t}$	-0.0237***	-0.0862***	0.0293*	0.0229***
	(3.22)	(6.94)	(1.78)	(3.47)
Tracking Error$_{i,t}$	-0.0002	-0.0070	-0.0053	0.0083***
	(0.07)	(1.40)	(0.80)	(2.96)
ln(AUM)$_{i,t}$	0.0168***	-0.0320***	0.0440***	0.0059***
	(12.16)	(8.27)	(9.69)	(3.67)
Observations	18,702	18,093	16,712	17,173
R-squared	0.36	0.29	0.30	0.23