INVESTOR PROTECTION AND CAPITAL FRAGILITY: EVIDENCE FROM HEDGE FUNDS AROUND THE WORLD

George O. Aragon
Arizona State University

Vikram Nanda
University of Texas at Dallas

Haibei Zhao*
Lehigh University

December 2019

Abstract

We find that capital flows to hedge funds in different countries are influenced by the strength and the enforcement of investor protection laws in these countries. Hedge funds that are located in weak investor protection countries exhibit a 22% greater sensitivity of investor outflow to poor performance, relative to funds in countries with strong protection. Furthermore, weak investor protection is associated with fund managers engaging in greater returns management. Our findings suggest that in countries with weak investor protection, poor fund performance exposes investors to a greater risk of fraud and legal jeopardy, thus triggering a larger outflow of capital.

JEL Classification: G15, G23, D73
Keywords: Investor protection, hedge funds, flow-performance, fragility, operational risk

---

*Aragon is with the Finance Department, W. P. Carey School of Business, Arizona State University, Tempe, AZ 85287, george.aragon@asu.edu, 480-965-5810. Nanda is with the Finance Department, Naveen Jindal School of Management, University of Texas at Dallas, Richardson, Texas 75080, vikram.nanda@utdallas.edu, 972-883-5004. Zhao is from the Perella Department of Finance, College of Business, Lehigh University, Bethlehem, PA 18015, haz816@lehigh.edu, 610-758-4629. We thank Vikas Agarwal, Oleg Chuprinin, Naveen Daniel, Richard Evans, Jiekun Huang, Wei Jiang, Juha Joenväärä, Andrew Karolyi, Bing Liang, Pedro Matos, Sergei Sarkissian, Michael Tang, Yuehua Tang, Zhaodong Zhang, conference participants at the Santiago Finance Workshop, UNC-Wells Fargo Hedge Fund Research Conference, Fourth Asset Management Conference at ESMT Berlin, China International Conference in Finance, Philly Five Research Symposium, and FMA Asia-Pacific Conference, as well as seminar participants at Chinese University of Hong Kong, Texas Tech University, and DePaul University for valuable comments. This work was conducted in part while Haibei Zhao was at Georgia State University. This paper was previously circulated under the title " Corruption perceptions and capital fragility: Evidence from hedge funds around the world".

1. Introduction

The literature on law and finance highlights the critical role of the legal system and investor rights in fostering the development of a country's financial markets. After all, participation in financial markets can occur only if the legal institutions assure investors of a reasonable opportunity to profit from their investments. In this paper, we examine investors' capital flows to an important investment vehicle – hedge funds – across countries that differ substantially in the quality of their institutions, as reflected in country-level investor protection. Our hedge fund setting is uniquely informative for two reasons. First, the global nature of the industry allows us to exploit wide variation in investor protection around the world. Second, hedge funds are lightly regulated investment vehicles with minimal disclosure requirements. Consequently, as noted by Brown et al. (2008), investors may lack relevant information to assess the operational risks of the investment manager.[1] The absence of regulatory oversight can increase the risk of management fraud and, in turn, generate large losses for fund investors.[2] In addition, hedge funds' use of leverage can expose investors to the risk of fund failure and, hence, legal risks related to asset recoveries during liquidation proceedings. Our contention is that, in environments with weak legal rules related to investor protection and poor enforcement of these rules, concerns about these operational risks are amplified and, hence, lead to capital fragility.

Our empirical analysis focuses on a large sample of hedge funds across 35 countries over the 1994-2013 period. We construct a score of weak investor protection (hereafter *WIP*) based on the World Bank's Worldwide Governance Indicators and assign the *WIP* score to each fund based on the country where its management office is located. Figure 1 plots our

[1] Operational risks typically include both internal control failures such as fraud and external events such as legal risks (see, e.g., Section 2.V of the Basel II regulations).

[2] Extant studies link suspicious patterns in hedge fund reported returns to return manipulation and a heightened risk of fraud. See, e.g., Brown et al. (2008, 2012), Bollen and Pool (2008, 2009, 2012), Agarwal, Daniel, and Naik (2011), Cici, Kempf, and Puetz (2013), Patton, Ramadorai, and Streatfield (2015), and Aragon and Nanda (2017).

capital fragility measure against *WIP* for each country in our sample and highlights our main finding: funds in high *WIP* countries face a greater sensitivity of investor flows to poor performance (i.e., greater capital fragility) compared to funds in countries with strong investor protection. These effects are also economically significant. Our baseline regression analysis (Table 3) shows that a one standard deviation increase in *WIP* leads to a 22% increase in flow-performance sensitivity conditional on bad performance. Moreover, following poor fund performance, *WIP* is positively related to extreme capital outflows as measured by fund liquidation (Table 6).

One potential concern is that investor protection is correlated with other country-level characteristics that impact capital flows and that these variables, not investor protection, generate capital fragility. We address this concern by exploiting a shock to investor protection in the Brazilian market stemming from the 2014 passage of Brazil's Clean Company Act (CCA). The CCA is a major anti-corruption law that imposes strict liability on Brazil companies for corruption, bribery, and fraud, and grants federal authorities expanded powers of legal enforcement. We expect that such a regulatory shock would attenuate investor concerns about operational risks in the hedge fund marketplace and, hence, reduce fragility. This is exactly what we find using a holdout sample of Brazilian hedge funds through 2018. Specifically, the sensitivity of flows to poor performance among Brazilian funds is significantly reduced following the passage of the Act, consistent with stronger protection having a stabilizing force on investor capital. The fact that a positive relation between investor protection and capital fragility changes over time *within the same country* helps address the concern that unobservable country-level variables could drive our results.

Our findings also survive many variations of the baseline analysis, including 1) additional control variables that capture cross-country differences in asset liquidity, investor clienteles, fund risk, economic development, education level, religiosity, and democratic rights;

2) alternative measures of investor protection; 3) subsample analysis that controls for cross-country differences in hedge fund regulations; 4) assigning *WIP* scores to the fund's domicile country rather than the country of its management office; and 5) the use of market share-adjusted fund flows (Spiegel and Zhang, 2013). Overall, these robustness checks reinforce our conclusion that weak investor protections make hedge fund capital more fragile and prone to investor runs.

Next, we investigate two aspects of operational risks that can drive the observed differences in capital fragility across countries: First, a misvaluation channel where managers are less concerned about legal jeopardy in weak protection environments and, hence, more willing to distort performance figures. In this case, poor returns are regarded as an attempt to hide a far worse performance that managers find difficult to camouflage. Consequently, fund investors may see a first-mover advantage and choose to exit the fund to redeem their shares at inflated net asset values relative to fundamental values in response to early warning signs of trouble. Second, an investor protection channel whereby weak investor protection and legal enforcement can intensify the risk and cost to investors of asset recoveries during fund bankruptcy or liquidation. In these environments, funds would be more prone to runs if enough investors, such as those with little political or economic influence, are concerned about inequitable treatment when funds are liquidated after poor fund performance.[3]

We find support for both channels leading to a stronger flow-performance sensitivity in high *WIP* countries. First, we observe a greater incidence of suspicious patterns in reported returns, as well as longer delays and more frequent revisions in the disclosure of returns, among funds that are managed in weak protection countries. This finding supports a key premise of the misvaluation channel: managers in high *WIP* countries engage in more returns management.

[3] These two mechanisms are not mutually exclusive: weak investor protection could, for instance, spur managers to misreport fund performance.

Second, our evidence on the investor protection channel comes from a sample of "twin" funds that are managed in different countries but have nearly identical returns and, hence, control for the effects of misvaluation. We find a greater sensitivity of flows to poor performance among funds managed in weak protection countries as compared to their twin funds managed in countries where investor protection is strong. The fact that cross-country differences in the flow-performance sensitivity remain even among funds with nearly-identical reported returns and underlying asset holdings helps isolate the effect of misvaluation and, hence, supports the investor protection channel.[4]

Our paper is related to the recent literature on investor runs in open-end funds and more broadly, fragility in the shadow banking system.[5] In this literature, investor fragility is a consequence of liquidity transformation services whereby funds hold illiquid assets while offering more generous funding liquidity terms to investors. While the prior literature on investor runs focuses on strategic complementarities emanating from the costly liquidation of fund assets (Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017), we contribute to the literature by linking capital fragility to governance in a global setting, in showing that the risk of fraud and weak legal protection associated with poor investor protection can induce fragility in the shadow banking system.

Our study also sheds light on whether operational risk matters for investors. Brown et al. (2008) find no significant relation between hedge funds' flow-performance sensitivities and operational risk measures constructed from Form ADV filings mandated by the Securities and Exchange Commission (SEC). They conclude that either operational risk information does not

[4] The twin funds sample also controls for other fund characteristics that the prior literature has shown to affect investor flows, including portfolio risk (Sirri and Tufano, 1998), risk exposure (Fung and Hsieh, 2004), portfolio liquidity (Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017), and risk shifting (Brown, Harlow and Starks, 1996).

[5] See, e.g., Chen, Goldstein, and Jiang (2010), Gennaioli, Shleifer, and Vishny (2013), Schmidt, Timmermann, and Wermers (2016), Goldstein, Jiang, and Ng (2017), Agarwal, Aragon, and Shi (2019), Franzoni and Giannetti (2019), and Agarwal and Zhao (2019).

matter to investors, or such information is generally not available and entails significant due diligence costs to procure. We build on this logic by focusing on a relatively conspicuous measure of operational risk – weak investor protection – that reflects the risk of fraud and legal protection in the management environment. Our findings suggest that operational risk indicators, when readily observable, are relevant to investors and influence the response of capital flows to fund performance.[6]

Finally, our paper is related to prior work showing that country characteristics are important determinants of mutual fund characteristics, performance, and flows.[7] We focus on the lightly-regulated hedge fund industry where little is known about whether the flow-performance relation works differently across countries and, specifically, in environments where investor protection and legal institutions are weak. Our results suggest that the quality of institutions indeed affects investors' tendency to monitor through their capital allocation choices, a new finding in the flow-performance literature.[8]

2. Hypothesis Development

Weak investor protection can generate capital fragility through two channels. First, in countries with weak legal rules and quality of enforcement of these rules, investors will be warier of returns reported by fund managers. The reason is that, in such environments, managers will be less restrained in embellishing their performance because they are liable to escape punishment and legal consequences (Leuz, Nanda, and Wysocki, 2003). Ipso facto, bad reported performance could be perceived as an indication that the actual performance was so

[6] Dimmock and Gerken (2016) show that the 2004 SEC oversight on hedge funds reduced return misreporting, increased the level of flows, and decreased the sensitivity of flows to poor performance. Gurun, Stoffman, and Yonker (2017) find that residents of communities affected by Madoff lost trust in financial intermediation services and withdrew assets from investment advisers, suggesting that operational risk could matter for investors.
[7] See, e.g., Khorana, Servaes, and Tufano (2005, 2009), Ferreira et al. (2012, 2013), Lin, Massa and Zhang (2014), Cremers et al. (2016), and Ferreira, Massa, and Matos (2018).
[8] Prior studies of the flow-performance relation identify several factors that explain this relation, including search costs (Sirri and Tufano, 1998), investor clienteles (Del Guercio and Tkac, 2002; Evans and Fahlenbrach, 2012), change in manager or strategy (Lynch and Musto, 2003), and fund age and size (Chevalier and Ellison, 1997; Spiegel and Zhang, 2013).

poor that it could no longer be concealed. Therefore, a fund manager reporting poor performance news would induce investors to revise downward their beliefs about the quality of the fund's assets, thereby triggering a greater outflow of capital. Returns management can also create strategic complementarities among investors. The reason is that, in the event of an overvaluation of fund assets, redeeming investors will receive a net asset value (NAV) that is inflated relative to its fundamental value, while the remaining investors hold shares worth less than the stated NAV. Therefore, the anticipated dilution impact of other investors' redemptions creates an additional incentive for investors to exit and run before others. We refer to this as the misvaluation channel.[9]

Second, capital fragility could emerge due to poor investor protection and weak legal enforcement during fund liquidations and severe financial distress. When protection is weak, the typical investor may face greater uncertainty about her expected payoff and greater difficulty in obtaining equitable treatment in the event of fund liquidation or bankruptcy, which becomes more likely following poor fund performance. In addition, during periods of financial distress, managers may become less interested in external financing and engage more in expropriation of outside investors, leading to further declines in firm value (Johnson et al., 2000). Investors are, therefore, more likely to exhibit run-like behavior following poor fund performance to avoid the costs associated with asset recoveries during the final liquidation process and greater expropriation by fund managers. We refer to this as the investor protection channel. Taken together, both channels lead to our central prediction that investor flows are more sensitive to poor hedge fund performance in countries with weak investor protection.

3. Data

[9] Note that flow-performance sensitivities and returns management behavior can also be reinforcing – that is, managers may be less willing to report bad fund performance if doing so triggers a strong outflow response by fund investors.

In this section we discuss the data and provide summary statistics for the key variables used in our analysis.

3.1. Hedge funds

Our hedge fund sample includes the live and defunct funds from the Lipper TASS (Tremont Advisory Shareholder Services), HFR (Hedge Fund Research), Morningstar, and Eureka databases. Our sample period covers January 1994 to December 2013. We begin our sample in 1994 to mitigate survivorship bias due to a lack of defunct fund coverage prior to 1994. We follow Agarwal, Daniel and Naik (2009) and re-classify a fund's stated investment strategy as either Directional, Relative Value, Security Selection, Multi-process, Fund-of-Funds or Other Traders. We use raw and style-adjusted returns (both net-of-fees) as our main performance measures for our flow-performance analyses. Style-adjusted returns are calculated as the difference between raw return and equally-weighted return of all funds in the same strategy during a quarter. We convert return and assets-under-management reported in various currencies to U.S. dollars to allow closer comparisons among funds operating in different currencies; however, this conversion does not materially impact our results.

We estimate quarterly net flow (*flow*) using the standard practice in the literature:

$$flow_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1}(1 + ret_{i,t})}{AUM_{i,t-1}} \quad (1)$$

where *AUM* is fund *i*'s assets under management, *ret* is net fund return, *t* denotes quarter, and *i* denotes fund. Table 1 shows that average quarterly flows and returns are 4% and 2%, respectively, for a total of 310,804 fund-quarter observations.

We also compute other variables that are standard in the hedge fund literature. Management fees (*mfee*) and incentive fees (*ifee*) have a sample median of 1.5% and 20%, respectively. *lockup* is the initial lockup period of investor capital (in years). *restrict* is the sum of redemption notice period and redemption frequency (in years) and measures the difficulty fund investors face in redeeming their shares after lockup period expires. For example, a fund with a 90-day notice period and quarterly redemption frequency has a restriction measure of 0.5 years (= 90/360 + 1/4). Fund age (*age*) is the number of years since fund inception. Fund risk (*sdret*) is the standard deviation of past 12 months' fund returns. We define *illiquid* for each fund-quarter as an indicator variable that equals one if 1) the fund's monthly returns are positively auto-correlated and 2) we reject the null hypothesis of zero autocorrelation at the 10% level. This is based on Getmansky, Lo, and Makarov's (2004) finding that, due to non-synchronous trading of illiquid assets, a fund's monthly return autocorrelation is a valid measure of its asset illiquidity exposure.

We consider four variables that prior studies link to returns management by hedge fund managers. The first two are composite measures of eight data quality flags considered by Straumann (2009), Bollen and Pool (2009, 2012), and Agarwal, Daniel, and Naik (2011), to uncover suspicious patterns in returns and detect fraud. The flags are indicator variables that equal one if a fund's return history has too many zero returns (*Zero*), too few negative returns (*Negative*), too few unique returns (*Unique*), too long of a maximum run of identical returns (*Maxrun*), too many recurring return blocks of length two (*Retblock*), a lack of uniformity of the second digit in returns (*Uniformity*), a spike in December versus other months (*Dec*), and too low of a correlation with the Fung and Hsieh (2004) factors (*MaxRsq*). Bollen and Pool (2012) consider three additional flags based on the autocorrelation, conditional return autocorrelation, and discontinuities in the distribution of fund returns; however, we exclude these to help rule out alternative interpretations of these variables related to asset illiquidity (Getmansky, Lo, and Makarov, 2004) and performance fees (Jorion and Schwarz, 2014).[10] We define *flag_sum* and *flag_pc* as the sum and first principal component of the eight indicators, respectively. They are calculated each year using the fund's entire return history through the

[10] Our results on fund return management behavior (Table 7) are qualitatively the same if we expand *flag_sum* and *flag_pc* to include these three additional flags.

end of the prior year. As an example, Kingate Management – a feeder fund of the notorious Madoff scandal – triggers five flags in our sample (*Negative*, *Unique*, *Retblock*, *Uniformity*, and *MaxRsq*). This is greater than the sample mean of *flag_sum* (1.77) shown in Table 1.

The next two returns management variables are based on whether a fund restates its return history (Patton, Ramadorai, and Streatfield, 2015) or fails to report its performance to commercial databases in a timely fashion (Aragon and Nanda, 2017). Specifically, *restate* is an indicator variable that equals one if a fund manager restated at least one monthly return in the past, while *delay* measures the number of days between month-end and the date when a fund reports its monthly return. Both *restate* and *delay* are updated monthly for each fund-month. Due to data availability, *restate* and *delay* are limited to TASS funds from 2009 to 2013 since daily snapshots of TASS are required to construct these variables. We mean-adjust *restate* and *delay* by funds' corresponding styles, which is the reason the sample means of these adjusted variables are zero as shown in Table 1. Further details on the construction of the four returns management variables are provided in Appendix A.

Finally, we extend our sample of Brazilian hedge funds in the TASS and Morningstar databases through the 2018 period. This "holdout" sample is used in our analysis of the 2014 Clean Company Act as a shock to investor protection in Section 4.1.2.

3.2. Index for weak investor protection (WIP)

We measure weak investor protection using the World Bank's Worldwide Governance Indicators (Kaufmann, Kraay, and Mastruzzi, 2010) corresponding to a country's regulatory quality, rule of law, and control of corruption. Regulatory quality captures perceptions of a government's ability to permit and promote private sector development through implementing policies and regulations. Rule of law captures the degree to which agents have confidence in and abide by rules related to contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Control of corruption measures the degree to which public power is used for corruption, as well as "capture" of the state by elites and private interests. These indexes are based on annual surveys of public and private-sector experts, encompass key elements that shape country-level investor protection (La Porta et al. 1998, 2000, and 2002; Svensson, 2005), and are used in many prior studies.[11] The Worldwide Governance Indicators are updated every two years between 1996 and 2002. For the years 1994-1995 we used the index as of 1996, and we interpolate the measures for the years of missing values between 1996 and 2002.

Our weak investor protection index (*WIP*) is minus one times the first principal component of the three governance indexes, plus three (so the minimum score is positive). Prior studies also use the principal component of the World Governance Indicators because it captures most of the variation in the individual indices and avoids multicollinearity issues given the strong correlation of the individual indices.[12] The three indexes of Regulatory Quality, Rule of Law, and Control of Corruption account for 33.6%, 33.6%, and 32.8% of the total variation in the first principal component.

We assign a *WIP* score to each fund based on the country of its principal office location, as reported in the hedge fund databases. A hedge fund's domicile country and management company's office address are reported as separate variables in the databases. Therefore, the data allow us to unambiguously identify the mailing address of the funds' management offices, which is how we assign our *WIP* measure to funds. Funds must adhere to the registration mandates and applicable regulations of its principal business location. For example, the

[11] See, e.g., Barth et al. (2009), Houston et al. (2010), Karolyi (2016), Doidge, Karolyi, and Stulz (2013), Beck, Lin, and Ma (2014), Braguinsky and Mityakov (2015), and Levine, Lin, and Xie (2016). We do not include the shareholder voting rights indicator from the Worldwide Governance Indicators since it is more suitable for corporations. Along the same lines, since our focus is on investor protection, we do not use the Worldwide Governance Indicators corresponding to freedom of speech, political stability, or violence/terrorism measures.

[12] See, e.g., Levine, Lin, and Xie (2016, 2018), Jordaan, Dima, and Golet (2016), Gächter and Schulz (2016), Ahamed and Mallick (2019), and Huang, Lin, and Yang (2019). Pairwise correlations between *WIP* and the three indexes are at least 95% in absolute value, indicating significant commonality among all three governance indicators, which is captured by *WIP*.

Alternative Investment Fund Managers Directive (AIFMD) classifies a hedge fund as being based in the European Union (EU) if the fund's office is located within an EU member country. Likewise, the Investment Advisers Act of 1940 relies on whether a fund's place of business is in the United States to classify domestic versus foreign advisers and to determine whether they are exempt from the registration and compliance requirements under the Act.[13] Appendix B provides further discussion on why the legal and regulatory environments of a hedge fund's principal business location is of primary concern for fund investors.

We apply the following filters to the raw hedge fund sample. First, we require funds to report their assets-under-management (AUM) to the databases so that we can compute fund flows. Second, we require each fund to have at least 12 months of returns data to compute certain fund characteristics, like return volatility. Third, following the hedge fund literature, we require funds to have AUM of at least five million dollars (Cao et al., 2013). Fourth, we require non-missing values for *WIP* and our control variables, such as management fees. Finally, we require at least 150 fund-quarter observations in a country to reliably estimate country-level capital fragility (Figure 1). The total number of countries represented in our final sample is 35, including several with weak investor protection such as Brazil, China, Grenada, Italy, Kuwait, Russia, United Arab Emirates, Malaysia, and Mauritius. Table 2 reports the averages of annual *WIP* measures for each country. Denmark has the strongest investor protection among countries in our matched *WIP*-hedge fund sample (annual average *WIP* = 0.99), while Russia is at the other extreme (annual average *WIP* = 6.12).

4. Analysis and results

[13] See Article 4(1)(l) of AIFMD and Sections 202(a)(30)(A) and 203(b)(3)) of the Investment Advisers Act.

We now present the results from our analysis of how investor protection is related to the sensitivity of investor flows to fund performance, and discuss further evidence linking capital fragility to the misvaluation and investor protection channels mentioned in Section 2.

4.1. Investor protection and flow-performance sensitivity

4.1.1. Baseline analysis

We follow Chen, Goldstein, and Jiang (2010) and estimate the following regression of quarterly flows:

$$flow_{i,t+1} = \alpha + \theta_j \cdot \kappa_t + \beta_1 perf_{i,t} + \beta_2 WIP_{j,t} \cdot perf_{i,t} + \eta control_{i,t} + \varepsilon_{i,t} \tag{2}$$

where *perf* denotes lagged quarterly performance as measured by raw returns or style-adjusted returns, θ_j and κ_t denote country and time fixed effects, respectively, and *control* is a vector of control variables. From β_2 we can infer the incremental effect that weak investor protection has on the flow-performance sensitivity. The presence of country×time fixed effects ($\theta_j \cdot \kappa_t$) absorbs country-specific variables that vary over time and could affect investors' flows, including macroeconomic conditions, market liquidity, interest rates, financial sector growth, and aggregate flows to the hedge fund industry.[14] Control variables include style dummies, management fee (*mfee*), incentive fee (*ifee*), high water mark dummy (*hwm*), lockup period (*lockup*), restriction period (*restrict*), natural logarithm of minimum investment amount (*mininv*), lagged observations of *flow*, natural logarithm of total net assets (*size*), fund age (*age*), asset illiquidity (*illiquid*), and fund risk (*sdret*). We also include the interaction of *age* and *perf*. Standard errors account for heteroskedasticity and are clustered at the country level.

The results are reported in Panel A of Table 3. Column (1) reveals a positive and significant estimate of β_1, indicating that investors respond favorably to higher past fund

[14] See, e.g., Goyenko and Sarkissian (2014) and Jain, Kuvvet, and Pagano (2017). Note that although country×time fixed effects control for unobserved country-level variables that affect the level of investor flows, these fixed effects do not rule out the possibility that other country-level variables affect the flow-performance relation. We address this concern in Panels C1 and C2 of Table 3 by controlling for other country characteristics, and in Table 4 using a shock to investor protection in the Brazilian market.

returns; and vice versa. Specifically, a 1% increase in fund return is associated with a 0.538% increase in investor flows. Importantly, Column (2) shows an even stronger average flow-performance relation among funds in weak protection countries, as indicated by a positive and significant estimate of β_2. The magnitude of the coefficient is 0.092, indicating that a one standard deviation increase in *WIP* is associated with an 14.7% (=0.86×0.092÷0.538) increase in the overall flow-performance sensitivity as reported in Column (1).

We now extend the analysis to allow for nonlinearities in the flow-performance relation and test whether the stronger relation in high *WIP* environments is mainly driven by periods of poor fund performance. Following Goldstein, Jiang, and Ng (2017), we use an indicator variable *Low* for poor fund performance and estimate the regression:

$$flow_{i,t+1} = \alpha + \theta_j \cdot \kappa_t + \beta_1 perf_{i,t} + \beta_2 WIP_{j,t} \cdot perf_{i,t} + \beta_3 perf_{i,t} \cdot Low_{i,t}$$
$$+\beta_4 WIP_{j,t} \cdot perf_{i,t} \cdot Low_{i,t} + \beta_5 WIP_{j,t} \cdot Low_{i,t} + \beta_6 Low_{i,t} + \eta control_{i,t} + \varepsilon_{i,t} \qquad (3)$$

where *Low* is equal to one if the corresponding *perf* is below its median among all funds in a country during a given quarter, and zero otherwise. From parameter β_4 we can infer the incremental effect that *WIP* has on the flow-performance relation conditional on poor fund performance.

Column (3) of Panel A, Table 3 shows that the estimated coefficient β_4 is positive and significant, indicating that weaker investor protection magnifies the responsiveness of flows to poor fund performance. Conditional on low returns, a one standard deviation change in *WIP* corresponds to an increase in the flow-performance sensitivity of 22% (=0.86×0.138÷0.538), relative to the overall sensitivity (0.538) reported in Column (1). In addition, the estimated coefficient β_2 is now negative, suggesting that good fund performance is viewed more skeptically in weak protection environments and, therefore, less indicative of manager skill. Specifically, if fund managers in such environments underreport losses and fully report or even overreport gains, then fund NAV is inflated when performance is either poor or good. Thus, investors flee after poor performance while discounting and responding less aggressively to good performance.

The remaining columns in Panel A of Table 3 present results from alternative specifications of the flow regression in Equation (3). Columns (4) and (6) report results where *perf* is measured using style-adjusted returns instead of raw returns, (5) and (6) include fund fixed effects, and (7) and (8) replace the *WIP* measure with an alternative measure of investor protection based on the indexes of LLSV (La Porta et al., 1998, 2000, and 2002; La Porta et al., 2006).[15] In these specifications, we continue to observe that weak investor protection is associated with a greater level of capital fragility.

Our main regression in Equation (4) controls for other important drivers of investor flows. For example, we include *illiquid* and its interactions with *perf* and *Low* to address the concern that markets in economies with weak investor protection tend to be less liquid, and a greater sensitivity to poor performance among funds with illiquid assets has been documented. Table 3 shows a positive and significant coefficient on *illiquid·perf·Low* across all specifications, indicating that illiquid funds are prone to greater fragility. This is consistent with the findings of Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017) for mutual funds. Importantly, however, we continue to find that the sensitivity of flows to poor performance is significantly greater in weak protection environments, as indicated by a positive and significant coefficient on *WIP·perf·Low*.[16]

Evans and Fahlenbrach (2012) find a stronger flow-performance sensitivity among institutional investors (versus retail investors) and conclude that institutions, due to greater sophistication, exhibit stronger monitoring. In our setting, a potential concern is that investors

[15] Specifically, we replace *WIP* with the inverse of the first principal component of five indexes of LLSV capturing the efficiency of the judicial system, rule of law, control of corruption, risk of expropriation, and anti-self-dealing. The LLSV-based measure is only available for 18 countries (versus 35 countries for *WIP*) and has a pairwise correlation with our World Bank-based *WIP* measure of more than 90%.

[16] Our inferences also remain unchanged if we replace *illiquid* with a continuous measure of return autocorrelation.

in funds managed in high *WIP* countries are inherently more sophisticated and that such sophistication, rather than weak investor protection, makes investors more sensitive to poor fund performance.[17] We address this concern by using a fund's minimum investment amount (*mininv*) as a measure of investor sophistication in our flow regressions.[18] We observe that the coefficient on the *mininv·perf* interaction term is positive across all specifications, i.e., relatively sophisticated investors monitor fund performance more closely. Importantly, the coefficient on *WIP·perf·Low* remains positive and significant, suggesting that our results are unlikely to be driven by differences in investor sophistication.

Our findings for other control variables in our hedge fund setting are also consistent with prior studies of mutual funds. For example, the negative coefficient on *age·perf* is consistent with Spiegel and Zhang's (2013) finding of a stronger flow-performance response among younger, "hot money" funds. The negative coefficient on *sdret* is consistent with evidence that fund investors dislike fund risk (Sirri and Tufano, 1998).

In Panel B of Table 3, we test whether any one of the three World Governance Indicators is primarily responsible for the results. We repeat our main flow analysis using each of the three components (rather than the composite measure *WIP*). To facilitate comparisons across models, we standardize each component to have the same mean and variance. The coefficient on our main variable of interest – *WIP·perf·Low* – is similar in magnitude and not statistically different across models, i.e., our results are not dominated by any one of the three governance indicators.

[17] Note that the correlation between *WIP* and the financial literacy measure from S&P Global FINLIT Survey is significantly negative, i.e., the average investors in high *WIP* countries are *less* sophisticated than those in other countries.

[18] Prior studies use income and wealth to infer investor sophistication in various settings, such as mutual fund investors (Bailey, Kumar, and Ng, 2011; Barber, Huang, and Odean, 2016), individual traders (Barber and Odean, 2000) and household finance (Massa and Simonov, 2006; Calvet, Campbell, and Sodini, 2007). This approach is similar in spirit to the classification of accredited investors based on net worth and income, since funds with higher minimum investments should attract wealthier investors with greater financial sophistication.

To illustrate our main result graphically, we estimate *country-level* capital fragility using the following regression:

$$flow_{i,t+1} = \alpha + \beta_1 perf_{i,t} + \beta_2 perf_{i,t} \cdot Low_{i,t} + \beta_3 Low_{i,t} + \eta control_{i,t} + \lambda_i + \kappa_t + \varepsilon_{i,t} \quad (4)$$

where *Low* is an indicator variable that is equal to one if *perf* is below its median among all funds within a country during a given quarter, λ_i denotes fund fixed effects, and *control* is the same vector of control variables in Equation (3). Larger estimates of β_2 signify greater fragility for a country since it indicates larger investor redemptions from hedge funds in that country in response to a given level of poor performance. Figure 1 plots the estimated values of β_2 ($\hat{\beta}_2$) on the y-axis against country-level average *WIP* (reported in Table 2) on the x-axis. The plot confirms our hypothesis that investor flows are more responsive to poor fund performance in environments with weaker investor protection. To gauge significance, we regress the country-level fragility ($\hat{\beta}_2$) against *WIP*. The estimated coefficient on *WIP* is 0.111 and statistically significant (*t*-statistic = 4.19).[19]

We acknowledge that investor protection is correlated with other country-level characteristics that can have their own independent effects on investor capital allocation. We address this concern using a two-step procedure. First, we regress *WIP* on country-level variables that measure economic development, education level, religiosity, and democratic rights.[20] We then define "orthogonalized *WIP*" (denoted *rWIP*) as the regression residual. Second, we re-estimate Equation (3) after replacing *WIP* with *rWIP*. By using *rWIP* in place of *WIP*, we test whether capital fragility in hedge funds is amplified by the portion of *WIP* that is uncorrelated with other country variables. The first and second stage results are reported in

[19] Appendix C plots the country-level capital fragility estimates against the first principal component of the LLSV indexes and shows similar results.

[20] The religiosity and democratic rights variables are from World Values Survey which are conducted every 3-4 years. Following Heather, Guille'n, and Zhou (2010), Morse and Shive (2011), Roulet and Touboul (2015), Dudley and Zhang (2016), and Wei and Zhang (2019), we linearly interpolate the survey data for years in between the waves.

Panels C1 and C2, respectively, of Table 3. Reassuringly, we find a positive and significant coefficient on our key interaction variable (*rWIP·perf·Low*), suggesting that our earlier findings for the raw *WIP* measure are not driven by confounding effects of the other country characteristics. In Appendix D, we repeat all of our subsequent analysis using the regression residual *rWIP* and show that our results are robust.

4.1.2. An Investor Protection Shock: Brazil's Clean Company Act

We exploit a regulatory shock to help establish a causal effect of investor protection on capital fragility. The 2014 Clean Company Act (CCA) is an aggressive anticorruption campaign in Brazil that imposes strict civil and administrative liability on domestic and foreign companies for engaging in corrupt practices (Tobolowsky, 2016). The law holds Brazilian companies strictly liable for actions taken by their agents to bribe public officials, and levies harsh fines and penalties on CCA offenders. It also creates incentives for companies to adopt internal controls that aim to force agents to comply with the law, since it allows courts to consider the content and effectiveness of a company's integrity program as a mitigating factor when determining punishment (Richard, 2014). Such internal controls include codes of ethics, periodic compliance training, whistleblower protection, and accurate accounting records. Therefore, Brazilian hedge funds can expect greater transparency about the financial performance of their underlying investments in Brazilian companies, and greater confidence that their interests are protected if the underlying companies become financially distressed.

In addition, since Brazilian hedge funds themselves are subject to the same laws under the CCA, fund investors can expect greater transparency about fund performance and greater protection of their interests, thereby weakening the misvaluation and investor protection channels that generate capital fragility. In sum, we would expect investors in Brazil funds to be less sensitive to poor performance in the post-2014 regulatory environment; in other words, hedge fund capital in Brazil is less fragile after the passage of the CCA as compared to before.

In Appendix E, we discuss evidence of post-regulation improvements in corporate governance and investor protection among Brazilian companies to further validate the CCA as a positive shock to investor protection.

The CCA went into force on January 29, 2014, which we use as our event date. To examine the change in the flow-performance sensitivity before and after the CCA, we construct an indicator variable *pre* that is equal to one before the event date, and zero otherwise. Likewise, *post* is an indicator variable that is equal to one after the event date, and zero otherwise. We then interact *pre* and *post* with *perf·Low* to allow for changes in the sensitivity of investor flow to poor performance in the Brazilian marketplace. Since the passage of the CCA in 2014 falls outside our main sample period (1994-2013), we extend our sample of Brazilian hedge funds from the TASS and Morningstar databases over the period 1994-2018.[21]

The results are reported in Columns (1) and (3) of Table 4 using raw return and style-adjusted return as performance measures, respectively. We observe that the coefficient on *pre·perf·Low* is positive, consistent with our main results in Table 3 that investors redeem heavily after poor fund performance in weak protection countries. Importantly, however, the interaction term *post·perf·Low* is insignificant, suggesting that the sensitivity of investor response to poor performance is significantly reduced after the CCA.

We further partition *pre* and *post* to shed more light on the dynamic effects of the regulatory shock. Specifically, we use indicator variables that are equal to one if it is two or more years before the CCA (*pre2*); one year before the CCA (*pre1*); one year after the CCA (*post1*); and two or more years after the CCA (*post2*); and zero otherwise. The results are reported in Columns (2) and (4) of Table 4. Consistent with our earlier findings, we find positive and significant coefficients on *pre2·perf·Low* and *pre1·perf·Low*, indicating a concave

[21] Due to data limitations, we use a sample of funds from TASS and Morningstar in this section, instead of the four databases in our main analysis. The ending date of the sample in this section is July 2018 rather than December 2013 as in the main analysis.

flow-performance relation before the regulatory change. However, we now see that the insignificant concavity of the flow-performance relation during the post-CCA period is evident both in the first year (*post1·perf·Low*), and in the second and later years (*post2·perf·Low*) after the CCA's passage. This suggests that the investor protection shock emanating from the CCA materialized soon after the passage of the CCA and did not reverse in subsequent years.

Overall, the evidence supports our main conclusion that stronger investor protection alleviates capital fragility. The fact that this pattern comes to light over time within the same country also helps allay concerns that omitted country-level variables are driving our results.

4.1.3. Twin funds

We now exploit pairs of "twin" hedge funds in our sample that hold nearly identical assets yet operate in different countries. An analysis of twin funds is useful for two reasons. First, since twin funds hold nearly identical assets, we can further assuage concerns that characteristics of funds' assets, not investor protection, drive the observed differences in flow-performance sensitivities across countries. In particular, we address concerns that funds managed in weaker protection countries may hold assets with greater risk exposures (Sirri and Tufano, 1998; Fung and Hsieh, 2004) and illiquidity (Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017), or engage in more risk shifting behavior (Brown, Harlow and Starks, 1996), all of which can affect fund flows. Second, because twin funds report nearly identical returns, we control for differences in the misvaluation of fund assets. As a result, differences in flow-performance sensitivities among twin funds would lend support to the investor protection channel.

To identify twin funds, we compute the return correlations for all possible pairs of funds within the same fund family. Our sample consists of 820 twins for which the return correlation is at least 99% and the management offices of the two funds are in different countries. For example, Equanum Partners LLC is a U.S. fund run by Equanum Capital Management LLC, while the family launched another fund in Singapore under Equanum Capital Management Pte Ltd. Panel A of Table 5 shows that twin funds have similar fund returns and fund characteristics. It is, therefore, unlikely that differences in the flow-performance relation between twin funds can be attributed to differences in portfolio investments (i.e., fundamental news) or fund characteristics besides geography.

We estimate the following regression on the twin funds sample:

$$\Delta flow_{i,k,t+1} = \alpha + \beta_1 perf_{i,k,t} + \beta_2 \Delta WIP_{i,k,t} \cdot perf_{i,k,t} + \beta_3 \Delta WIP_{i,k,t} + \beta_4 perf_{i,k,t} \cdot Low_{i,k,t} + \beta_5 \Delta WIP \cdot perf_{i,k,t} \cdot Low_{i,k,t} + \beta_6 \Delta WIP_{i,k,t} \cdot Low_{i,k,t} + \beta_7 Low_{i,k,t} + \eta \Delta control_{i,k,t} + \kappa_t + \varepsilon_{i,k,t} \quad (5)$$

where i and k denote twin fund pairs, and $\Delta flow$ and ΔWIP are the differences in flows and investor protection between a pair of twin funds, respectively. We utilize the same set of control variables as in Equation (3) but take the difference between twin fund observations for each variable (rather than the level). We use two methods to account for residual correlation among funds within the same country. First, we double-cluster the standard errors at both countries for the twins to allow for the possibility that the errors are correlated at the level of either country among the twins (Ahern, Daminelli, and Fracassi, 2015). Second, we re-estimate Equation (5) for a subsample of twin pairs where one twin fund in each pair is in either the U.K. or U.S. We then cluster the standard error by the other twin's country. For example, if one twin fund is in U.S. while the other twin is in country X, we cluster the standard error by country X.

The results are presented in Panel B of Table 5 and show that the coefficient on *ΔWIP·perf·Low* is positive and significant – i.e., run-like behavior is greater among investors in the twin operating in a high *WIP* country. This indicates that our previous findings on flow-performance sensitivity in Table 3 (full-sample) also prevail among funds with near-identical portfolios. As discussed earlier, such evidence supports the investor protection channel: in environments with weak investor protection and legal enforcement, investors promptly remove their capital from poorly performing funds to avoid uncertainty about payoffs in the event of a fund bankruptcy or liquidation (since the twins are otherwise identical except for differences in the degree of investor protection after liquidations).

4.1.4. Weak investor protection and performance-related liquidations

If poor fund performance triggers investor runs when investor protection is weak, then it could also be a significant predictor of fund liquidation in such environments. Liquidation is an extreme case of capital fragility since it is often associated with substantial capital outflows. We model the determinants of fund liquidation in year *t* using fund returns and characteristics in year *t*-1. We classify a fund as being liquidated if and only if it disappears from the databases and the reason for disappearance (provided by the databases) is fund liquidation.

Table 6 presents the results from estimating our models of fund liquidation using linear probability models (Columns (1) and (2)) and logistic regressions (Columns (3) and (4)). The dependent variable is an indicator variable that is equal to one if the fund is liquidated in the next year, and zero otherwise. As expected, the coefficients on fund returns are negative, indicating that worse performance increases the likelihood of fund liquidation. Importantly, the interaction between return and *WIP* is also negative, indicating that the predictive power of returns is even stronger among funds that are managed in high *WIP* countries. This finding provides additional evidence that, in such environments, poor fund performance generates more capital fragility and run-like behavior. The greater propensity of performance-related liquidations in high *WIP* countries could either be the cause and/or the outcome of investors fleeing at the first sign of trouble. While the results in Table 6 cannot separate these two effects, they indicate that investor action is consistent with investor runs and fund failure reinforcing each other.

4.2. Manager behavior

A key premise of our misvaluation channel is that managers engage in more returns management when investor protection is weak. The reason is that, in such environments, managers may feel less concerned about the legal consequences of distorting their reported performance because these environments are typically associated with inefficient and weak legal systems (Djankov et al., 2002; Leuz, Nanda, and Wysocki, 2003; Svensson, 2005). In turn, managers can benefit from returns management through higher incentive fees associated with greater reported returns and higher management fees associated with attracting and retaining investor capital. This is in line with Becker's (1968) economic theory of crime: people commit crimes because the gains outweigh the expected costs of getting caught and punished.

Besides distorting fund returns, managers can also impact the timing of performance disclosure. Aragon and Nanda (2017) find evidence that hedge fund managers strategically delay the disclosure of bad news about fund performance. Managers can also strategically revise and restate their reported returns to commercial databases (Patton, Ramadorai, and Streatfield, 2015). We expect reporting delays and restatements to be more prevalent among funds that are managed in high *WIP* countries, where managers have fewer legal and reputational concerns.

To examine whether the tendency of managers to engage in returns management is greater in weak protection environments, we estimate the following regression:

$$ReturnMgmt_{i,t+1} = \alpha + \mu WIP_{j,t} + \eta control_{i,j,t} + \kappa_t + \varepsilon_{i,t} \quad (6)$$

where *ReturnsMgmt* is one of the four returns management variables defined in the data section: *flag_sum*, *flag_pc*, *delay*, and *restate*. Panel A of Table 7 shows that weak investor protection is positively related to returns management. For example, the coefficient on *WIP* is positive and significant in Columns (1) and (2), which correspond to our two indexes of suspicious patterns in reported returns. To gauge economic significance, a one standard deviation increase in *WIP* corresponds to a 0.089 (=0.86×0.102) increase in the number of suspicious return flags (*flag_sum*), representing 6% of the sample standard deviation of *flag_sum.*

Column (3) of Table 7 reveals a positive and significant relation between *WIP* and *delay*. A one standard deviation increase in *WIP* corresponds to a 1.08 (0.86×1.258) increase in the number of days between the end of the month and when the fund reports its monthly return to the database (adjusted for style category). This represents 7% of one standard deviation of the reporting delay measure reported in Table 2. Finally, Column (4) shows the results from a linear probability model in which the dependent variable is a dummy for whether the fund restates or revises any of its prior returns (*restate*). We find that the probability of restatement is also positively related to weak investor protection – specifically, a one standard deviation increase in *WIP* corresponds to a 3.1% (0.86×0.036) increase in the probability of a restatement, which is 6% of the standard deviation of *restate*.

There is a close connection between asset illiquidity exposure and strategic return management. While the opportunity to strategically manage returns is greater when assets are illiquid and their values need to be imputed, an exposure to asset illiquidity could generate suspicious patterns in reported returns due to innocuous reasons (e.g., infrequent trading, marking-to-model). To address this concern, in our baseline returns management regressions (Panel A of Table 7), we control for asset illiquidity exposure using lockup and restriction periods (Aragon, 2007) and style fixed effects. As an additional robustness check, in Panel B of Table 7 we re-run the return management regressions by excluding funds following illiquid investment styles such as emerging markets, fixed income arbitrage, and convertible arbitrage. For the remaining funds belonging to relatively liquid styles, we again find that weak investor protection is positively associated with a greater incidence of return management.

Finally, we investigate whether Brazilian hedge funds exhibit less return management after the Clean Company Act (CCA). For each fund, we compute the suspicious return flags based on fund returns in two subperiods: four years before and four years after the shock.[22] This is to ensure that the calculation of pre and post-event return flag measures only use pre and post-event returns, respectively. The results are reported in Panel C of Table 7. Columns (1) and (2) show a decline in the return management flags among Brazilian funds after the shock. Specifically, the CCA leads to a 0.117 decline in the number of suspicious return flags (*flag_sum*), representing 10.9% of the sample standard deviation of *flag_sum* for the subsample of Brazilian funds. Furthermore, Columns (3) and (4) show lower reporting delays and fewer restatements after the CCA. Specifically, *delay* experiences a decline of 4.175 days, or, 11.3% of the standard deviation of *delay* for Brazilian funds; and *restate_ret* shows a decline of 0.3%, or, 6.9% of the standard deviation of *restate_ret* for Brazilian funds. These results are consistent with a strengthening of corporate governance and internal controls for Brazilian firms following the CCA.[23]

Overall, the evidence in Table 7 reveals that weak investor protection fosters returns management behavior by fund managers, thus supporting a key premise of the misvaluation channel. The evidence also suggests that returns management and capital fragility may be reinforcing: the threat of severe investor outflows in response to poor fund performance further strengthens a manager's aversion to reporting losses.

4.3. Discussion of results

Our findings link country-level governance with the vulnerability of hedge funds to investor runs. This opens the questions about whether funds can adopt policies to reduce capital fragility in weak investor protection environments. For example, hedge fund managers could

[22] We do not use a one-year window as in Table 4 since we require a minimum of 24 months of return data to compute the suspicious return flags from simulated returns.
[23] In Panel C, *restate_ret* is an indicator variable that is equal to one if a given fund-month reported return is later restated, and zero otherwise. In contrast, *restate* in Panel A is an indicator variable that is equal to one if a given fund restates *any* of its monthly reported returns, and therefore will mechanically increase over time for a given fund. Given that our Brazil test compares the restatement behavior of Brazilian funds before and after the CCA event, we use *restate_ret* to avoid this mechanical relation.

impose more restrictions on investor redemptions at fund inception to pre-empt the impact of flow-induced trading. Alternatively, managers can invest their personal capital in the fund, and convey a positive signal to investors about the quality of the fund's investments (Leland and Pyle, 1977), or commit to lower rates of diverting value from fund investors (Himmelberg, Hubbard, and Love, 2004). We find that both share restrictions and manager personal investment reduce, but do not fully offset, the greater sensitivity of investor flows to poor performance for funds in high *WIP* countries (not tabulated). The lack of a full offset perhaps reflects the costs of these policies in the form of 1) a higher liquidity premium required by fund investors as compensation for a loss of redemption rights (Aragon, 2007) and 2) considerable diversifiable risk being borne by the manager as a result of their larger personal investment in the fund (Leland and Pyle, 1977).

We also consider whether other fund policies, besides share restrictions and personal capital investment, inspire confidence among investors and discourage investor runs in high *WIP* environments. However, we find no evidence that an affiliation with a top global investment bank, the use of a top auditing firm, or the use of a third-party administrator help reduce the flow-performance sensitivity in weak investor protection environments (not tabulated). This suggests that, compared to redemption restrictions and managerial skin-in-the-game, third-party certifications are less effective for funds to establish their reputation or restore investor confidence when investor protection is weak.

4.4. Robustness tests

In this section, we perform a variety of robustness tests to ascertain the strength of our flow-performance results.

4.4.1. Risk aversion and tail risk

A potential concern is that, due to home bias in hedge fund holdings, fund investors in different countries could react to returns differently because they have differing levels of risk aversion. If risk aversion is greater in high *WIP* countries, and risk tends to increase when fund performance is low, then a positive coefficient on *WIP·perf·Low* could reflect a stronger negative reaction of risk-averse investors to an increase in fund risk. To control for this possibility, we include an additional interaction term – *Fund risk·WIP* – in our main flow regression, where *Fund risk* is either the standard deviation of the fund's monthly returns over the prior 12 months in Row (1) of Table 8, or Agarwal, Ruenzi, and Weigert's (2017) tail risk measure in Row (2) of Table 8. This interaction term controls for the possibility that investors in *WIP* countries allocate their capital differently given the same level of fund risk taking. Our main findings for the key capital fragility variable – *WIP·perf·Low* – are robust after including these control variables. This evidence further allays concerns that investor heterogeneity (e.g., risk aversion) are driving our results.

Hedge funds in countries with weak investor protection could also have higher tail risk exposures if these funds are more likely to invest locally and their returns are subject to the fragility of the entire system of these countries. To help alleviate this concern, we re-run the main analysis for the subsample of funds with zero tail risk exposure. The results are reported in Row (3) of Table 8. We continue to observe a positive and significant coefficient on *WIP·perf·Low*. This evidence, together with our analysis of twin funds, suggests that our results are not driven by differences in tail risk exposure.

4.4.2. Voluntary Reporting

Since hedge fund data are voluntarily reported, funds that choose to self-report to our databases may not be representative of all hedge funds in their home country. Therefore, one caveat of our result is the sample selection issue is inevitable since we do not observe all funds from all countries. We note, however, that this selection issue could change our conclusion only if within the non-reporting funds, those from weak investor protection countries are *less* fragile, i.e., if fragile funds from weak investor protection countries are *more* willing to voluntarily report. If this conjecture is true, we should also expect the results to be stronger among funds that engage in more voluntary reporting. We separate funds into those only reporting to one commercial database, and those reporting to multiple databases. Rows (4) and (5) of Table 8 show that our result is actually stronger in the first subsample of funds that make less voluntary reporting, suggesting that voluntary reporting is likely to bias against our findings.

4.4.3. Delisting bias

Agarwal, Fos, and Jiang (2013) show that funds stop reporting to databases in anticipation of future poor performance and investor outflows, leading to a form of delisting bias in estimates based on database returns and flows. In our setting, we would expect such a delisting bias to make it more difficult to uncover evidence that the flow-performance relation is greater (i.e., capital is more fragile) in high *WIP* countries, to the extent that poor returns and outflows are underreported in countries with weak investor protection. To be sure, we perform a robustness check where we re-run the main analysis in Table 3 after imputing a "delisting flow" of –100% for all liquidated funds during the quarter after the funds are liquidated. The results are reported in Row (6) of Table 8 and show that our results are qualitatively unchanged from our main analysis. In addition, the estimated fragility for high *WIP* countries is indeed a bit larger than the baseline estimates in Table 3.

4.4.4. Domicile location vs. management office location

Hedge funds may be subject to regulations based on its country of domicile, in addition to the investor protection laws and their enforcement in the country in which the fund is managed. As a result, it could be challenging to assign funds to one specific country and investor protection score. However, our key *WIP* variable has a 95% pairwise correlation with an alternative "domicile-based" *WIP* variable constructed based on the fund's domicile country, indicating significant agreement in the degree of investor protection between these two countries. In addition, we re-run our main analysis in Table 3 using 1) the domicile-based *WIP* variable (rather than the country of location), and 2) the subsample of funds with the same domicile country and country of business location. The results are reported in Rows (7) and (8) of Table 8 and, reassuringly, show that our inferences are unchanged from our main analysis.

Next, we explore whether the investor protection environment of the fund's management office location matters over and above the fund's domicile country. Specifically, we examine a subsample of funds that are domiciled in offshore island countries (i.e., Cayman Islands and Bermuda) while maintaining management offices in other countries. By focusing on a sample of funds that are all domiciled in offshore islands, we hold fixed domicile country-specific factors common to these island domiciles. The results are shown in Row (9) of Table 8. We continue to find more fragility in high *WIP* countries, which suggests that the investor protection environment of the management office impacts investor flows even after controlling for domicile country.

Finally, as mentioned earlier, we provide further discussions in Appendix B on why the regulations of hedge funds' business location country is relevant for fund investors, even when the funds are domiciled in another country.

4.4.5. U.S. vs. foreign investors

A potential concern is related to the representativeness of our hedge fund sample. Specifically, foreign hedge funds that report to U.S. hedge fund databases might cater more towards U.S. institutional clients (who provide the data to the database) or are trying to attract foreign clients by making this data available. In contrast, non-reporting foreign funds might cater more to local investors who, potentially, may be less prone to withdraw their capital in response to poor performance when investor protection is weak. To address this concern, we first note that, although three – HFR, Morningstar, and Lipper TASS – of our four hedge fund databases have U.S. headquarters, all four databases operate globally, gathering data across several countries. For example, Morningstar has offices in 27 countries that gather data. Therefore, our combined database is global in nature and not focused mainly on the U.S. marketplace. Second, in Row (10) of Table 8 we re-run our main analysis on a subsample of funds that are denominated in their local currencies. Among such funds that are presumably sold to local investors, we still observe greater capital fragility among funds operating in high *WIP* countries. This evidence, together with our prior analyses that address potential heterogeneity in investor risk aversion and sophistication, helps further alleviate concerns about heterogeneity in investor clienteles.

4.4.6. Does weak investor protection also impact changes in funds' overall market share?

Our evidence in Table 3 shows that hedge funds in countries with weak investor protection shrink more in assets following poor fund performance. If smaller funds are the ones located in high *WIP* countries, then a further decline in their assets would necessarily be magnified given their already small market shares. For example, a one dollar decline in net flows implies a –10% net flow for funds managing $10 in assets, but just –1% for a larger fund managing $100 in assets. To address this concern, we follow Spiegel and Zhang (2013) and re-run our flow regressions using the change in the fund's market share (over all funds in the global hedge fund market) as our dependent variable. The results are shown in Row (11) of Table 8 and are similar to our baseline analysis of percentage flows in Table 3 – that is, we again find a positive and significant coefficient on *WIP·perf·Low*.

4.4.7. Country-level differences in hedge fund regulations

Cumming and Dai (2009) examine differences in hedge fund regulations across countries, including permissible distribution channels, minimum capital requirements to start a fund, restrictions on the location of key service providers, and offshore status. They find that permissible distribution channels affect the flow-performance relation in hedge funds, but other types of regulations do not. Specifically, distribution via wrappers that involves the bundling of products weakens the flow-performance relation, because tied selling dilutes the informativeness of the performance signals of hedge funds. On the other hand, distributions via investment managers and fund distribution companies strengthen the flow-performance relation, because funds are more aggressively marketed through these channels.

Using data from Cumming and Dai (2010) on country-level fund distribution channels, in Table 8 we repeat our flow-performance analysis using subsamples of funds based on whether they are managed in countries that allow distributions via 1) wrappers (Rows (12) and (13)); 2) investment managers (Rows (14) and (15)); and 3) fund distribution companies (Rows (16) and (17)). The results indicate that, in general, our findings of a concave flow-performance relation in high *WIP* countries are not driven by cross-country differences in the regulation of how hedge funds are sold to the investing public.

4.4.8. Smoothing-adjusted returns

In our main analysis, we control for asset liquidity using autocorrelation of fund returns in Table 3. In addition, as we mentioned earlier, cross-country differences in asset illiquidity are unlikely to drive our results because the greater flow-performance sensitivity associated with higher *WIP* prevails even among twin funds holding the same underlying assets (Table 5). Nevertheless, we run our baseline flow regression using smoothing-adjusted returns following Getmansky, Lo, and Makarov (2004) to control for the heterogeneity in quality of measures of returns due to fund liquidity. These results are shown in Row (18) of Table 8 and further confirm that our main findings are unlikely to be driven by country-level differences in the illiquidity of hedge funds' assets.

4.4.9. Change in management office location

A potential concern is that funds in our sample move across countries and one snapshot of the databases may not accurately reflect historical fund locations. We examined several annual snapshots of the TASS database taken in 2002, 2003, 2005, 2013, 2016, 2017, and 2018. Among the 10,333 unique hedge funds that report addresses during this 17-year period, 10,002 (i.e., 97%) report just one country of address across all snapshots. Since fund movements across countries appear to be quite rare, they are unlikely to substantively change our results. Even so, we repeated our tests for the subsample of TASS funds that report just one country of address to the database across all vintages in Row (19) of Table 8 and find similar results.

4.4.10. Excluding multi-national funds

In our previous analyses, in case of large financial conglomerates with multiple hedge fund management firms, we assign the investor protection index based on where the specific fund's management office is located, rather than where its parent company is located. For example, Goldman Sachs is headquartered in the United States, but it is parent to hedge fund management firms operating in several different countries, including Goldman Sachs SIF-Global Tracker Port (Luxembourg), Goldman Sachs Hedge Qualificado FICFI Multi (Brazil), Goldman Sachs JBWere Multi Stategy Managed Funds (Australia), Goldman Sachs Global Tactical Trading Pl (Ireland), and several others located in the United States. In Row (20) of Table 8, we find that our results are robust after excluding such multi-national funds.

4.4.11. Data filters

We require funds to have AUM of at least five million dollars and a minimum of 150 fund-quarter observations in a country to reliably estimate country-level capital fragility as shown in Figure 1. As a result, some countries such as India, Israel, Mexico, and Poland are dropped in our analysis. In Row (21) of Table 8 we drop the AUM and the fund-quarter observation filters, so more countries are included, and find that our inference is unchanged.

4.4.12. Additional robustness

We conduct additional robustness checks of the baseline results. Row (22) of Table 8 uses the average (instead of the first principal component) of the three World Governance Indicators. Row (23) excludes Brazil funds since they have a relatively large number of observations among high-*WIP* countries. Row (24) clusters the standard errors at both the country and time levels. Row (25) reports the estimates using Fama and Macbeth (1973) regressions. Among these specifications, we continue to observe that weak investor protection is associated with a greater level of capital fragility.

Lastly, we use funds' raw returns and style-adjusted returns as performance measures. We now repeat our flow-performance analysis using other performance measures that could be relevant for investor decision-making. Specifically, we follow prior studies (e.g., Griffin, 2002; Ferreira et al., 2013; Fama and French, 2015; Cremers et al., 2016) and compute fund alphas using investment region-specific versions of factor models, including the Carhart (1997) four-factor model and the seven-factor model of Fung and Hsieh (2004) although our results are also robust using the CAPM alpha. We report the results in Row (26) of Table 8. Consistent with our prior results, the triple interaction terms *WIP·perf·Low* are positive and significant across both models, echoing our earlier findings that weak investor protection magnifies the flow response to bad fund performance. The adjusted R-squared in these regressions are generally smaller than those in our baseline analysis (Table 3). This suggests that raw returns and style-adjusted returns have more explanatory power for investor-decision making than alphas from multi-factor models.

5. Conclusions

Weak investor protections are usually regarded as a drag on the economy because they can distort economic decisions and lead to a misallocation of resources (Shleifer and Vishny, 1993). In this paper, we uncover another adverse consequence of weak investor protection in the form of greater capital fragility in the hedge fund industry. We find robust evidence that, when investor protections are weak, hedge funds face more redemptions from investors via their decisions to withdraw capital from poorly performing funds. Operational risk concerns related to the misvaluation of fund assets likely contribute to the greater capital fragility in these environments, since the reported returns in environments with weak investor protection exhibit patterns consistent with returns management. We also find evidence that concerns about weak investor protection in the event of fund liquidation also motivate investors to pull their capital from poorly performing funds in such environments. Overall, our study contributes to the literature on investor runs among non-bank financial intermediaries and informs the debate on how operational risks in the asset management industry impact the capital allocation decisions of fund investors.

Given the strong evidence of fragility in hedge funds managed in countries with weak investor protection, one may wonder how the results will look like in other global asset management settings, like mutual funds. For example, Khorana, Servaes, and Tufano (2005) show that the mutual fund industry is larger in countries with stronger investor protection, suggesting that investor protection matters for mutual fund investor decision-making and, potentially, the sensitivity of fund flows to poor performance. On the other hand, compared to hedge funds, mutual funds generally face tighter regulations that are designed to protect fund investors, suggesting that our capital fragility hypothesis is less relevant for mutual funds. A study of capital fragility in the global mutual fund industry and other asset classes is an interesting avenue for future empirical work.

References

Agarwal, V., G. O. Aragon, and Z. Shi. 2019. Liquidity transformation and financial fragility: Evidence from funds of hedge funds. *Journal of Financial and Quantitative Analysis* 54: 2355−2381.

Agarwal, V., N. Daniel, and N. Naik. 2009. Role of managerial incentives and discretion in hedge fund performance. *Journal of Finance* 64:2221–2256.

Agarwal, V., N. Daniel, and N. Naik. 2011. Do hedge funds manage their reported returns? *Review of Financial Studies* 24:3282–3320.

Agarwal, V., V. Fos, and W. Jiang. 2013. Inferring reporting-related biases in hedge fund databases from hedge fund equity holdings. *Management Science* 59:1271–1289.

Agarwal, V., S. Ruenzi, and F. Weigert. 2017. Tail risk in hedge funds: A unique view from portfolio holdings. *Journal of Financial Economics* 125:610-636.

Agarwal, V., and H. Zhao, 2019. Interfund lending in mutual fund families: Role in liquidity management. *Review of Financial Studies* 32: 4079–4115.

Ahamed, M. M, and S. K. Mallick. 2019. Is financial inclusion good for bank stability? International evidence. *Journal of Economic Behavior and Organization* 157:403−427.

Ahern, K. R., D. Daminelli, and C. Fracassi. 2015. Lost in translation? The effect of cultural values on mergers around the world. *Journal of Financial Economics* 117:165–189.

Aragon, G. O. 2007. Share restrictions and asset pricing: Evidence from the hedge fund industry. *Journal of Financial Economics* 83:33–58.

Aragon, G. O., and V. Nanda. 2017. Strategic delays and clustering in hedge fund reported returns. *Journal of Financial and Quantitative Analysis* 52:1–35.

Bailey, W., A. Kumar, and D. Ng. 2011. Behavioral biases of mutual fund investors. *Journal of Financial Economics* 102:1–27.

Barber, B. M., and T. Odean. 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance* 55:773–806.

Barber, B. M., X. Huang, and T. Odean. 2016. Which factors matter to investors? Evidence from mutual fund flows. *Review of Financial Studies* 29:2600–2642.

Barham, S. 2003. The capital guide to hedge funds. ISI Publications Ltd.

Barth, J. R., C. Lin, P. Lin, and F. M. Song. 2009. Corruption in bank lending to firms: Cross-country micro evidence on the beneficial role of competition and information sharing. *Journal of Financial Economics* 91:361–388.

Beck, T., C. Lin, and Y. Ma. 2014. Why do firms evade taxes? The role of information sharing and financial sector outreach. *Journal of Finance* 69:763–817.

Becker, G. 1968. Crime and punishment: an economic approach. *Journal of Political Economy* 76 169–217.

Bollen, N., and V. Pool. 2008. Conditional return smoothing in the hedge fund industry. *Journal of Financial and Quantitative Analysis* 43:267–298.

Bollen, N., and V. Pool. 2009. Do hedge fund managers misreport returns? Evidence from the pooled distribution. *Journal of Finance* 64:2257–2288.

Bollen, N., and V. Pool. 2012. Suspicious patterns in hedge fund returns and the risk of fraud. *Review of Financial Studies* 25:2673–2702.

Braguinsky, S. and S. Mityakov. 2015. Foreign corporations and the culture of transparency: Evidence from Russian administrative data. *Journal of Financial Economics* 117:139–164.

Brown, K., W. V. Harlow, and L. Starks. 1996. Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry. *Journal of Finance* 51:85–110.

Brown, S. J., W. N. Goetzmann, B. Liang, and C. Schwarz. 2008. Mandatory disclosure and operational risk: Evidence from hedge fund registration. *Journal of Finance* 63:2785–2815.

Brown, S. J., W. N. Goetzmann, B. Liang, and C. Schwarz. 2012. Trust and delegation. *Journal of Financial Economics* 103:221–234.

Calvet, L. E., J. Y. Campbell, and P. Sodini. 2007. Down or out: Assessing the welfare costs of household investment mistakes. *Journal of Political Economy* 115:707–747.

Cao, C., Y. Chen, B. Liang, and A. W. Lo. 2013. Can hedge funds time market liquidity? *Journal of Financial Economics* 109:493–516.

Carhart, M. M. 1997. On persistence in mutual fund performance. *Journal of Finance* 52:57–82.

Chen, Q., I. Goldstein, and W. Jiang. 2010. Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics* 97:239–62.

Chevalier, J., and G. Ellison. 1997. Risk taking by mutual funds as a response to incentives. *Journal of Political Economy* 105:1167–200.

Cici, G., A. Kempf, and A. Puetz. 2013. The valuation of hedge funds' equity positions. *Journal of Financial and Quantitative Analysis* 51:1013–1037.

Cremers, M., M. A. Ferreira, P. Matos, and L. Starks. 2016. Indexing and active fund management: International evidence. *Journal of Financial Economics* 120:539–560.

Cumming, D., and N. Dai. 2009. Capital flows and hedge fund regulation. *Journal of Empirical Legal Studies* 6:848–873.

Cumming, D., and N. Dai. 2010. Hedge fund regulation and misreported returns. *European Financial Management* 16:829–857.

Del Guercio, D., and P. A. Tkac. 2002. The determinants of the flow of funds of managed portfolios: Mutual funds vs. pension funds. *Journal of Financial and Quantitative Analysis* 37:523–557.

Dimmock, S. G., and W. C. Gerken. 2016. Regulatory oversight and return misreporting by hedge funds. *Review of Finance* 20:795–821.

Djankov, S., R. La Porta, F. Lopez-de-Silanes, and A. Shleifer. 2002. The regulation of entry. *Quarterly Journal of Economics* 117:1–37.

Doidge, C., G. A. Karolyi, and R. M. Stulz. 2013. The US left behind? Financial globalization and the rise of IPOs outside the US. *Journal of Financial Economics* 110:546–573.

Dudley, E., and N. Zhang. 2016. Trust and corporate cash holdings. *Journal of Corporate Finance* 41:363–387.

Evans, R. B., and R. Fahlenbrach. 2012. Institutional investors and mutual fund governance: Evidence from retail-institutional fund twins. *Review of Financial Studies* 25:3530–71.

Fama, E., and K. French. 2015. International tests of a five-factor asset pricing model. Working Paper, University of Chicago and Dartmouth College.

Fama, E., and J. D. Macbeth. 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81:607–636.

Ferreira, M. A., A. Keswani, A. F. Miguel, and S. B. Ramos. 2012. The flow-performance relationship around the world, *Journal of Banking and Finance* 36:1759–1780.

Ferreira, M. A., A. Keswani, A. F. Miguel, and S. B. Ramos. 2013. The determinants of mutual fund performance: A cross-country study. *Review of Finance* 17:483–525.

Ferreira, M. A., M. Massa, and P. Matos. 2018. Investor-stock decoupling in mutual funds. *Management Science* 64:2144–2163.

Franzoni, F. A. and M. Giannetti. 2019. Costs and benefits of financial conglomerate affiliation: Evidence from hedge funds. *Journal of Financial Economics* 134: 355–380.

Fung, W., and D. A. Hsieh. 2001. The risk in hedge fund strategies: theory and evidence from trend followers. *Review of Financial Studies* 14:313–341.

Fung, W., and D. A. Hsieh. 2004. Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal* 60:65–80.

Gächter, S., and J. Schulz. 2016. Intrinsic honesty and the prevalence of rule violations across societies. *Nature* 531:496−499.

Gennaioli, N., A. Shleifer, and R. W. Vishny. 2013. A model of shadow banking. *Journal of Finance* 68:1331–1363.

Getmansky, M., A. W. Lo, and I. Makarov. 2004. An econometric model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial Economics* 74:529–609.

Goldstein, I., H. Jiang, and D. T. Ng. 2017. Investor flows and fragility in corporate bond funds. *Journal of Financial Economics* 126:592–613.

Goyenko, R., and S. Sarkissian. 2014. Treasury bond illiquidity and global equity returns. *Journal of Financial and Quantitative Analysis* 49:1227–1253.

Griffin, J. M. 2002. Are the Fama and French factors global or country specific? *Review of Financial Studies* 15:783–803.

Gurun, U. G., N. Stoffman, and S. E. Yonker. 2017. Trust busting: The effect of fraud on investor behavior. *Review of Financial Studies* 31:1341–1376.

Heather B., M. F. Guille'n, and N. Zhou. 2010. An institutional approach to cross-national distance. *Journal of International Business Studies* 41:1460–1480.

Himmelberg, C. P., R. G. Hubbard, and I. Love. 2004. Investor protection, ownership, and the cost of capital. World Bank Policy Research Paper.

Houston, J. F., C. Lin, P. Lin, and Y. Ma. 2010. Creditor rights, information sharing, and bank risk taking. *Journal of Financial Economics* 96:485–512.

Huang, W., S. Lin, and J. Yang. 2019. Institutional quality and sovereign credit default swap spreads. *Journal of Futures Markets* 39:686–703.

Jain, P. K., E. Kuvvet, and M. S. Pagano. 2017. Corruption's impact on foreign portfolio investment. *International Business Review* 26:23–35.

Johnson, S., P. Boone, A. Breach, and E. Friedman. 2000. Corporate governance in the Asian financial crisis. *Journal of Financial Economics* 58:141–186.

Jordaan, J. A., B. Dima, and I. Golet. 2016. Do societal values influence financial development? New evidence on the effects of post materialism and institutions on stock markets. *Journal of Economic Behavior and Organization* 132:197−216.

Jorion, P., and C. Schwarz. 2014. Are hedge fund managers systematically misreporting? Or not? *Journal of Financial Economics* 111:311–327.

Karolyi, A. G. 2016. Home bias, an academic puzzle. *Review of Finance* 20:2049–2078.

Kaufmann, D., A. Kraay, and M. Mastruzzi. 2010. The worldwide governance indicators: Methodology and analytical issues. World Bank Policy Research Paper.

Khorana, A., H. Servaes and P. Tufano. 2005. Explaining the size of the mutual fund industry around the world. *Journal of Financial Economics* 78:145–185.

Khorana, A., H. Servaes and P. Tufano. 2009. Mutual fund fees around the world. *Review of Financial Studies* 22:1279–1310.

La Porta, R., F. Lopez-de-Silanes, and A. Shleifer. 2006. What works in security laws? *Journal of Finance* 61:1–33.

La Porta, R., F. Lopez-de-Silanes, A. Shleifer, and R. Vishny. 1998. Law and finance. *Journal of Political Economy* 106:1113–1155.

La Porta, R., F. Lopez-de-Silanes, A. Shleifer, and R. Vishny. 2000. Investor protection and corporate governance. *Journal of Financial Economics* 58:3–27.

La Porta, R., F. Lopez-de-Silanes, A. Shleifer, and R. Vishny. 2002. Investor protection and corporate valuation. *Journal of Finance* 57:1147–1170.

Leland, H., and D. Pyle. 1977. Information asymmetries, financial structure, and financial intermediation. *Journal of Finance* 32:371–387.

Leuz, C., D. Nanda, and P. D. Wysocki. 2003. Earnings management and investor protection: an international comparison. *Journal of Financial Economics* 69:505–527.

Levine, R., C. Lin, and W. Xie. 2016. Spare tire? Stock markets, banking crises, and economic recoveries. *Journal of Financial Economics* 120:81–101.

Levine, R., C. Lin, and W. Xie. 2018. Corporate resilience to banking crises: The roles of trust and trade credit. *Journal of Financial and Quantitative Analysis* 53:1441−1477.

Lin, C., M. Massa, and H. Zhang. 2014. Mutual funds and information diffusion: The role of country-level governance. *Review of Financial Studies* 24:3343–3387.

Lynch, A. W., and D. K. Musto. 2003. How investors interpret past fund returns. *Journal of Finance* 58:2033–2058.

Massa, M., and A. Simonov. 2006. Hedging, familiarity and portfolio choice. *Review of Financial Studies* 19:633–685.

Morse, A., and S. Shive. 2011. Patriotism in your portfolio. *Journal of Financial Markets* 14:411–440.

Patton, J. A., T. Ramadorai, and M. Streatfield. 2015. Change you can believe in? Hedge fund data revisions. *Journal of Finance* 70:963–999.

Richard, M. 2014. Brazil’s landmark anti-corruption law. *Law and Business Review of the Americas* 20:141–148.

Roulet, T. J., and S. Touboul. 2015. The intentions with which the road is paved: Attitudes to liberalism as determinants of greenwashing. *Journal of Business Ethics* 128:305–320.

Schmidt, L., A. Timmermann, and R. Wermers. 2016. Runs on money market mutual funds. *American Economic Review* 106:2625–57.

Shleifer, A., and R. Vishny. 1993. Corruption. *Quarterly Journal of Economics* 108:599–617.

Sirri, E., and P. Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53:1589–1622.

Spiegel, M., and H. Zhang. 2013. Mutual fund risk and market share-adjusted fund flows. *Journal of Financial Economics* 108:506–528.

Straumann, D. 2009. Measuring the quality of hedge fund data. *Journal of Alternative Investments* 12:26–40.

Svensson, J. 2005. Eight questions about corruption. *Journal of Economic Perspectives* 19:19–42.

Tobolowsky, Z. B. 2016. Brazil finally cleans up its act with the Clean Company Act: The story of a nation's long overdue fight against corruption. *Law and Business Review of the Americas* 22:383–413.

Wei, C., and L. Zhang. 2019. Trust and local bias. *Journal of Financial and Quantitative Analysis*, forthcoming.

Figure 1: Investor Protection and Capital Fragility

This figure plots country-level estimates of capital fragility (y-axis) against country-level measures of weak investor protection (*WIP*, x-axis). A country's capital fragility is the estimated regression coefficient (β_2) on *perf·Low* in country-level flow-performance regressions in Equation (4). The stars denote the country-level capital fragility measures and their corresponding countries' average *WIP*. The letters denote the two-digit ISO 3166 code for the corresponding country reported in Table 2. The solid line denotes the fitted regression estimate. The estimation result is *fragility* = –0.325+ 0.111×*WIP* and the *t*-statistic of the slope is 4.19. The sample period is 1994-2013.

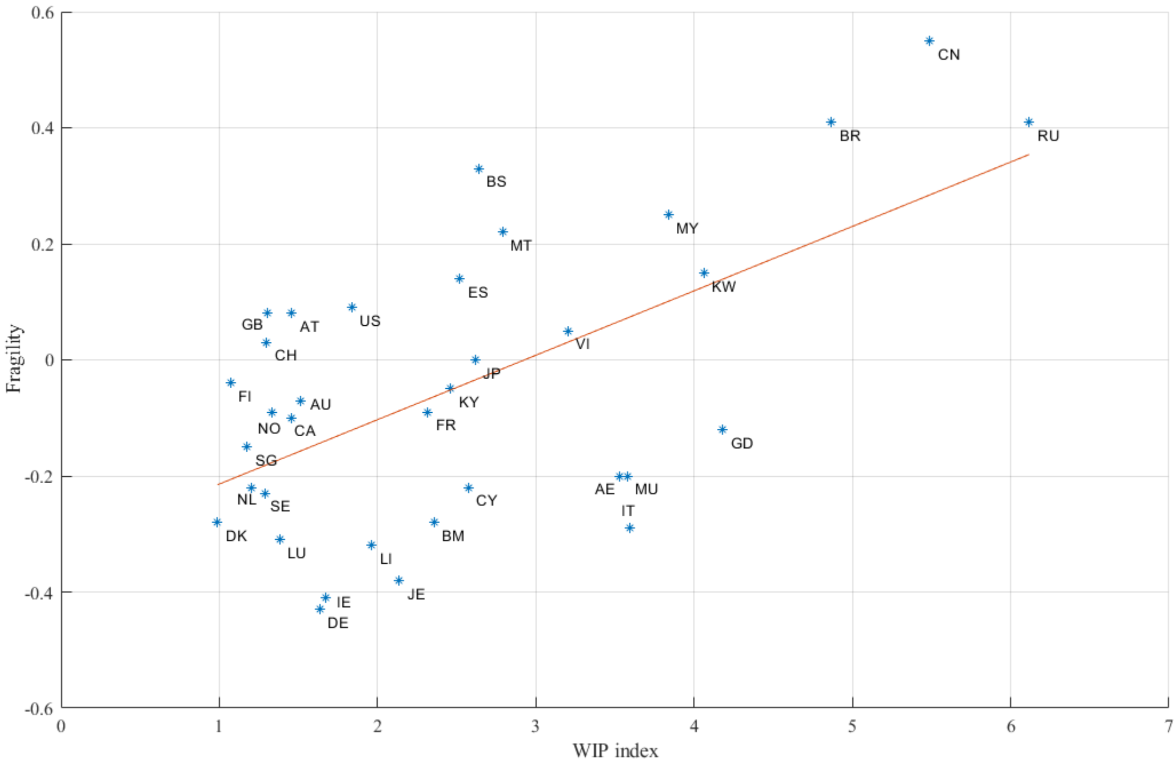


Table 1: Summary Statistics

This table summarizes key variables from the union of the TASS, EUREKA, Morningstar, and HFR hedge funds databases. *WIP* is 3 minus the first principal component of three World Governance Indicators from the World Bank: regulatory quality, rule of law, and control of corruption. *ret* and *flow* are the fund's quarterly return and flow, respectively. *ifee*, *mfee*, *lockup*, *restrict*, and *hwm* are the fund's incentive fee, management fee, lockup period in years, restriction period (notice period plus redemption frequency) in years, and the high-water-mark indicator variable, respectively. *age* is the number of years since fund inception. *sdret* is the standard deviation of fund's monthly returns during the last 12 months. *illiquid* is an indicator variable that is equal to one if the autocorrelation of a fund's past monthly returns is positive and the null hypothesis of zero autocorrelation is rejected at the 10% level. *tail* is the tail risk measure as in Agarwal, Ruenzi, and Weigert (2017) where the market return is based on funds' regions of investments such as North America, Europe, Asia-Pacific, and Global. *mininv* is the logarithm of minimum fund investment. *size* is the logarithm of fund size. *flag_sum* is the sum of eight suspicious return flags as in Aragon and Nanda (2017): having too many zero returns, too few negative returns, too few unique returns, the maximum run of identical returns, too many recurring return blocks of length two, a lack of uniformity of the second digit in returns, too little correlation with the Fung and Hsieh (2004) factors measured by regression R-squared, and a significant December return spread (relative to non-December returns). *flag_pc* is the first principal component of the eight return flags. *delay* is the number of days between month-end and the date when fund reports its monthly return to TASS. *restate* is an indicator variable that is equal to one if the fund experiences a subsequent data revision on its reported returns, and zero otherwise. *delay* and *restate* are adjusted by the mean values of the funds in the same investment style.

Variables	N	Mean	STD	25%	Median	75%
WIP	310,804	2.95	0.86	2.49	2.80	2.96
ret	310,804	0.02	0.07	−0.01	0.02	0.04
flow	310,804	0.04	0.23	−0.06	0.00	0.08
ifee	310,804	14.71	7.97	10.00	20.00	20.00
mfee	310,804	1.51	0.74	1.00	1.50	2.00
lockup	310,804	0.24	0.54	0.00	0.00	0.00
restrict	310,804	0.26	0.28	0.09	0.16	0.37
hwm	310,804	0.70	0.46	0.00	1.00	1.00
age	310,804	5.74	4.52	2.25	4.50	8.00
sdret	310,804	0.03	0.03	0.01	0.02	0.04
illiquid	310,804	0.28	0.45	0.00	0.00	1.00
tail	310,804	0.27	0.42	0.00	0.12	0.39
mininv	310,804	12.31	2.37	11.51	12.61	13.82
size	310,804	17.68	1.52	16.53	17.58	18.71
flag_sum	65,100	1.77	1.47	1.00	1.00	3.00
flag_pc	65,100	0.00	0.81	−0.62	−0.33	0.36
delay	127,558	0.00	15.20	−9.32	−2.95	5.67
restate	127,558	0.00	0.49	−0.43	−0.43	0.57

Table 2: Investor Protection Index by Country

This table reports the two-digit ISO 3166 country code, country-level averages of weak investor protection index (*WIP*), and the number of fund-quarter observations for each country (NOBS).

Country	CODE	*WIP*	NOBS
Australia	AU	1.51	4,170
Austria	AT	1.46	1,915
Bahamas	BS	2.79	2,843
Bermuda	BM	2.32	5,525
Brazil	BR	4.87	14,440
Canada	CA	1.46	6,927
Cayman Islands	KY	2.46	4,390
China	CN	5.49	1,748
Cyprus	CY	2.58	300
Denmark	DK	0.99	549
Finland	FI	1.07	788
France	FR	2.36	13,092
Germany	DE	1.67	1,236
Grenada	GD	4.18	308
Ireland	IE	1.64	3,046
Italy	IT	3.59	2,625
Japan	JP	2.62	1,266
Jersey	JE	2.14	176
Kuwait	KW	4.06	638
Liechtenstein	LI	1.96	772
Luxembourg	LU	1.30	5,565
Malaysia	MY	3.84	259
Malta	MT	2.64	993
Mauritius	MU	3.58	509
Netherlands	NL	1.21	1,636
Norway	NO	1.38	581
Russia	RU	6.12	563
Singapore	SG	1.18	3,154
Spain	ES	2.52	1,124
Sweden	SE	1.30	2,506
Switzerland	CH	1.29	24,329
U.K.	GB	1.33	53,474
United Arab Emirates	AE	3.53	260
U.S.	US	1.84	148,755
U.S. Virgin Islands	VI	3.20	342

Table 3: Investor Protection and Capital Fragility

This table reports the coefficient estimates of flow-performance regressions in Equations (2) and (3). Panel A reports the baseline results. The dependent variable is the current quarter's net investor flow and the independent variables are lagged fund characteristics. *perf* denotes fund performance measured by raw returns or style-adjusted returns. *Low* is an indicator variable that is equal to one if *perf* is below its median value among all funds in a country during a given quarter, and zero otherwise. *WIP·perf·Low* is a triple interaction term of *WIP*, *perf*, and *Low*. In Columns (1) through (6), *WIP* is 3 minus the first principal component of three World Governance Indicators from the World Bank: regulatory quality, rule of law, and control of corruption. In Columns (7) and (8), *WIP* is the inverse of the principal component of five investor protection indexes in LLSV (La Porta et al., 1998, 2000, and 2002; La Porta, Lopez-de-Silanes, and Shleifer, 2006): efficiency of the judicial system, rule of law, control of corruption, risk of expropriation, and anti self-dealing. The regressions use fund-quarter observations and the standard errors are clustered at the country level. Panel B uses each individual World Governance Indicators as measures of weak investor protection, and tests for the differences in the estimated coefficients on *WIP·perf·Low* across the three indicators. All control variables are the same as those in Columns (3) and (4) of Panel A. Panel C1 models the determinants of *WIP* using country-level characteristics. *religion* measures the frequency of attending religious services in a given country from *World Values Survey*. *democrat* is the perception of having a democratic political system in a country from *World Values Survey*. *education* is the percentage of total working-age population with basic education in a country from the World Bank. *lgdp_pc* is the logarithm of GDP per capita from the World Bank. The regressions use country-year observations and the standard errors are clustered at the country level. Panel C2 reports results of re-estimating Equation (3) using the regression residual from Panel C1 (*rWIP*) as the weak investor protection measure. All control variables are the same as those in Columns (3) and (4) of Panel A. All regressions use fund-quarter observations except for Panel C1 and the standard errors are clustered at the country level. "***", "**", and "*" indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A

WIP Measures:	World Bank						LLSV	
Perf Measures:	Raw Return	Raw Return	Raw Return	Style Return	Raw Return	Style Return	Raw Return	Style Return
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
perf	0.538***	0.301***	0.372***	0.513***	0.335***	0.501***	0.258***	0.279**
	(26.47)	(2.81)	(3.58)	(4.30)	(3.53)	(4.17)	(2.73)	(2.27)
WIP·perf		0.092**	−0.068**	−0.108***	−0.058*	−0.124***	−0.057*	−0.068
		(2.47)	(−2.21)	(−3.68)	(−1.99)	(−3.38)	(−1.95)	(−1.17)
WIP·perf·Low			0.138***	0.114***	0.104***	0.133***	0.328**	0.362**
			(3.72)	(5.78)	(4.41)	(6.04)	(2.26)	(2.71)
perf·Low			−0.218***	−0.123**	−0.110*	−0.134***	−0.097	−0.072
			(−2.69)	(−2.63)	(−1.73)	(−2.93)	(−1.15)	(−0.94)
WIP·Low			−0.000	−0.006	0.000	−0.007	−0.004	−0.005
			(−0.08)	(−1.19)	(0.05)	(−1.35)	(−1.19)	(−1.22)
Low			−0.032***	−0.006	−0.026***	0.005	−0.029***	−0.018***
			(−2.97)	(−0.48)	(−3.10)	(0.37)	(−11.99)	(−6.41)
illiquid·perf·Low			0.061*	0.095**	0.102*	0.138***	0.070**	0.105***

			(1.91)	(2.62)	(1.98)	(2.68)	(2.06)	(2.99)
illiquid·Low			0.009***	0.004**	0.003	0.000	0.008***	0.000
			(3.81)	(2.18)	(1.18)	(0.04)	(3.81)	(0.31)
illiquid·perf			−0.081***	−0.106***	−0.108***	−0.116***	−0.087***	−0.131***
			(−5.89)	(−7.23)	(−5.70)	(−5.29)	(−7.18)	(−9.44)
mininv·perf			0.014***	0.014**	0.010***	0.013***	0.013**	0.014*
			(2.75)	(2.11)	(3.26)	(2.66)	(2.10)	(1.79)
age·perf	−0.028***	−0.029***	−0.025***	−0.027***	−0.018***	−0.018***	−0.026***	−0.028***
	(−21.20)	(−20.66)	(−20.20)	(−19.64)	(−10.92)	(−11.85)	(−29.25)	(−22.06)
illiquid	−0.009***	−0.009***	−0.012***	−0.010***	−0.016***	−0.015***	−0.012***	−0.008***
	(−6.93)	(−6.94)	(−7.98)	(−13.23)	(−7.92)	(−9.71)	(−7.27)	(−9.56)
age	−0.003***	−0.003***	−0.003***	−0.003***	−0.005	−0.005	−0.003***	−0.003***
	(−33.05)	(−32.72)	(−32.37)	(−32.47)	(−1.31)	(−1.44)	(−31.91)	(−34.67)
flow	0.242***	0.242***	0.241***	0.244***	0.184***	0.187***	0.243***	0.246***
	(49.59)	(49.33)	(48.95)	(50.87)	(26.30)	(27.90)	(51.64)	(52.55)
size	−0.012***	−0.012***	−0.012***	−0.012***	−0.064***	−0.064***	−0.012***	−0.012***
	(−20.04)	(−20.08)	(−20.44)	(−21.33)	(−25.30)	(−25.87)	(−20.40)	(−21.12)
sdret	−0.002***	−0.002***	−0.002***	−0.002***	−0.003***	−0.003***	−0.002***	−0.002***
	(−8.15)	(−7.95)	(−7.15)	(−7.50)	(−9.16)	(−9.79)	(−7.94)	(−8.69)
mininv	0.001**	0.001**	0.001**	0.001**			0.001**	0.001**
	(2.34)	(2.35)	(2.26)	(2.27)			(2.29)	(2.15)
ifee	−0.000*	−0.000	−0.000*	−0.000			−0.000	−0.000
	(−1.68)	(−1.65)	(−1.69)	(−1.48)			(−1.02)	(−0.97)
mfee	0.000	0.000	0.000	0.000			0.000	0.000
	(0.17)	(0.17)	(0.17)	(0.25)			(0.24)	(0.29)
lockup	−0.003***	−0.003***	−0.003***	−0.003***			−0.003***	−0.003***
	(−2.85)	(−2.92)	(−3.10)	(−3.37)			(−3.02)	(−3.31)
restrict	0.008***	0.008***	0.007***	0.007***			0.007***	0.007***
	(3.42)	(3.34)	(3.03)	(3.01)			(2.98)	(2.93)
hwm	0.006***	0.006***	0.006***	0.006***			0.006***	0.006***
	(5.64)	(5.55)	(5.71)	(5.55)			(5.30)	(4.98)
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	No	No	Yes	Yes	No	No
Observations	310,804	310,804	310,804	310,804	310,804	310,804	286,956	286,956
Adj. R^2	0.156	0.156	0.159	0.157	0.253	0.251	0.158	0.156

Panel B: Individual World Governance Indicators

	perf = Raw Return			*perf* = Style Return		
	Coeff.	*t*-stat	Adj R^2	Coeff.	*t*-stat	Adj R^2
(1) Regulatory quality	0.111***	(3.71)	0.156	0.075***	(2.75)	0.153
(2) Rule of law	0.115***	(3.57)	0.155	0.079***	(3.25)	0.153
(3) Control of corruption	0.104***	(3.07)	0.156	0.071**	(2.03)	0.153
	Coeff.	P-val	χ^2	Coeff.	P-val	χ^2
Diff: (1) − (2)	−0.004	0.335	0.93	−0.004	0.312	1.02
Diff: (2) − (3)	0.011	0.236	1.40	0.008	0.120	2.41
Diff: (3) − (1)	−0.007	0.327	0.96	−0.004	0.424	0.64

Panel C1: First-stage regression

	(1)
religion	−0.081
	(−1.21)
democrat	0.711
	(0.10)
education	0.667
	(0.51)
lgdp_pc	−2.192**
	(−14.36)
Year FE	Yes
Observations	1,080
Adj. R^2	0.820

Panel C2: Second-stage regression

Perf Measures:	Raw Return	Style Return
	(1)	(2)
rWIP·perf·Low	0.092***	0.087***
	(3.06)	(3.19)
Controls	Yes	Yes
Style FE	Yes	Yes
Country×Quarter FE	Yes	Yes
Observations	277,121	277,121
Adj. R^2	0.156	0.154

Table 4: Flow-performance Analysis Around the Clean Company Act

This table reports results from estimating the flow-performance regression for Brazil hedge funds around the passage of Clean Company Act in 2014 (the event date). The regressions use a sample of Brazilian hedge funds from TASS and Morningstar from January 1994 to July 2018. *pre* is an indicator variable that is equal to one before the event date, and zero otherwise. *post* is an indicator variable that is equal to one after the event date, and zero otherwise. *pre1*, *pre2*, *post1*, and *post2* are indicator variables that are equal to one if it is two or more years before the event date, one year before the event date, one year after the event date, and two or more years after the event date, respectively; and zero otherwise. Control variables are omitted for brevity and include *flow*, *sdret*, *age*, *age·perf* and *size* in all specifications, as well as the interaction terms *pre·perf*, *post·perf*, *pre·Low*, and *post·Low* in Columns (1) and (3); and *pre2·perf*, *pre1·perf*, *post1·perf*, *post2·perf*, *pre2·Low*, *pre1·Low*, *post1·Low*, and *post2·Low* in Columns (2) and (4). The regressions use fund-quarter observations and the standard errors are clustered at the fund level. "***", "**", and "*" indicate significance at the 1%, 5%, and 10% levels, respectively.

Perf Measures:	Raw Return		Style Return	
	(1)	(2)	(3)	(4)
pre·perf·Low	0.591***		0.546**	
	(2.64)		(2.45)	
post·perf·Low	−0.184		−0.145	
	(−0.93)		(−0.70)	
pre2·perf·Low		0.516**		0.569**
		(2.15)		(2.23)
pre1·perf·Low		0.753*		0.978**
		(1.94)		(2.12)
post1·perf·Low		−0.492		−0.455
		(−1.55)		(−1.36)
post2·perf·Low		−0.132		−0.179
		(−0.58)		(−0.75)
Controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	28,569	28,569	28,569	28,569
Adj. R^2	0.168	0.178	0.173	0.173

Table 5: Twin Funds

This table reports results from the flow-performance estimation using a subsample of twin hedge funds. Twin funds belong to the same fund family, have a pairwise return correlation of at least 99%, and are managed in two different countries. Prefix "Δ" before each variable name indicates the difference between the corresponding variable among twins. For example, Δ*mfee* is the difference in twin funds' management fees. Panel A shows the difference in twin funds' characteristics. Panel B repeats the analysis in Table 3 using the twin funds sample. The control variables are the same as those in Columns (3) and (4) in Table 3 (after taking the differences among twins). In Columns (1) and (2), the regressions use fund-quarter observations and the standard errors are double-clustered at the countries where the twins are located. In Columns (3) and (4), the regressions use a subsample of fund-quarter observations where one twin is located in either U.S. or U.K., and the standard errors are clustered at the countries where the other twin is located. "***", "**", and "*" indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A

	(1) Δ*ret*	(2) Δ*mfee*	(3) Δ*ifee*	(4) Δ*lockup*	(5) Δ*restrict*	(6) Δ*hwm*
mean	0.02%	0.01%	0.00%	0.000	0.000	0.003
p-value (H_0: mean=0)	1.00	0.99	1.00	0.99	0.99	1.00

Panel B

	Double-Clustered Std. Err.		Single-Clustered Std. Err.	
Perf Measures:	Raw Return	Style Return	Raw Return	Style Return
	(1)	(2)	(3)	(4)
ΔWIP·perf·Low	0.004**	0.003**	0.008***	0.005*
	(2.08)	(2.67)	(3.23)	(1.82)
Controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	18,320	18,320	13,480	13,480
Adj. R^2	0.017	0.017	0.016	0.020

Table 6: Fund Liquidation

This table reports the results from estimating regressions of fund liquidation. The dependent variable is an indicator variable that is equal to one if a fund is liquidated in the subsequent year, and zero otherwise. A fund is liquidated if and only if it disappears from the databases, and fund liquidation is the reason the databases provide for the fund's disappearance. The regressions use fund-year observations and the standard errors are clustered at the country level. Columns (1) and (2) use Ordinary Least Squares (OLS) regressions while Columns (3) and (4) use logistic regressions. All explanatory variables are as defined in Table 2. "***", "**", and "*" indicate significance at the 1%, 5%, and 10% levels, respectively.

	OLS		Logistic	
	(1)	(2)	(3)	(4)
ret	−0.123***	−0.059***	−2.543***	−1.271**
	(−21.54)	(−2.67)	(−20.33)	(−2.54)
WIP·ret		−0.025***		−0.479***
		(−2.96)		(−2.60)
WIP	−0.006***	−0.004***	−0.110***	−0.101***
	(−5.21)	(−3.42)	(−5.10)	(−4.66)
ifee	0.001***	0.001***	0.016***	0.016***
	(6.24)	(6.29)	(6.14)	(6.19)
mfee	−0.002	−0.002	−0.038	−0.039
	(−1.45)	(−1.47)	(−1.61)	(−1.63)
lockup	−0.001	−0.001	−0.029	−0.029
	(−0.65)	(−0.67)	(−0.96)	(−0.97)
restrict	0.001	0.001	−0.007	−0.007
	(0.22)	(0.22)	(−0.11)	(−0.10)
hwm	−0.005**	−0.005**	−0.105***	−0.107***
	(−2.49)	(−2.53)	(−2.83)	(−2.86)
size	−0.000	−0.000	−0.012	−0.012
	(−0.58)	(−0.55)	(−1.11)	(−1.08)
Style FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	69,696	69,696	69,696	69,696
Adj. R^2	0.025	0.026	0.060	0.061

Table 7: Investor Protection and Returns Management

This table reports the results from regressions of return management variables. In Panel A, Columns (1) and (2) include fund-year observations of *flag_sum* and *flag_pc* for the full sample of funds, and control for style fixed effects and year fixed effects. Columns (3) and (4) include fund-month observations of *delay* and *restate* for the subsample of funds reporting to the TASS database over 2009-2013, and control for style fixed effects and month fixed effects. Panel B repeats the analysis in Panel A after excluding funds following emerging markets, fixed income arbitrage, or convertible arbitrage investment styles (illiquid styles). In Panel C, Columns (1) and (2) include two observations of *flag_sum* and *flag_pc* for each Brazilian fund, computed based on the fund's monthly returns four years before and four year after the Clean Company Act, respectively. Columns (3) and (4) include fund-month observations of *delay* and *restate_ret* for the subsample of Brazilian funds. *restate_ret* is an indicator variable that is equal to one if a given fund-month reported return is later restated, and zero otherwise. Additional control variables are the same as in Panel A and are suppressed for brevity. The standard errors are clustered at the country level. "***", "**", and "*" indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Full Sample

	(1) *flag_sum*	(2) *flag_pc*	(3) *delay*	(4) *restate*
WIP	0.102***	0.075***	1.258***	0.036***
	(2.94)	(2.81)	(5.79)	(4.24)
ret	0.337***	0.242***	−0.126***	0.000
	(6.25)	(4.60)	(−7.89)	(0.04)
flow	−0.024	−0.038***	−0.842	−0.053***
	(−1.60)	(−3.30)	(−1.53)	(−2.76)
ifee	0.009***	0.005***	0.014	−0.001
	(3.90)	(3.42)	(0.40)	(−0.47)
mfee	−0.025	−0.011	−0.241	0.021*
	(−1.41)	(−1.15)	(−1.02)	(1.89)
lockup	0.107**	0.089***	1.700***	0.019
	(2.45)	(3.77)	(5.61)	(1.52)
restrict	0.071*	0.037	4.869***	−0.085***
	(1.91)	(1.44)	(5.66)	(−2.72)
hwm	−0.051	−0.042**	1.545***	0.040**
	(−1.48)	(−2.10)	(3.41)	(2.12)
size	−0.026**	−0.012***	−0.213***	0.013***
	(−2.60)	(−3.94)	(−2.62)	(3.21)
age	0.051***	0.030***	−0.115***	0.009***
	(19.76)	(14.50)	(−3.88)	(4.26)
Style FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	65,100	65,100	127,558	127,558
Adj. R^2	0.062	0.095	0.033	0.084

Panel B: Excluding Illiquid Styles

	(1) *flag_sum*	(2) *flag_pc*	(3) *delay*	(4) *restate*
WIP	0.095***	0.068***	1.396***	0.038***
	(3.09)	(2.97)	(6.10)	(4.23)
Additional controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	61,396	61,396	114,658	114,658
Adj. R^2	0.058	0.087	0.039	0.085

Panel C: Brazil Funds around the Clean Company Act

	(1) *flag_sum*	(2) *flag_pc*	(3) *delay*	(4) *restate_ret*
post	−0.117**	−0.149**	−4.175***	−0.003***
	(−1.96)	(−2.14)	(−8.56)	(−3.18)
Additional controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	1,558	1,558	20,983	20,983
Adj. R^2	0.652	0.699	0.142	0.095

Table 8: Robustness

This table reports coefficient estimates on *WIP·perf·Low* for several variations of our flow-performance estimation. Rows (1) and (2) control for the interaction terms of *WIP·sdret* and *WIP·tail*, respectively. Row (3) uses a subsample of funds where *tail* is equal to zero. Row (4) uses a subsample of funds that only report to one hedge fund database and Row (5) uses a subsample reporting to multiple databases. Row (6) reports results after adding a –100% flow for the last quarter after funds are liquidated. Rows (7), (8), and (9) report results for *WIP* scores constructed based on funds' domicile country, subsample of funds with the same domicile and management office country, and subsample of funds domiciled in Bermuda or Cayman Islands, respectively. Row (10) uses a subsample of funds that report their returns in local currencies. Row (11) reports estimates using Spiegel and Zhang (2013)'s market share-adjusted flows as the dependent variable (instead of *flow*), i.e., change in the subsequent quarter's fund market share over all funds from the previous quarter (see Equation (15) of Spiegel and Zhang, 2013). Market share is scaled after multiplying by 10,000 for expositional convenience. Rows (12)−(17) use subsamples based on country-level regulations regarding hedge fund distribution channels reported in Cumming and Dai (2010): wrappers, investment managers, and fund distribution companies, respectively. Row (18) uses smoothing adjusted returns following the procedures in Getmansky, Lo, and Makarov (2004). Row (19) uses a subsample of TASS funds that report only one country of management office location across seven annual snapshots of the database: 2002, 2003, 2005, 2013, 2016, 2017, and 2018. Row (20) excludes multi-national funds. Row (21) reports the coefficient estimates after dropping the size filter and the requirement of a minimum of 150 fund-quarter observations. In Row (22), *WIP* is 3 minus the average of the three World Governance Indicators. Row (23) excludes all funds managed in Brazil. Row (24) double-clusters the standard errors at the country and quarter levels. Row (25) reports the estimates using the Fama-Macbeth (1973) regressions. Row (26) reports estimates using the Carhart (1997) four-factor and Fung and Hsieh (2004) seven-factor alphas as performance measures. Risk factors for each fund are based on its investment region, such as North America, Europe, Asia-Pacific, and Global. Risk factors in the Carhart's four-factor model include the regional market, high-minus-low, small-minus-big, and momentum factors which are obtained from Ken French's website. Risk factors in the Fung and Hsieh (2004) seven-factor model include regional market and small-minus-big factors, augmented with their bond and trend-following factors.[24] The first 12 months of reported returns for each fund are dropped to mitigate the backfill bias. Alphas are estimated out of sample for each fund-quarter using factor loadings estimated over 36-month rolling windows. All control variables are the same as those in Columns (3) and (4) of Panel A in Table 3 but are untabulated for brevity. The regressions use fund-quarter observations. Standard errors are clustered at the country level except for Row (24). "***", "**", and "*" indicate significance at the 1%, 5%, and 10% levels, respectively.

[24] The trend-following factors are discussed in Fung and Hsieh (2001) and are available for download from David Hsieh's website here: http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls.

		Coeff.	*t*-stat	Adj R^2	Coeff.	*t*-stat	Adj R^2
		perf = Raw Return			*perf* = Style Return		
(1)	Fund risk (*sdret·WIP*)	0.137***	(3.89)	0.159	0.113***	(5.50)	0.157
(2)	Fund risk (*tail·WIP*)	0.123***	(4.41)	0.110	0.123***	(5.43)	0.109
(3)	Tail risk measure *tail*=0	0.192***	(4.75)	0.114	0.171***	(4.02)	0.111
(4)	Funds reporting to one database	0.137***	(3.67)	0.157	0.120***	(2.98)	0.155
(5)	Funds reporting to multiple databases	0.120***	(3.21)	0.165	0.107***	(4.94)	0.163
(6)	Delisting flow = –100%	0.164***	(5.32)	0.158	0.115***	(5.85)	0.156
(7)	*WIP* based on fund domicile	0.123***	(4.67)	0.159	0.106***	(6.46)	0.157
(8)	Country of domicile same as management office	0.133***	(3.61)	0.154	0.117***	(4.79)	0.153
(9)	Domicile country Cayman Islands or Bermuda	0.163***	(3.41)	0.184	0.121***	(2.92)	0.180
(10)	Returns reported in local currencies	0.154***	(5.66)	0.157	0.123***	(3.64)	0.155
(11)	Fund flow measured as change in market share	0.214***	(3.12)	0.040	0.366***	(4.06)	0.038
(12)	Wrapper=0	0.137***	(3.27)	0.152	0.115***	(4.43)	0.149
(13)	Wrapper=1	0.195***	(5.24)	0.168	0.068**	(2.53)	0.166
(14)	Investmgr=0	0.168***	(4.04)	0.152	0.079***	(9.17)	0.149
(15)	Investmgr=1	0.130*	(1.80)	0.164	0.065**	(2.46)	0.163
(16)	Distrcomp=0	0.183***	(3.16)	0.156	0.071***	(2.91)	0.153
(17)	Distrcomp=1	0.084*	(1.80)	0.163	0.097***	(2.64)	0.163
(18)	Smoothing-adjusted returns	0.161***	(5.75)	0.157	0.078***	(4.29)	0.154
(19)	Exclude funds that change locations (TASS)	0.138***	(3.72)	0.159	0.070***	(2.84)	0.157
(20)	Exclude multi-national funds	0.143***	(3.66)	0.159	0.095***	(3.50)	0.157
(21)	Drop data filters	0.140***	(3.93)	0.159	0.112***	(5.66)	0.156
(22)	Alternative measure of *WIP*: Avg. WGI	0.095***	(4.10)	0.159	0.083***	(3.26)	0.157
(23)	Exclude Brazil funds	0.171***	(4.91)	0.159	0.103***	(4.45)	0.156
(24)	Double cluster standard errors	0.138***	(2.77)	0.156	0.114**	(2.02)	0.155
(25)	Fama-Macbeth regressions	0.202***	(4.52)	0.173	0.138***	(3.85)	0.172
		perf = Carhart alpha			*perf* = Fung and Hsieh alpha		
(26)	Alternative performance measures	0.082***	(2.85)	0.107	0.094***	(2.80)	0.105

Appendix A: Construction of suspicious return flags

In this Appendix, we describe the procedure used to calculate the four returns management variables. The first two variables are composite measures of eight data quality flags and are based on the December return spread of Agarwal, Daniel, and Naik (2011) and seven data quality measures of Straumann (2009) and Bollen and Pool (2012). For example, Bollen and Pool (2012) note that too few negative returns could capture fraudulent reporting since "…if returns are simply fabrications, as in Ponzi schemes, then managers naturally will report few losses (p. 2680)," and that a low correlation with portfolio benchmarks could indicate fraud since "…a manager such as Madoff who reports a random positive return every month will artificially generate a correlation between the fund's returns and any other time series very close to zero. (p. 2678)."

To compute the data quality flags we first round a fund's monthly return history to the second digit, and then compute several sample statistics from the rounded returns. To determine whether the sample statistics are sufficiently unusual (and therefore indicative of poor data quality), we run 10,000 simulations where we draw rounded returns from a Normal distribution with mean and variance equal to the fund's actual sample mean and variance. In each simulation, we draw the same number of simulated returns as the actual number of fund returns. *Zero* flag is triggered if the fund's actual number of zero returns ranks in the top 10% of simulated number of zero returns. *Negative* is triggered if the actual number of negative returns ranks in the bottom 10% of simulated measures. *Unique* is triggered if the actual number of unique returns ranks in the bottom 10% of simulated measures. *Maxrun* is triggered if the actual maximum length of identical returns ranks in the top 10% of simulated measures. *Retblock* is triggered if the actual number of recurring return blocks of length two ranks in the top 10% of simulated measures. *Uniformity* is triggered if the actual measure of whether the second digit is uniformly distributed between 0 and 9 (Straumann, 2009) ranks in the top 10% percentile of simulated measures. Our seventh flag *Dec* follows Agarwal, Daniel, and Naik (2011) and is triggered if the actual December return spread ranks in the top 10% of simulated December return spreads. Lastly, the eighth flag is based on too little correlation with the Fung and Hsieh (2004) factors measured by regression R^2. For each fund, we select 3 out of the 14 Fung and Hsieh (2004) factors (including 7 contemporaneous and 7 lagged) that maximizes the adjusted R^2 where the dependent variable is fund's monthly excess return. Similarly, we regress each set of simulated excess returns on all possible combinations of 3 factors, identify the set that maximizes the adjusted R^2, and then form the distribution of simulated maximum adjusted R^2. By construction, these simulated returns are independent from the 14 factors. *MaxRsq* is equal to one if the actual maximal adjusted R^2 is less than the 90% percentile of the simulated R^2 distribution.

The above procedures deliver eight variables that capture suspicious patterns of reported returns. For parsimony in our analysis, we reduce the number of flags to two by aggregating *Zero*, *Negative*, *Unique*, *Maxrun*, *Retblock*, *Uniformity*, *Dec*, *MaxRsq*. We do so by summing the eight return flags (*flag_sum*) and using the first principal component calculated from the cross section of the eight flags in a given year (*flag_pc*).

The final two return management variables – *restate* and *delay* – are based on the fund's reporting delay and whether a fund's return history has been restated over our sample period. These variables are based on 1,257 snapshots of the TASS returns history that we collected over 01/2009-03/2014. We use the multiple snapshots to identify the earliest day that a fund reports its monthly return for a given month to the TASS database and, therefore, its reporting delay defined as the number of days between month-end and the earliest report date (*delay*) . Similarly, we use the snapshots to identify return restatement – that is, a change in returns reported by a fund. Following Patton, Ramadorai, and Streatfield (2015), we define a restatement as a change to an earlier reported return of at least one basis point, and that the change is made at least 90 days after the corresponding performance period. For example, to identify which funds restated their returns for the May 2009 performance period, we only consider changes to May 2009 returns made August 29, 2009 or later relative to the May 2009 returns as reported in the August 28, 2009 snapshot. The *restate* flag is triggered if the fund restated at least one return using all available snapshots as of the prior month. Therefore, once *restate* is triggered for a particular month and fund, it takes the value of unity for all subsequent months.

Appendix B: Regulatory Issues for Offshore Funds

In this appendix, we discuss specific cases to illustrate why funds are subject to the regulatory and legal environment of their principal business locations, even if they are domiciled elsewhere. This helps motivate the construction of our *WIP* variable, which assigns the scores to funds based on the country in which their management offices are located.

(1) On January 18, 2000 the SEC charged a New York based hedge fund Manhattan Capital Management, Inc. and its manager Michael W. Berger with securities fraud although the fund was domiciled in British Virgin Islands (SEC Litigation Release No. 16412). The fund lost more than $300 million between 1996 and 2000 due to short selling, and Berger created fraudulent statements and sent them to fund investors. Although Berger argued that the United States District Court for the Southern District of New York lacked the jurisdiction over the subject matter of this case, the District Court concluded the opposite (322 F.3d 187). Specifically, the court argued that although the majority of fund activity was outside of the U.S., the fraud "was run from the United States and the decisions made in the United States were directly responsible for investor losses". The court mentioned that whether Section 10(b) of the Securities Exchange Act of 1934 and Rule 10b-5 should apply extraterritorially was based on two factors: 1. the conduct test (whether the wrongful conduct occurred in the United States) and 2. the effects test (whether the wrongful conduct had a substantial effect in the United States or upon United States citizens). These two tests indicate that the fund does not have to be domiciled in the U.S. in order to be subject to the U.S. regulations.

(2) In *Morrison v. National Australia Bank Ltd*. (561 U.S. 247), the Supreme Court's announced a new test for applying Section 10(b) of the Securities Exchange Act of 1934 and Rule 10b-5 extraterritorially in 2010. The test suggests that the application is based on whether the case involves "transactions in securities listed on domestic exchanges and domestic transactions in other securities, i.e. the "transactional test". The rulings by the Supreme Court

have several implications. First, although it suggests that the extraterritorial application of these laws is no longer based on the place of origination of the fraud, as long as an offshore fund has material business transactions with the U.S. (which is most likely to be the case if the fund has a principal office here), either through securities selling to U.S. clients or trading on the U.S. stock exchanges, the fund can be subject to U.S. laws even if it is domiciled in an island country. One related case is *SEC v. Ficeto* (839 F.Supp.2d 1101) where eight hedge funds domiciled in the Cayman Islands allegedly engaged in a fraudulent scheme to manipulate the prices of microcap stocks on the U.S. OTC market from their California offices in order to "pump" the portfolio values of these offshore hedge funds. Another related case is *United States v. Isaacson* (752 F.3d 1291) where a hedge fund domiciled in British Virgin Islands allegedly manipulated the prices of publicly traded shell companies from its New York office and produced false business reports to auditors.

Second, a month after the Supreme Court decided *Morrison*, the Dodd-Frank Act was signed with Section 929P adding the following to the '33 Act and the '34 Act about extraterritorial jurisdiction: *"The district courts of the United States and the United States courts of any Territory shall have jurisdiction of an action or proceeding brought or instituted by the Commission or the United States alleging a violation of the antifraud provisions of this chapter involving (1) conduct within the United States that constitutes significant steps in furtherance of the violation, even if the securities transaction occurs outside the United States and involves only foreign investors; or (2) conduct occurring outside the United States that has a foreseeable substantial effect within the United States."* This change suggests that the U.S. courts now have jurisdiction over a much broader set of fraud cases than those covered by the transactional test defined in *Morrison*.

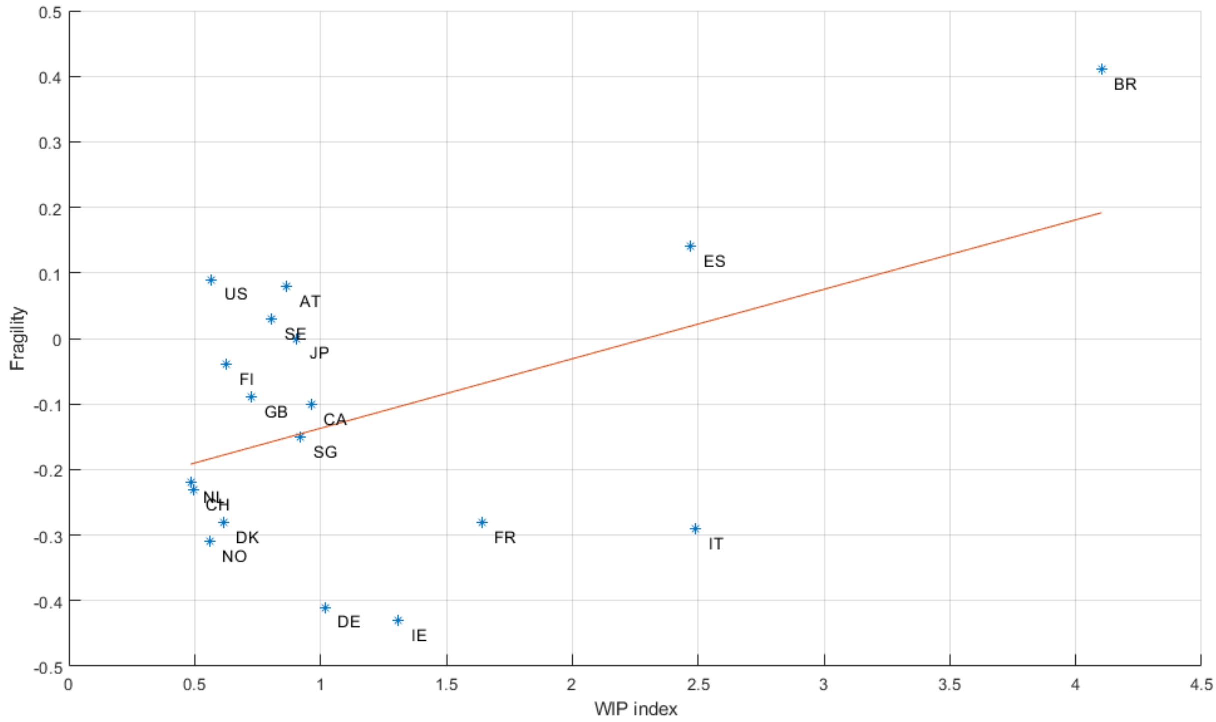
(3) Besides Rule 10b-5, the SEC have charged hedge funds based on other regulations (see *SEC v. Gruss*, 859 F.Supp.2d 653). In *United States v. Lay* (566 F.Supp.2d 652), Lay was

charged by the District Court for the Northern District of Ohio for fraud related to a Bermuda domiciled hedge fund MDL Active Duration Fund due to violations of the Investment Advisers Act of 1940. Offshore hedge funds with business operations in the U.S. can also be subject to the Exchange Act, Commodity Futures Trading Commission Regulations, and anti-money laundering laws (see Chapter 12 of Barham, 2003). For example, the FBI in 2013 charged John C. Tausche and Helmut Keiner running two BVI based hedge funds K1 (in Spain) and Oceanus (in Kansas) with bank fraud and money laundering since their money funneling scheme caused a $311 million loss for investors.

In addition to U.S. regulations, the recent Alternative Investment Fund Managers Directive (AIFMD) lays out compliance requirements for offshore hedge funds that have management or marketing business in the European Union countries. Overall, these legal cases help establish the rational of using funds' business location to construct the *WIP* measure in our main analyses.

Appendix C: Investor Protection and Capital Fragility: LLSV Measure

This figure plots country-level estimates of capital fragility (y-axis) against country-level measures of weak investor protection (*WIP*, x-axis). A country's capital fragility is the estimated regression coefficient (β_2) on *perf·Low* in country-level flow-performance regressions in Equation (4). The stars denote the country-level capital fragility measures and their corresponding countries' average *WIP*. *WIP* is the inverse of the principal component of five investor protection indexes in LLSV (La Porta et al., 1998, 2000, and 2002; La Porta, Lopez-de-Silanes, and Shleifer, 2006): efficiency of the judicial system, rule of law, control of corruption, risk of expropriation, and anti self-dealing. The letters denote the two-digit ISO 3166 code for the corresponding country reported in Table 2. The solid line denotes the fitted regression estimate. The estimation result is *fragility* = –0.243+ 0.106×*WIP* and the *t*-statistic of the slope is 2.10. The sample period is 1994-2013.



Appendix D: Repeat All Analysis with Residual *WIP*

This table repeats the analyses in Table 5 through Table 8 in the paper using the residual *WIP* (*rWIP*) estimated from Panel C1 of Table 3.

Panel A: Twin Funds

	Double-Clustered Std. Err.		Single-Clustered Std. Err.	
Perf Measures:	Raw Return	Style Return	Raw Return	Style Return
	(1)	(2)	(3)	(4)
ΔrWIP·perf·Low	0.005**	0.004**	0.019*	0.017***
	(2.39)	(2.07)	(1.92)	(3.00)
Controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	17,407	17,407	11,216	11,216
Adj. R^2	0.025	0.025	0.110	0.143

Panel B: Fund Liquidation

	OLS		Logistic	
	(1)	(2)	(3)	(4)
ret	−0.126***	−0.072***	−2.464***	−1.613***
	(−20.80)	(−3.55)	(−19.48)	(−3.70)
rWIP·ret		−0.020***		−0.313**
		(−2.67)		(−2.03)
Style FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	66,032	66,032	66,032	66,032
Adj. R^2	0.023	0.024	0.055	0.055

Panel C1: Investor Protection and Returns Management (Full Sample)

	(1)	(2)	(3)	(4)
	flag_sum	*flag_pc*	*delay*	*restate*
rWIP	0.065**	0.057***	1.074***	0.031***
	(2.30)	(2.74)	(5.32)	(3.70)
Controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	61,747	61,747	117,063	117,063
Adj. R^2	0.061	0.093	0.036	0.082

Panel C2: Investor Protection and Returns Management (Excluding Illiquid Styles)

	(1) *flag_sum*	(2) *flag_pc*	(3) *delay*	(4) *restate*
rWIP	0.057**	0.050***	1.214***	0.033***
	(2.22)	(2.74)	(5.53)	(3.67)
Controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	58,249	58,249	97,063	97,063
Adj. R^2	0.058	0.087	0.036	0.082

Panel D: Robustness

		Coeff.	*t*-stat	Adj R^2	Coeff.	*t*-stat	Adj R^2
		perf = Raw Return			*perf* = Style Return		
(1)	Fund risk (*sdret·rWIP*)	0.099***	(3.38)	0.155	0.094***	(3.12)	0.153
(2)	Fund risk (*tail·rWIP*)	0.089***	(4.01)	0.109	0.103***	(3.58)	0.107
(3)	Tail risk measure *tail*=0	0.173***	(4.95)	0.110	0.174***	(3.43)	0.108
(4)	Funds reporting to one database	0.092**	(2.59)	0.153	0.108**	(2.24)	0.152
(5)	Funds reporting to multiple databases	0.112***	(3.81)	0.161	0.091***	(3.61)	0.158
(6)	Delisting flow = –100%	0.147***	(3.04)	0.136	0.116***	(4.39)	0.134
(7)	*rWIP* based on fund domicile	0.069*	(1.97)	0.153	0.049*	(1.84)	0.151
(8)	Country of domicile same as management office	0.094**	(2.66)	0.152	0.067***	(2.20)	0.150
(9)	Domicile country Cayman Islands or Bermuda	0.147***	(3.50)	0.178	0.108**	(2.40)	0.174
(10)	Returns reported in local currencies	0.118***	(5.75)	0.155	0.122***	(3.85)	0.153
(11)	Fund flow measured as change in market share	0.058***	(5.02)	0.030	0.049***	(3.76)	0.029
(12)	Wrapper=0	0.100***	(2.91)	0.148	0.180***	(5.22)	0.146
(13)	Wrapper=1	0.139***	(3.66)	0.162	0.047*	(1.88)	0.160
(14)	Investmgr=0	0.129***	(4.43)	0.149	0.139***	(8.49)	0.146
(15)	Investmgr=1	0.064*	(2.09)	0.158	0.149**	(2.58)	0.157
(16)	Distrcomp=0	0.137***	(3.56)	0.152	0.146***	(4.41)	0.149
(17)	Distrcomp=1	0.085*	(1.70)	0.159	0.174*	(1.84)	0.160
(18)	Unsmoothed returns	0.133***	(8.05)	0.153	0.105***	(4.25)	0.150
(19)	Exclude funds that change locations (TASS)	0.094**	(2.16)	0.175	0.091***	(3.51)	0.172
(20)	Exclude multi-national funds	0.103***	(2.97)	0.156	0.095***	(3.50)	0.157
(21)	Drop data filters	0.096***	(3.24)	0.156	0.088***	(3.50)	0.153
(22)	Exclude Brazil funds	0.121***	(3.73)	0.156	0.087***	(3.19)	0.154
(23)	Double cluster standard errors	0.092**	(2.49)	0.156	0.087*	(1.72)	0.154
(24)	Fama-Macbeth regressions	0.155***	(3.25)	0.166	0.125***	(3.55)	0.165
		perf = Carhart alpha			*perf* = Fung and Hsieh alpha		
(25)	Alternative performance measures	0.085***	(2.70)	0.106	0.104***	(3.29)	0.104

Appendix E: Survey and Anecdotal Evidence of the Clean Company Act

In this Appendix, we list survey and anecdotal evidence related to the improvement in governance and enforcement in Brazil companies after the Clean Company Act (CCA).

Survey evidence

First, survey results by DoingBusiness (a project by the World Bank Group) show that Brazil's ranking on investor protection jumped from 80th in 2013 to 35th in 2014, and its ranking on resolving insolvency jumped from 135th to 55th.[1] Second, surveys by Deloitte show that Brazilian companies' response on whether they have existing compliance programs jumped from 30% in 2013 to 65% in 2015.[2] The report mentions that there was a major effort implementing actions of supervision and control by the companies, and explicitly cites the CCA as a source of regulatory pressure to adopt stricter internal controls, compliance, and reporting processes. As a consequence, under the category of "motivations for structuring a corporate governance framework", survey score on item "regulation pressure" jumped from 12% in 2013 to 37% in 2015, and score on "effectiveness of corporate governance framework" went from 25% to 44%. Third, Moody's (2017) notes that several state-owned companies have improved their corporate governance standards since 2014, and these improvements "will strengthen protections of the interests of their key stakeholders, including creditors and both controlling and minority shareholders."[3] Fourth, Transparency International notes that Brazil was one of the largest improvers in legal enforcement in the period 2014-2017, and recently upgraded the country's enforcement category from "little to no enforcement" to "moderate enforcement" in its report "Progress report 2018: Assessing enforcement of the OECD Anti-

[1] https://www.doingbusiness.org/content/dam/doingBusiness/media/Annual-Reports/English/DB14-Full-report.pdf; https://www.doingbusiness.org/content/dam/doingBusiness/media/Annual-Reports/English/DB15-Full-report.pdf.

[2] https://www2.deloitte.com/content/dam/Deloitte/br/Documents/governance-risk-compliance/acaminhodatransparencia.pdf

[3] "Improving corporate governance bodes well for Brazilian state-owned enterprises," Moody's Investors Service, September 11, 2017.

Bribery Convention".[4] The task force of "operation cash wash", the largest investigation uncovering cases of state capture and corruption in Brazil, won Transparency International's 2016 Anti-Corruption Award.[5]

Anecdotal evidence

Brazil launched several large-scale enforcement actions against corruption after the passage of the CCA, such as Operation Car Wash (Operação Lava Jato), Operation Zealots (Operação Zelotes), Operation Weak Flesh (Operação Carne Fraca), and Operation Bullish (Operação Bullish). Hundreds of high-profile politicians and business executives received severe fines and punishment in these operations, including the former president Luiz Inácio Lula da Silva who went to jail in April 2018. Construction firm Odebrecht SA signed the largest anticorruption settlement in history and agreed to pay between $2.6 billion and $4.5 billion in fines, and its chief executive officer was sent to prison.[6]

The popular press observes that the demand for compliance and corporate ethics among Brazilian companies skyrocketed after the CCA.[7] [8] [9] One practitioner notes that "the culture of compliance in Brazil – which was practically nonexistent in 2013 – has now taken off to a level of professionalism never imagined."[10] According to the Moody's (2017) report cited above, several state-owned companies have taken steps to improve corporate governance including, Petrobras, Eletrobras, Banco do Brasil, and Sabesp. In addition, the parent

[4] https://www.transparency.org/whatwedo/publication/exporting_corruption_2018
[5] https://www.transparency.org/news/pressrelease/brazils_carwash_task_force_wins_transparency_international_anti_corruption
[6] https://www.wsj.com/articles/odebrecht-to-pay-2-6-billion-to-settle-bribery-claims-1482325309? mod=article_inline
[7] https://www.wsj.com/articles/brazil-corruption-scandal-has-companies-rushing-to-bulk-up-compliance-ranks-1487854801
[8] https://www.leadersleague.com/en/news/the-rise-of-compliance-within-brazilian-corporations-challenges-successes-and-what-the-future-holds
[9] https://www.reuters.com/article/us-brazil-corruption-compliance-insight/brazil-graft-crackdown-spurs-work-for-lawyers-corporate-change-idUSKCN0WQ1G1
[10] "Law firms rake in millions, staff up compliance chops in post-`Operation Car Wash' Brazil," *The American Lawyer*, July 16, 2019.

companies of many Brazilian asset management firms now reference the CCA in their corporate compliance policies and codes of conducts. Claritas, which runs several Brazilian hedge funds (e.g., Claritas Long Short FIC FIM, Claritas Institucional FIM, and several others as listed in the TASS database), mentions in its 2017 compliance manual that the CCA applies to Claritas and its affiliated companies, foreign or domiciled in Brazil, and the liability extends to all Claritas employees who commit, participate in, or assist in the commission of unlawful act.[11] BB DTVM, parent company of several Brazil hedge funds listed in the TASS database, mentions in its 2018 financial statement that it established several programs to strengthen the company's governance in compliance with the CCA.[12] Anti-corruption policy documents of other parent companies of Brazil hedge funds in our databases, including Itau Unibanco,[13] Votorantim,[14] Mapfre[15], and the code of conduct of Daycoval[16] also explicitly cite the CCA.

Connection to WGI Indicators

Despite the above evidence, the three Worldwide Governance Indicators underlying *WIP* do not improve for Brazil over the four years following the enactment of the CCA. However, the World Bank cautions against relying on the composite indicators to study specific country-level governance reforms (e.g., the CCA), and instead recommends basing such evaluation on more detailed data connecting reforms to governance outcomes. They note that, "The six composite WGI measures are useful as a tool for broad cross-country comparisons and for evaluating broad trends over time. However, they are often too blunt a tool to be useful in formulating specific governance reforms in particular country contexts. Such reforms, and

[11] "Manual de Compliance, Etica e Conduta Corporativa, Claritas," A member of Principal Financial Group, Agosto 2017.

[12] https://www.bb.com.br/docs/pub/siteEsp/ri/eng/dce/dwn/annualreport2017.pdf

[13] https://s3.sa-east-1.amazonaws.com/static.itausa.aatb.com.br/Documentos/7776_ITS%202018-09-24%20RD%20Pol%20Relacionamento%20e%20Prev%20Corrup%c3%a7%c3%a3o%20(FOR)%20ING.PDF

[14] http://www.votorantim.com.br/assets/public/files/anti-corruption-policy-eng.pdf

[15] https://www.mapfre.com.br/seguro-br/images/MAPC-P-008_Politica_Anticorrupcao_03_2018_tcm909-178602.pdf CSHG

[16] https://www.daycoval.com.br/RI/Site/Pt/documentos/governancacorporativa/C%C3%B3digo%20de%20Cond ut a%20-%20Grupo%20Daycoval.pdf

evaluation of their progress, need to be informed by much more detailed and country-specific diagnostic data that can identify the relevant constraints on governance in particular country circumstances."[17] Our review of the evidence (discussed above) indicates that the CCA coincided with a crackdown on corruption that brought to light cases of corruption that were not widely known before, including a high-profile corruption scandal at state-run oil firm Petrobras. Thus, corruption perceptions (as measured in the underlying data sources and as reflected in the aggregate WGI ratings) could fail to improve or even deteriorate, precisely because the strengthening of legal rules related to investor protection and the enforcement of those rules led to some very conspicuous cases. Therefore, the detailed survey and anecdotal evidence discussed above is more relevant and strengthens our case that the CCA is a valid instrument for a positive shock to investor protection.

[17] https://info.worldbank.org/governance/wgi/#doc