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THE IMPACT OF SOCIAL CAPITAL ON MUTUAL FUND FLOWS

By

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A DISSERTATION

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Abstract

Mutual fund investing is one of the main drivers of the U.S. economy. Mutual fund returns on managed assets is one of the most researched topics in business academics, but mutual fund flows (the growth in fund assets controlling for fund returns) has been studied to a much lesser extent. Social capital is derived from the mutual trust and collective altruistic tendencies between people within communities that drive unselfish and compassionate behavior. Many examples in the prior literature have used social capital to explain social, political, and business phenomena. This research delves into the relationship between mutual fund flows and social capital, focusing not only on the direct relationship between mutual fund flows and social capital, but also on the moderating effect that social capital has on previously identified drivers of fund flows, including fund returns and the mutual fund agency problem of window dressing. Fund returns have been shown to have a positive direct effect on mutual fund flows as investors chase returns. Conversely, window dressing has been shown to have a negative effect on mutual fund flows, because fund managers engaging in window dressing behaviors implicitly deceive investors by exiting poorly performing equity holdings and by increasing highly performing equity holdings during a reporting period delay, thus making a risky bet on their performance during the delay period. The present research adds to the literature by demonstrating not only social capital's positive and direct impact on mutual fund flows and its negative and direct impact on mutual fund window dressing, but also its moderating effect on the impact that fund returns have on mutual fund flows, and the moderating effect that social capital has on window dressing behavior's impact on fund flows. The research also demonstrates that these impacts are not only statistically significant, but also practically significant. Suggestions for practitioners are identified, as is potential future research.

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1. Introduction and Research Question

It is generally accepted that people from large metropolitan areas act differently and have different decision-making processes than people from the suburbs, and that suburbanites differ considerably from those that reside in rural areas. Additionally, people from different regions of the world—and, indeed, different regions of any given country—act and make decisions differently from one another. Often these decision-making differences lead to dramatically different outcomes in all aspects of life: from political leanings, to family decisions, to religiosity, to career choices. In academic and other research, the amorphous “regional differences exist” has been used to explain many phenomena. What if a construct existed that enabled the explanation of these differences?

Social capital is just such a construct—a concept that explains why people of different *communities* act and make decisions differently. Specifically, social capital is the collective altruistic tendencies and mutual trust between people within communities that drive unselfish and compassionate behavior (Putnam 2000, 2001; La Porta et al., 1997; Huang & Shang, 2019). Robert Putnam brought mainstream attention to the field of social capital through his various and impactful academic and non-academic works in the early part of this century (2000, 2001). Putnam proposed that it was these social-capital differences that cause people of different communities and regions to act differently and make different decisions. Putnam identified many reasons that drove social capital to be established, including participation in organizations and clubs, participation in charitable causes, and trust between community members.

Other more contemporary researchers have further defined what drives the establishment of community, the basis for social capital. Harari (2019), for example, argues that human beings cannot sustain networks greater than a maximum number of contacts without the level of community breaking down, resulting in the establishment of “fictions,” which are artificial constructs that simplify connections between people. Probably the best example of a social fiction is religion, where trust or community can be established immediately, simply by individuals collectively identifying with a religious group. These fictions allow communities to grow and flourish as community members participate together in multiple fictions, resulting in tight-knit communities having a large amount of social capital (Harari, 2019).

The theory of social capital is not without criticism, namely for the contention that diverse social networks are the result of other social considerations not assessed by Putnam, Harari, and others.

Gelderblom (2018), for example, identifies several drivers not considered by other researchers that cause social networks to form and then to become either cooperative or competitive. Gelderblom also condemns social-capital researchers' tendency to generalize findings from micro to macro settings (2018).

Even so, after Putnam pushed social capital into the limelight, social capital as a construct has exhibited citation counts about 100 times greater than it did previously. By 2008, the term "social capital" was cited 75% as much as "human capital" (Woolcock, 2010), which often is considered to be its own academic discipline (e.g., the study of organizational behavior or human resources). Woolcock (2010) contends that this meteoric rise in social capital as a field of study was driven by the fact that it highlights the importance of social relationships generally, but also can be precise and appropriate for specialist audiences.

The behaviors associated with U.S. equity-based mutual fund investing is one example where social capital could be explanatory. Generally, mutual fund investing is one of the main drivers of the U.S. economy, with more than 44% of all U.S. households investing in some form of mutual fund (Mordor Intelligence, 2019). Drivers of mutual fund *returns* have been studied extensively in the academic literature, but the drivers of mutual fund *flows,* the growth in fund assets controlling for fund returns (Sirri & Tufano, 1998), has not been as exhaustively researched. The main driver of social capital is mutual trust between actors (Putnam, 2000, 2001), which has also been shown to drive mutual fund flows (Cochardt et al., 2019).

These facts taken together lead to the primary research question: Does social capital positively impact U.S. equity-based net mutual fund flows and mitigate agency issues associated with these funds?

This research question leads to several hypotheses, provided and discussed below.

> **Hypothesis 1: Social capital is positively related to mutual fund flows, when controlling for all other known drivers of mutual fund flows.**

More precisely, Hypothesis 1 is that regions of high social capital will have greater net mutual fund flows, and regions of lower social capital will have lesser net mutual fund flows, *ceteris paribus*.

In the prior literature, the most common control variables employed in the analysis of mutual fund flows are fund returns, fund size, and year fixed effects. However, many other measurable predictors of mutual fund flows have been identified, including fund patronage in the form of fund tenure (Chevalier & Ellison, 1997; Friesen & Sapp, 2007), fund type/sector/strategy (Barber et al., 2016; Röder & Walter, 2019), and fund fees and costs (Barber et al., 2005). These variables (and others) are included as additional controls to isolate the effects of social capital on net mutual fund flows.

Delving further into the relationship between social capital and mutual fund flows leads to two additional hypotheses closely related to Hypothesis 1, namely:

> **Hypothesis 1a: The marginal impact of social capital on fund flows increases as social capital increases; and**
>
> **Hypothesis 1b: Social capital moderates the effect that fund returns have on mutual fund flows, such that social capital has a greater impact on mutual fund flows when prior-period fund returns are high than when prior period fund returns are low, with this effect becoming more pronounced as social capital increases.**

These supplemental hypotheses seek to further define the relationship between social capital and fund flows. Specifically, Hypothesis 1a postulates that high levels of social capital have a greater impact on fund flows than do lower levels of social capital, likely driven by the concept that trust in a person or entity motivates action greater than a lack of trust does (Putnam, 2000, 2001). Hypothesis 1b proposes that the impact that social capital has on the primary driver of fund flows (fund returns) varies with the level of social capital, exhibiting a moderating effect. Following Baron and Kenny (1986), this moderating affect is assessed by identifying whether both the slope and the y-intercept of the linear relationship between social capital and fund flows are significantly different with varying degrees of fund returns.

> **Hypothesis 2: Social capital is negatively related to mutual fund agency problems.**

In Hypothesis 2, the agency problem of mutual fund window dressing is specifically assessed. Because the agency problem of window dressing has been shown to negatively affect fund flows (Agarwal et al., 2014), and social capital has been shown to reduce other agency problems (Jensen & Meckling, 1976; Huang & Shang, 2019; Bebchuk & Fried, 2003; Woolcock, 1998), it is hypothesized that regions of high social capital will have a lower incidence of window dressing behaviors by fund managers, and regions of lower social capital will engage in more window dressing, *ceteris paribus*. Mutual fund window dressing is an agency problem whereby mutual fund managers, prior to the fund reporting date but after the period end, either increase their holdings in stocks that have shown strong recent performance or sell their holdings in recently underperforming stocks to appear more attractive to fund investors (Ling & Arias, 2013). Fund managers in regions of high social capital therefore would avoid window dressing behaviors because they are trusted by their investors, and therefore will maintain high fund flows regardless of whether they window dress. Although beyond the scope of this dissertation and left for future research, it is likely that other mutual fund agency problems would be similarly affected by social capital.

> **Hypothesis 2a: Social capital moderates the impact that agency problems have on mutual fund flows, such that when social capital is low, window dressing behaviors have a significant impact on fund flows, and when social capital is high, window dressing behaviors have little impact on fund flows.**

Building on the prior hypotheses and the work of Agarwal and colleagues (2014) and Cochardt and colleagues (2019), Hypothesis 2b is that social capital will have a moderating effect on the impact that the mutual fund agency problem of window dressing has on net mutual fund flows. Specifically, the purpose of this hypothesis is to further investigate the question of "under what conditions" does social capital impact fund flows. Following the methodology developed by Baron and Kenny (1986), these hypotheses are shown graphically in Figure 1 below.

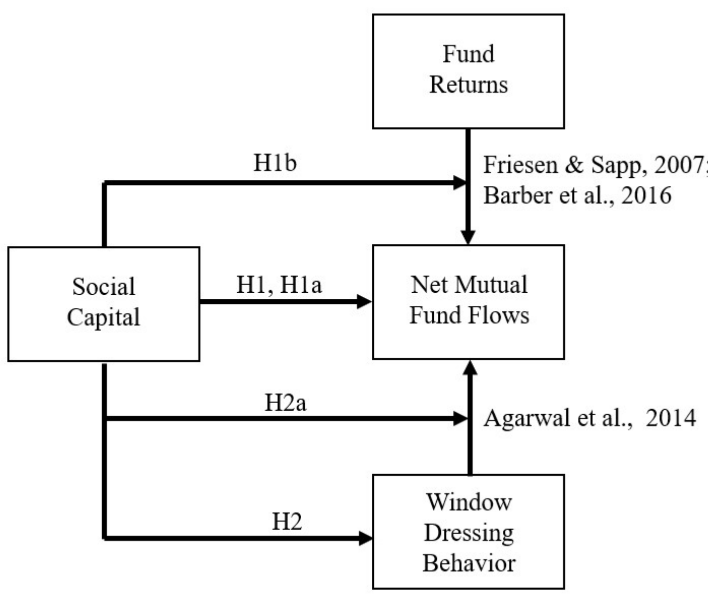


Figure 1. Hypotheses summary

2. Literature Review

The following section provides an overview of the academic literature upon which this research is based. Initially, a description is provided of what mutual funds are and how important they are to the U.S. economy. This is followed by a detailed description of social capital and its primary measurement, the RGF U.S. county-level social capital index. Finally, this literature review establishes that trust between fund managers and investors is the link between social capital and mutual fund flows—specifically, that trust is inherent in the development of regional social capital, and that this mutual trust drives net fund flows.

2.1. Mutual Funds and Mutual Fund Flows

2.1.1. The Mutual Fund Industry

Mutual funds are an investment category in which professional fund managers actively invest and manage a pool of capital raised from individual and institutional investors. These funds normally are invested in assets of a single class—common or preferred equities, debt securities, money market instruments, or commodities—usually with a goal to generate income for the fund's investors via asset appreciation and dividend and interest income. The portfolio of asset investments generally follows a strategy stated in a fund-specific investment prospectus. These fund strategies vary across many dimensions, including sector-based funds that invest in equities of a specific economic sector such as healthcare stocks or technology stocks, capitalization-based funds that invest in stocks of various sizes (large, medium, small, or micro cap), or style-focused funds that invest for income or growth/asset appreciation, or are hedge funds. Additionally, mutual funds can be tied to an index, such as the Dow, S&P 500, or NASDAQ; can be traded via a market (known as exchange-traded funds or ETFs); and can be sold directly to investors (known as open-ended funds) or have a fixed number of shares sold initially via an initial public offering and then traded on a public exchange (known as close-ended funds) (Gremillion, 2012; Baker et al., 2015).

As an asset class, mutual funds are a major driver of the U.S. economy, with net assets exceeding $17.7 trillion at the end of 2018 and expecting to eclipse the $23 trillion mark by the end of 2024. The U.S. mutual fund market has grown at a 5.2% annually compounded rate during the period of 2012 to 2020, a rate much greater than that of inflation. Funds that primarily invest in corporate equities account for slightly more than half the value of all U.S. mutual funds, with bond funds representing 23%, money market funds at more than 16%, and hybrid funds comprising the remainder. As of 2018, there were 8,094 mutual funds in the United States (Statista, 2020; Mordor Intelligence, 2019). Behind only primary-residence ownership, mutual funds are the second largest investment vehicle for U.S. families, with more than 44% of all U.S. households having mutual funds as a component of their investment portfolios (Mordor Intelligence, 2019).

2.1.2. Net Mutual Fund Flows

Much research has been done on fund returns, with comparatively less research on how and why capital is invested into specific mutual funds. This dissertation is focused primarily on open-ended U.S. mutual funds with a stated investment strategy of investing in U.S. equities, and aims to shed some light on investors' fund-selection criteria, as well as how fund managers and fund marketers should optimally generate that demand.

The proposed research is oriented around net mutual fund flows, defined as the measurement of a mutual fund's return-adjusted growth rate (Sirri & Tufano, 1998). By way of example, if a fund had no capital appreciation in a period, but the fund size (measured in total assets under management) grew by 25%, then the fund flow would be 25% for that period. This implies that all growth in the fund during that period was driven by new capital from investors. If that same fund had the same fund size at the beginning and end of the period but had exhibited asset appreciation of 10% during the period (as opposed to 0% in the initial example), however, then the net fund flows would be only 15%, implying that 15% of the fund growth is due to net fund flows and 10% of the fund growth is due to asset appreciation.[1] Because funds grow from flows *and* from capital appreciation, this research aims to further investigate what drives flows.

The academic literature identifies many drivers of mutual fund flows, including prior returns (Ippolito, 1992; Gruber, 1996; Chevalier & Ellison, 1997; Sirri & Tufano, 1998; Karceski, 2002; Barber et al., 2005); fund exposure via media attention (Sirri & Tufano, 1998; Jain & Wu, 2000), marketing (Sirri & Tufano, 1998; Jain & Wu, 2000; Barber et al., 2005; Cooper et al., 2005), and investor sentiment (Frazzini & Lamont, 2008; Ben-Rephael et al., 2012); branding and fund ratings (Guercio & Tkac, 2008; Wellman & Zhou, 2008); fund patronage in the form of fund tenure and size (Chevalier & Ellison, 1997; Friesen & Sapp, 2007); fund family relationships (Sirri & Tufano, 1998; Massa, 2003); fund type/sector/strategy (Barber et al., 2016; Röder & Walter, 2019); fund fees and costs (Barber et al., 2005); and fund manager skill and trust (Barber et al., 2016; Cochardt et al., 2019).

2.1.3. *“Chasing Returns,” the Main Driver of Net Fund Flows*

Asset appreciation, in the form of fund returns, is the largest diver of mutual fund flows (Friesen & Sapp, 2007; Barber et al., 2016) and therefore has received much attention in the academic literature. Due to its relative importance as a driver of fund flows, a thorough discussion of prior fund returns as a driver of mutual fund flows is warranted.

It is exceptionally well-documented in the academic literature that mutual fund investors “chase returns,” meaning that they invest in funds that have recently exhibited returns in excess of benchmarks. This results in funds with greater prior-period returns receiving higher net fund flows (Ippolito, 1992; Chevalier & Ellison, 1997; Sirri & Tufano, 1998). Unlike in corporate finance, where excess capital without corresponding high net present value projects result in lower stock prices, mutual funds that are not traded on an exchange have no way to reach market equilibrium without positive net fund flows following periods of superior returns, resulting in investors chasing those returns (Berk & Green, 2004). This return chasing is not just a fund effect. Investors “chase returns across funds and through time” (Karceski, 2002, p. 584). In bull markets, investors overinvest in mutual funds. In both bull and bear markets, investors flock to funds that have been successful in the recent past. However, these flows are asymmetrical. Return chasing occurs to a much greater degree than does the fleeing of poorly performing mutual funds by investors (Gruber, 1996; Sirri & Tufano, 1998; Karceski, 2002). This means that when new capital flows into the mutual fund market, it more often than not flows into funds that recently have performed well, but does not necessarily mean that the funds will be rebalanced in the short term. This convex relationship is partially explained by the behavioral literature, specifically that overconfidence causes people to overestimate the precision of their information, with the opposite also being true (Odean, 1998)—investors trust their belief that a fund will perform well in the future when it has performed well in the prior period, but have much less trust in the belief of future poor performance when the same fund’s performance begins to wane.

Much prior research has been focused on whether return chasing behavior is a rational investment strategy. Early research, which focused on longer-term performance in conjunction with return chasing, finds that there is a lack of persistence in fund returns, and therefore return chasing is not a successful strategy (Ippolito, 1992). Subsequent research, however, investigated return chasing in the short and long term.

The “Smart Money” effect is the concept that investors can indeed outperform benchmarks in the short term (a quarter or less) by chasing returns (Gruber, 1996). Studies have shown that chasing returns is an effective strategy for the quarter after a fund exhibits superior returns, even on a risk-adjusted basis and controlling for all fees paid (Frazzini & Lamont, 2006). The "Dumb Money" effect is when investors fail to flee these funds when the superior performance does not persist (Friesen & Sapp, 2007), presumedly because the "Smart Money" effect is simply stock return momentum that is persistent in only the very short term (Sapp & Tiwari, 2004). As discussed above, fund flows are asymmetrical (high return chasing behavior is exhibited with recent superior fund performance, but only moderate fleeing behavior is exhibited with poor recent fund performance) (Gruber, 1996; Sirri & Tufano, 1998; Karceski, 2002). This results in the Dumb Money effect dominating the Smart Money effect, so the overall strategy of chasing returns is indeed a poor investment strategy for those investors who fail to rebalance after one quarter (Frazzini & Lamont, 2006). Indeed, studies that investigated investor timing find that those investors who chase returns tend to have the worst timing of all investors, specifically, they have too long a fund-holding period (Friesen & Sapp, 2007). Simply put, mutual fund returns, on average, regress to the mean (Friesen & Sapp, 2007), so the optimal mutual fund investment strategy is to consistently chase returns *each and every* quarter (Frazzini & Lamont, 2006).

2.1.4. "Smart" and "Dumb" Money's Impact on Return Persistence

The aforementioned lack of persistence in mutual fund returns is also important for a complete understanding of fund flows and the drivers of these flows. The "Smart Money" effect led researchers to infer that fund flows were a good indicator of the unobserved "skill" of fund managers (Berk & Green, 2004; Huang et al., 2007). As discussed above, however, these superior returns are short lived (Ippolito, 1992), as studies demonstrate that fund managers do not outperform benchmarks in steady state (Jensen, 1968). The lack of return persistence in mutual funds is likely caused by the incentives of fund managers. Fund managers are primarily compensated as a function of fund capital under-management (Ma et al., 2019). Because of this, new fund flows are actively embraced by fund managers. The manager skill that drove superior prior performance is diluted when more capital is required to be invested, however, explaining the lack of persistence in fund returns over time (Berk & Green, 2004).

This lack of sustainable fund performance also could be a function of the market cycles. In bull markets, successful fund managers overinvest in high beta stocks (usually high growth equities) (Gruber, 1996) to outperform their competition on returns, but as markets inevitably turn bear, these high beta stocks underperform (Karceski, 2002). Additionally, the lack of persistence in returns of mutual funds is further dampened by the breakdown of investors by type, mainly because not all investors make rational decisions (Sapp & Tiwari, 2004). Studies find that sophisticated investors understand and can access alpha and beta funds (Huang et al., 2012), identify new investments very quickly (Friesen & Sapp, 2007), and chase returns performing well in the short term and in the long term if they consistently rebalance their holdings on a quarterly basis (Sapp & Tirawi, 2004). Unsophisticated investors, however, fall prey to advertising and to brokers who are not peddling the best performing funds. Certain other investors cannot chase returns for institutional reasons (for example, their pension funds restrict the universe of mutual funds available from which they can select) or tax reasons (for example, high capital gains tax liabilities preclude them from selling) (Gruber, 1996). The academic research indicates that all of these findings, taken together, explain the lack of persistence in superior mutual fund returns.

2.1.5. The Potential Impact of Agency Problems on Net Fund Flows

Agency problems, normally driven by the misalignment of incentives, occur when agents take actions that benefit themselves but that are detrimental to their principals (Jensen & Meckling, 1976). A simple example of an agency problem is a CEO issuing bonuses to the management team just prior to a company failing, thus reducing the stockholders' pro-rata share of residual cash upon the winding of the entity. Of course, corporate governance and other measures are normally undertaken to minimize agency problems in the case where incentives cannot be completely aligned between agents and principals.

Window dressing is a mutual fund agency problem whereby fund managers, prior to the federally mandated fund reporting date, either increase their holdings in stocks that have shown strong recent performance or sell their holdings in recently underperforming stocks to appear more attractive to fund investors (Ling & Arias 2013). Prior research shows that window dressing behaviors drive significant capital flows in and out of mutual funds. Specifically, when window dressing behaviors are exhibited, greater than expected fund outflows occur when the delay-period performance is poor and greater than expected fund inflows occur when the delay-period performance is good (Agarwal et al., 2014). Overall, however, window dressing behaviors are shown to depress fund performance and net fund flows because poor performance outweighs good performance during the delay period as poorly skilled managers chase returns (Frazzini & Lamont, 2008).

In corporate finance, the agency problem normally is a conflict of interest between management and other stakeholders, but can also be between other principals and agents (Jensen & Meckling, 1976). Agency problems have been shown to be less prevalent in regions of high social capital, resulting in lower requirements for traditional and non-traditional corporate governance measures. Because agency problems are mitigated by social capital, stakeholder-mandated corporate borrowing schemes (which nearly always require covenants as a check on management) are less common in regions of high social capital. Because of this, firms in regions of higher social capital have lower firm borrowing rates and longer maturities of their debt, with the opposite also being true (Huang & Shang, 2019). Agency issues can also result in "rent extraction" by managers, meaning that senior management demands greater than expected compensation not tied to positive firm outcomes (Bebchuk & Fried, 2003). Rent extraction is inconsistent with norms of high social capital regions. Moreover, high social capital is associated with communication and enforcement of such values (Woolcock, 1998). Therefore, firms located in high social capital regions have lower costs associated with rent extraction resulting in lower levels of CEO pay (Hoi et al., 2019). Additionally, prior literature demonstrates that firms in high social capital regions have lower costs of capital, both debt and equity (Cheng et al., 2017; Hasan et al., 2017; Huang & Shang, 2019; Ferris et. al., 2017; Gupta et. al., 2018), are more likely to survive the first five years post-IPO (Fischer & Pollock, 2004), have better access to debt (Jonsson & Lindbergh, 2013), enjoy lower audit costs (Jha & Chen, 2015), and are less likely to go bankrupt (Agarwal et al., 2011). All of this is a function of reduced agency problems in regions of high social capital.

As discussed above, because window dressing behaviors are another example of an agency problem, it is hypothesized that mutual funds headquartered in regions of high social capital should exhibit fewer window dressing behaviors, with the converse also being true. Also hypothesized is that social capital moderates the negative impact that window dressing has on mutual fund flows.

2.1.6. Other Drivers of Net Fund Flows

As discussed above, fund returns (Barber et al., 2016; Friesen & Sapp, 2007) and the minimization of agency problems are two drivers of net flows of mutual funds. Many other drivers have been identified by previous research, however, including the following.

- **Information Exposure.** Exposure to information provides knowledge to investors (Ippolito, 1992), driving down investor search costs, leading to higher fund flows (Sirri & Tufano, 1998). Exposure is generally a result of effective marketing efforts and therefore positive (Frazzini & Lamont, 2008), which increases mutual fund flows (Sirri & Tufano, 1998; Jain & Wu, 2000; Barber et al., 2005; Cooper et al., 2005). Exposure also drives media attention, which increases fund flows (Sirri & Tufano, 1998; Jain & Wu, 2000).

Marketing spending itself is positively correlated with fund flows (Sirri & Tufano, 1998; Jain & Wu, 2000; Barber et al., 2005; Cooper et al., 2005). Exposure also is greater for funds with patronage—older and larger funds (Chevalier & Ellison, 1997; Friesen & Sapp, 2007) and those funds with large fund-family complexes (Sirri & Tufano, 1998; Massa, 2003).

- **Fund Ratings.** Fund ratings, such as those provided by Morningstar are shown to significantly increase mutual fund flows for those funds that are rated highly (Guercio & Tkac, 2008; Wellman & Zhou, 2008). Of course, these ratings are a function of, and therefore highly correlated with, other drivers of fund flows, especially prior returns.
- **Fund Fees.** Information exposure and fund ratings are correlated with fund expenses because they are a function of marketing costs. The costs and fees that an investor must pay to purchase or own a mutual fund are shown to impact fund flows (Gruber, 1996; Carhart, 1997; Sirri & Tufano, 1998; Barber et al., 2005), with greater fees generally associated with lesser fund flows, even though 84% of investors believe that higher expense funds outperform lower expense funds (Alexander et al., 1998). Huang and colleagues (2007) further find that indirect costs, such as informationals costs, dampen flows.
- **Fund Manager Skill and Trust.** As highlighted above, manager skill drives fund flows, with skill being inferred by past performance (Barber et al., 2016). Investor trust in fund managers also increases mutual fund flows, with trust being proxied by the managers' military veteran status (Cochardt et al., 2019).

2.1.7. Importance of Understanding Net Fund Flows

Understanding mutual fund flows is not only important at the micro level (meaning the fund investor and the fund manager or marketer), but also at the macro level. For example, the mutual fund market is a summation of all the assets of all funds. Controlling for market returns, fund flows can be positive or negative. In periods of positive fund flows, there would be additional capital available which would be quickly invested by fund managers (who are less likely to meet or beat benchmarks without investing all available capital), which would result in sectors of the market increasing in value (Khan et al., 2012). For this reason, understanding fund flows at the macro level is important to investors and economists alike.

This section identifies and discusses the known drivers of mutual fund flows. Even this seemingly exhaustive assessment of fund growth drivers does not entirely explain fund flows, however, which is the prime motivation for this study. Further, many of these fund flow drivers are difficult for all but the most sophisticated of investors to assess when pursuing a mutual fund investment strategy. Because social capital is associated with trust, and the clear identification of regions of high social capital would reduce search costs when selecting funds, it is likely that regions of high social capital would exhibit greater fund flows (and vice versa) (Sirri & Tufano, 1998; Cochardt et al., 2019).

2.2. Social Capital and Social Capital Measures

Although many drivers of fund flows have been identified through academic research, the ability to predict future fund flows accurately has been elusive, mainly because the drivers of fund flow themselves are difficult to predict. One of the goals of this research is to determine another set of fund flow predicates that could also be *predictive*. Social capital might be an important predictive driver.

Combining the many different definitions in the literature, social capital can be described as the altruistic tendencies and mutual trust among people within communities that drive unselfish and compassionate behavior (Putnam 2000, 2001; La Porta et al., 1997; Huang & Shang, 2019). There are two main types of social capital: “External/ Bridging” social capital (connections between heterogeneous groups of people) and “Internal/Bonding” social capital (connections between homogeneous groups of people) (Putnam, 2000).

External/Bridging social capital views social capital as a resource that links a person to another person or a firm to another firm (Knoke, 1999), especially when that social capital helps to connect people that otherwise might not interact with one another. An example of this is a competitive road-biking club, drawing members of many ethnicities and including riders ranging from students to blue collar workers to professionals. Internal/Bonding social capital is a function of the bonds between individual members of organizations, communities, or nations, specifically those linkages that give the entity cohesiveness and the willingness to pursue collective goals (Brehm & Rahn, 1997). An example of Internal/Bonding social capital is an exclusive country club whose members are predominately of one social class and ethnicity. In these examples, a mutual fund manager could easily find him or herself a member of both of these entities, so External/Bridging social capital and Internal/Bonding social capital can happen simultaneously in a community. Regardless of the category of social capital, in most of the published research the dominate driver of social capital is the mutual trust between actors.

Social capital as a construct is very difficult to identify and measure, but for many years social capital *regions* have been used to explain behaviors. Because social capital is a community-based concept, assessing social capital at the lowest societal level is critical. Rupasingha, Goetz, and Freshwater (2006) developed a U.S. county-level social capital index, referred to hereinafter as the "RGF Social Capital Index." A county-based model was desired for four reasons: (1) social capital is predicated upon joint community action, and joint community action is most often seen at the local level; (2) the major rationale for social capital investment is to drive economic development, a community phenomenon; (3) any level lower than the county level (e.g., municipality level) would prove unwieldy in data acquisition, would be difficult to tie to other datasets, and would likely add little to any analysis; and (4) any geographic level higher than the county level (e.g., the state or national level) would not have the desired resolution, treating metropolitan and non-metropolitan areas as if they shared the same economic dynamics, which, of course, they do not.

The RGF index is computed using principal component analysis (PCA) with four equally weighted factors. The first factor is the total of the number of certain organizations divided by the county population in thousands. The organizations that comprise this factor are listed below.

- Religious organizations
- Civic and social associations
- Business associations
- Political organizations
- Professional organizations
- Labor organizations
- Bowling centers
- Fitness and recreational sports centers
- Golf courses and country clubs
- Sports teams and clubs

The other three factors of the PCA are voter turnout, the county's U.S. census response rate, and the number of domestically oriented nonprofit organizations (Rupasingha et al., 2006). The RGF index is normalized with a mean of zero and a standard deviation of one.

Table 1 below provides examples of the highest and lowest U.S. counties ranked by the most recent RGF index, excluding counties with less than 5,000 citizens. The average of all counties in shown for comparative purposes.

Table 1. Examples of High and Low Social Capital Counties

Metric	Low Social Capital	Average Social Capital	High Social Capital
County	Chattahoochee, GA	National Average	Murray, MN
RGF Score	-3.18	0.00	4.50
Population	11,898	101,912.4	8,447
Number of Orgs.	2	95.5	37
Citizens per Org.	5,949.0	1,066.9	228.3
Voter Turnout	35.9%	66.9%	85.1%
Census Participation	58.0%	70.6%	75.0%
Number Nonprofits	9	464.3	101
Citizens per Nonprofit	1,322.0	219.5	83.6

The U.S. county with the lowest RGF score in the most recent RGF update (2014) was Chattahoochee County, Georgia, with a rating of -3.18. The opposite end of the RFG continuum is Murray County, Minnesota, with a normalized RGF score of 4.50. Because the index is normalized, the average RGF index in the United States is 0.00.

Of the largest U.S. counties, one would need to look to the 13th largest county to find an RGF index above the mean (King County, Washington, home to Seattle), with an RGF score of 0.13. Of the lowest 20 social capital counties, 9 are in Texas, 6 are in the South, the rest are in the Dakotas. Of the highest 20 social capital counties, 10 are in Kansas or Nebraska, the rest are in Colorado (2), Montana (2), Minnesota (2), North Dakota (2), Texas (1), and Virginia (1). A map of the RGF Social Capital regions is shown in Figure 2.[2]

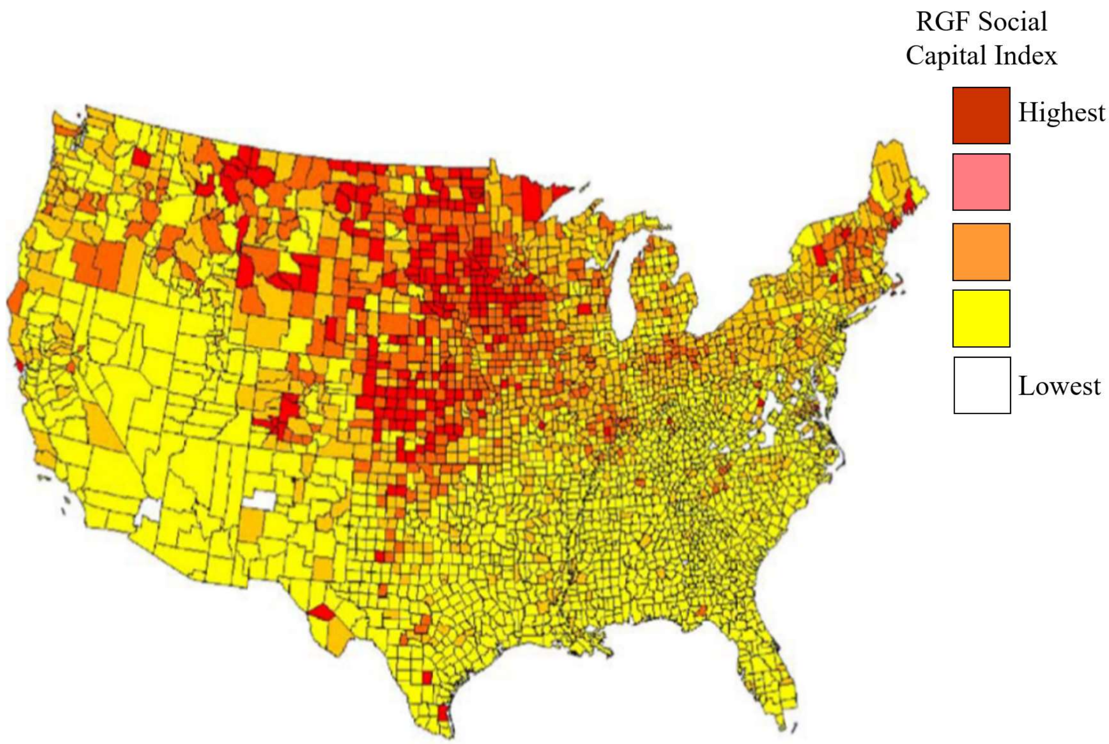


Figure 2. RGF social capital index

The RGF social capital index has been shown to be explanatory and predictive of many political, social, economic, and business phenomena.

2.3. Trust, Social Capital, and Fund Flows

The U.S. military is one of the most trusted institutions in American society (Malešič, 2012; Burk, 1994). A recent study finds that mutual funds managed by military veterans exhibit higher net fund flows than do other funds, driven by the fact that the military is a highly trusted U.S. institution. These researchers conclude that high trust levels drove higher mutual fund flows, with the opposite also being true (Cochardt et al., 2019). Similar to the "esprit de corps" community-building aspect of the military, social capital is developed and driven by mutual trust between people. The ability to predict trust based upon social capital region is important because other reasons to impart trust on a fund manager (other than veteran status, perhaps) are quite elusive but regional social capital is known. This logic leads to the research question discussed above, namely: Does social capital have an important impact on mutual fund flows?

Fund flows are important and understanding the drivers of fund flows is paramount to several stakeholders. If these hypotheses are supported, fund managers and fund marketers might consider this when establishing funds or when hiring managers. This is also important for fund investors because fund flows are predictive of fund returns (Fortune, 1999).

3. Methods

Generally, this section focuses on the dataset and the statistical methods employed to answer the research questions posed. Initially in Section 3, the model equation is specified, the variables of interest are defined, and the control variables are discussed. This is followed by a discussion of the disparate data sources and the development of the dataset. The section closes with a summary of the estimation methods for hypothesis testing and the software package used for all analyses.

3.1. Calculation of Net Fund Flows

The primary purpose of this dissertation is to assess social capital's impact on net fund flows for U.S. equity–based open-ended mutual funds. As discussed in detail in Section 2.1, net mutual fund flows are a measurement of a mutual fund's growth in excess of the fund's return (Sirri & Tufano, 1998). The rationale for this fund metric is that changes in assets under management for mutual funds are not *fully* explained by fund returns, and that is precisely what this study aims to analyze. Following the work of Sirri & Tufano (1998), the Equation 1 (below) is employed to calculate net fund flows.

Equation 1. Net Fund Flows Equation

$$\boldsymbol{Net\ Fund\ Flows\ Percent}_{\,i,t} = \frac{\left[\boldsymbol{Assets}_{\,i,t} - \boldsymbol{Assets}_{\,i,t-1} \times \left(\mathbf{1} + \boldsymbol{Return}_{\,i,t}\right)\right]}{\boldsymbol{Assets}_{\,i,t-1}}$$

Note that, throughout the remainder of this dissertation, net fund flows percent is referred to as "net fund flows" or simply "fund flows" to be consistent with prior literature.

Multiplying prior-period fund assets by period returns and netting the result from current-period assets results in the numerator of Equation 1. Dividing this return-adjusted asset value by prior-period assets yields net fund flows, the primary dependent variable in the present analyses.

3.2. Model Equation Specification

For the prediction of net fund flows, the previous work of Agarwal and colleagues (2014) was followed, with the predictors from that study being replaced with the RGF county-level social capital index as the variable of interest. The initial model equation is specified in in Equation 2.

Equation 2. Fund Flows Prediction Model Equation

$$\begin{aligned}
\textit{Net Fund Flows}_{\,i,t} = \; & \beta_0 + \\
& \beta_1 \times \textit{RGF Social Capital Index}_{\,t} + \\
& \beta_2 \times \textit{Fund Returns}_{\,i,t} + \\
& \beta_3 \times \textit{Fund Size}_{\,i,t} + \\
& \beta_4 \times \textit{Controls Matrix}_{\,i,t} + \\
& \beta_5 \times \textit{Year}_{\,t} + \\
& \varepsilon_{\,i,t}
\end{aligned}$$

- The dependent variable in this model is net mutual fund flows by firm and by quarter and is calculated as shown in Section 3.1. above.
- The social capital index is the county-level RGF index and is tied to the location of the office in which the mutual fund manager operates and the index at the time the fund flows were exhibited.
- The RGF index is the variable of interest in this model and is expected to positively predict net fund flows as explained in Section 2.3. above.
- Fund returns and fund size are the main drivers of net fund flows and therefore are important independent variables in all analyses.
- The matrix of control variables is discussed in detail in Section 3.5 below. The year categorical variable is included to assess time fixed effects.

The main limitation of these variables is that they might not be the only independent and control variables to explain the variability of the dependent variable, resulting in potentially biased coefficients. Variable outliers also could be a concern; however, the large sample size helps to ensure robustness. Regardless, removal of outliers in both the dependent and control variables is assessed through robustness tests.

3.3. Variable of Interest

The independent variable of interest is the RGF U.S. county-level social capital index (Rupasingha et al., 2006). As discussed above, the purpose of this study is to determine whether social capital is a positive predictor of mutual fund flows. The RGF index, because it is a U.S. county-level index, is likely the appropriate index to be used for this assessment as the county-level should be indicative of *community,* which is of paramount importance in the development of social capital. The RGF index has been updated periodically since 2006, both retroactively and prospectively (for the years, 1990, 1997, 2005, 2009, and 2014).

3.4. Other Primary Independent Variables

As discussed in Section 3.1 above, net fund flows are a function of fund returns and the changes in fund size. Because of this, both fund returns and fund sizes (measured as total net assets) are considered important independent variables. As one would expect, the existing literature demonstrates that fund returns have a strong positive effect on net fund flows as investors chase returns (Frazzini & Lamont, 2008; Friesen & Sapp, 2007; Barber et al., 2016). Prior research findings on the impact of fund size on net fund flows, however, are mixed. Sirri & Tufano (1998) find that larger funds tend to have lower net fund flows, because a dollar that flows into a smaller fund has a greater percentage impact than a dollar flowing into a larger fund, however, that analysis includes few control variables. Some research findings are consistent with those of Sirri and Tufano, but others demonstrate either a positive impact of fund size, a concave impact, or a non-significant impact (Bodson et al., 2011). Following prior literature, fund size was transformed via natural log, specifically because a great majority of funds are small, leading to a skewed distribution (Sirri & Tufano, 1998; Bodson et al., 2011). Both fund returns and fund size are continuous variables.

3.5. Control Variables

Control variables are included in regression analyses to explain variance of the dependent variable resulting in the isolation of the effects of a predictor variable or variables (Spector & Brannick, 2010). Prior literature has identified many drivers of mutual fund flows. These drivers of fund flows are systematically investigated (in the Appendix) to determine which control variables should be included to find whether social capital is indeed a true predictor of net mutual fund flows. Additionally, to meet the mathematical assumptions of ordinary least squares regression, not all predictors can be simultaneously included as controls because they could be strongly correlated with each other or with the variable of interest, so this also must be assessed. Section 3.5 identifies the control variables assessed for inclusion in the analyses in this dissertation.

3.5.1. Lagged Returns

Based upon the prior literature, in addition to current-period returns, fund returns lagged one quarter should have a positive effect on net fund flows (Warther, 1995; Fant, 1999; Friesen &

Sapp, 2007), but will likely have a lesser impact than the returns of the most recent quarter. This control variable is continuous and is referred to as "Lagged Returns Control."

3.5.2. Year Fixed Effects

As in most studies of mutual funds, a time-based categorical variable is used to control for the year fixed effects associated with the growth and contraction of the equities markets that occur over time (Gupta-Mukherjee, 2020). These control variables are referred to as the "Year Fixed Effects Matrix."

3.5.3. Time-Based Controls

In addition to the year fixed effects discussed above, other time-based controls have been used in the prior literature to explain the variance of mutual fund flows. These secondary time-based controls include fund vintage or fund age, and the quarter in which the fund flows are exhibited. According to the literature, fund vintage should affect net fund flows with older funds having lower flows, presumedly because older funds have a better reputation and sentiment is negatively predictive of net fund flows (Frazzini & Lamont, 2008). In this case, because of the magnitude of year-vintages (57 in total), decade-vintages are assessed. Because fund vintage by decade seems to lack precision, the age of each fund also is assessed as a control, with a cube root transformation being required to normalize the distribution. Finally, there might be a quarter effect on net fund flows (Li et al., 2004; Blocher, 2016), because most funds pay distributions in the 4th quarter, so a quarter categorical variable is assessed. These control variables are categorical, except the cube root of fund age (which is continuous). These variables collectively are referred to as the "Time-Based Controls Matrix."

3.5.4. Fund Expenses

Based upon the prior literature, fund expense ratio (fund management fees and operating expenses divided by fund total net assets) should have a dampening effect on fund flows (Sirri & Tufano, 1998; Barber et al., 2005; Kostovetsky, 2016). The "Fund Expense Ratio Control" variable is continuous.

3.5.5. Investor Type

Frazzini and Lamont (2008) famously refer to chasing returns (investing in funds immediately after a period with good returns or fleeing funds that exhibit poor period returns) as the "dumb money" effect, and many researchers find that individual investors chase returns, but institutional investors are less likely to follow the practice (Frazzini & Lamont, 2008; Warther, 1995; Ivković

& Weisbenner, 2009). These findings lead to the conclusion that investor type is important as a control. In this case, a categorical variable was introduced to identify the case where a fund is open to institutional investors as limited partners, with the null being the case where the funds' investors are primarily individuals. The control variable is called "Investor-Type Control" in the present analyses.

3.5.6. Index Funds and Exchange-Traded Funds

The indexing of a mutual fund is when the investments of a fund closely (or exactly) follow the makeup a specific index whose data is available to the public (Elton et al., 2004). Although the most common mutual fund index is the S&P 500 index, this type of fund can follow any available index, including the NASDAQ (often also viewed as a tech or growth fund) or the Dow Industrial (which also could be viewed as an income fund), but there are even funds that follow relatively obscure indexes such as livestock futures or an index that tracks equities whose management teams are disabled. Exchange-traded funds or are another category of mutual funds that are traded on public exchanges (Ben-David et al., 2018). Exchange-traded funds currently account for more than 45% of the mutual fund market (Statista, 2020). Although not all index funds are ETFs most are, which is the rationale for including both index funds and ETFs in this section.

Prior research demonstrates that index funds as a class exhibit lower net fund flows (Fant, 1999; Agapova, 2011; Ferson & Kim, 2012), presumedly because investors in those type of funds believe in the category in which they have invested and therefore are willing to take the highs and lows as the index follows a relatively random walk. However, EFTs are exchange-traded just like any public equity, and it is the ease of which these funds can be traded that likely results in higher net fund flows than funds that are not ETFs (Agapova, 2011; Staer, 2017; Broman & Shum, 2018).

Adding these two additional control variables should further isolate the effect of social capital on net fund flows. These control variables are categorical and referred to as the "Index and ETF Controls Matrix."

3.5.7. Fund Strategy

There are many different ways to define the strategy of an individual mutual fund, but the University of Chicago's Center for Research in Security Prices (CRSP, the source of much of the data here) categorizes mutual fund strategies based upon how a *fund defines itself* in its investment prospectus. This methodology leads to three main categories of U.S. equity–based mutual fund strategies: strategy based upon fund sector (sector based), strategy based upon fund capitalization (cap based), and strategies oriented around investor objective (goal based) (CRSP, 2020).

Sector-based funds are those funds that invest in equities of a specific sector of the U.S. economy such as:

- Technology,
- Financial,
- Healthcare,
- Telecommunications,
- Consumer Goods,
- Consumer Services,
- Real Estate,
- Utilities,
- Industrials,
- Materials,
- Natural Resources,
- Commodities, and
- Gold.

Cap-based funds are those funds that invest in equities of a particular band of equity market capitalization, such as:

- Large Cap (the largest 85% of mutual funds by investable market capitalization),
- Medium Cap (funds larger than Small Cap funds and smaller than Large Cap funds),
- Small Cap (the smallest 15% of mutual funds by investable market capitalization, excluding Micro Cap funds), and
- Micro Cap (the smallest 2% of mutual funds by investable market capitalization).

Investor goal-based funds are those funds that invest in equities that allow for specific investor goals to be achieved, usually a function of risk acceptance or risk aversion. Goal-based funds include:

- Income-producing strategies,
- Growth and income-producing strategies,
- Growth strategies,
- Hedging strategies, and
- Short-selling strategies.

Based upon this, another set of controls was added, categorical variables of self-identified fund strategy defined by whether a fund is a sector-fund, a cap-based fund, or a goal-based fund. In the published literature, many researchers include fund sector as a control when predicting net fund flows (Sirri & Tufano, 1998; Chakraborty et al., 2018), and other authors exclude sector funds from their analyses because these fund investors can have fundamentally different decision-making criteria than other investors (Jain & Wu, 2000; Friesen & Sapp, 2007). As one would expect, the size of companies in which a fund invests is also often used as a control (Pollet & Wilson, 2008; Gallo et al., 2008; Cao et al., 2017), as are the investor goals (Sirri & Tufano, 1998; Jain & Wu, 2000; Fant & O'Neal, 2000). These controls hereinafter are referred to as the "Fund Strategy Controls Matrix."

3.5.8. Controls Summary

In summary, the following variables are used as controls to isolate the effect of social capital on mutual fund net flows.

- Lagged Returns Control (fund quarterly returns, lagged one period)
- Year Fixed Effects Matrix
- Time-Based Controls Matrix (fund decade vintage, cube root of fund age, and the quarter of the reported fund flows)
- Fund Expense Ratio Control
- Investor-Type Control (discriminates retail funds from institutional funds)
- Index and ETF Controls Matrix (identifies funds as index funds, exchange-traded funds, or both)

- Fund Strategy Controls Matrix (sector-based fund, capitalization-based fund, style-based fund)

3.6. Data Sources

The sample is restricted to U.S. funds whose stated strategy is to invest in U.S. equities. The main sample period is 1999 to 2017, which is the longest period where all required variables are available for these analyses. Because of data insufficiency, for certain analyses the period is shortened as additional variables are added.

This study requires data from many sources, listed here.

- The RGF social capital index data is sourced from aese.psu.edu/nercrd/community/social-capital-resources.
- Components of net fund flows are sourced from both the Thomson Reuters Mutual Fund database ("Thompson Reuters") and from the Center for Research in Security Prices ("CRSP") database.
- Key fund-level characteristic variables are sourced from both Thomson Reuters and CRSP.
- Fund location and timing information are sourced from CRSP.
- MFLINKS from the Wharton Research Data Service ("WRDS") are used to tie this information together via common fund-naming conventions.
- Data from the U.S. Census Bureau provides information on locations by zip code.

3.7. Dataset Development

As discussed above, the dataset primarily is derived from five sources. The steps taken to create the initial dataset are shown here.

Step 1: Thompson Reuters provided the quarterly fund holdings information for each fund, along with fund identification information.

Step 2: CRSP provided monthly fund return information, along with fund identification information, and other fund-specific variables.

Step 3: WRDS MFLink information was used to merge all information into one dataset based upon several fund identifying variables.

Step 4: Three-month return information was calculated for every period, and then all three-month periods that were not the end of a quarter were excluded, resulting in a dataset that was quarter-specific.

Step 5: A quarter lag was applied to assets, and net fund flows were calculated for each period.

Step 6: Fund location information was accessed from another CRSP database and linked to the dataset via fund identifiers for the specific periods that the fund location information was relevant.

Step 7: Zip codes for each county in the United States were accessed from the U.S. Census Bureau, and the county was identified for each fund at each period.

Step 8: The RGF social capital index measurements were linked by county to the dataset for the specific period that the index was relevant for the specific location of each fund by period. Because the RGF index is updated periodically, the year of the most recent RGF update was tied to the specific quarter in the dataset.

Step 9: Control variable information was gathered from a variety of sources.

Step 10: Each variable was assessed for normality as a precursor to any transformations, with all variables appearing to follow a normal distribution with the exception of the asset variable and fund age. The asset variable was natural log transformed, as discussed above, with the resultant variable appearing to follow a normal distribution. Fund age required a cube root transformation to approach normality.

Step 11: Each variable was assessed for the existence of outliers on a post-transformation basis. A methodology was followed whereby records were removed if any variable had a value exceeding four standard deviations separation from the mean.

The resultant sample size is 164,177 records from 15 years (2003 through 2017), with all 4 quarters of each year represented, and with data from 11,990 unique funds.

Specific fund identifiers, such as fund name, ticker, and fund address were maintained throughout the dataset development for quality-control purposes.

3.8. Estimation Methods for Hypothesis Testing

Pearson correlations are assessed to better understand univariate relationships, followed by multivariate analyses via ordinary least squares regression modelling for hypothesis testing. In all hypothesis testing, the coefficient of the RGF social capital index is positive and statistically significant if support is to be given to the supposition that social capital has a positive and direct impact on the dependent variable (net fund flows in most analyses).

The main limitation of ordinary least squares regression here is that the coefficients could be biased in the case where unidentified explanatory variables are not included, or in the case where there is not a strictly linear relationship between the dependent, independent, and control variables. These potential limitations are addressed in the robustness test section below. All analyses were conducted using "R" version 3.6.3 (R Core Team, 2019).

4. Results

This results section includes a set of statistics summarizing the dataset used for hypothesis testing, followed by an assessment and discussion of univariate correlations. The section ends with the tabular results of hypotheses tests and a discussion of the results, demonstrating support for all hypotheses.

4.1. Summary Statistics

Descriptive statistics for the variables of interest and the primary independent variables are exhibited in Table 2 below.

Table 2. Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
N. Fund Flows	164,177	1.51%	13.76%	-92.46%	-4.53%	5.77%	97.35%
RGF	164,177	-0.14	0.83	-2.36	-0.64	0.34	3.90
Qtr. Return $_t$	164,177	0.79%	2.36%	-7.66%	-0.20%	1.98%	13.01%
Qtr. Return $_{t-1}$	164,177	0.83%	2.36%	-7.66%	-0.16%	2.02%	13.09%
Assets $_t$	164,177	$3,497.5	$16,179.6	$0.01	$132.5	$1,816.7	$661,615.4
Assets $_{t-1}$	164,177	$3,421.9	$15,548.1	$0.01	$131.4	$1,789.7	$617,539.4
Asset Growth	164,177	2.30%	14.88%	-88.47%	-4.58%	7.64%	95.29%
Fund Age	164,177	3,955.9	3,306.1	121	1,794	5,202	34,045

Fund Vintage							
1920s	131						
1930s	361						
1940s	362						
1950s	657						
1960s	1,198						
1970s	837						
1980s	6,304						
1990s	48,383						
2000s	85,077						
2010s	20,867						
Flows Quarter							
1st Quarter	39,583						
2nd Quarter	43,129						
3rd Quarter	41,668						
4th Quarter	39,797						
Expense Ratio	164,177	1.21%	0.59%	0.00%	0.82%	1.58%	3.76%
Investor Type							
Individual	95,436						
Institutional	68,741						
Index Funds	18,339						
ETFs	7,618						
Fund Strategy							
Cap. Based	48,677						

Sector Based	21,246
Style Based	94,254

Note: Assets in millions of dollars. Categorical variables (Fund Vintage, Flows Quarter, Investor Type, Index Funds, ETFs, and Fund Strategy) do not have meaningful values for the mean, standard deviation, or quartile values. Fund Age is in days.

The sample represents 15 years of data, from 2003 through 2017. Because RGF is normalized, a mean of 0.0 and a standard deviation of 1.0 is expected, but for this sample of data, the mean and standard deviation are somewhat different because not all U.S. counties had mutual funds, and the sample is drawn across multiple years. The mean of quarterly returns is 0.79%, with a range of -7.66% to 13.10%. Assets under management range from \$10K to \$661.6B with a mean of \$3.50B and a median of \$543.5M. Asset growth averages 2.30% per quarter and net fund flows, as expected, are lower with an average 1.51% per quarter. Every decade since the 1920s is represented, but 94.0% of all funds were established after 1989. The mean fund age is 10.8 years with the median fund age of 9.4 years. Fund expense ratios range from 0.00% to 3.76% with a mean of 1.21%. Funds catering to institutional investors represent 41.87% of the sample, with the remainder of funds primarily selling to individuals. Index funds are 11.7% of the sample, but only 4.64% of funds are marketed on exchanges. Style-based funds represent 57.41% of the sample, but 29.65% of funds follow a capitalization-based strategy, and only 12.94% of funds use a sector-based approach. Univariate correlations are shown for the transformed non-categorical variables in Table 3 below.

Table 3. Pearson Correlation Matrix

	N. F. Flows$_t$	**RGF**	**Return$_t$**	**Returns$_{t-1}$**	**Log Assets$_t$**	**Cube Root Age**
RGF	0.015^{***}	1.000^{***}				
Return $_t$	0.408^{***}	-0.003	1.000^{***}			
Return $_{t-1}$	0.079^{***}	0.002	0.090^{***}	1.000^{***}		
Log Assets $_t$	-0.010^{***}	-0.011^{***}	0.029^{***}	0.032^{***}	1.000^{***}	
Cube Root Age	-0.128^{***}	-0.015^{***}	0.015^{***}	0.015^{***}	0.263^{***}	1.000^{***}

Exp. Ratio	-0.054***	-0.008**	-0.012***	0.000	-0.237**	0.011***

Note: *p<.050; **p<.010; ***p<.001; p-values are reported based upon t-statistics.

As shown in Table 3, the RGF index is significantly and positively univariately correlated with net fund flows (r = 0.015, p<.001), giving initial credence to Hypothesis 1. Supporting the prior literature, net fund flows are positively correlated with returns (r = 0.408, p<.001), as investors chase those returns. Also, as predicted by Sirri and Tufano (2008), fund size is significantly and negatively correlated with net fund flows (r = -0.010, p<.001) indicating that smaller funds have higher fund flows. Older funds and funds with higher expense ratios are negatively correlated with fund flows: Cube root Age: (r = -0.128, p<.001), Expense Ratio: (r = -0.054, p<.001). These findings are also consistent with prior research.

On a univariate basis, quarterly returns are not significantly correlated with social capital (r = -0.003, p=.220). Interestingly, fund size, measured by assets under management and transformed via natural log, are negatively correlated with social capital (r = -0.011, p<.001), indicating that funds generally are smaller in areas of high social capital and, as demonstrated in the prior literature and also demonstrated here, that larger funds tend to have higher returns (r = 0.029, p<.001). Additionally, older funds tend to be found in regions of lower social capital (r = -0.015, p<.001), and, as one might expect, fund fees are lower in regions of high social capital (r = -0.008, p<.001).

4.2. Hypothesis 1: Model Equation

As discussed above, Hypothesis 1 is that regions of high social capital in the United States are positively associated with higher net fund flows. Predicting net fund flows is important for several reasons. Positive net fund flows are correlated with positive returns, so if net fund flows can be predicted, this would be beneficial to investors when selecting funds (as discussed briefly in Section 2.3., returns have been shown to drive fund flows) (Sirri & Tufano, 1998), but fund flows have also been shown to drive returns (Fortune, 1999). At the fund level, higher net fund flows result in more capital for the fund to invest (driving higher carried interest income for managers and the fund), and higher management fees.

4.2.1. Hypothesis 1: Model Equation

Equation 2 above identified the generalized fund flows prediction model equation. After an exhaustive analysis of all potential control variables (all analyses included in Appendix) the final model specification was developed and is shown as Equation 3 here.

Equation 3. Detailed Fund Flows Prediction Model Equation

$$
\begin{aligned}
\textit{Net Fund Flows}_{\,i,t} = \;& \beta_0 + \\
& \beta_1 \times \textit{RGF Social Capital Index}_{\,t} + \\
& \beta_2 \times \textit{Primary Independent Variables}_{\,i,t} + \\
& \beta_3 \times \textit{Lagged Returns Control}_{\,i,t} + \\
& \beta_4 \times \textit{Time-Based Control Matrix}_{\,i,t} + \\
& \beta_5 \times \textit{Fund Expense Control}_{\,i,t} + \\
& \beta_6 \times \textit{Investor Type Control}_{\,i,t} + \\
& \beta_7 \times \textit{Index and ETF Control Matrix}_{\,i,t} + \\
& \beta_8 \times \textit{Fund Strategy Control Matrix}_{\,i,t} + \\
& \beta_9 \times \textit{Year Fixed Effects}_{\,t} + \\
& \varepsilon_{\,i,t}
\end{aligned}
$$

The specific control variables are as follows.

1. The social capital index used is the RGF county-level social capital index.
2. The primary independent variables are quarterly returns and the log of fund size (measured in net fund assets).
3. The lagged returns control is fund quarterly returns, lagged one period.
4. The time-based control matrix is the cube root of fund age and the quarter of the reported fund flows.
5. The fund expense control is fund expense ratio.
6. The investor-type controls are whether a fund is a retail fund catering to individuals or is an institutional fund with a focus on professional investors.
7. The index and ETF control matrix are whether a fund is an index fund, an exchange-traded fund, or both.

8. The fund strategy control matrix is whether a fund is a sector-based fund, capitalization-based fund, or goal-based fund.
9. Year fixed effects control for the year the fund flows were exhibited to control for business cycles.

4.2.2. Hypothesis 1: Results and Discussion of Analyses

To assess Hypothesis 1, a series of ordinary least squares regression analyses was undertaken, assessing the RGF social capital index's impact on fund flows, including all control variables. The results of these analyses are shown in Table 4.

Table 4. Fund Flows Predicted by RGF and Primary Independent Variables, with Controls

	Dependent Variable			
Panel A	**(1) Net Fund Flows**	**(2) Net Fund Flows**	**(3) Net Fund Flows**	**(4) Net Fund Flows**
Constant	0.023^{***}	-0.001	0.046^{***}	0.067^{***}
	(25.51)	(-0.28)	(21.38)	(28.68)
RGF Index	3.599^{***}	2.739^{***}	2.337^{***}	2.281^{***}
	(8.89)	(7.29)	(6.29)	(6.15)
Primary Indep. Vars.				
Log Assets		-1.094^{***}	0.934^{***}	0.027
		(-7.00)	(5.88)	(0.16)
Quarter Return		2.481^{***}	2.511^{***}	2.510^{***}
		(161.82)	(164.51)	(164.67)
Controls				
Lagged Quarter Return			0.359^{***}	0.359^{***}
			(25.62)	(25.67)

Cube Root Age			-4.710***	-4.482***
			(-57.17)	(-54.12)
Quarter				
2nd Quarter			1.597	1.355
			(1.84)	(1.56)
3rd Quarter			-5.542***	-5.904***
			(-6.29)	(-6.71)
4th Quarter			-1.645	-2.140*
			(-1.82)	(-2.37)
Expense Ratio				-1.320***
				(-23.86)
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	164,177	164,177	164,177	164,177
R^2	0.040	0.1718	0.1915	0.1943
Adjusted R^2	0.040	0.1718	0.1914	0.1941
Residual Standard Error	0.135 (df = 164,161)	0.125 (df = 164,159)	0.124 (df = 164,154)	0.123 (df = 164,153)
F Statistic	452.9*** (df = 15; 164,161)	2,003.7*** (df = 17; 164,159)	1,767.0*** (df = 22; 164,154)	1,720.7*** (df = 23; 164,153)

Panel B	Dependent Variable			
	(5) Net Fund Flows	(6) Net Fund Flows	(7) Net Fund Flows	(8) Net Fund Flows
Constant	0.087***	0.112***	0.119***	0.107***
	(34.38)	(35.96)	(38.44)	(33.11)
RGF Index	2.942***	3.224***	3.477***	3.395***
	(7.91)	(8.65)	(9.35)	(9.08)
Primary Indep. Vars.				
Log Assets	0.234	0.422*	0.574***	0.416*
	(1.433)	(2.57)	(3.49)	(2.52)
Quarter Return	2.511***	2.510***	2.363***	2.513***
	(164.97)	(164.96)	(180.94)	(164.99)
Controls				
Lagged Quarter Return	0.361***	0.361***	0.264***	0.364***
	(25.87)	(25.89)	(20.20)	(26.06)
Cube Root Age	-5.034***	-5.022***	-5.262***	-4.998***
	(-57.80)	(-57.69)	(-61.83)	(-57.25)
Quarter				
2nd Quarter	1.381	1.347	0.359	1.367
	(1.60)	(1.56)	(0.42)	(1.58)
3rd Quarter	-5.832***	-5.966***	-6.704***	-5.938***
	(-6.64)	(-6.80)	(-7.72)	(-6.76)
4th Quarter	-2.090*	-2.128*	-2.599**	-2.125*
	(-2.32)	(-2.36)	(-2.95)	(-2.36)

Expense Ratio	-1.893***	-1.806***	-1.634***	-1.757***
	(-30.48)	(-27.84)	(-25.08)	(-26.75)
Institutional	-15.230***	-17.040***	-18.182***	-16.670***
	(-20.22)	(-22.33)	(-23.97)	(-21.79)
Index		-8.942***	-7.232***	-7.975***
		(-7.21)	(-5.77)	(-6.37)
Non-ETF		-27.690***	-25.990***	-26.960***
		(-14.78)	(-13.55)	(-14.08)
Sector-Based			3.788***	2.886***
			(3.62)	(2.76)
Goal-Based			3.361***	4.120***
			(4.77)	(5.85)
Year Fixed Effects	Yes	Yes	No	Yes
Observations	164,177	164,177	164,177	164,177
R^2	0.1963	0.1973	0.1929	0.1975
Adjusted R^2	0.1961	0.1972	0.1928	0.1974
Residual Standard Error	0.123 (df = 164,152)	0.123 (df = 164,150)	0.124 (df = 164,162)	0.123 (df = 164,148)
F Statistic	1,670.2*** (df = 24; 164,152)	1,552.2*** (df = 26; 164,150)	2,801.9*** (df = 14; 164,162)	1,442.9*** (df = 28; 164,148)

Note: $^{*}p<.050$; $^{**}p<.010$; $^{***}p<.001$; *t*-stats are reported parenthetically below each coefficient. RGF coefficients, Log Asset coefficients, Quarter coefficients, Cube Root Fund Age, Investor Type coefficients, Index Fund coefficients, ETF coefficients, and Fund Strategy coefficients are scaled by a factor of 10^3. For Year Fixed Effects, the year 2017 is excluded to avoid unity.

For Flows Quarter, the 4th quarter is excluded to avoid unity. For Investor Type, Individual Investors are excluded to avoid unity. For Fund Strategy, Capitalization-based strategy is excluded to avoid unity.

Treatment (8), with the inclusion of all controls, is the best linear unbiased estimate of the coefficient of the RGF index, and subsequently the best predictor model of net fund flows (*Adjusted* R^2 =0.1974, $F(28; 164{,}148)$= 1,442.9, p<.001). This model explains 19.7% of the variation of net fund flows. In Treatment (8), the RGF index has a value of 3.395 (β=3.395, p<.001). The social capital index is both positive and statistically significant, indicating that regions of high social capital exhibit higher mutual fund net flows, with the opposite also being true.

The results of this analysis support Hypothesis 1: Social capital is positively related to mutual fund flows, when controlling for all other known drivers of mutual fund flows.

4.2.3. Hypothesis 1: Practical Significance

The next two analyses aim to assess the practical significance of the finding that social capital is positively related to mutual fund flows. The first analysis is a scenario analysis where the only difference between two hypothetical funds is their social capital region, and the second analysis is a regression analysis with net fund flows as the dependent variable, with all non-categorical independent variables and control variables being standardized (enabling the direct comparison of the impact of social capital with all previously known drivers of net fund flows).

For the first analysis, the following scenario was developed.

- Two hypothetical funds, both $500 million in assets.
- Both exhibit 1.0% quarterly returns in each of the prior two quarters.
- One fund is located in Houston, Texas (RGF index score of -2.649); the other fund is located in Fairfax, Virginia (RGF score of 3.805).
- Both funds are of the same vintage and are three years old.
- Each fund has a 1% expense ratio.
- Both funds have individual investors as their primary investors.
- Neither are index funds, but both are ETFs.
- Both are cap-based funds.

- The analysis is performed using data from Q1, 2017.

Using Treatment (8) in Table 4 above, the Houston-based fund would exhibit quarterly net fund flows of 6.04%, whereas the Fairfax-based fund would exhibit quarterly net flows of 8.24%. On an annualized basis, the Fairfax-based fund would grow by $31.2 million more than the Houston-based fund (6.3% of the overall fund size). This increase is due solely to varying the level of social capital, because all other variables are held constant, exhibiting practical as well as statistical significance.

The second analysis used to assess practical significance is to standardize all non-categorical independent variables and control variables. Standardization simply rescales variables to a mean of zero and a standard deviation of one. The RGF index already is standardized, so the other variables that require standardization are the log of fund net assets, fund quarterly returns, lagged fund quarterly returns, the cube root of fund age, and fund expense ratio. The remainder of the variables are categorical and therefore are not standardized. The results are shown in Table 5.

Table 5. Fund Flows Predicted by RGF and Standardized Independent Variables and Controls

	Dependent Variable	
	(1) Net Fund Flows	**(2) Net Fund Flows**
Constant	0.107^{***}	0.107^{***}
	(33.11)	(33.11)
RGF Index	3.395^{***}	3.395^{***}
	(9.08)	(9.08)
Primary Independent Variables		
Log Assets	0.416^{*}	
	(2.52)	
Standardized Log Assets		0.835^{*}
		(2.52)

Quarterly. Return	2.513***	
	(164.99)	
Standardized Quarterly Return		59.301***
		(164.99)
Controls		
Lagged Quarterly Return	0.364***	
	(26.06)	
Standardized Lagged Quarterly Return		8.572***
		(26.06)
Cube Root Age	-4.998***	
	(-57.25)	
Standardized Cube Root Age		-19.509***
		(-57.25)
Quarter		
2nd Quarter	1.367	1.367
	(1.58)	(1.58)
3rd Quarter	-5.938***	-5.938***
	(-6.76)	(-6.76)
4th Quarter	-2.125*	-2.125*
	(-2.36)	(-2.36)
Expense Ratio	-1.757***	
	(-26.75)	
Standardized Expense Ratio		-10.297***
		(-26.75)

Institutional Fund	-16.670***	-16.670***
	(-21.79)	(-21.79)
Index Fund	-7.975***	-7.975***
	(-6.37)	(-6.37)
Non-ETF Fund	-26.960***	-26.960***
	(-14.08)	(-14.08)
Sector-Based Fund	2.886***	2.886***
	(2.76)	(2.76)
Goal-Based Fund	4.120***	4.120***
	(5.85)	(5.85)
Year Fixed Effects	Yes	Yes
Observations	164,177	164,177
R^2	0.1975	0.1975
Adjusted R^2	0.1974	0.1974
Residual Standard Error	0.123 (df = 164,148)	0.123 (df = 164,148)
F Statistic	1,442.9*** (df = 28; 164,148)	1,442.9*** (df = 28; 164,148)

Note: *p<.050; **p<.010; ***p<.001; *t*-stats are reported parenthetically below each coefficient. RGF coefficients, Log Asset coefficients, Quarter coefficients, Cube root Fund Age, Investor Type coefficients, Index Fund coefficients, ETF coefficients, Fund Strategy coefficients, and all coefficients for standardized variables are scaled by a factor of 10^3. For Year Fixed Effects, the year 2017 is excluded to avoid unity. For Flows Quarter, the 4th quarter is excluded to avoid unity. For Investor Type, Individual Investors are excluded to avoid unity. For Fund Strategy, Capitalization-based strategy is excluded to avoid unity.

As shown in Table 5, the scaling of the non-categorical variables has no impact on any of the coefficient t-statistics, the analyses R^2 values, the residual standard error values, or the analysis F-statistics. In essence, all this scaling does is make the non-categorical variables comparable with each other. As shown above, social capital is 4.07 times more impactful on the variance of net fund flows than log assets. By way of example, if Treatment (2) is used to predict net fund flows in percentage terms, a one standard deviation increase in the RFG social capital index increases fund flows by 1.36% on an annualized basis, but a one standard deviation increase in log assets only increases fund flows by 0.33% on an annualized basis (calculation not shown here for brevity).

4.3. Results of Hypothesis 1a Assessment

As discussed above, Hypothesis 1a is that the marginal impact of social capital on fund flows increases as social capital increases. To assess this hypothesis, two different sets of analyses were undertaken.

The first analysis is a quartile analysis, whereby the sample is subset based upon quartiles of the RGF index to assess how fund flows are affected by social capital at high values of social capital (above the mean and above the highest quartile of the RGF index) and low values of the RGF index (below the mean and below the bottom quartile of the RGF index). For support to be found for Hypothesis 1a in these analyses, the value of the coefficient of the RGF index would increase with higher RGF quartiles.

The second analysis simply converts the RGF index into a categorical variable (High RGF = 1), with the cutoff for a high versus a low social capital occurring at different values. In this case, support for Hypothesis 1a would be indicated by the loss of significance for the "High RGF" coefficient occurring at a value less than the mean of the RGF index.

4.3.1. Hypothesis 1a: Analysis 1, Quartile Analysis

The model and control variables employed for the RGF quartile analyses are as shown in Equation 3 above. To investigate Hypothesis 1a, the impact of social capital on net fund flows is assessed by RGF quartile. Treatment (1) includes the records corresponding to the smallest 25% of the RGF index values (the regions of very low social capital), Treatment (2) includes only the records that are below the mean of the social capital index, Treatment (3) includes only the records that are above the mean of RGF, and Treatment (4) includes the records corresponding to the largest 25% of the RGF index values (the regions of very high social capital). As discussed above, for support to be found for Hypothesis 1a in these analyses, the value of the coefficient of the RGF index would increase with higher RGF quartiles. Results are shown in Table 6 below.

Table 6. The Impact of Social Capital on Net Fund Flows by RGF Index Quartile

	Dependent Variable			
	(1) Fund Flows, Lowest 25% of RGF	**(2) Fund Flows, Lowest 50% of RGF**	**(3) Fund Flows, Highest 50% of RGF**	**(4) Fund Flows, Highest 25% of RGF**
Constant	0.108***	0.092***	0.135***	0.115
	(16.50)	(22.33)	(25.43)	(17.34)
RGF Index	-0.888	2.444***	7.595***	7.731***
	(-0.68)	(2.91)	(10.78)	(9.99)
Primary Indep. Vars.	Yes	Yes	Yes	Yes
Controls				
Lagged Return	Yes	Yes	Yes	Yes
Time Based	Yes	Yes	Yes	Yes
Expense	Yes	Yes	Yes	Yes
Investor Type	Yes	Yes	Yes	Yes
Index & ETF	Yes	Yes	Yes	Yes
Fund Strategy	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	42,776	93,895	70,282	40,031
R^2	0.2452	0.2005	0.1984	0.2220
Adjusted R^2	0.2447	0.2003	0.1980	0.2215

Residual Standard Error	0.114 (df = 42,747)	0.123 (df = 93,866)	0.124 (df = 70,253)	0.111 (df = 40,002)
F Statistic	495.8*** (df = 28; 42,747)	840.7*** (df = 28; 93,866)	620.9*** (df = 28; 70,253)	407.8*** (df = 28; 40,002)

Note: $^{*}p$<.050; $^{**}p$<.010; $^{***}p$<.001; *t*-stats are reported parenthetically below each coefficient; RGF coefficient scaled by a factor of 10^3.

This analysis gives credence to Hypothesis 1a, that the marginal impact of social capital on fund flows increases as social capital increases. In other words, high levels of social capital have a greater impact on mutual fund flows than do lower levels of social capital. This is indicated by the increasing values of the RGF coefficient from Treatment (1) through Treatment (4): Treatment (1): β=-0.888, p=.496; Treatment (2): β=2.444, p<.001; Treatment (3): β=7.595, p<.001; and Treatment (4): β=7.731, p<.001.

The unexpected negative value of the RGF index in Treatment (1) can be discounted because this is a non-significant finding, driven, to some degree, by a relatively low sample size. Although non-significant, the result of Treatment (1) is important in that that it demonstrates the lack of impact of social capital on fund flows in regions where social capital is very low.

This initial support for Hypothesis 1a, that the marginal impact of Social Capital on fund flows increases as social capital increases, will be further investigated in Section 4.3.2.

4.3.2. Hypothesis 1a: Analysis 2, RGF Categorical Analysis

Equation 4 below is used for the analyses to further assess Hypothesis 1a. This equation simply modifies Equation 3 by replacing the RGF index value with an RGF categorical variable of a high value equaling 1, and a low value equaling 0.

Equation 4. Detailed Fund Flows Prediction Model Equation with RGF Categorial Variable

$$
\begin{aligned}
\textit{Net Fund Flows}_{\mathrm{i,t}} = \; & \beta_0 + \\
& \beta_1 \times \textit{High RGF Social Capital Index Categorical}_{t} + \\
& \beta_2 \times \textit{Primary Independent Variables}_{\mathrm{i,t}} + \\
& \beta_3 \times \textit{Lagged Returns Control}_{\mathrm{i,t}} +
\end{aligned}
$$

$\beta_4 \times$ *Time-Based Control Matrix* $_{i,t}$ +

$\beta_5 \times$ *Fund Expense Control* $_{i,t}$ +

$\beta_6 \times$ *Investor Type Control* $_{i,t}$ +

$\beta_7 \times$ *Index and ETF Control Matrix* $_{i,t}$ +

$\beta_8 \times$ *Fund Strategy Control Matrix* $_{i,t}$ +

$\beta_9 \times$ *Year Fixed Effects* $_{t}$ +

$\varepsilon_{i,t}$

The control variables are unchanged from previous analyses.

To further assess Hypothesis 1a, a series of ordinary least squares regression analyses was undertaken with the RGF social capital index's value being treated as either high (categorical variable equal to 1) or low (categorical variable equal to 0), but with different cutoff values. The cutoff values selected for these analyses are:

- Treatment (1): High RGF are values greater than the RGF index sample mean minus 2 standard deviations of the RGF sample (a value of -1.80);
- Treatment (2): High RGF are values greater than the RGF index sample mean minus 1 standard deviation of the RGF sample (a value of -0.97);
- Treatment (3): High RGF are values greater than the RGF index sample mean (a value of -0.14);
- Treatment (4): High RGF are values greater than the RGF index sample mean plus 1 standard deviation of the RGF sample (a value of 0.69); and
- Treatment (5): High RGF are values greater than the RGF index sample mean plus 2 standard deviations of the RGF sample (a value of 1.52).

To find support for Hypothesis 1a, the cutoff value whereby statistical significance is lost should be less than the mean of the RGF. The results of these analyses are shown in Table 7.

Table 7. Fund Flows Predicted by RGF Categorical Variable with Varying Cutoff Values

	Dependent Variable				
	(1) Net Fund Flows, RGF Cutoff = Mean - 2 SD	**(2) Net Fund Flows, RGF Cutoff = Mean - 1 SD**	**(3) Net Fund Flows, RGF Cutoff = Mean**	**(4) Net Fund Flows, RGF Cutoff = Mean + 1 SD**	**(5) Net Fund Flows, RGF Cutoff = Mean + 2 SD**
Constant	0.108***	0.106***	0.105***	0.107***	0.108***
	(26.83)	(35.96)	(32.13)	(32.97)	(33.26)
High RGF	-1.485	0.335	3.135***	8.872***	22.271***
	(-0.62)	(0.36)	(5.01)	(6.28)	(11.61)
Primary Indep. Vars.	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Lagged Return	Yes	Yes	Yes	Yes	Yes
Time Based	Yes	Yes	Yes	Yes	Yes
Expense	Yes	Yes	Yes	Yes	Yes
Investor Type	Yes	Yes	Yes	Yes	Yes
Index & ETF	Yes	Yes	Yes	Yes	Yes
Fund Strategy	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	164,177	164,177	164,177	164,177	164,177
R^2	0.1971	0.1971	0.1972	0.1973	0.1978
Adjusted R^2	0.1970	0.1970	0.1971	0.1972	0.1976
Residual Standard Error	0.123 (df = 164,148)	0.123 (df = 164,148)	0.123 (df = 164,148)	0.123 (df = 164,148)	0.123 (df = 164,148)

F Statistic	1,439.2*** (df = 28; 164,148)	1,439.2*** (df = 28; 164,148)	1,440.3*** (df = 28; 164,148)	1,441.0*** (df = 28; 164,148)	1,445.2*** (df = 28; 164,148)

Note: $^{*}p<.050$; $^{**}p<.010$; $^{***}p<.001$; *t*-stats are reported parenthetically below each coefficient. RGF coefficients are scaled by a factor of 10^3. The reason that NA is indicated for the coefficient and *t*-statistic for the RGF Index Categorical in Treatment (8) is because there are no values in the sample with an RGF index greater than 3 standard deviations greater than the mean.

As the cutoff for high RGF versus low RGF shifts along the distribution continuum, there becomes a point where the statistical significance is lost. This occurs at the RGF mean minus 0.896 standard deviations (results of this analysis are not shown in Table 7). This value being lower than the mean indicates that high levels of social capital have a greater impact on mutual fund flows than do lower levels of social capital, in other words, the marginal impact of social capital on fund flows increases as social capital increases. This finding provides additional support for Hypothesis 1a.[3]

Also, consistent with the findings in Section 4.3.1., the RGF coefficients increase as the cutoff value increases (specifically because the High RGF = 1 indicator represents a higher mean value of the RGF index as the cutoff increases in value).

In summary, the results of these analyses support Hypothesis 1a: The marginal impact of social capital on mutual fund flows increases as social capital increases.

4.4. Results of Hypothesis 1b Assessment

As discussed above, Hypothesis 1b is that social capital will moderate the effect that fund returns have on mutual fund flows such that social capital has a greater impact on mutual fund flows when prior-period fund returns are high then when prior-period fund returns are low, with this effect becoming more pronounced as social capital increases.

4.4.1. Hypothesis 1b: Model Equation

Equation 2 above identified the generalized fund flows prediction model equation. Equation 5 below modifies this equation by replacing the RGF index with a categorical variable (High RGF = 1, similar to Equation 4, above) and adding an interaction variable between quarterly fund returns and the RGF categorical. In moderation analysis, the interaction variable is used to determine whether the impact that the independent variable has on the dependent variable varies based upon the value of the moderator. In this case, the interaction term is included to determine whether the impact of quarterly fund returns on fund flows is different for varying levels of social capital (mathematically, a statistically significant change in the slope of the linear approximation of net fund flows as a function of quarterly returns for high versus low values of social capital).

Equation 5. Hypothesis 1b Model Equation

$$
\begin{aligned}
\textit{Net Fund Flows}_{\mathrm{i,t}} = \; & \beta_0 + \\
& \beta_1 \times \textit{High RGF Social Capital Index Categorical}_{t} + \\
& \beta_1 \times \textit{High RGF}_{t} \times \textit{Fund Quarterly Returns}_{i,t} + \\
& \beta_2 \times \textit{Primary Independent Variables}_{\mathrm{i,t}} + \\
& \beta_3 \times \textit{Lagged Returns Control}_{\mathrm{i,t}} + \\
& \beta_4 \times \textit{Time-Based Control Matrix}_{\mathrm{i,t}} + \\
& \beta_5 \times \textit{Fund Expense Control}_{\mathrm{i,t}} + \\
& \beta_6 \times \textit{Investor Type Control}_{\mathrm{i,t}} + \\
& \beta_7 \times \textit{Index and ETF Control Matrix}_{\mathrm{i,t}} + \\
& \beta_8 \times \textit{Fund Strategy Control Matrix}_{\mathrm{i,t}} + \\
& \beta_9 \times \textit{Year Fixed Effects}_{\mathrm{t}} + \\
& \varepsilon_{\mathrm{i,t}}
\end{aligned}
$$

The specific control variables are unchanged from the analyses above.

4.4.2. Hypothesis 1b: Results and Discussion of Analyses

To assess Hypothesis 1b, a series of ordinary least squares regression analyses was undertaken, assessing the RGF social capital index's impact on fund flows, with both an RGF categorical variable (High RGF = 1) and a Quarterly Returns x High RGF interaction variable. All previously identified controls were also included in all analyses. For support to be found for Hypothesis 1b, the interaction variable must be positive and statistically significant, indicating that social capital impacts net fund flows generally, but to a higher degree when both quarterly returns and social capital are high. Similar to the analyses discussed in Section 4.3.2, the RGF index cutoff for High RGF was assessed at different levels to ensure robustness. The results of these analyses are shown in Table 8.

Table 8. Fund Flows Predicted by RGF Categorical and RGF x Returns Interaction Variable

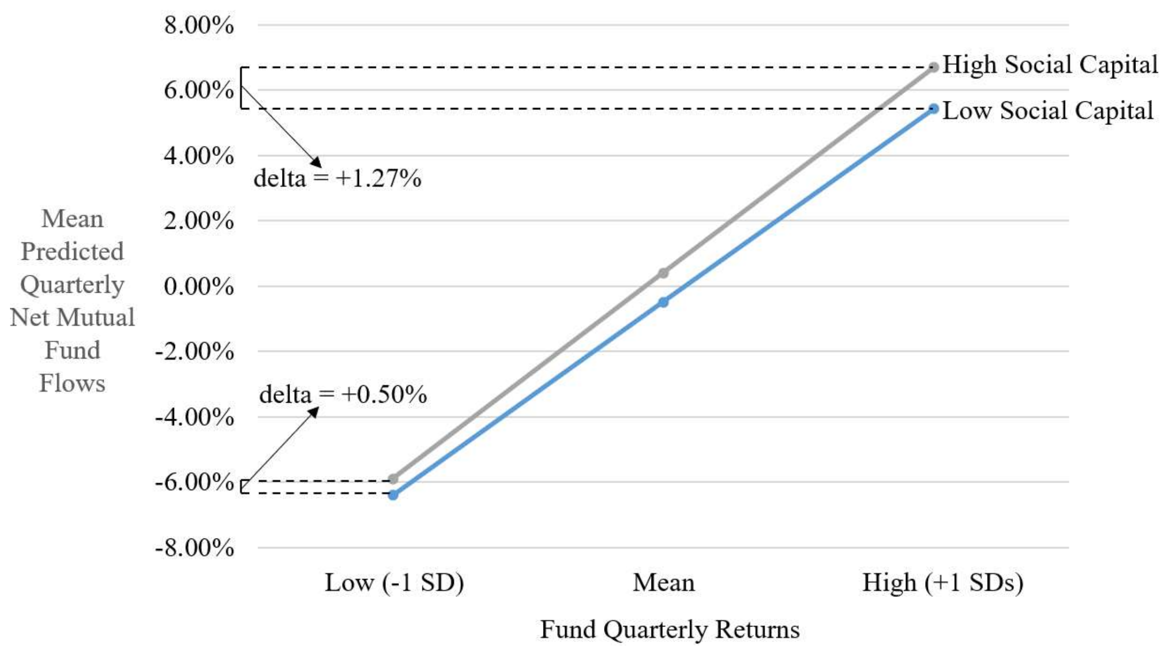
	Dependent Variable		
	(1) Net Fund Flows, RGF Cutoff = Mean	**(2) Net Fund Flows, RGF Cutoff = Mean + 1 SD**	**(3) Net Fund Flows, RGF Cutoff = Mean + 2 SD**
Constant	0.105***	0.107***	0.108***
	(32.29)	(32.99)	(33.29)
High RGF	1.503*	7.628***	19.460***
	(2.29)	(5.12)	(9.23)
High RGF x Returns	0.211***	0.161**	0.316**
	(8.09)	(2.66)	(3.20)
Primary Indep. Vars.	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Lagged Return	Yes	Yes	Yes
Time Based	Yes	Yes	Yes
Expense	Yes	Yes	Yes
Investor Type	Yes	Yes	Yes
Index & ETF	Yes	Yes	Yes
Fund Strategy	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	164,177	164,177	164,177
R^2	0.1975	0.1973	0.1978
Adjusted R^2	0.1974	0.1972	0.1977

Residual Standard Error	0.123 (df = 164,147)	0.123 (df = 164147)	0.123 (df = 164,147)
F Statistic	1,393.4*** (df = 29; 164,147)	1,391.6*** (df = 29; 164,147)	1,395.8*** (df = 29; 164,147)

Note: *p<.050; **p<.010; ***p<.001; t-stats are reported parenthetically below each coefficient. RGF coefficients are scaled by a factor of 10^3.

In all treatments, both the RGF categorical and the interaction between high RGF and quarterly fund returns are positive and significant, indicating support for Hypothesis 1b, that social capital has a greater impact on mutual fund flows when prior-period fund returns are high versus when prior-period fund returns are low, with this effect becoming more pronounced as social capital increases.

A graph of Treatment (2) is shown in Figure 3 below. The scenario only varies high versus low social capital and fund quarterly returns, and assumes the sample means for all continuous variables, a 1st-quarter observation in 2017, an institutional fund, a non-index fund, a non-ETF, and a cap-based strategy.



Note that the cutoff value for high versus low social capital is the mean of the sample RGF index plus one standard deviation of the RGF sample standard deviation.

Figure 3. Fund flows as a function of quarterly returns for high versus low social capital

The scenario graphed in Figure 3 indicates both a different y-intercept (a function of the RGF High coefficient) and a different slope (a function of the interaction coefficient) on the relationship between net fund flows and quarterly returns. Because these relationships are all statistically significant it can be definitively stated that, in this scenario, at quarterly returns of a value one standard deviation below the sample mean (-1.57%), a region of high social capital will exhibit a higher predicted net fund flow than a region of low social capital by 0.50%. Annualized, this fund flows differential is 2.00%, which is both a significant practical and significant statistical difference (*see* Section 4.2.3). However, this impact is significantly greater when fund quarterly returns are high, in this case at a fund quarterly return of the mean plus one standard deviation (3.15%). Quantifying this difference yields a 1.27% fund flow difference between low and high social capital regions on a quarterly basis, or an annualized difference of 5.08%. Other scenarios result in very similar results because the focus here is on the differences and not the magnitude of predicted quarterly flows.

The results of this analysis support Hypothesis 1b: Social capital moderates the effect that fund returns have on mutual fund flows, such that social capital has a greater impact on mutual fund flows when prior-period fund returns are high than when prior-period fund returns are low, with this effect becoming more pronounced as social capital increases.

4.5. Results of Hypothesis 2 Assessment

As discussed, Hypothesis 2 is that social capital is negatively related to mutual fund agency problems. In this case—as discussed at length in Section 2.1.5—the agency problem assessed is when window dressing behaviors are undertaken by fund managers in an attempt to make their performance appear superior to what financial metrics would indicate, in an effort to reduce fund outflows subsequent to periods of underperformance.

4.5.1. Hypothesis 2: Variable of Interest Is Backward Holding Return Gap

As discussed, window dressing is "an agency problem in the mutual fund industry where managers alter or distort their portfolios in an attempt to mislead investors about their true ability by disclosing disproportionately higher (lower) holdings in stocks that have done well (poorly) over a reporting period" (Agarwal et al., 2014, p. 3,135). Relying on prior literature, the Backward Holding Return Gap (BHRG) is used as the proxy variable for window dressing behaviors. The BHRG is the difference between a mutual fund's actual return and the hypothetical return a fund would have had if it held its end-of-quarter portfolio for the entire previous quarter (Kacperczyk et al., 2008). To calculate the BHRG, the actual fund return is subtracted from the hypothetical return (had the fund maintained the basket of equities that it held at the end of quarter for the entirety of the previous quarter), adjusted for trading expenses associated with the window dressed equities.

4.5.2. Hypothesis 2: Model Equation

Equation 6 identifies the model equation that is used to assess Hypothesis 2.

Equation 6. Hypothesis 2 Model Equation

$$
\begin{aligned}
\mathit{BHRG}_{\mathrm{i,t}} = {} & \beta_0 + \\
& \beta_1 \times \mathit{RGF\ Social\ Capital\ Index}_{t} + \\
& \beta_2 \times \mathit{Primary\ Independent\ Variables}_{\mathrm{i,t}} + \\
& \beta_3 \times \mathit{Lagged\ Returns\ Control}_{\mathrm{i,t}} +
\end{aligned}
$$

$$\beta_4 \times \textit{Time-Based Control Matrix}_{\,i,t} +$$
$$\beta_5 \times \textit{Fund Expense Control}_{\,i,t} +$$
$$\beta_6 \times \textit{Investor Type Control}_{\,i,t} +$$
$$\beta_7 \times \textit{Index and ETF Control Matrix}_{\,i,t} +$$
$$\beta_8 \times \textit{Fund Strategy Control Matrix}_{\,i,t} +$$
$$\beta_9 \times \textit{Year Fixed Effects}_{\,t} +$$
$$\varepsilon_{\,i,t}$$

The specific control variables employed in this model are unchanged from the analyses above; however, various combinations of controls are assessed to demonstrate analyses robustness.

4.5.3. Hypothesis 2: Dataset Development

To assess Hypothesis 2, the BHFG variable was appended to the dataset developed for the assessment of Hypothesis 1. Due to non-availability of the primary datasets required to develop the BHRG variable, this information was sourced directly from Dr. Vikas Agarwal at Georgia State University, whose original research was motivation for this hypothesis (Agarwal et al., 2014). This information was then merged into the Hypothesis 1 dataset via the following process.

Step 1: The starting point for the dataset, as sourced from Dr. Agarwal, was the BHRG for fund quarterly flows and returns for the years 2003 to 2008 (hereinafter, the "BHRG dataset").

Step 2: The BHRG dataset, however, only identified funds via the Wharton Financial Institution Center Number (WFICN) with no fund names or any other way to identify the associated funds with observed flows and BHRG data. Because of this, the Mutual Fund Links translator (MFLinks), via WRDS, was used to identify CRSP proprietary fund numbers ("FundNos") along with fund names and ticker symbols.

Step 3: The fund location information then was sourced from the CRSP database via WRDS to access address, city, state, zip code, and the specific dates for which the location information was valid by FundNo.

Step 4: With this information, begin/end dates for CRSP location info were associated with the window dressing variable dates to ensure proper fund manager location during the window dressing reporting period.

Step 5: Unfortunately, WFICNs mapped to multiple FundNos, because FundNos are identified for each share class of a mutual fund and WFICNs collapse all share classes on a fund basis. Each WFICN had an average of 3.95 records (or 3 to 4 share classes on average per fund). To exclude redundant data by share class, a new variable was created by combining the date and WFICN and trimming the Fund Name variable to exclude share class, resulting in a working dataset of only WFICNs relevant by date with the appropriate location information and parent fund.

Step 6: Accessing the U.S. Census Bureau database for a list of U.S. states and counties by zip code allowed the merger of RGF location at the window dressing reporting period.

Step 7: Because the RGF index is updated every few years, the dataset was bifurcated into year groups, and the appropriate RGF index year information was merged into the bifurcated datasets (via a derived county-state variable) and then all years were merged back into the dataset.

Step 8: Additionally, all the steps identified to create the dataset for Hypothesis 1 were required to properly associate the net fund flows and control variables with the window dressing fund/date combinations, resulting in the final dataset to assess Hypothesis 2 and Hypothesis 3.

Specific fund identifiers, such as fund name, ticker, and fund address, were maintained throughout the dataset development for quality-control purposes.

At 13,019 records, the resultant sample size only is 7.9% the size of the Alternate Hypothesis 1 dataset, due to a smaller (and older) set of years observed, and because of the share class compression discussed in Step 5 above. Future research could be undertaken to update this dataset to determine whether a more complete dataset would change any of these findings, but access to the underlying data would have to be acquired.

4.5.4. Hypothesis 2: Dataset Summary Statistics and Univariate Correlations

Summary statistics for the Hypothesis 2 dataset are shown in Table 9 below.

Table 9. Descriptive Statistics for Hypothesis 2 and 3 Dataset (Sample Size is 13,019)

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
BHRG	0.00	0.03	-0.09	-0.01	0.01	0.16

RGF	-0.18	0.84	-2.36	-0.87	0.34	3.90
Quarter Return	0.41%	2.29%	-7.69%	-0.77%	1.88%	9.33%
$Assets_t$	$1,937.6	$7,321.6	$4.2	$88.3	$1,144.6	$177,326.6
N. Fund Flows	1.15%	12.92%	-50.57%	-5.58%	5.89%	73.82%

Note: Assets in millions of dollars. Control variable descriptive statistics not shown for brevity.

The sample represents 6 years of data, from 2003 through 2008. As discussed above, this is a subset of the dataset associated with Hypothesis 1, chosen because these were the only years with data available for the BHRG variable. Because RGF is normalized, a mean of 0.0 and a standard deviation of 1.0 is expected. For this sample of data, however, the mean and standard deviation are somewhat different because not all counties are represented and the sample is drawn across multiple years. The mean of quarterly returns is 0.41%, with a range of -7.69% to 9.33%. Assets under management range from $4.2MM to $177.3B with a mean of $1.9B.

Table 10 shows univariate Pearson correlations for the Hypothesis 2 dataset.

Table 10. Pearson Correlation Matrix for Hypothesis 2 Dataset

	BHRG	**RGF**	**Quarterly Return**	**$Assets_t$**
BHRG	1.000^{***}			
RGF	-0.034^{***}	1.000^{***}		
Quarterly Return	0.057^{***}	0.043^{***}	1.000^{***}	
$Assets_t$	-0.034^{***}	-0.095^{***}	0.000	1.000^{***}
Net Fund Flows	-0.008	0.025^{**}	0.443^{***}	0.000

Note: $^{*}p<.050$; $^{**}p<.010$; $^{***}p<.001$; p-values are reported based upon t-statistics. Control variable correlations not shown for brevity.

As hypothesized, the RGF index is significantly and negatively correlated with the BHRG window dressing measure ($r(13{,}109) = -0.034$, $p<.001$), giving preliminary univariate support to Hypothesis 2. As with the broader dataset, the social capital index RGF is positively correlated with net fund flows (Rank Gap, $r(13{,}109) = 0.025$, p=.005). Given the previously noted findings of Agarwal (2014), the positive correlation between BHRG and quarterly returns ($r(13{,}109 = 0.057$ $p<.001$) is unexpected, albeit this finding might not be maintained on a multivariate basis. As was noted in the broader dataset, window dressing behaviors are associated with smaller funds ($r(13{,}109) = -0.034$, $p<.001$).

4.5.5. Hypothesis 2: Results and Discussion of Analyses

To assess Hypothesis 2, a series of ordinary least squares regression analyses was undertaken, assessing the RGF social capital index's impact on BHRG window dressing. All previously identified controls also were systematically included to assess their impact on the results. For support to be found for Hypothesis 2, the coefficient of the RGF index must be negative and statistically significant, indicating that social capital decreases the likelihood of window dressing behaviors. The results of these analyses are shown in Table 11.

Table 11. The Impact of Social Capital on Window Dressing Behaviors

	Dependent Variable			
	(1) BHRG	**(2) BHRG**	**(3) BHRG**	**(4) BHRG**
Constant	3.873^{***}	17.289^{***}	15.342^{*}	12.571^{*}
	(16.95)	(13.41)	(2.57)	(2.10)
RGF Index	-1.029^{***}	-1.155^{***}	-1.124^{***}	-1.098^{***}
	(-3.88)	(-4.38)	(-4.23)	(-4.14)
Primary Indep. Vars.	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Lagged Return	No	No	Yes	Yes
Time Based	No	No	Yes	Yes
Expense	No	No	Yes	Yes
Investor Type	No	No	Yes	Yes
Index & ETF	No	No	Yes	Yes

Fund Strategy	No	No	Yes	Yes
Year Fixed Effects	No	No	No	Yes
Observations	13,019	13,019	13,019	13,019
R^2	0.0012	0.0134	0.0206	0.0264
Adjusted R^2	0.0011	0.0132	0.0195	0.0250
Residual Standard Error	0.025 (df = 13,017)	0.025 (df = 13,015)	0.025 (df = 13,004)	0.025 (df = 12,999)
F Statistic	15.1*** (df = 1; 13,017)	58.8*** (df = 3; 13,015)	19.5*** (df = 14; 13,004)	18.6*** (df = 19; 12,999)

Note: $^{*}p<.050$; $^{**}p<.010$; $^{***}p<.001$; *t*-stats are reported parenthetically below each coefficient. RGF and constant coefficients are scaled by a factor of 10^3.

In all treatments, the RGF social capital index is negative and statistically significant, indicating that social capital has a dampening effect on window dressing behaviors and that this finding is robust to the inclusion of control variables that are shown to affect the driver of window dressing behaviors (e.g., capital flight, as measured by net fund flows). The results of these analyses support that Hypothesis 2: Social capital is negatively related to mutual fund agency problems.

4.6. Results of Hypothesis 2a Assessment

As discussed above, Hypothesis 2a is that social capital will moderate the impact that agency problems have on mutual fund flows, such that when social capital is low, window dressing behaviors have a strong impact on fund flows, and when social capital is high, window dressing behaviors have little impact on fund flows.

4.6.1. Hypothesis 2a: Model Equation

Equation 2 above identified the generalized fund flows prediction model equation. Similar to the approach taken in Section 4.4.1., here Equation 7 is modified by adding an interaction variable between the RGF social capital index and the BHGR proxy for window dressing. In moderation analysis, the interaction variable is used to determine whether the impact of the independent variable on the dependent variable varies based upon the value of the moderator. In this case, the interaction term is included to determine whether the impact of window dressing behaviors on fund flows was different for varying levels of social capital (mathematically, a statistically significant change in the slope of the linear approximation of net fund flows as a function of window dressing at high versus low values of social capital).

Equation 7. Hypothesis 2a Model Equation

$$
\begin{aligned}
\textit{Net Fund Flows}_{\mathrm{i,t}} = \;& \beta_0 + \\
& \beta_1 \times \textit{RGF Social Capital Index}_{t} + \\
& \beta_2 \times \textit{BHRG Window Dressing Proxy}_{i,t} + \\
& \beta_3 \times \textit{RGF}_{t} \times \textit{BHRG}_{i,t} + \\
& \beta_4 \times \textit{Primary Independent Variables}_{\mathrm{i,t}} + \\
& \beta_5 \times \textit{Lagged Returns Control}_{\mathrm{i,t}} + \\
& \beta_6 \times \textit{Time-Based Control Matrix}_{\mathrm{i,t}} + \\
& \beta_7 \times \textit{Fund Expense Control}_{\mathrm{i,t}} + \\
& \beta_8 \times \textit{Investor Type Control}_{\mathrm{i,t}} + \\
& \beta_9 \times \textit{Index and ETF Control Matrix}_{\mathrm{i,t}} + \\
& \beta_{10} \times \textit{Fund Strategy Control Matrix}_{\mathrm{i,t}} + \\
& \beta_{11} \times \textit{Year Fixed Effects}_{\mathrm{t}} + \\
& \varepsilon_{\mathrm{i,t}}
\end{aligned}
$$

For the sake of brevity, the control variables are not defined here because they are identical to those controls used in prior analyses.

The BHRG variable is integral to this analysis, therefore the Hypothesis 2 dataset is again employed.

4.6.2. Hypothesis 2a: Results and Discussion of Analyses

To assess Hypothesis 2a, a series of ordinary least squares regression analyses was undertaken, assessing the interaction variable derived by multiplying the RGF index by the BHRG window dressing proxy. All previously identified controls also were included in all analyses. For support to be found for Hypothesis 2a, the interaction variable must be statistically significant, indicating that the impact of the independent variable (BHRG) on the dependent variable (net fund flows) varies with changes in the moderator (the RGF social capital index). The results of these analyses are shown in Table 12.

Table 12. Social Capital's Moderating Effect of Window Dressing on Fund Flows

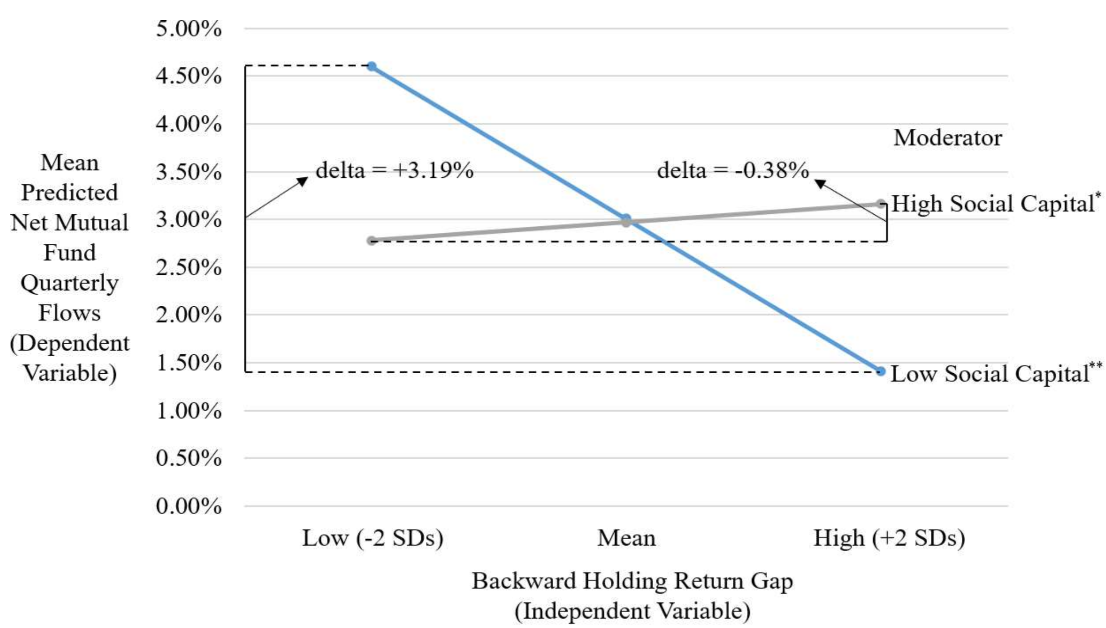
	Dependent Variable		
	(1) Net Fund Flows	(2) Net Fund Flows	(3) Net Fund Flows
Constant	0.012***	0.092***	0.093***
	(13.41)	(3.45)	(3.47)
RGF Index	0.006		-0.100
	(0.05)		(-0.08)
BHRG		-0.159***	-0.138***
		(-4.07)	(-3.43)
RGF x BHRG			0.104*
			(2.23)
Primary Indep. Vars.	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Lagged Return	Yes	Yes	Yes
Time Based	Yes	Yes	Yes
Expense	Yes	Yes	Yes
Investor Type	Yes	Yes	Yes
Index & ETF	Yes	Yes	Yes
Fund Strategy	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	13,019	13,019	13,019
R^2	0.2469	0.2478	0.2481
Adjusted R^2	0.2458	0.2467	0.2469

Residual Standard Error	0.112 (df = 12,999)	0.112 (df = 12,999)	0.112 (df = 12,997)
F Statistic	224.3*** (df = 19; 12,999)	225.4*** (df = 19; 12,999)	204.3*** (df = 21; 12,997)

Note: *p<.050; **p<.010; ***p<.001; t-stats are reported parenthetically below each coefficient. RGF coefficients are scaled by a factor of 10^3.

As shown in Treatment (3), the interaction variable is positive and statistically significant (β=0.104, p=.026), indicating that the RGF social capital index significantly moderates the relationship between BHRG and net funds flows, giving support to Hypothesis 2a. It is important to note that statistical significance of the RGF coefficient itself is not a requirement to make this conclusion (Baron & Kenny, 1986).[4]

A graph of the findings of Treatment (3) is shown as Figure 4 below. The scenario only varies high versus low social capital and BHRG, and assumes the sample means for all continuous variables, a 1st-quarter observation in 2017, an institutional fund, a non-index fund, a non-ETF, and a cap-based strategy.



*Note that *High Social Capital is the sample mean of the RGF index plus two standard deviations; **Low Social Capital is the sample mean of the RGF index minus two standard deviations.*

Figure 4. Fund flows as a function of BHRG window dressing, for high versus low social capital

The scenario graphed in Figure 4 indicates both a different y-intercept (a function of BHRG) and a different slope (a function of the interaction coefficient) on the relationship between net fund flows and BHRG at different levels of social capital.

In this scenario, when social capital is high window dressing behaviors have the effect that fund managers seek when employing these behaviors: net fund flows increase (although the difference is quite small at a gradient of -0.38%). This effect is likely caused by the underlying trust in fund managers that occurs when social capital is high, although this trust would be misplaced in this case. When social capital is low, however, window dressing behaviors have a severe and negative effect on net fund flows, with a large gradient (+3.19%). This is likely caused by the lack of trust inherent when social capital is low, resulting in investors identifying the window dressing behaviors for what they are—a move to deceive them.

Other scenarios will result in similar results because the focus here is on the differences not the magnitude of predicted quarterly flows.

The results of this analysis support Hypothesis 2a: Social capital moderates the impact that agency problems have on mutual fund flows, such that when social capital is low, window dressing behaviors have a great impact on fund flows, and when social capital is high, window dressing behaviors have little impact on fund flows.

4.7. Results Summary

As summarized in Figure 5 below, support was found for all hypotheses, and the prior findings related to the direct relationship between fund returns and net fund flows (Friesen & Sapp, 2007; Barber et al., 2016) was replicated, as were the prior research findings on the direct relationship between window dressing behaviors and net fund flows (Agarwal et al., 2014).

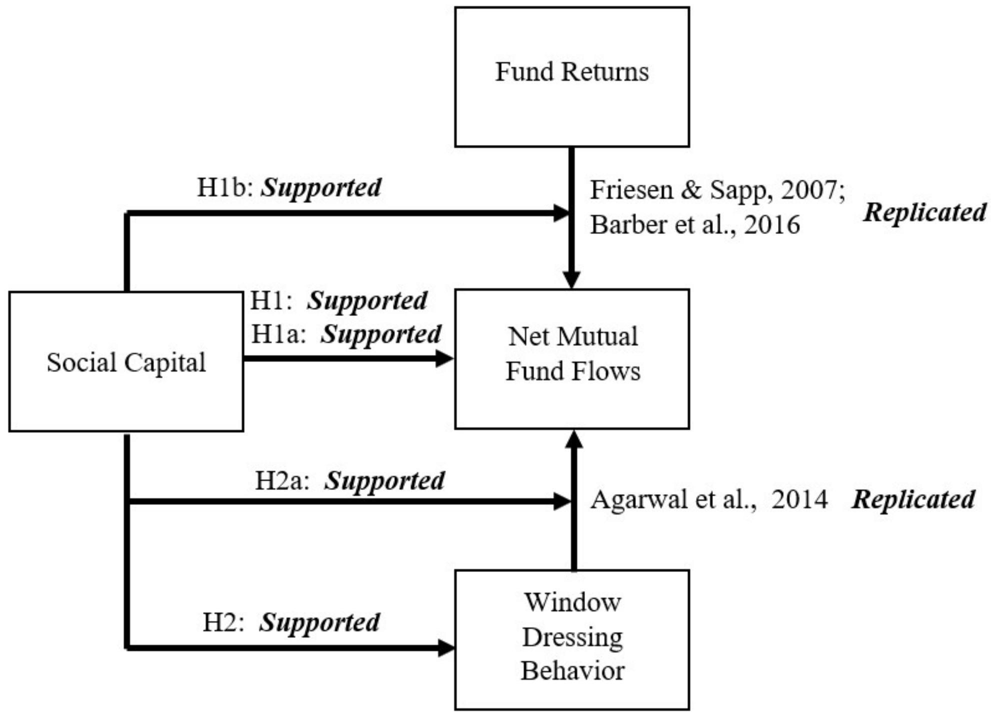


Figure 5. Summary findings

Specifically, social capital is positively related to mutual fund flows (H1), meaning that regions of high social capital exhibit higher fund flows, with the opposite also being true. Also, the marginal impact of social capital on fund flows increases as social capital increases (H1a), demonstrating the importance of trust—high trust levels drive action, and low trust levels do not. Social capital was found to moderates the effect that fund returns have on mutual fund flows (H1b), such that social capital has a greater positive impact on mutual fund flows when prior period fund returns are high than when prior period fund returns are low, with this effect becoming more pronounced as social capital increases. It also was found that social capital is negatively related to mutual fund agency problems (H2), meaning that there is comparatively very little window dressing behavior exhibited when social capital levels are high, with the opposite also being true. Finally, it was demonstrated that social capital moderates the impact that agency problems have on mutual fund flows, such that when social capital is low, window dressing behaviors have a large impact on fund flows, and when social capital is high, window dressing behaviors have little impact on fund flows.

5. Robustness Tests

The definition of robustness of an empirical procedure is "a measure of its capacity to remain unaffected by small but deliberate variations in method parameters and provides an indication of its reliability during normal usage (Vander Heyden et al., 2001, p. 724)." Section 5 aims to demonstrate that social capital is a statistically significant driver of net mutual fund flows when varying the model parameters previously identified. The RGF index itself will be assessed to see whether it or any of its components (or combinations of them) are the true predictor of mutual fund flows. Alternative measures of social capital and net fund flows also are assessed. Finally, an analysis of social capital's impact on fund flows was conducted by quartile of each of the non-categorical control variables.

5.1. Robustness Tests: Analysis of the RGF Social Capital Index

As a robustness analysis, the components of the RGF index as predictors of net fund flows are analyzed to further understand the underlying drivers of net fund flows. Summary statistics for the data are exhibited in Table 13 below.

Table 13. Descriptive Statistics for RGF Component Analysis Dataset (Sample Size Is 164,143 Records)

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
RGF	-0.14	0.83	-2.36	-0.64	0.33	3.90
F1: Religious	622.4	639.5	15.0	257.0	704.0	3,258.0
F1: Civic	158.7	118.1	0.0	66.0	274.0	625.0
F1: Business	108.1	89.6	0.0	44.0	212.0	486.0
F1: Political	23.4	19.1	0.0	9.0	40.0	149.0
F1: Professional	72.1	64.7	0.0	27.0	146.0	319.0
F1: Labor	116.8	86.8	0.0	49.0	233.0	353.0
F1: Bowl Centers	11.9	13.4	0.0	6.0	11.0	61.0
F1: Fitness Centers	201.9	176.3	0.0	103.0	363.0	743.0

F1: Golf	22.5	27.2	0.0	8.0	24.0	142.0
F1: Sports	6.4	5.7	0.0	3.0	9.0	29.0
Total F1	1,353.2	1,133.4	24.0	692.0	2,078.0	5,497.0
F2: Voting	54.2%	9.3%	36.0%	45.8%	60.8%	81.0%
F3: Census	70.3%	6.6%	45.0%	64.0%	76.0%	86.0%
F4: Nonprofit	10,968.5	9,226.5	66.0	4,986.0	20,349.0	41,125.0
Total F1 and F4	12,321.7	10,317.5	90.0	5,635.0	22,427.0	46,622.0
Population	1,542,451	1,910,244	14,015	716,214	1,583,431	9,787,400
Fund Flows	1.50%	13.75%	-92.46%	-4.53%	5.77%	97.35%
Quarter Return	0.79%	2.35%	-7.66%	-0.20%	1.98%	12.17%
Assets	$3,498.1	$16,181.2	$0.01	$132.4	$1,817.4	$661,615.4
Asset Growth	2.29%	14.86%	-88.47%	-4.58%	7.63%	95.29%

Note: Assets in millions of dollars; "F" in the table above annotates the factor in the principal component analysis used to determine the RGF index with which a variable is associated.

As discussed above, the Principal Component Analysis (PCA) Factor 1 variables refer to the number of organizations, by type, that exist in the county when computing the RGF index. The types of organizations are religious, civic, business, political, professional, labor, bowling centers, golf courses, and sporting organizations. The variable "Total F1" is the total number of these organizations combined, because it could be the case that the number of total organizations is the driver of net fund flows, rather than the type of organization. The percentage of the county that voted in the most recent presidential election (prior to the date that the RGF index was computed), and the percentage of the county that participated in the most recent national census (prior to the date that the RGF index was computed) are referred to as Factor 2 and Factor 3, respectively. Factor 4 is the number of nonprofit organizations in the county. These four factors are equally weighted and a PCA is conducted to derive the RGF index. An additional variable called "Total F1 and F4" is simply the total number of all organizations in the county. Additionally, as is discussed below, the organization numbers are also considered on a per capita basis, because the participation rate could be a more important driver than the number of organizations when it comes to predicting net fund flows.

The correlations between the RGF component variables and the variables of interest and control variables are shown in Table 14 below.

Table 14. Pearson Correlations for RGF Component Analysis Dataset

	RGF	N. Fund Flows	Qtr. Return	Assets $_{t-1}$	Assets $_t$	Asset Growth
RGF	1.000***					
N. Fund Flows	0.015***	1.000***				
Qtr. Returns	-0.003	0.407***	1.000***			
Assets$_{t-1}$	-0.106***	-0.002	0.002	1.000***		
Assets	-0.104***	0.007**	0.013***	0.999***	1.000***	
Asset Growth	0.014***	0.989***	0.535***	-0.001	0.008***	1.000***
Religion	-0.329***	-0.011***	0.000	0.243***	0.229***	-0.010
Civic	-0.074***	-0.001	0.011***	0.184***	0.180***	-0.001***
Business	0.094***	-0.008**	0.005*	0.083***	0.081***	0.007
Political	0.076***	-0.004	0.005*	0.070***	0.068***	-0.003
Professional	0.152***	-0.013***	0.005*	0.030***	0.029***	-0.011***
Labor	0.058***	-0.005*	0.012***	0.089***	0.086***	-0.003
Bowling	-0.309***	-0.010***	-0.006**	0.193***	0.189***	-0.010*
Fitness	-0.073***	-0.011***	0.008**	0.165***	0.161***	-0.009***
Golf	-0.383***	-0.010***	-0.012***	0.230***	0.226***	-0.012***
Sports	-0.226***	-0.005	-0.009***	0.220***	0.215***	-0.003
Voting %	0.414***	-0.001	-0.029***	-0.040***	-0.038***	-0.006**
Census %	0.162***	-0.027***	-0.029***	0.059***	0.059***	-0.029***

Nonprofit	-0.037***	-0.008***	0.011***	0.173***	0.169***	-0.006***
Population	-0.387***	-0.008**	0.003	0.263***	0.259***	-0.007

Note: *p<.050; **p<.010; ***p<.001; p-values are reported based upon t-stats

As expected, the components of the RGF index are all statistically univariately correlated to the RGF itself. In this particular sample, however, some of the directions of these correlations are unexpected; for example, the number of religious organizations is negatively correlated with the RFG index (r(164,143) = -0.329, p<.001). This effect is likely due to the fact that most mutual fund managers are located in areas of high populations, underrepresenting rural counties in the sample. Further, as expected based upon the prior analyses, the RGF is positively and statistically significantly univariately correlated with net fund flows (r(164,143) = 0.015, p<.001), but all of its components are negatively correlated with net fund flows, a very unexpected finding, indeed. These findings dramatically demonstrate the limitations of univariate analyses.

Multivariate ordinary least squares regression analysis was conducted to determine which of the components of the RGF index were the actual drivers of fund flow prediction, and if these components were better predictors than the RGF index itself. For the analysis to be successful, a relatively small number of easily identified predictor variables leads to better explanation of variance (e.g., higher *adjusted* R^2) than does using the composite RGF index. The results are shown in Table 15.

Table 15. Net Fund Flows Predicted by the Components of the RGF Index, with Controls

	Dependent Variable			
Panel A	**(1) Net Fund Flows**	**(2) Net Fund Flows**	**(3) Net Fund Flows**	**(4) Net Fund Flows**
Constant	0.107***	0.145***	0.122***	0.126***
	(33.12)	(20.52)	(22.93)	(23.76)
RGF Index	3.521***			
	(8.70)			

F1: Religion	-0.085*		
	(-1.99)		
F1: Civic	0.436***		
	(3.47)		
F1: Business	2.959***		
	(9.50)		
F1: Political	-6.762***		
	(-8.27)		
F1: Professional	-2.730***		
	(-10.76)		
F1: Labor	-0.523*		
	(-2.27)		
F1: Bowling	-1.332		
	(-1.43)		
F1: Fitness	-0.509***		
	(-5.07)		
F1: Golf	1.198***		
	(3.49)		
F1: Sports	-3.995*		
	(-1.98)		
Factor 1 Total		-0.179***	
		(-7.38)	
F2: Voting %	0.051***	0.055***	0.045***
	(8.75)	(10.27)	(8.64)

F3: Census %		-0.092***	-0.059***	-0.061***
		(-8.89)	(-7.73)	(-7.96)
F4: Nonprofit		0.021***	0.013***	
		(6.94)	(6.86)	
Factor 1,4 Total				-0.000
				(-0.60)
Population	0.128	-0.119***	4.948***	0.277
	(0.73)	(-1.33)	(7.02)	(0.90)
Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	164,143	164,143	164,143	164,143
R^2	0.1968	0.1981	0.1971	0.1969
Adjusted R^2	0.1967	0.1979	0.1970	0.1967
Residual Standard Error	0.123 (df = 164,113)	0.123 (df = 164,101)	0.123 (df = 164,110)	0.123 (df = 164,111)
F Statistic	1,387.0*** (df = 29; 164,113)	988.9*** (df = 41; 164,101)	1,259.2*** (df = 32; 164,110)	1,297.7*** (df = 31; 164,111)

	Dependent Variable			
Panel B	**(5) Net Fund Flows**	**(6) Net Fund Flows**	**(7) Net Fund Flows**	**(8) Net Fund Flows**
Constant	0.107***	0.152***	0.114***	0.115***
	(33.12)	(22.40)	(21.27)	(21.37)
RGF Index	3.406***			
	(9.14)			

F1: Rel, per Capita	-0.063		
	(-1.64)		
F1: Civic, per Capita	-0.155		
	(-1.58)		
F1: Bus, per Capita	1.153***		
	(6.26)		
F1: Pol, per Capita	-1.929***		
	(-3.71)		
F1: Profess, per Capita	-1.062***		
	(-5.64)		
F1: Labor, per Capita	-0.803***		
	(-4.61)		
F1: Bowl, per Capita	2.452***		
	(3.48)		
F1: Fitness, per Capita	0.118		
	(1.51)		
F1: Golf, per Capita	0.910**		
	(2.96)		
F1: Sports, per Capita	4.592**		
	(3.14)		
F1 Total, per Capita		-0.059**	
		(-3.13)	
F2: Voting %	0.035***	0.045***	0.041***
	(6.85)	(9.16)	(8.61)

F3: Census %		-0.095***	-0.045***	-0.048***
		(-10.08)	(-6.01)	(-6.42)
F4: Nonprofit, p. c.		0.011***	0.009***	
		(6.54)	(6.00)	
F1, F2 Total, per Capita				0.005***
				(5.74)
Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	164,143	164,143	164,143	164,143
R^2	0.1968	0.1979	0.1971	0.1970
Adjusted R^2	0.1967	0.1977	0.1969	0.1969
Residual Standard Error	0.123 (df = 164,114)	0.123 (df = 164,102)	0.123 (df = 164,111)	0.123 (df = 164,112)
F Statistic	1,436.5*** (df = 28; 164,114)	1,012.4*** (df = 40; 164,102)	1,299.4*** (df = 31; 164,111)	1,342.3*** (df = 30; 164,112)

Note: *p<.050; **p<.010; ***p<.001; *t*-stats are reported parenthetically below each coefficient; RGF coefficients scaled by a factor of 10^3; Factor 1 and Factor 4 coefficients scaled by a factor of 10^4; Population coefficients scaled by a factor of 10^9. Controls employed in these analyses are consistent with the control variables identified in Section 4: log assets, the cube root of fund age in days, the quarter in which observations occurred, fund expense ratio, a categorical to discriminate institutional versus retail funds, categoricals indicating index funds and ETFs, and fund strategy categoricals.

Treatment (1) and Treatment (5) predict net fund flows by the RGF index, controlling for fund controls and year fixed effects (and the population of the U.S. county in which the fund is headquartered, in the case of Treatment (1)). The *adjusted R^2* for both analyses is 0.197, meaning that 19.7% of the variation of net fund flows is explained by these variables: Treatment (1):

R^2 =.197, F(29; 164,113)= 1,387.0, p<.001; Treatment (5): R^2 =.197, F(28; 164,114)= 1,436.5, p<.001.

The intent of Treatment (2) and Treatment (6) is to break down the RGF index into its components to assess which of the RGF elements are the drivers of net fund flows. Treatment (2) looks only at the number of organizations, and includes county population as a control variable. Treatment (6) looks at the number of organizations on a per capita basis to determine whether the rate of organizational participation is actually the driver. The respective predictive powers of these analyses are virtually unchanged from Treatment (1) and Treatment (5), but the models are much more complex, although these analyses do show that certain components of the RGF index are not predictors of net fund flows because their coefficients are not statistically significant. In the case of Treatment (2), the number of bowling centers in the county is the only variable that is not predictive of net fund flows (β=-1.332, p=.153). In the case of Treatment (6), nine of the twelve variables are predictive of net fund flows. Those variables that are not predictive are religious organizations (β=-0.063, p=.102), civic organizations (β=-0.155, p=.114), and fitness centers (β=0.118 p=.131). All other individual variables are significant predictors of net fund flows for Treatment (2) and Treatment (6).

The intent of Treatment (3), Treatment (4), Treatment (7), and Treatment (8) is to investigate whether the true driver of net fund flows is the total number of organizations in the county as opposed to the number of organizations by type, but these analyses all were marginally worse at explaining variance due to their reduced resolution, even though they were simpler models (which should improve *adjusted* R^2).

The conclusion drawn here is that the RGF index itself is a better predictor of net fund flows than more complex models using any number of the components of the RGF index. Additionally, it would be more difficult for a practitioner in the mutual fund market to access the data used to derive the RGF index than to access the RGF index.

5.2. Robustness Tests: Other Measures of Social Capital

Most researchers agree that social capital is a community effect (Rupasingha et al., 2006), thus the RGF U.S. county–level social capital index was employed for all analyses described above. However, social capital has been studied at all levels of society, from the community level to the national level (Gelderblom, 2018). In 2000, Inkeles developed the concept for a global social capital measure. He suggested that institutions, patterns in culture, methods of national communication, income equality, and personal associations were important aspects of a country’s ability to attain goals (Inkeles, 2000). However, Inkeles did not actually develop the index. Seemingly the only global index of social capital is the World Bank's GCI 4.0: Social Capital Index, which each year ranks countries on a scale of 1 to 100. The basis for the index is social engagement and cohesion, community/family networks, participation in the political process, and trust in institutions (govdata360.worldbank.org/indicators/ha5376100). This dissertation is focused on net fund flows of U.S. equity–based mutual funds, therefore an assessment of national social capital impact on net fund flows is beyond the scope of this study but would be an important topic of future research.

A U.S. state-level social capital index was developed by Robert Putnam in 2001 (referred to hereinafter as the "Putnam Social Capital Index" or the "Putnam Index"). Variables used to compute Putnam's Social Capital Index include membership in national chapter-based associations, percentage of people who have served as officers or committee members for local clubs or organizations, attendance at club meetings, percent of people who believe that "most people can be trusted," and charitable donations by individuals.

The states with the highest social capital are, in order, (1) North Dakota, (2) South Dakota, (3) Vermont, (4) Minnesota, (5) Montana, (6) Nebraska, (7) Iowa, (8) New Hampshire, (9) Wyoming, and (10) Washington. On the other end of the continuum, the states with the lowest social capital are (50) Nevada, (49) Mississippi, (48) Georgia, (47) Alabama, (46) Louisiana, (45) Tennessee, (44) South Carolina, (43) West Virginia, (42) North Carolina, and (41) Kentucky. A mapping of Putnam's Social Capital Index is shown in Figure 6, but the Putnam Index has not been updated since 2001.

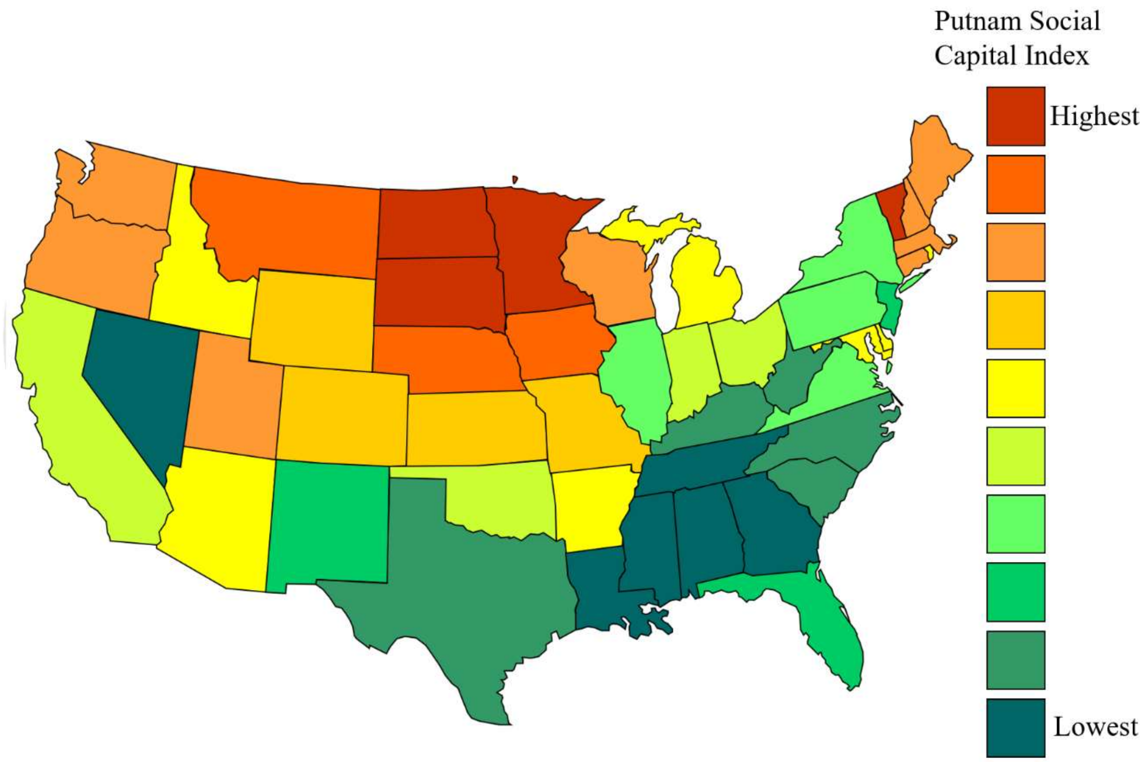


Figure 6. Putnam's Social Capital Index

Although the Putnam Index does not have the county-level resolution of the RGF index, it has been used extensively in the literature to assess social capital impacts, and therefore is assessed here as a robustness test.

Mirroring the primary analyses above, the Putnam Index was used as an alternative predictor of net fund flows. For the robustness test to be successful, the coefficient of the Putnam Index in these analyses should be positive and statistically significant in all treatments. The results are shown in Table 16 below.

Table 16. Net Fund Flows Predicted by the Putnam Index

	Dependent Variable		
	(1) Net Fund Flows	**(2) Net Fund Flows**	**(3) Net Fund Flows**
Constant	0.023^{***}	0.119^{***}	0.107^{***}
	(25.30)	(38.18)	(32.94)

Putnam Index	3.572^{***}	3.127^{***}	3.253^{***}
	(4.65)	(4.41)	(4.60)
Controls	No	Yes	Yes
Year Fixed Effects	Yes	No	Yes
Observations	164,143	164,143	164,143
R^2	0.0394	0.1918	0.1965
Adjusted R^2	0.0393	0.1918	0.1964
Residual Standard Error	0.135 (df = 164,127)	0.124 (df = 164,128)	0.123 (df = 164,114)
F Statistic	448.5^{***} (df = 15; 164,127)	$2{,}782.9^{***}$ (df = 14; 164,128)	$1{,}433.7^{***}$ (df = 28; 164,114)

Note: $^{*}p<.050$; $^{**}p<.010$; $^{***}p<.001$; *t*-stats are reported parenthetically below each coefficient; Putnam coefficients scaled by a factor of 10^3; Controls employed in these analyses are consistent with the control variables identified in Section 4: log assets, the cube root of fund age in days, the quarter in which observations occurred, fund expense ratio, a categorical to discriminate institutional versus retail funds, categoricals indicating index funds and ETFs, and fund strategy categoricals.

As with the county-level index of social capital (the RGF index), whether controlling for year fixed effects only (Treatment 1), fund characteristics only (Treatment 2), or both (Treatment 3), the Putnam state-level Social Capital Index is demonstrated to be positively associated with higher net fund flows, adding support to the conclusions drawn above, namely that social capital positively predicts net mutual fund flows.

5.3. Robustness Tests: Modified Net Fund Flows

Equation 1 above is the calculation of net fund flows as outlined in Sirri and Tufano's 1998 seminal work on fund flows. As derived, this equation implicitly assumes that the capital inflows occur at the end of each quarter but, of course, they do not; they are invested at all times during a quarter. Quarterly dividends, however, if paid, typically are paid at the quarter end. To partially control for these effects (and as an additional robustness test) a new fund flow variable, "modified net fund flows," is introduced here. The modified net fund flows variable, shown as Equation 8 below, is similar to the net fund flows variable, except the denominator of the equation is prior-period assets adjusted for current-period returns (instead of simply prior-period assets).

Equation 8. Modified Net Fund Flows Equation

$$Modified\ Net\ Fund\ Flows_{\ i,t} = \frac{\left[Assets_{\ i,t} - Assets_{\ i,t-1} \times \left(1 + Return_{\ i,t}\right)\right]}{\left[Assets_{\ i,t-1} \times \left(1 + Return_{\ i,t}\right)\right]}$$

Further, an additional dependent variable—average net fund flows—is defined as the average of net fund flows and modified net fund flows for each record.

Table 17 shows the results of regression analyses with the three different dependent variables being predicted by the RGF index with controls. For the robustness test to be successful, the coefficient of the RGF index should be positive and statistically significant in all treatments. Note that Treatment (1) is net fund flows from Equation 1 and is used here for comparative purposes.

Table 17. Net Fund Flows Versus Modified Net Fund Flows, All Identified Control Variables

	Dependent Variable		
	(1) Net Fund Flows	**(2) Modified Net Fund Flows**	**(3) Average Net Fund Flows**
Constant	0.107***	0.105***	0.107***
	(33.11)	(33.01)	(33.07)
RGF Index	3.395***	3.406***	3.401***
	(9.08)	(9.20)	(9.14)
Log Assets	0.416*	0.452**	0.434**
	(2.52)	(2.77)	(2.65)
Quarter Return	2.513***	2.495***	2.504***
	(164.99)	(165.41)	(165.22)

Lagged Quarter Return	0.364***	0.367***	0.365***
	(26.06)	(26.57)	(26.32)
Cube Root Age	-5.000***	-4.961***	-4.980***
	(-57.25)	(-57.37)	(-57.32)
Quarter			
2nd Quarter	0.001	0.001	0.001
	(1.58)	(1.26)	(1.42)
3rd Quarter	-0.006***	-0.006***	-0.006***
	(-6.76)	(-7.38)	(-7.07)
4th Quarter	-0.002*	-0.002**	-0.002*
	(-2.36)	(-2.63)	(-2.49)
Expense Ratio	-1.757***	-1.763***	-1.760***
	(-26.75)	(-27.10)	(-26.93)
Institutional	-0.017***	-0.017***	-0.017***
	(-21.79)	(-21.82)	(-21.80)
Index	-0.008***	-0.008***	-0.008***
	(-6.37)	(-6.75)	(-6.56)
Non-ETF	-0.027***	-0.027***	-0.027***
	(-14.08)	(-14.10)	(-14.10)
Sector Based	2.886***	1.901	2.393*
	(2.76)	(1.84)	(2.30)
Goal Based	4.120***	4.450***	4.285***
	(5.85)	(6.38)	(6.11)

Year Fixed Effects	Yes	Yes	Yes
Observations	164,177	164,177	164,177
R^2	0.198	0.198	0.198
Adjusted R^2	0.197	0.198	0.198
Residual Standard Error	0.123(df = 164,148)	0.122 (df = 164,148)	0.123 (df = 164,148)
F Statistic	$1,442.9^{***}$ (df = 28; 164,148)	$1,449.6^{***}$ (df = 28; 164,148)	$1,446.4^{***}$ (df = 28; 164,148)

Note: $^{*}p$<.050; $^{**}p$<.010; $^{***}p$<.001; *t*-stats are reported parenthetically below each coefficient; RGF coefficient, log asset coefficient, cube root age, and strategy coefficients scaled by a factor of 10^3.

Given the statistical significance of the RGF social capital index in all treatments (net fund flows: β=3.395, p<.001; modified net fund flows: β=3.406, p<.001; average net fund flows: β=3.401, p<.001), the conclusion that social capital has a positive impact on fund flows is robust to alternative measures of net fund flows.

5.4. Fund Flow Drivers: Quartiles Analyses

As an additional robustness test, the impact on fund flows is assessed here at the quartile values of the non-categorical control variables to determine whether large (or small) values of the control variables drive the analyses. For these robustness tests to be successful, the RGF coefficient of all treatments at each quartile would exhibit positive and statistically significant results, expecting, however, that it is likely that the magnitudes of the coefficients can vary (these analyses are left for future research).

5.4.1. Robustness Tests: Quartiles of Fund Size

This section assesses quartiles of fund size. Treatment (1) includes all observations for comparative purposes, Treatment (2) includes the largest 25% of funds, Treatment (3) includes only the records that are above the mean of fund size, Treatment (4) includes only the records that are below the mean of fund size, and Treatment (5) includes the smallest 25% of funds. As discussed above, for this robustness test to be successful, the RGF coefficient of all treatments would exhibit positive and statistically significant results, expecting, however, that it is likely that the magnitudes of the coefficients can vary. Results are shown in Table 18 below.

Table 18. The Impact of Social Capital on Net Fund Flows by Firm Size Quartile

	Dependent Variable				
	(1) Fund Flows, All Records	(2) Fund Flows, Largest 25% of Assets	(3) Fund Flows, Largest 50% of Assets	(4) Fund Flows, Smallest 50% of Assets	(5) Fund Flows, Smallest 25% of Assets
Constant	0.107^{***}	0.004	0.028^{***}	0.130^{***}	0.136^{***}
	(33.11)	(0.68)	(6.16)	(22.54)	(14.33)
RGF Index	3.395^{***}	2.521^{***}	2.408^{***}	4.317^{***}	7.760^{***}
	(9.08)	(5.64)	(6.73)	(6.26)	(6.85)
Log Assets	0.416^{*}	2.050^{***}	2.178	1.842^{***}	3.540^{***}
	(2.52)	(5.50)	(7.84)	(4.29)	(4.23)
Primary Indep. Vars.	Yes	Yes	Yes	Yes	Yes
Controls					
Lagged Return	Yes	Yes	Yes	Yes	Yes
Time Based	Yes	Yes	Yes	Yes	Yes
Expense	Yes	Yes	Yes	Yes	Yes
Investor Type	Yes	Yes	Yes	Yes	Yes
Index & ETF	Yes	Yes	Yes	Yes	Yes
Fund Strategy	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	164,177	41,046	82,089	82,088	41,047

R^2	0.1975	0.3276	0.2731	0.1792	0.1647
Adjusted R^2	0.1974	0.3272	0.2728	0.1789	0.1641
Residual Standard Error	0.123 (df = 164,148)	0.069 (df = 41,017)	0.086 (df = 82,060)	0.151 (df = 82,059)	0.173 (df = 41,018)
F Statistic	1,442.9*** (df = 28; 164,148)	713.7*** (df = 28; 41,017)	1,101.0*** (df = 28; 82,060)	639.8*** (df = 28; 82,059)	288.8*** (df = 28; 41,018)

Note: $^{*}p<.050$; $^{**}p<.010$; $^{***}p<.001$; *t*-stats are reported parenthetically below each coefficient; RGF and log assets coefficients scaled by a factor of 10^3.

Although fund size, measured in natural log of net fund assets, is not significant in every treatment, the RGF index is significant in all treatments, indicating that the RGF index, as a predictor of net fund flows, is robust to fund size. This analysis also demonstrates that social capital likely has a stronger impact on smaller funds, as the RGF coefficients generally increase from Treatment (2) through Treatment (5). This is yet another area of potential future research.

5.4.2. Robustness Tests: Quartiles of Fund Quarterly Returns

Section 5.4.2. presents an assessment of quartiles of fund returns. Treatment (1) includes all records for comparative purposes, Treatment (2) includes the largest 25% of fund quarterly returns observed, Treatment (3) includes only the records that are above the mean of fund quarterly returns, Treatment (4) includes only the records that are below the mean of fund quarterly returns, and Treatment (5) includes the smallest 25% of observed quarterly returns. As discussed, for this robustness test to be successful the RGF coefficient of all treatments would exhibit positive and statistically significant results, expecting, however, that it is likely that the magnitudes of the coefficients can vary. Results are shown in Table 19 below.

Table 19. The Impact of Social Capital on Net Fund Flows by Quartile of Quarterly Returns

	Dependent Variable				
	(1) Fund Flows, All Records	(2) Fund Flows, Highest 25% of Returns	(3) Fund Flows, Highest 50% of Returns	(4) Fund Flows, Lowest 50% of Returns	(5) Fund Flows, Lowest 25% of Returns
Constant	0.107^{***}	0.090^{***}	0.110^{***}	0.096^{***}	0.067^{***}
	(33.11)	(0.68)	(23.51)	(21.06)	(8.48)
RGF Index	3.395^{***}	6.183^{***}	4.321^{***}	2.746^{***}	1.813^{*}
	(9.08)	(7.59)	(8.03)	(5.33)	(2.51)
Quarterly Returns	2.513^{***}	2.769^{***}	2.846^{***}	2.319^{***}	2.250^{***}
	(164.99)	(50.23)	(76.38)	(78.96)	(50.18)
Primary Indep. Vars.	Yes	Yes	Yes	Yes	Yes
Controls					
Lagged Return	Yes	Yes	Yes	Yes	Yes
Time Based	Yes	Yes	Yes	Yes	Yes
Expense	Yes	Yes	Yes	Yes	Yes
Investor Type	Yes	Yes	Yes	Yes	Yes
Index & ETF	Yes	Yes	Yes	Yes	Yes
Fund Strategy	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	164,177	41,044	82,088	82,089	41,044
R^2	0.1975	0.1200	0.1216	0.1380	0.1125
Adjusted R^2	0.1974	0.1194	0.1213	0.1377	0.1119

Residual Standard Error	0.123 (df = 164,148)	0.134 (df = 41,015)	0.126 (df = 82,059)	0.119 (df = 82,060)	0.121 (df = 41,015)
F Statistic	1,442.9*** (df = 28; 164,148)	199.8*** (df = 28; 41,015)	405.5*** (df = 28; 82,059)	469.1*** (df = 28; 82,060)	185.6*** (df = 28; 41,015)

Note: *p<.050; **p<.010; ***p<.001; *t*-stats are reported parenthetically below each coefficient; RGF coefficient scaled by a factor of 10^3.

This analysis gives further credence to Hypothesis 1b (as discussed in Section 4.4, above), that social capital has a greater impact on mutual fund flows when prior-period fund returns are high than when prior-period fund returns are low. This is indicated by the declining values of the RGF coefficient from Treatment (2) through Treatment (5): Treatment (2): β=6.183, p<.001; Treatment (3): β=4.321, p<.001; Treatment (4): β=2.746, p<.001; Treatment (5): β=1.813, p=.012. This set of analyses indicates that the RGF index as a predictor of mutual fund flows is robust to fund return levels, with the impact of social capital on fund flows being the greatest when fund returns are highest.

5.4.3. Robustness Tests: Quartiles of Fund Age

Section 5.4.3. gives an assessment of quartiles of fund age. Treatment (1) includes all records for comparative purposes, Treatment (2) includes the oldest 25% of funds, Treatment (3) includes only the records that are above the mean fund age, Treatment (4) includes only the records that are below the mean fund age, and Treatment (4) includes the newest 25% of funds. As discussed above, for this robustness test to be successful the RGF coefficient of all treatments would exhibit positive and statistically significant results, expecting, however, that it is likely that the magnitudes of the coefficients can vary. Results are shown in Table 20 below.

Table 20. The Impact of Social Capital on Net Fund Flows by Quartile of Fund Age

	Dependent Variable

	(1) Fund Flows, All Records	(2) Fund Flows, Oldest 25%	(3) Fund Flows, Oldest 50%	(4) Fund Flows, Newest 50%	(5) Fund Flows, Newest 25%
Constant	0.107^{***}	-0.037^{***}	-0.037^{***}	0.201^{***}	0.291^{***}
	(33.11)	(-5.20)	(-7.54)	(39.73)	(35.96)
RGF Index	3.395^{***}	0.043	0.210	5.498^{***}	3.064^{***}
	(9.08)	(0.07)	(0.45)	(9.68)	(3.36)
Cube Root Age	-4.998^{***}	-0.911^{***}	-1.265^{***}	-10.000^{***}	-13.663^{***}
	(-57.25)	(-4.68)	(-8.56)	(-44.17)	(-26.71)
Primary Indep. Vars.	Yes	Yes	Yes	Yes	Yes
Controls					
Lagged Return	Yes	Yes	Yes	Yes	Yes
Other Time Based	Yes	Yes	Yes	Yes	Yes
Expense	Yes	Yes	Yes	Yes	Yes
Investor Type	Yes	Yes	Yes	Yes	Yes
Index & ETF	Yes	Yes	Yes	Yes	Yes
Fund Strategy	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	164,177	41,069	82,090	82,087	41,056
R^2	0.1975	0.2442	0.2260	0.1856	0.1689
Adjusted R^2	0.1974	0.2437	0.2257	0.1854	0.1683
Residual Standard Error	0.123 (df = 164,148)	0.092 (df = 41,040)	0.102 (df = 82,061)	0.140 (df = 82,058)	0.155 (df = 41,027)

F Statistic	1,442.9*** (df = 28; 164,148)	473.5*** (df = 28; 41,040)	855.6*** (df = 28; 82,061)	668.1*** (df = 28; 82,058)	297.8*** (df = 28; 41,027)

Note: $^{*}p<.050$; $^{**}p<.010$; $^{***}p<.001$; t-stats are reported parenthetically below each coefficient; RGF and cube root of fund age coefficients scaled by a factor of 10^3.

This analysis demonstrates that social capital—proxied by the RGF index—has a positive and significant impact on fund flows of newer funds (Treatment (4), the newest 50% of funds: β=5.498, p<.001; Treatment (5), the newest 25% of funds: β=3.064, p<.001). For funds older than the mean, however, the RGF is not a significant driver of fund flows (Treatment (3), the oldest 50% of funds: β=0.210, p=.654; Treatment (2), the oldest 25% of funds: β=0.043, p=.945). This finding warrants future research, but it could indicate that a fund's reputation, a function of age, could dampen the effect of social capital's impact on fund flows. The fact that the RGF index's impact on fund flows is not robust for the entire range of fund age highlights the requirement to include fund age as a control variable.

5.4.4. Robustness Tests: Quartiles of Fund Expenses

Finally, Section 5.4.4. presents an assessment of quartiles of fund expenses. Treatment (1) includes all records for comparative purposes, Treatment (2) includes the highest 25% of fund expense ratios, Treatment (3) includes only the funds with expense ratios above the mean, Treatment (4) includes only the funds with expense ratios below the mean, and Treatment (5) includes the lowest 25% of fund expense ratios. As discussed above, for this robustness test to be successful the RGF coefficient of all treatments would exhibit positive and statistically significant results, expecting, however, that it is likely that the magnitudes of the coefficients can vary. Results are shown in Table 21 below.

Table 21. The Impact of Social Capital on Net Fund Flows by Quartile of Expense Ratio

	Dependent Variable

	(1) Fund Flows, All Records	(2) Fund Flows, Highest 25% of Exp. Ratio	(3) Fund Flows, Highest 50% of Exp. Ratio	(4) Fund Flows, Lowest 50% of Exp. Ratio	(5) Fund Flows, Lowest 25% of Exp. Ratio
Constant	0.107***	-0.042***	0.004	0.131***	0.149***
	(33.11)	(-4.86)	(0.10)	(33.50)	(29.19)
RGF Index	3.395***	2.558**	3.390***	2.596***	3.175***
	(9.08)	(2.86)	(6.03)	(6.04)	(4.47)
Expense Ratio	-1.757***	0.079	-0.726***	-4.318***	-5.755***
	(-26.75)	(0.32)	(-5.88)	(-27.66)	(-21.76)
Primary Ind. Vars.	Yes	Yes	Yes	Yes	Yes
Controls					
Lagged Return	Yes	Yes	Yes	Yes	Yes
Time Based	Yes	Yes	Yes	Yes	Yes
Investor Type	Yes	Yes	Yes	Yes	Yes
Index & ETF	Yes	Yes	Yes	Yes	Yes
Fund Strategy	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	164,177	41,283	82,685	81,492	41,865
R^2	0.1975	0.1951	0.1983	0.2037	0.210
Adjusted R^2	0.1974	0.1946	0.1980	0.2034	0.210
Residual Standard Error	0.123 (df = 164,148)	0.141 (df = 41,255)	0.133 (df = 82,656)	0.112 (df = 81,463)	0.114 (df = 41,836)

F Statistic	1,442.9*** (df = 28; 164,148)	370.4*** (df = 27; 41,255)	730.1*** (df = 28; 82,656)	744.3*** (df = 28; 81,463)	398.1*** (df = 28; 41,836)

Note: *p<.050; **p<.010; ***p<.001; *t*-stats are reported parenthetically below each coefficient; RGF coefficient is scaled by a factor of 10^3.

Although fund expense ratios are not significant in every treatment, the RGF index is significant in all treatments, indicating that the RGF index, as a predictor of net fund flows, is robust to fund expense levels.

5.5. Robustness Summary

Robustness tests were undertaken to demonstrate that the conclusions presented in Section 4 (Results) would not be affected by variations in model parameters. It was found that the RGF index itself was a better predictor of net mutual fund flows than any of its components individually or in combination. It was also demonstrated that alternate measures of both net fund flows and social capital result in conclusions consistent with that of the prior analyses—that social capital is positively predictive of net mutual fund flows. The quartiles analyses also resulted, generally, in a demonstration of the robustness of the previous findings. Specifically, is shows that the RGF index, as a predictor of mutual fund flows, is:

- Robust to fund return levels, with the impact of social capital on fund flows being the greatest when fund returns are highest, giving further support for Hypothesis 1b (*see* Section 4);
- Robust to fund size, with social capital having a stronger impact on smaller funds;
- Robust to fund age for newer funds but not for older funds, which could indicate that a fund's reputation—a function of age—could dampen the effect of social capital's impact on fund flows; and
- Robust to fund expense levels.

Overall, these robustness tests demonstrate that the results given in Section 4 are reliable.

6. Implications and Other Potential Research

This section identifies and discusses implications of the present research on both academic theory and practice. This is followed by a discussion of proposed research prompted by these findings.

6.1. Implications for Theory and Practice

6.1.1. Implications for Theory

Generally, this study adds to the growing body of literature on social capital which tends to explain the amorphous "regional differences exist" finding often seen in many business and other research studies. Social capital has been used to explain these regional differences and other variations of many business and economic phenomena, including traditional debt and equity acquisition by companies (Hasan et al., 2017; Gupta et al., 2018; Huang & Shang, 2019), venture capital acquisition (Maula et al., 2003), corporate governance (Stevenson & Radin, 2009), management practices (Carroll & Teo, 1996), organizational behavior (Leana & Van Buren, 1999), economics (Fukuyama, 1995), strategy (Dyer & Singh, 1998; Nahapiet & Ghoshal, 1998), market development (Ellis, 2000), corporate research and development (Gabbay & Zuckerman 1998), technology innovation (Cooke & Wills, 1999), entrepreneurism (Chung & Gibbons, 1997; Anderson & Jack, 2002), and negotiations (Kumar & Worm, 2003). This dissertation adds to the literature by demonstrating the impact that social capital has on mutual fund flows, and provides an explanation for the regional differences previously identified in prior studies (Annaert et al., 2008).

Additionally, this dissertation contributes to the emerging research examining the impact of social factors on investing behaviors. Examples of prior studies include the impact of social interactions on public equity investment participation rates (Hong et al., 2004), real estate investing (Hebb et al., 2010), and impact investing (Combs, 2014). Indeed, Borgers and colleagues (2015) investigate the degree to which social factors influence mutual fund holdings by individuals, tertiary to this study on social capital's impact on mutual fund flows.

The present study also delves into the impact that social capital has on mutual fund window dressing, expanding the research on both the agency problems affected by social capital (Hoi et al., 2019), and identifying social capital as an important predictor of window dressing behavior (Agarwal et al., 2011).

Finally, and perhaps most importantly, this dissertation adds to the body of literature on the drivers of mutual fund flows. The literature has previously identified many drivers of mutual fund growth, including prior returns (Ippolito, 1992; Gruber, 1996; Chevalier & Ellison, 1997; Sirri & Tufano, 1998; Karceski, 2002; Barber et al., 2005); media attention (Sirri & Tufano, 1998; Jain & Wu, 2000), marketing (Sirri & Tufano, 1998; Jain & Wu, 2000; Barber et al., 2005; Cooper et al., 2005); fund ratings (Guercio & Tkac, 2008; Wellman & Zhou, 2008); fund tenure and size (Chevalier & Ellison, 1997; Friesen & Sapp, 2007); fund type/sector/strategy (Barber et al., 2016; Röder & Walter, 2019); fund fees and costs (Barber et al., 2005); and fund manager trust (Barber et al., 2016; Cochardt et al., 2019). To the extent possible, these previously identified drivers of fund flows were included as control variables. In addition to this study's findings in relation to social capital's impact on fund flows, it also adds to the literature by identifying the previously heretofore undetected bias in the findings of these earlier studies caused by not considering social capital as a predictor of fund flows. An example of this effect is discussed in Section A3. of the Appendix, assessing social capital's impact on mutual fund size when used as an independent variable in predicting fund flows.

6.1.2. Implications for Practice

As discussed above, much research has been done on mutual fund returns, with comparatively less research on how and why capital is invested into specific mutual funds. Determining predictors of net fund flows is important for investors, investment managers and marketers, and economists. These predictors have been elusive, but this research adds to the literature by determining a predictor of net fund flows (social capital) that has not been identified previously and also is measurable and therefore actionable. This study offers further insight into how investors make fund selections, as well as how fund managers and fund marketers should optimally generate demand. This dissertation demonstrates practical significance of all important findings in an effort to assist practitioners (investors and fund management personnel alike) in quantifying the degree to which the decisions made based upon these findings could assist them.

Agarwal and colleagues (2011) demonstrated that mutual fund managers who engage in window dressing behaviors perform poorly relative to those that do not engage in such behaviors. Specifically, window dressing behaviors are shown to depress fund performance and net fund flows, because poor performance outweighs good performance during delays in reporting as poorly skilled managers chase returns. This study could assist investors by predicting where window dressing is likely to occur (and not occur). Additionally, fund family executives could elect to change the location of funds or prioritize locations for new funds based upon this information.

6.2. Potential Future Research

This dissertation is focused on open-ended U.S. mutual funds with a stated investment strategy of investing in U.S. equities. Many of the analyses here could be employed in the assessment of the impact of social capital on other U.S. mutual fund types, international funds, and domestic and international investment vehicles that are not mutual funds.

Exchange-traded funds are included in the analyses in this study as a control variable, shown to have a positive effect on fund flows. Because ETFs are passively traded and follow an index, they are dissimilar to traditional mutual funds where a manager is actively trading securities to increase returns for investors (Ben-David et al., 2018). Today, ETFs account for more than 45% of the mutual-fund market but have increased more than thirtyfold since 2000 (Statista, 2020). Future research could be undertaken to assess the effect that this dramatic increase in ETFs has had on social capital's impact on net fund flows over time (and indeed on other drivers of net fund flows generally).

This study assesses the impact on mutual fund flows at the quartile values of the RGF index and the non-categorical control variables to ensure that the conclusions of the primary analyses held at all levels of these predictor variables. Delving into the changes in the magnitudes of these coefficients is left for future research. For example, results of this dissertation show that social capital has a positive and significant impact on fund flows of newer funds. For funds older than the mean, however, social capital is not a significant driver of fund flows. This finding could indicate that a fund's reputation (a function of age) could dampen the effect of social capital's impact on fund flows. This also could indicate that trust can be developed in different ways—as a function of time or exposure, or as a function of social capital. Another example of potential additional research is assessing the theory that social capital has a greater impact on smaller funds.

This dissertation demonstrates that social capital is negatively related to mutual fund agency problems. In this case, the agency problem assessed is window dressing behaviors undertaken by fund managers (an attempt to make their performance appear superior to what the returns would indicate, in an effort to reduce fund outflows subsequent to this underperformance). Although left for future research, it is likely that other mutual fund agency problems—such as excessive compensation by managers and unreasonable fee structures—would be comparably affected by social capital. Similarly, there is preliminary evidence in the univariate analyses provided above that fund fees are inversely correlated with social capital and could warrant additional research.

Finally, due to a lack of access to primary data, the assessments of Hypothesis 2 and Hypothesis 2a are based upon the analyses of a dataset that is a fraction of the size of the dataset assessed for the other hypotheses. Although this sample is a robust 13,019 records, it is only 7.9% the size of the dataset developed for Hypothesis 1 and Hypothesis 1a, due to a smaller (and older) set of years observed, and because share classes had to be compressed in the flows data to be matched to the window dressing data. Future research could be undertaken to update this dataset to determine whether a more recent dataset would change any of these findings, but this requires access to the underlying data.

Generally, this dissertation serves not only to investigate the impact of social capital on mutual fund flows, but also to develop a research agenda that can be undertaken as a beginning to an academic career.

Appendix: Analysis of Control Variables

Assessing the hypotheses in this dissertation required an ordinary least squares linear model that not only was consistent with prior literature, but that also would result in the best linear unbiased estimators of model coefficients. This is not as straightforward as simply using the most recent models discussed in articles that have been peer-reviewed, because there have been many different independent variables of interest introduced as the study of mutual fund flows has matured with time. Often these independent variables of interest might be sufficiently correlated with one another that both should not be included in an analysis due to the resulting violation of regression assumptions. In other cases, inclusion of previously unidentified independent variables could influence the identified and included variables, either resulting in them becoming non-significant or, in extreme cases, causing them to change signs.

For these reasons, a systematic assessment of control variables (those controls identified and discussed in Section 3.5 above) was undertaken to identify the optimal model for hypotheses assessment. To this end, a series of ordinary least squares regression analyses beginning with net fund flows being predicted by the county-level RGF index and the primary independent variables (quarterly fund returns and fund size), and then systematically and sequentially assessing and adding the remaining controls. As discussed above, the goal of these analyses was to determine the best set of linear unbiased estimators of Equation 2. Sections 4 and 5 above discuss the use of this model and the model's outputs.

The analyses steps taken are listed below.

Step 1: Assess the Primary Independent Variables (social capital, quarterly returns, log of fund size, and year fixed effects) for analysis inclusion.

Step 2: Assess the Lagged Returns Control (fund quarterly returns, lagged one period) for analysis inclusion.

Step 3: Assess the Time-Based Controls (fund decade vintage, cube root of fund age, and the quarter of the reported fund flows) for analysis inclusion.

Step 4: Assess the Fund Expense Ratio Control for analysis inclusion.

Step 5: Assess the Investor-Type Controls (retail funds versus institutional funds) for analysis inclusion.

Step 6: Assess the Index and ETF Controls (index funds, exchange-traded funds, or both) for analysis inclusion.

Step 7: Assess the Fund Strategy Controls (sector-based funds, capitalization-based funds, style-based funds) for analysis inclusion.

Step 8: Determine final model.

A1. Step 1: Assess the Primary Independent Variables

The purpose of Step 1 is to assess the initial independent variables, and predict net fund flows only including the social capital, quarterly returns, and log of fund size variables, with and without year fixed effects.

As discussed above, the univariate correlations and the existing literature suggest that fund returns should have a strong positive effect on net fund flows as investors chase returns (Frazzini & Lamont, 2008; Friesen & Sapp, 2007; Barber et al., 2016). Also as demonstrated in early prior works and the univariate analyses, fund size is expected to have a negative effect on net fund flows because a dollar that flows into a smaller fund has a greater percentage impact than a dollar flowing into a larger fund (Sirri & Tufano, 1998; Bodson et al., 2011). The results of this analysis are shown in Table A.1 below.

Table A.1. Net Fund Flows Predicted by Social Capital and the Primary Independent Variables

	Dependent Variable			
Panel A	**(1) Net Fund Flows**	**(2) Net Fund Flows**	**(3) Net Fund Flows**	**(4) Net Fund Flows**
Constant	0.015***	-0.003***	0.022***	0.013***
	(44.86)	(-9.91)	(12.09)	(7.38)
RGF Index	2.501***	2.706***	2.483***	2.667***
	(6.11)	(7.24)	(6.06)	(7.13)
Primary Indep. Vars.				
Quarterly Returns		2.379***		2.382***
		(181.10)		(181.35)

Log Assets			-0.648***	-1.466***
			(-3.83)	(-9.50)
Year Fixed Effects	No	No	No	No
Observations	164,177	164,177	164,177	164,177
R^2	0.0002	0.1667	0.0003	0.1672
Adjusted R^2	0.0002	0.1667	0.0003	0.1671
Residual Standard Error	0.138 (df = 164,175)	0.126 (df = 164,174)	0.138 (df = 164,174)	0.126 (df = 164,173)
F Statistic	37.3*** (df = 1; 164,175)	16,421.6*** (df = 2; 164,174)	26.0*** (df = 2; 164,174)	10,983.7*** (df = 3; 164,173)

Panel B	**Dependent Variable**			
	(5) Net Fund Flows	**(6) Net Fund Flows**	**(7) Net Fund Flows**	**(8) Net Fund Flows**
Constant	0.023***	-0.013***	0.025***	-0.001***
	(25.51)	(-14.26)	(12.04)	(-0.28)
RGF Index	3.599***	2.791***	3.592***	2.739***
	(8.89)	(7.42)	(8.88)	(7.29)
Primary Indep. Vars.				
Quarterly Returns		2.476***		2.481***
		(161.65)		(161.82)
Log Assets			-0.138	-1.094***
			(-0.82)	(-7.00)
Year Fixed Effects				
2003	0.095***	0.034***	0.095***	0.034***

	(21.37)	(8.26)	(21.35)	(8.07)
2004	0.018***	0.027***	0.018***	0.027***
	(8.85)	(14.17)	(8.80)	(13.88)
2005	0.010***	0.026***	0.010***	0.025***
	(6.35)	(16.99)	(6.27)	(16.48)
2006	0.006***	0.018***	0.006***	0.018***
	(4.01)	(12.98)	(3.96)	(12.56)
2007	-0.019***	0.009***	-0.019***	0.008***
	(-12.58)	(6.19)	(-12.60)	(5.79)
2008	-0.073***	0.023***	-0.073***	0.022***
	(-45.4)	(14.41)	(-45.32)	(13.96)
2009	0.046***	0.000	0.046***	-0.001
	(31.78)	(0.12)	(31.59)	(-0.52)
2010	-0.010***	0.008***	-0.010***	0.008***
	(-5.85)	(5.25)	(-5.88)	(4.97)
2011	-0.042***	0.017**	-0.043***	0.016**
	(-7.73)	(3.24)	(-7.75)	(3.06)
2012	-0.007	0.003	-0.007	0.002
	(-1.41)	(0.53)	(-1.42)	(0.46)
2013	-0.008	-0.028**	-0.008	-0.027**
	(-0.75)	(-2.84)	(-0.74)	(-2.75)
2014	-0.008***	0.010***	-0.008***	0.010***
	(-6.33)	(7.98)	(-6.32)	(8.04)
2015	-0.029***	0.009***	-0.029***	0.010***

	(-23.00)	(7.75)	(-22.99)	(7.86)
2016	-0.017***	-0.005***	-0.017***	-0.005***
	(-12.96)	(-4.55)	(-12.96)	(-4.51)
Observations	164,177	164,177	164,177	164,177
R^2	0.0397	0.1716	0.0398	0.1718
Adjusted R^2	0.0397	0.1715	0.0397	0.1718
Residual Standard Error	0.135 (df = 164,161)	0.125 (df = 164,160)	0.135 (df = 164,160)	0.125 (df = 164,159)
F Statistic	452.9*** (df = 15; 164,161)	2,125.3*** (df = 16; 164,160)	424.7*** (df = 16; 164,160)	2,003.7*** (df = 17; 164,159)

Note: $^{*}p$<.050; $^{**}p$<.010; $^{***}p$<.001; *t*-stats are reported parenthetically below each coefficient; RGF and Log Assets coefficients scaled by a factor of 10^3. For Year Fixed Effects, the year 2017 is excluded to avoid unity.

In all treatments and consistent with the prior literature, quarterly returns are significant and have positive coefficients. The negative and statistically significant impact of fund size is consistent with the analysis conducted by Sirri and Tufano (2008) and the univariate analysis conducted above, likely because this analysis has few controls (as shown below, the inclusion of additional control variables has a significant effect on this variable). In Treatment (5) through Treatment (8), the analysis demonstrates that year fixed effects also are statistically relevant. Therefore, Treatment (8), which includes all independent variables, is likely the best estimator of these initial treatments. The positive and statistically significant coefficients for the RGF index as a predictor variable preliminarily indicate that regions of higher social capital could be associated with greater net fund flows, with the opposite also being true. This is the case for every treatment (Treatment (1) with no other independent variables: β=2.501, p<.001; Treatment (4) with the primary independent variables but no year fixed effects: β=2.666, p<.000; Treatment (8) with the primary independent variables and year fixed effects: β=2.739, p<.001). All of these coefficients are likely biased, however, because this set of analyses does not include all known predictors of net fund flows. With the inclusion of only these variables, Treatment (8) in Table A.1 explains 17.2% of the variance of net mutual fund flows (R^2 =.172, F(17; 164,159)= 2,003.7, p<.001).

This set of analyses indicates that the RGF index, fund quarterly returns, the log of fund size, and year fixed effects should be included in subsequent analyses.

A2. Step 2: Assess the Lagged Returns Control

The purpose of Step 2 is to assess whether one-quarter lagged fund returns is a positive predictor of net fund flows when included in the analysis, and to determine its impacts on the variable of interest and the other independent variables.

As previously discussed, fund returns lagged one quarter should have a positive effect on net fund flows (Warther, 1995; Fant, 1999; Friesen & Sapp, 2007), but likely will have a lesser impact than the returns of the most recent quarter. Table A2 shows the results of including this control variable.

Table A.2. Net Fund Flows Predicted by RGF, the Primary Independent Variables, and Lagged Returns

	Dependent Variable			
	(1) Net Fund Flows	**(2) Net Fund Flows**	**(3) Net Fund Flows**	**(4) Net Fund Flows**
Constant	0.013***	0.012***	-0.001	-0.004*
	(7.38)	(6.81)	(-0.28)	(-2.10)
RGF Index	2.667***	2.644***	2.739***	2.675***
	(7.13)	(7.08)	(7.29)	(7.13)
Primary Indep. Vars.				
Log Assets	-1.466***	-1.553***	-1.094***	-1.240***
	(-9.50)	(-10.07)	(-7.00)	(-7.95)
Quarterly Returns	2.382***	2.360***	2.481***	2.515***
	(181.35)	(179.15)	(161.82)	(163.69)
Controls				
Lagged Returns		0.252***		0.349***

		(19.07)		(24.83)
Year Fixed Effects	No	No	Yes	Yes
Observations	164,177	164,177	164,177	164,177
R^2	0.1672	0.1690	0.1718	0.1749
Adjusted R^2	0.1671	0.1690	0.1718	0.1749
Residual Standard Error	0.126 (df = 164,173)	0.125 (df = 164,172)	0.125 (df = 164,159)	0.125 (df = 164,158)
F Statistic	10,983.7*** (df = 3; 164,173)	8,346.9*** (df = 4; 164,172)	2,003.7*** (df = 17; 164,159)	1,933.8*** (df = 18; 164,158)

Note: $^{*}p<.050$; $^{**}p<.010$; $^{***}p<.001$; t-stats are reported parenthetically below each coefficient; RGF and Log Assets coefficients scaled by a factor of 10^3. For Year Fixed Effects, the year 2017 is excluded to avoid unity.

In Treatment (2) and Treatment (4), consistent with the prior literature, lagged quarterly returns are significant and have positive coefficients. As expected, the impact of lagged returns appears to be less than that of current period returns, as exhibited by both smaller regression coefficients and t-statistics. Additionally, *adjusted* R^2 increases modestly with the inclusion of this control variable, indicating that it is effective in explaining variance. The inclusion of this control variable also does not change the sign or the statistical significance of the previously identified independent variables. Taking all of this into account, Treatment (4), which includes all independent variables and lagged quarterly returns, is likely the best estimator of these treatments. The positive and statistically significant coefficients for the RGF index as a predictor variable continue to indicate that regions of higher social capital might be associated with greater net fund flows, with the opposite also being true. As discussed above, however, all of these coefficients are likely biased because this set of analyses does not include all known predictors of net fund flows. With the inclusion of the lagged returns, Treatment (4) in Table A.2 improves on Treatment (8) in Table A.1 and explains 17.5% of the variance of net mutual fund flows (R^2=.175, F(18; 164,158)= 1,933.8, $p<.001$).

This set of analyses indicates that the RGF index, fund quarterly returns, the log of fund size, lagged quarterly returns, and year fixed effects should be included in subsequent analyses.

A3. Step 3: Assess the Time-Based Controls

The purpose of Step 3 is to assess whether any of several time-based controls individually or collectively impact fund flows when included in the analysis, and to determine the variables' effect on the variable of interest and the other independent variables and controls. These time-based controls are fund age, fund vintage, and the quarter in which the fund flows are exhibited.

As discussed in Section 3.5 above, fund vintage or fund age should affect net fund flows, with newer funds having higher flows (Chevalier & Ellison, 1997). Because of the magnitude of year-vintages (57 in total), decade-vintages are assessed. Fund vintage by decade seems to lack precision, therefore the age of each fund also is assessed as a control, and a cube root transformation is employed to normalize the distribution. Finally, there might be a quarter effect on net fund flows (Li et al., 2004; Blocher, 2016), because most funds pay distributions in the 4th quarter, so a quarter categorical variable was included. Table A.3., shows these results.

Table A.3. Fund Flows Predicted by RGF, Primary Independent Variables, Time-Based, Other Controls

	Dependent Variable			
Panel A	**(1) Net Fund Flows**	**(2) Net Fund Flows**	**(3) Net Fund Flows**	**(4) Net Fund Flows**
Constant	0.012^{***}	0.014^{***}	0.027^{***}	0.059^{***}
	(6.81)	(7.66)	(14.08)	(30.62)
RGF Index	2.644^{***}	2.655^{***}	2.269^{***}	2.384^{***}
	(7.08)	(7.11)	(6.10)	(6.46)
Primary Indep. Vars				
Quarterly Returns	2.360^{***}	2.356^{***}	2.356^{***}	2.361^{***}
	(179.15)	(178.01)	(178.62)	(180.32)
Log Assets	-1.553^{***}	-1.542^{***}	-0.892^{***}	0.940^{***}
	(-10.07)	(-10.00)	(-5.74)	(5.94)
Controls				

Lagged Returns	0.252***	0.254***	0.259***	0.259***
	(19.07)	(19.18)	(19.64)	(19.75)
Flows Quarter				
2nd Quarter		0.640	0.264	0.502
		(0.73)	(0.30)	(0.58)
3rd Quarter		-6.809***	-7.351***	-6.422***
		(-7.73)	(-8.38)	(-7.37)
4th Quarter		-2.707**	-3.333***	-2.241*
		(-3.03)	(-3.74)	(-2.53)
Fund Vintage				
1920s			-43.155***	
			(-3.91)	
1930s			-39.003***	
			(-5.92)	
1940s			-28.022***	
			(-4.19)	
1950s			-32.136***	
			(-6.48)	
1960s			-34.208***	
			(-9.20)	
1970s			-39.140***	
			(-8.88)	
1980s			-32.458***	
			(-17.97)	

1990s			-32.976***	
			(-31.71)	
2000s			-15.604***	
			(-16.12)	
Cube Root Age				-4.862***
				(-59.79)
Year Fixed Effects	No	No	No	No
Observations	164,177	164,177	164,177	164,177
R^2	0.1690	0.1695	0.1758	0.1872
Adjusted R^2	0.1690	0.1694	0.1757	0.1871
Residual Standard Error	0.125 (df = 164,172)	0.125 (df = 164,169)	0.125 (df = 164,160)	0.124 (df = 164,168)
F Statistic	8,346.9*** (df = 4; 164,172)	4,785.2*** (df = 7; 164,169)	2,188.3*** (df = 16; 164,160)	4,725.2*** (df = 8; 164,168)

	Dependent Variable			
Panel B	**(5) Net Fund Flows**	**(6) Net Fund Flows**	**(7) Net Fund Flows**	**(8) Net Fund Flows**
Constant	-0.004***	-0.003	0.006**	0.046***
	(-2.10)	(-1.28)	(2.96)	(21.38)
RGF Index	2.675***	2.673***	2.393***	2.337***
	(7.13)	(7.13)	(6.41)	(6.29)
Primary Indep. Vars				
Quarterly Returns	2.515***	2.508***	2.510***	2.511***
	(163.69)	(162.66)	(163.90)	(164.51)

Log Assets	-1.240***	-1.229***	0.233	0.934***
	(-7.95)	(-7.88)	(1.47)	(5.88)
Controls				
Lagged Returns	0.349***	0.352***	0.357***	0.359***
	(24.83)	(24.89)	(25.46)	(25.62)
Flows Quarter				
2nd Quarter		1.771*	1.112	1.597
		(2.02)	(1.28)	(1.84)
3rd Quarter		-5.859***	-6.672***	-5.542***
		(-6.59)	(-7.55)	(-6.29)
4th Quarter		-2.133*	-3.255***	-1.645
		(-2.34)	(-3.59)	(-1.82)
Fund Vintage				
1920s			-59.383***	
			(-5.41)	
1930s			-56.228***	
			(-8.57)	
1940s			-43.603***	
			(-6.56)	
1950s			-50.782***	
			(-10.25)	
1960s			-52.740***	
			(-14.15)	
1970s			-57.411***	

			(-13.04)	
1980s			-50.196***	
			(-27.04)	
1990s			-50.624***	
			(-44.64)	
2000s			-28.082***	
			(-27.24)	
Cube Root Age				-4.710***
				(-57.17)
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	164,177	164,177	164,177	164,177
R^2	0.1749	0.1754	0.1869	0.1915
Adjusted R^2	0.1749	0.1753	0.1867	0.1914
Residual Standard Error	0.125 (df = 164,158)	0.125 (df = 164,155)	0.124 (df = 164,146)	0.124 (df = 164,154)
F Statistic	1,933.8*** (df = 18; 164,158)	1,662.4*** (df = 21; 164,155)	1,257.4*** (df = 30; 164,146)	1,767.0*** (df = 22; 164,154)

Note: *p<.050; **p<.010; ***p<.001; *t*-stats are reported parenthetically below each coefficient. RGF coefficients, Log Asset coefficients, Quarter coefficients, Vintage coefficients, and Cube Root Fund Age coefficients are scaled by a factor of 10^3. For Year Fixed Effects, the year 2017 is excluded to avoid unity. For Flows Quarter, the 4th quarter is excluded to avoid unity. For Fund Vintage, the decade of the 2010s is excluded to avoid unity.

In all treatments, consistent with the prior literature, quarterly differences have an impact on net mutual fund flows, with the 1st quarter and 2nd quarter having higher fund flows, and the 3rd quarter and 4th quarter demonstrating lower flows. The age of funds also is predictive of net fund flows, as expected based upon prior research. Fund age has a greater impact than does the less-precise fund vintage, however, as seen in the R^2 increases in Treatment (2) versus Treatment (3), and Treatment (6) versus Treatment (7). Because vintage is a function of fund age, both variables should not be included as controls. These time-based control variables are assessed with and without year fixed effects, as these controls are all time functions. It does appear that fixed effects are important to include in further analyses, however, given that with their inclusion (Treatment (4) versus Treatment (8)) Treatment (8) explains more variance. The inclusion of these time-based control variables does not change the sign or the statistical significance of the previously identified independent variables or controls, with the exception of log assets, which changes from a negative sign to a positive sign in Treatment (4), Treatment (7), and Treatment (8). This change in sign is expected, because the prior literature demonstrates a negative sign when few controls are included (Sirri & Tufano, 2008) and a positive sign when appropriate controls are included (Bodson et al., 2011). Taking all of this into account, Treatment (8), which includes all independent variables, lagged quarterly returns, flow quarter, and the cube root of fund age (as well as time fixed effects), is likely the best estimator of these treatments. The positive and statistically significant coefficients for the RGF index as a predictor variable continue to indicate that regions of higher social capital might be associated with greater net fund flows, with the opposite also being true. As discussed above, however, all of these coefficients are likely biased because this set of analyses does not include all known predictors of net fund flows. With the inclusion of the time-based control variables, Treatment (8) in Table A.3 improves on Treatment (4) in Table A.2 and explains 19.1% of the variance of net mutual fund flows (R^2 =.191, F(22; 164,154)= 1,767.0, p<.001).

This set of analyses indicates that the RGF index, fund quarterly returns, the log of fund size, lagged quarterly returns, the quarter of the fund flows, the cube root of fund age, and year fixed effects should be included in subsequent analyses.

A4. Step 4: Assess the Fund Expense Ratio Control

The purpose of Step 4 is to assess whether fund expenses have a statistical impact on net fund flows when included in the analysis, and to determine its impacts on the variable of interest and the other independent variables and controls.

As discussed in Section 3.5. above, fund expense ratio (fund management fees and operating expenses divided by fund total net assets) should have a dampening effect on fund flows (Sirri & Tufano, 1998; Barber et al., 2005; Kostovetsky, 2016). Table A.4. shows the results of the inclusion of this variable.

Table A.4. Fund Flows Predicted by RGF, Primary Independent Variables, Expense Ratio, and Other Controls

	Dependent Variable			
	(1) Net Fund Flows	**(2) Net Fund Flows**	**(3) Net Fund Flows**	**(4) Net Fund Flows**
Constant	0.059***	0.079***	0.046***	0.067***
	(30.62)	(36.36)	(21.38)	(28.68)
RGF Index	2.384***	2.308***	2.337***	2.281***
	(6.46)	(6.26)	(6.29)	(6.15)
Primary Indep. Vars.				
Log Assets	0.940***	0.113	0.934***	0.027
	(5.94)	(0.69)	(5.88)	(0.16)
Quarterly Returns	2.361***	2.360***	2.511***	2.510***
	(180.32)	(180.42)	(164.51)	(164.67)
Controls				
Lagged Returns	0.259***	0.261***	0.359***	0.359***
	(19.75)	(19.91)	(25.62)	(25.67)
Flows Quarter				
2nd Quarter	0.502	0.329	1.597	1.355
	(0.58)	(0.38)	(1.84)	(1.56)
3rd Quarter	-6.422***	-6.696***	-5.542***	-5.904***
	(-7.37)	(-7.69)	(-6.29)	(-6.71)
4th Quarter	-2.241*	-2.590**	-1.645	-2.140*
	(-2.53)	(-2.93)	(-1.82)	(-2.37)

Cube Root Age	-4.862***	-4.731***	-4.710***	-4.482***
	(-59.79)	(-58.07)	(-57.17)	(-54.12)
Expense Ratio		-1.100***		-1.320***
		(-20.41)		(-23.86)
Year Fixed Effects	No	No	Yes	Yes
Observations	164,177	164,177	164,177	164,177
R^2	0.1872	0.1892	0.1915	0.1943
Adjusted R^2	0.1871	0.1892	0.1914	0.1941
Residual Standard Error	0.124 (df = 164,168)	0.124 (df = 164,167)	0.124 (df = 164,154)	0.123 (df = 164,153)
F Statistic	4,725.2*** (df = 8; 164,168)	4,257.1*** (df = 9; 164,167)	1,767.0*** (df = 22; 164,154)	1,720.7*** (df = 23; 164,153)

Note: $^{*}p<.050$; $^{**}p<.010$; $^{***}p<.001$; *t*-stats are reported parenthetically below each coefficient. RGF coefficients, Log Asset coefficients, Quarter coefficients, and Cube Root Fund Age coefficients are scaled by a factor of 10^3. For Year Fixed Effects, the year 2017 is excluded to avoid unity. For Flows Quarter, the 4th quarter is excluded to avoid unity.

In all treatments, consistent with the prior literature, fund expenses have a negative impact on net mutual fund flows. The inclusion of expense ratio does not change the sign or the statistical significance of the previously identified independent variables or controls. Taking all of this into account, Treatment (4), which includes all independent variables, lagged quarterly returns, flow quarter, the cube root of fund age, and expense ratio (as well as time fixed effects) is likely the best estimator of these treatments. The positive and statistically significant coefficients for the RGF index as a predictor variable continue to indicate that regions of higher social capital could be associated with greater net fund flows, with the opposite also being true. As discussed above, however, all of these coefficients are likely biased because this set of analyses does not include all known predictors of net fund flows. With the inclusion of expense ratio, Treatment (4) in

Table A.4 improves on Treatment (8) in Table A.3 and explains 19.4% of the variance of net mutual fund flows (R^2 =.194, F(23; 164,153)= 1,720.7, p<.001).

This set of analyses indicates that the RGF index, fund quarterly returns, the log of fund size, lagged quarterly returns, the quarter of the fund flows, the cube root of fund age, fund expense ratio, and year fixed effects should be included in subsequent analyses.

A5. Step 5: Assess the Investor-Type Controls

The purpose of Step 5 is to assess whether fund limited partner type (specifically, whether the funds are considered institutional funds with professional investors, or are considered retail funds catering to individuals), has a statistical impact on net fund flows when included in the analysis, and to determine how the inclusion of this variable impacts the variables of interest and the other independent variables and controls.

As discussed Section 3.5 above, the potential inclusion of investor-type controls stems from the concept that individual investors tend to chase returns more frequently than do institutional investors (Warther, 1995; Ivković & Weisbenner, 2009; Frazzini & Lamont, 2008). In this case, a categorical variable is introduced delineating between the case where a fund is open to institutional investors as limited partners, with the null being the case where the fund's investors are primarily individuals. Table A.5. shows the results of the inclusion of this control variable.

Table A.5. Fund Flows Predicted by RGF, Primary Independent Variables, Investor Type, and Other Controls

	Dependent Variable			
	(1) Net Fund Flows	**(2) Net Fund Flows**	**(3) Net Fund Flows**	**(4) Net Fund Flows**
Constant	0.079^{***}	0.010^{***}	0.067^{***}	0.087^{***}
	(36.36)	(42.51)	(28.68)	(34.38)
RGF Index	2.308^{***}	3.053^{***}	2.281^{***}	2.942^{***}
	(6.26)	(8.26)	(6.15)	(7.91)
Primary Indep. Vars.				
Log Assets	0.113	0.368	0.026	0.234

	(0.69)	(2.25)	(0.16)	(1.43)
Quarterly Returns	2.360***	2.362***	2.510***	2.511***
	(180.42)	(180.85)	(164.67)	(164.97)
Controls				
Lagged Returns	0.261***	0.262***	0.359***	0.361***
	(19.91)	(20.05)	(25.67)	(25.87)
Flows Quarter				
2nd Quarter	0.329	0.361	1.355	1.381
	(0.38)	(0.42)	(1.56)	(1.60)
3rd Quarter	-6.696***	-6.606***	-5.904***	-5.832***
	(-7.69)	(-7.60)	(-6.71)	(-6.64)
4th Quarter	-2.590**	-2.565**	-2.140*	-2.090*
	(-2.93)	(-2.91)	(-2.37)	(-2.32)
Cube Root Age	-4.731***	-5.279***	-4.482***	-5.034***
	(-58.07)	(-62.14)	(-54.12)	(-57.80)
Expense Ratio	-1.100***	-1.766***	-1.320***	-1.893***
	(-20.41)	(-28.72)	(-23.86)	(-30.48)
Investor Type				
Institutional		-16.680***		-15.230***
		(-22.38)		(-20.22)
Year Fixed Effects	No	No	Yes	Yes
Observations	164,177	164,177	164,177	164,177
R^2	0.1892	0.1917	0.1943	0.1963

Adjusted R^2	0.1892	0.1916	0.1941	0.1961
Residual Standard Error	0.124 (df = 164,167)	0.124 (df = 164,166)	0.123 (df = 164,153)	0.123 (df = 164,152)
F Statistic	4,257.1*** (df = 9; 164,167)	3,893.1*** (df = 10; 164,166)	1,720.7*** (df = 23; 164,153)	1,670.2*** (df = 24; 164,152)

Note: $^{*}p<.050$; $^{**}p<.010$; $^{***}p<.001$; *t*-stats are reported parenthetically below each coefficient. RGF coefficients, Log Asset coefficients, Quarter coefficients, Cube Root Fund Age, and Investor Type coefficients are scaled by a factor of 10^3. For Year Fixed Effects, the year 2017 is excluded to avoid unity. For Flows Quarter, the 4th quarter is excluded to avoid unity. For Investor Type, Individual Investors are excluded to avoid unity.

In all treatments, consistent with the prior literature, institutional investors have a negative impact on net mutual fund flows, presumedly because they are less likely to chase returns. The inclusion of investor type in these analyses does not change the sign or the statistical significance of the previously identified independent variables or controls, except for fund size (measured in log assets) which is not statistically significant in any of the treatments. Taking all of this into account, however, Treatment (4), which includes all independent variables, lagged quarterly returns, flow quarter, the cube root of fund age, expense ratio, and investor type (as well as time fixed effects) is likely the best estimator of these treatments. The positive and statistically significant coefficients for the RGF index as a predictor variable continue to indicate that regions of higher social capital could be associated with greater net fund flows, with the opposite also being true. As discussed above, however, all of these coefficients are likely biased because this set of analyses does not include all known predictors of net fund flows. With the inclusion of investor type, Treatment (4) in Table A.5 improves on Treatment (4) in Table A.4 and explains 19.6% of the variance of net mutual fund flows (R^2 =.196, F(24; 164,152)= 1,670.2, p<.001).

This set of analyses indicates that the RGF index, fund quarterly returns, the log of fund size, lagged quarterly returns, the quarter of the fund flows, the cube root of fund age, fund expense ratio, investor type, and year fixed effects should be included in subsequent analyses.

A6. Step 6: Assess the Index and Exchange-Traded Funds Controls

The purpose of Step 6 is to assess whether funds that are index funds, exchange-traded funds, or both, have a statistical impact on net fund flows when included in the analysis, and to determine how the inclusion of these variables impacts the variables of interest and the other independent variables and controls.

As discussed above, prior research demonstrates that index funds, as a class, exhibit lower net fund flows (Fant, 1999; Agapova, 2011; Ferson & Kim, 2012), presumedly because investors in those type of funds believe in the category in which they have invested, and therefore are willing to take the highs and lows as the index follows a relatively random walk. However, EFTs are exchange-traded just like any public equity, and it is the ease of which these funds can be traded that likely results in higher net fund flows than funds that are not ETFs (Agapova, 2011; Staer, 2017; Broman & Shum, 2018).

Here, these control variables are added with a goal to further isolate the effect of social capital on net fund flows. These control variables are categorical variables: the first has a value of 1 if the fund is an index fund (expecting a negative coefficient in the regression); the second has a value of 1 if the fund is not an ETF (also expecting a negative coefficient). Table A.6. shows the results of the inclusion of these control variables.

Table A.6. Fund Flows Predicted by RGF, Primary Independent Variables, Index Funds/ETFs, and Other Controls

	Dependent Variable			
	(1) Net Fund Flows	**(2) Net Fund Flows**	**(3) Net Fund Flows**	**(4) Net Fund Flows**
Constant	0.010***	0.124***	0.087***	0.112***
	(42.51)	(41.67)	(34.38)	(35.96)
RGF Index	3.053***	3.316***	2.942***	3.224***
	(8.26)	(8.95)	(7.91)	(8.65)
Primary Indep. Vars.				

Log Assets	0.368*	0.559***	0.234	0.422*
	(2.25)	(3.41)	(1.43)	(2.57)
Quarterly Returns	2.362***	2.361***	2.511***	2.510***
	(180.85)	(180.92)	(164.97)	(164.96)
Controls				
Lagged Returns	0.262***	0.263***	0.361***	0.361***
	(20.05)	(20.12)	(25.87)	(25.89)
Flows Quarter				
2nd Quarter	0.361	0.347	1.381	1.347
	(0.42)	(0.40)	(1.60)	(1.56)
3rd Quarter	-6.606***	-6.721***	-5.832***	-5.966***
	(-7.60)	(-7.74)	(-6.64)	(-6.80)
4th Quarter	-2.565**	-2.591**	-2.090*	-2.128*
	(-2.91)	(-2.94)	(-2.32)	(-2.36)
Cube Root Age	-5.279***	-5.273***	-5.034***	-5.022***
	(-62.14)	(-62.11)	(-57.80)	(-57.69)
Expense Ratio	-1.766***	-1.666***	-1.893***	-1.806***
	(-28.72)	(-25.95)	(-30.48)	(-27.84)
Investor Type				
Institutional	-16.680***	-18.494***	-15.230***	-17.040***
	(-22.38)	(-24.47)	(-20.22)	(-22.33)
Index Fund		-8.063***		-8.942***
		(-6.49)		(-7.21)
Not ETF		-27.165***		-27.690***

		(-14.47)		(-14.78)
Year Fixed Effects	No	No	Yes	Yes
Observations	164,177	164,177	164,177	164,177
R^2	0.1917	0.1927	0.1963	0.1973
Adjusted R^2	0.1916	0.1927	0.1961	0.1972
Residual Standard Error	0.124 (df = 164,166)	0.124 (df = 164,164)	0.123 (df = 164,152)	0.123 (df = 164,150)
F Statistic	3,893.1*** (df = 10; 164,166)	3,266.2*** (df = 12; 164,164)	1,670.2*** (df = 24; 164,152)	1,552.2*** (df = 26; 164,150)

Note: $^{*}p<.050$; $^{**}p<.010$; $^{***}p<.001$; *t*-stats are reported parenthetically below each coefficient. RGF coefficients, Log Asset coefficients, Quarter coefficients, Cube Root Fund Age, Investor Type coefficients, Index Fund coefficients, and ETF coefficients are scaled by a factor of 10^3. For Year Fixed Effects, the year 2017 is excluded to avoid unity. For Flows Quarter, the 4th quarter is excluded to avoid unity. For Investor Type, Individual Investors are excluded to avoid unity.

In all treatments, as expected given previous research findings, index funds have lower net mutual fund flows, presumedly because investors believe in the long-term viability of the underlying index. Conversely, as predicted by the prior literature, exchange-traded funds have higher flows, likely because of the ease with which they can be traded coupled with the fact that they are normally traded by individuals, who have a greater likelihood of chasing returns than do institutional investors, as discussed above. The inclusion of these variables does not change the sign or the statistical significance of the previously identified independent variables or controls, and fund size (measured in log assets) continues to not be statistically significant (except in Treatment (4) where it exhibits a positive sign and is statistically significant)—the prior literature on this is mixed, but Bodson and colleagues (2011) suggests that larger funds can exhibit higher net fund flows when the appropriate controls are in place. Taking all of this into account, Treatment (4), which includes all independent variables, lagged quarterly returns, flow quarter, the cube root of fund age, expense ratio, investor type, whether a fund is an index fund, and whether a fund is an exchange-traded fund (as well as time fixed effects) is likely the best estimator of these treatments. The positive and statistically significant coefficients for the RGF index as a predictor variable continue to indicate that regions of higher social capital might be associated with greater net fund flows, with the opposite also being true. As discussed above, however, all of these coefficients are likely biased because this set of analyses does not include all known predictors of net fund flows. With the inclusion of ETFs and Index Fund categoricals as independent variable, Treatment (4) in Table A.6 improves on Treatment (4) in Table A.5 and explains 19.7% of the variance of net mutual fund flows (R^2=.197, F(26; 164,150)= 1,552.2, p<.001).

This set of analyses indicates that the RGF index, fund quarterly returns, the log of fund size, lagged quarterly returns, the quarter of the fund flows, the cube root of fund age, fund expense ratio, investor type, whether a fund is an index fund, whether a fund is an EFT, and year fixed effects should be included in subsequent analyses.

A7. Step 7: Assess the Fund Strategy Controls

The purpose of Step 7 is to assess whether fund strategy has a statistical impact on net fund flows when included in the analysis, and to determine how this inclusion impacts the variables of interest and the other independent variables and controls. As discussed above, there are many ways to define the strategy of an individual mutual fund. Here, however, the CRSP self-defined categories from each fund prospectus was employed. This methodology leads to three main categories of U.S. equity–based mutual fund strategies: strategy based upon fund sector (sector-based), strategy based upon fund capitalization (cap-based), and strategies oriented around investor objective (goal-based). By way of example, a sector-based fund is a fund that invests in equities of a specific sector of the U.S. economy, such the technology sector or healthcare. A cap-based fund is a fund that invests in equities of a particular band of equity market capitalization such as large cap, medium cap, small cap, or micro cap. An investor goal-based fund is a fund that invests in equities that allow for specific investor goals to be achieved, usually a function of risk acceptance or risk aversion, such as an income fund or a hedge fund. To assess fund strategy, categorical variables were used to identify sector-funds, cap-based funds, or goal-based funds. The results are shown in Table A.7.

Table A.7. Fund Flows Predicted by RGF, Primary Independent Variables, Fund Strategy, and Other Controls

	Dependent Variable

	(1) Net Fund Flows	(2) Net Fund Flows	(3) Net Fund Flows	(4) Net Fund Flows
Constant	0.124***	0.119***	0.112***	0.107***
	(41.67)	(38.44)	(35.96)	(33.11)
RGF Index	3.316***	3.477***	3.224***	3.395***
	(8.95)	(9.35)	(8.65)	(9.08)
Primary Indep. Vars.				
Log Assets	0.559***	0.574***	0.422*	0.416*
	(3.41)	(3.49)	(2.57)	(2.52)
Quarterly Returns	2.361***	2.363***	2.510***	2.513***
	(180.92)	(180.94)	(164.96)	(164.99)
Controls				
Lagged Returns	0.263***	0.264***	0.361***	0.364***
	(20.12)	(20.20)	(25.89)	(26.06)
Flows Quarter				
2nd Quarter	0.347	0.359	1.347	1.367
	(0.40)	(0.42)	(1.56)	(1.58)
3rd Quarter	-6.721***	-6.704***	-5.966***	-5.938***
	(-7.74)	(-7.72)	(-6.80)	(-6.76)
4th Quarter	-2.591**	-2.599**	-2.128*	-2.125*
	(-2.94)	(-2.95)	(-2.36)	(-2.36)
Cube Root Age	-5.273***	-5.262***	-5.022***	-4.998***
	(-62.11)	(-62.83)	(-57.69)	(-57.25)
Expense Ratio	-1.666***	-1.634***	-1.806***	-1.757***

	(-25.95)	(-25.08)	(-27.84)	(-26.75)
Investor Type				
Institutional	-18.494***	-18.182***	-17.040***	-16.670***
	(-24.47)	(-23.97)	(-22.33)	(-21.79)
Index Fund	-8.063***	-7.232***	-8.942***	-7.975***
	(-6.49)	(-5.77)	(-7.21)	(-6.37)
Not ETF	-27.165***	-25.990***	-27.690***	-26.960***
	(-14.47)	(-13.55)	(-14.78)	(-14.08)
Fund Strategy				
Sector Based		3.788***		2.886**
		(3.62)		(2.76)
Goal Based		3.361***		4.120***
		(4.77)		(5.85)
Year Fixed Effects	No	No	Yes	Yes
Observations	164,177	164,177	164,177	164,177
R^2	0.1927	0.1929	0.1973	0.1975
Adjusted R^2	0.1927	0.1928	0.1972	0.1974
Residual Standard Error	0.124 (df = 164,164)	0.124 (df = 164,162)	0.123 (df = 164,150)	0.123 (df = 164148)
F Statistic	3,266.2*** (df = 12; 164,164)	2,801.9*** (df = 14; 164,162)	1,552.2*** (df = 26; 164,150)	1,442.9*** (df = 28; 164,148)

Note: *p<.050; **p<.010; ***p<.001; t-stats are reported parenthetically below each coefficient. RGF coefficients, Log Asset coefficients, Quarter coefficients, Cube Root Fund Age, Investor Type coefficients, Index Fund coefficients, ETF coefficients, and Fund Strategy coefficients are scaled by a factor of 10^3. For Year Fixed Effects, the year 2017 is excluded to avoid unity. For Flows Quarter, the 4th quarter is excluded to avoid unity. For Investor Type, Individual Investors are excluded to avoid unity. For Fund Strategy, Capitalization-based strategy is excluded to avoid unity.

In all treatments, consistent with prior research, fund strategy has a statistically significant impact on net mutual fund flows. Sector- and goal-based funds have a positive impact on net fund flows, implying that capitalization-based funds have a dampening effect on flows. In all treatments, larger funds exhibit a positive and statistically significant impact on net fund flows. As discussed above, this is not inconsistent with previous findings, when the appropriate control variables are in place (Bodson et al., 2011). All other independent variables and control variables have statistically significant impacts consistent with prior research. Taking all of this into account, Treatment (4), which includes all primary independent variables, lagged quarterly returns, flow quarter, the cube root of fund age, expense ratio, investor type, whether a fund is an index fund, whether a fund is an exchange-traded fund, and fund strategy (as well as time fixed effects) is likely the best estimator of these treatments.

Treatment (4) in Table A.7 explains 19.7% of the variance of net mutual fund flows (*Adjusted* R^2 =.1974, $F(28; 164{,}148)$= 1,442.9, p<.001).

A8. Step 8: Identify the Final Model

Because Treatment (4) in Table A.7. above includes all the appropriate variables identified in the prior literature, with the exception of certain difficult-to-obtain controls which are proxies for included variables (e.g., veteran status as a measure of trust versus social capital region as a measure of trust), the assessment was made that this model is the best linear unbiased estimator of net mutual fund flows. This model was used as the basis for the hypothesis assessments discussed above, and is expressed as Equation A.1 below.

Equation A.1. Fund Flows Prediction Model Equation

$$\begin{aligned} \textit{Net Fund Flows}_{i,t} = \; & \beta_0 + \\ & \beta_1 \times \textit{RGF Social Capital Index}_{t} + \\ & \beta_2 \times \textit{Primary Independent Variables}_{i,t} + \\ & \beta_3 \times \textit{Lagged Returns Control}_{i,t} + \end{aligned}$$

$\beta_4 \times$ *Time-Based Control Matrix* $_{\text{i,t}}$ +

$\beta_5 \times$ *Fund Expense Control* $_{\text{i,t}}$ +

$\beta_6 \times$ *Investor Type Control* $_{\text{i,t}}$ +

$\beta_7 \times$ *Index and ETF Control Matrix* $_{\text{i,t}}$ +

$\beta_8 \times$ *Fund Strategy Control Matrix* $_{\text{i,t}}$ +

$\beta_9 \times$ *Year Fixed Effects* $_{\text{t}}$ +

$\varepsilon_{\text{i,t}}$

In summary, the specific variables included in Equation A.1 are as follows.

1. The social capital index used is the RGF county-level social capital index.
2. The primary independent variables are quarterly returns and the log of fund size (measured in net fund assets).
3. The lagged returns control is fund quarterly returns, lagged one period.
4. The time-based control matrix is the cube root of fund age and the quarter of the reported fund flows.
5. The fund expense control is fund expense ratio.
6. The investor-type controls are whether a fund is a retail fund catering to individuals or is an institutional fund with a focus on professional investors.
7. The index and ETF control matrix are whether a fund is an index fund, an exchange-traded fund, or both.
8. The fund strategy control matrix is whether a fund is a sector-based fund, capitalization-based fund, or goal-based fund.
9. Year fixed effects control for the year the fund flows were exhibited to control for business cycles.

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[1] These simplified examples do not discuss the impact of cash distributions funds are required to pay to shareholders. Inherent to the Sirri & Tufano (1998) calculation of net mutual fund flows, to have a positive net fund flow for a period by a mutual fund, the amount of any required cash distributions paid to shareholders in a period must be exceeded by capital investment in that same period. Scenarios can exist where the fund has a positive return during a period, but a negative fund flow if redemptions are net-negative.

[2] The RGF Index is available at aese.psu.edu/nercrd/community/social-capital-resources for the years: 1990, 1997, 2005, 2009, and 2014.

[3] The arbitrary choice of High RGF being categorized as 1 is irrelevant to the analyses' conclusions. By way of example, a categorical cutoff where High RGF is defined as the RGF mean plus one standard deviation is the same as if Low RGF is defined as the RGF mean minus one standard deviation, resulting in identical coefficient magnitudes, but with opposite signs.

[4] The limitations of the dataset, as discussed in Section 4.5.3., are likely the root cause of the lack of significance of the RGF coefficient. Reference should be made to Section 4.2. for a better assessment of the direct effect of the RGF social capital index on net fund flows.