Online Appendix for Delegated Monitoring, Institutional Ownership, and Corporate Misconduct Spillovers

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Abstract

This Online Appendix describes the types of events in our enforcement action data and then presents robustness tests related to 1) whether poor-stocking by institutional investors affects the spillover to non-fraudulent firms for being a portfolio peer to a financial misconduct firm, 2) whether general stock return co-movement within a portfolio related to the poor stock picking abilities of institutional investors or fund flow price pressure explains the spillover, and 3) matched sample and matched counterfactual analyses.

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I. Types of Events

As described in Karpoff et al. (2017), the initial revelation date of potential misconduct is captured in one of six possible event types in the database: (1) a "trigger" which is a misconduct related event described in regulatory proceedings or an announcement by the firm or third party of possible misreporting misconduct; (2) an "informal inquiry" announcement by the firm they have been informally requested to supply additional information regarding previously disclosed information; (3) a "formal investigation" announcement by the firm or news media that the firm or its executives were compelled to provide additional information either through a either a subpoena or arrest warrants; (4) a "Wells or settlement event" where a Wells notice was delivered to potential respondents notifying of the Commission's intent to file civil proceedings in federal district court or by an announcement by the firm of settlement discussions with the SEC or DOJ regarding the enforcement matter; (5) a "private action" which is the filing of a related private civil, class, or derivative action alleging the same misconduct in the regulatory proceedings; or (6) the filing of the first or initial administrative, civil, or criminal regulatory proceeding. A trigger event may include one or more of a variety of announcements such as: internal firm investigation; delayed filings; termination of management; unusual trading; auditor change or withdrawn audit; non-reliance on previously issued financial statements or restatement; default, receivership, or bankruptcy; third-party accusations of misconduct, etc.

II. Robustness to Poor Stock-Picking

Institutional investors differ in skill when pursing their investment and money management strategies (e.g. Graham and Harvey (1996)). Two observations related to institutional investor skill could contribute to the documented negative overall spillover effects. First, poor stock-selection skills in a prior period can lead to systematically poor portfolio performance next period. Second, a fraud event occurring in a portfolio can be evidence of poor stock-selection by institutional investors. At the same time, ex-ante, the stock-picking explanation is not likely for most institutional investors as they have diversified portfolios.

Nevertheless, to investigate this possibility, we construct two sets of measures of institutional investor skill. First, we compute standard performance evaluation metrics via using the monthly portfolio return in quarters $t-4$ to $t-1$ prior to a given quarter t for all institutional investors. The performance evaluation metrics are the market-adjusted alpha (MKT), the Fama and French (1993) three factor-alpha (FF3), and the Carhart (1997) four factor-alpha (Carhart). Second, we compute the forward looking picking, timing, and recession-weighted skill measures proposed by Kacperczyk, van Nieuwerburgh, and Veldkamp (2014). Specifically, for quarter t, the picking measure is the hypothetical idiosyncratic return generated in quarter $t+1$ based on the institutional investor's portfolio using each holding's portfolio weights in quarter t minus the same firm's market portfolio weight. Similarly, for quarter t, the timing measure is the hypothetical systematic return generated in quarter $t+1$ on the institutional investor's portfolio using each holding's portfolio weights in quarter t minus the market portfolio weight for each holding. Therefore, institutional investors skilled at stock-picking (timing) tilt their portfolios toward higher idiosyncratic (market beta) positions. Finally, the recession-weighted skill measure is the picking and timing measure weighted by the real-time recession probabilities estimated by Chauvet and Piger (2008).

With these measures, we test whether institutional investors connected to fraud events are skilled on average. To do so, taking into account the distribution of skill across institutional investors, we standardize each skill measure by computing the percentile rank of every institutional investor based on each skill measure for a given quarter. So by construction, a percentile rank of 0.50 is an average and median institution in terms of stock-picking skills. In Panel A of Table 1, we report summary statistics related to each skill measure for our sample of institutional investors holding fraud firms in the quarter of the initial revelation date. For the three risk-adjusted alpha measures, the mean and median are close to 0.50. More formally, we are unable to reject the null hypothesis that the mean percentile rank is 0.50 for all three risk-adjusted alpha measures. As a result, on average our sample of institutional investors appear to be average in terms of risk-adjusted performance. Moving to the forward looking skill measures proposed by Kacperczyk, van Nieuwerburgh, and Veldkamp (2014), we find that fraud connected institution investors appear to be skilled (unskilled) at stock-picking (timing), via overweighting (underweighting) stocks that have high idiosyncratic (beta) future return. Overall, based on the recession-weighted skill, our sample of institutional investors appear to be marginally skilled at the 10% level.

To explore the extent to which skill can explain the documented negative spillovers, in Panel B of Table 1, we run regressions of the spillover CAR on each skill measure. If skill can fully explain the spillover, then the intercept should be insignificant compared to 0. We find negative and significant intercepts in columns (1) through (3), indicating that the historical risk-adjusted portfolio alphas cannot fully explain the negative spillover. We note that the alphas are converted to ranks, with the average rank being 0.5. This means, for example in column (1), for the intercept of -0.101%, the alpha of the average firm is 0.5 times the coefficient of -0.24 which is -0.120%. As a result, for the average institution, risk-adjusted alphas explain about half of the documented spillover. Moving to columns (3) to (6), we see that again the intercepts are significant and negative at 1% level. While institutional investors skilled at timing can explain about 40% of the spillover, the skill related to stock-picking is actually associated with a reduction in the negative spillover. This means that some institutional investors who can pick high idiosyncratic return but non-fraudulent stocks in the next period manage to reduce the negative spillover from picking a fraud firm. Overall, these results provide some support for the poor stock-picking hypothesis for explaining the documented negative spillovers. The spillover however remains significant and economically large after controlling for these skill measures.

III. Robustness to Fund Flow Price Pressure

The negative spillover is potentially related to fund flow price pressure as prior literature documents significant negative abnormal returns when institutional investors or funds experience outflows or are forced to sell (e.g., Coval and Stafford (2007)). Furthermore, Lou (2012) finds that expected flows based on past flows predict future returns. As a result, the negative spillover across stocks can be due price pressure from either mutual funds' contemporaneous outflows or past flows.

In our tests of this hypothesis, we construct fund flow following Edmans, Goldstein and Jiang (2012). That is, we compute, for each institutional investor, the change in the current quarter's portfolio value compared to the prior quarter's portfolio value after subtracting out the quarter's hypothetical capital gain. Then, to verify whether fund flow contributes toward the negative overall spillover, in the full cross-section of institutional investors, we sort institutional investors into quintiles based on fund flow, with the 1st quintile representing the most extreme outflows, and the 5th quintile representing the highest inflows. We conduct the sorting based on either contemporaneous flows or lagged flows in either the prior quarter or the prior year. Table 2 reports on the results of the average spillover conditional on institutional investor fund flow. Across all quintiles, and for conditioning either on contemporaneous or past fund flows, we find significantly negative spillovers at the 1% level. Overall, these results point to a lack of a clear relationship between contemporaneous or past fund flows and the negative spillovers.

IV. Matched Sample and ROA Counterfactual Analysis

Our evidence indicates that there is a substantial negative overall spillover effect to institutional investors. However, there may be endogeneity concerns due to possible omitted variables, with corporate misconduct events being non-random. As a result, we conduct (1) a matched sample analysis to better identify the treatment effect of corporate misconduct on the market reaction to the institutional investor's portfolio, and (2) a negative performance counterfactual to support the idea that a discrete monitoring failure is central to the overall spillover.

To do so, we select a control holding by the same institutional investor in another quarter while matching on the fraud firm's portfolio weight, ownership % in the fraud firm, and the fraud firm's institutional ownership. Therefore, the matched control holding closely matches in terms of ex-ante monitoring incentive, ownership structure, and the unobservable characteristics of the institutional investor (e.g., investing style). The top section of Table 3 Panel A reports on the post-match balance of the matched sample versus the treatment sample. Out of the initial sample size of 55,989 observations, 47,504 are successfully matched based 1) an exact match of the fraud-connected institutional investor, and 2) a Mahalanobis distance match based on the ex-ante monitoring incentive and ownership structure variables. After running an OLS regression of these variables to predict treatment versus control status, the OLS coefficients are all insignificant, whilst the intercept is close to 50%. Therefore, the matching is successful, as after this procedure the matching criteria predicts the treatment status no better than a coin flip.

In the bottom section of Table 3 Panel A, we report the market reaction excluding fraud firm for the treatment group, the matched control group, and the difference between the two groups. Consistent with the matched group having no connection with fraud, the market reactions of the matched control group are economically small and a magnitude lower than the treatment group. As a result, the difference between the treatment group which is connected to fraud, and the matched control group identifies a highly significant, at 1% level, negative spillover to institutional investors.

Similarly, in Panel B of Table 3, we construct a counterfactual matched sample using the same matching procedure based on the fraud firm's portfolio weight and ownership % in the fraud firm, except we also choose a holding that experiences negative operating performance, based on return on assets (ROA). We choose this counterfactual in order to point out that a discrete and significant revelation of a monitoring failure is central toward identifying a spillover effect, as opposed to a less acute but more continuous drop in performance by a monitored firm. In the top section of Table 9 Panel B, reports on the matching balance, except for the critical difference that the counterfactual has had a -7.385% drop in ROA over the prior fiscal year. In Panel B, we observe that the original sample maintains the statistically significant and negative spillover effect. When we compute the difference between the two samples, we find that the original treatment sample's spillover CAR is a magnitude higher and remains significant.

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Table 1: Spillover Effects and Stock-picking Abilities

This table reports on the relation between the skill of the institutional investor and the portfolio-level spillover CARs for the rest of an institutional investor's portfolio. In Panel A, we report summary statistics for the skill of the institutional investors associated with fraud events. We measure institutional investor skill in two ways: 1) historical abnormal retirm performance in the prior year to the fraud event using market-adjusted alpha (α^{MKT}), Fama French three factor-adjusted alpha (α^{FF3}), and Carhart four factor-adjusted alpha ($\alpha^{Carhart}$); and 2) the Timing, Picking, and real time recession-probability weighted Skill measures of Kacperczyk, van Nieuwerburgh, and Veldkamp (2014). In Panel A, all the skill measures are transformed into quarterly cross-sectional percentile ranks, with 1 (0) denoting the highest (lowest) skill. In the final column, we test the null hypothesis that the mean skill percentile rank is 0.50. In Panel B, we report univariate regressions of the portfolio-level spillover CAR over [-2,+2] on the skill measures. Variable definitions are provided in the variable appendix. We report Driscoll and Kraay (1998) standard errors, which are clustered by quarter, with 4 lags. N represents the sample size at institutional investor-quarter level. The sample period is from 1980 to 2011. The unit of CAR is in percentage points. ***,**, and * represent significance at 1%, 5%, and 10% level, respectively.

Panel A - Skill Summary Statistics

Percentile Rank	Mean	SD	Median	IQR	Q0.25	Q0.75	t-stat$\|H_0$: Mean=0.50
α^{MKT}	0.499	0.243	0.501	0.375	0.311	0.686	-0.090
α^{FF3}	0.503	0.241	0.504	0.367	0.318	0.685	0.568
$\alpha^{Carhart}$	0.504	0.239	0.505	0.366	0.320	0.686	0.808
Timing	0.461	0.307	0.435	0.579	0.169	0.748	-1.803
Picking	0.540	0.306	0.564	0.578	0.254	0.832	1.830
Skill	0.539	0.306	0.561	0.579	0.253	0.832	1.835

Panel B - Spillover and Skill

	Dependent Variable: Spillover CAR [-2,+2]					
	(1)	(2)	(3)	(4)	(5)	(6)
α^{MKT}	-0.240^{***}					
	(0.024)					
α^{FF3}		-0.238^{***}				
		(0.027)				
$\alpha^{Carhart}$			-0.221^{***}			
			(0.025)			
Timing				-0.262^{***}		
				(0.099)		
Picking					0.249^{**}	
					(0.098)	
Skill						0.273^{***}
						(0.096)
Constant	-0.101^{***}	-0.114^{***}	-0.130^{***}	-0.188^{***}	-0.443^{***}	-0.459^{***}
	(0.036)	(0.038)	(0.039)	(0.050)	(0.099)	(0.099)
N	54,519	54,519	54,519	54,519	54,519	54,519
R^2	0.062	0.058	0.052	0.005	0.004	0.005

Table 2: Spillover Effects and Institutional Investor Flow

This table reports on whether the portfolio-level spillover CARs experienced by institutional investors varies according to the percentage flow to their holdings. The sorting variables are the end-of-quarter portfolio weighted contemporaneous or historical percentage flow to each stock in the institutional investor's portfolio. We sort institutional investors into quintile groups in the full cross-section of institutional investors in a fraud quarter. For a fraud quarter t, we investigate the spillover CAR within each quintile sorted on contemporaneous percentage flows in quarter t, the lagged flows in quarter $t-1$, and the lagged total flows from quarter $t-4$ to $t-1$. Variable definitions are provided in the variable appendix. We report Driscoll and Kraay (1998) standard errors in parentheses below the estimate with 4 lags. N represents the sample size at institutional investor-quarter level. The sample period is from 1980 to 2018. The unit of CAR is in percentage points. ***,**, and * represent significance at the 1%, 5%, and 10% level, respectively.

	Low	2	3	4	High
	Sorting on Contemporaneous Flows to II Portfolio				
Spillover CAR [-2,+2]	-0.260^{***}	-0.199^{***}	-0.228^{***}	-0.271^{***}	-0.315^{***}
	(0.068)	(0.052)	(0.058)	(0.057)	(0.063)
N	9,737	14,484	16,336	14,727	10,911
	Sorting on Prior Quarter's Flows to II Portfolio				
Spillover CAR [-2,+2]	-0.310^{***}	-0.248^{***}	-0.232^{***}	-0.223^{***}	-0.266^{***}
	(0.076)	(0.065)	(0.061)	(0.050)	(0.050)
N	9,533	14,209	15,921	14,276	10,975
	Sorting on Prior Year's Flows to II Portfolio				
Spillover CAR [-2,+2]	-0.307^{***}	-0.223^{***}	-0.227^{***}	-0.225^{***}	-0.280^{***}
	(0.070)	(0.063)	(0.054)	(0.053)	(0.056)
N	9,149	12,645	13,167	12,418	10,108

Table 3: Matched and Counterfactual Sample Analysis

This table reports on the results of matched sample and matched counterfactual analysis. In Panel A, we perform a matched sample analysis, selecting a matched portfolio holding based on the same institutional investor, its portfolio weight, the ownership % in the holding, and its overall institutional ownership, to control for unobserved effects on the spillover CAR. In Panel B, we perform a matched counterfactual analysis, selecting a matched portfolio holding based on the same institutional investor, its portfolio weight, the ownership % in the holding, and poor operating performance as measured by return on assets. In all tests, we report Driscoll and Kraay (1998) standard errors in parentheses below the estimate, with N representing the sample size at institutional investor-quarter level. The unit of the spillover CAR is in percentage points. ***,**, and * represent significance at the 1%, 5%, and 10% level, respectively.

Panel A - Matched Sample Analysis

	Treatment	Matched	OLS Coefficient
N	47,504	47,504	
Same Institutional Investor	Yes	Yes	
Fraud Firm's Portfolio Weight	0.235	0.235	-0.000 $t = -0.026$
Ownership % in Fraud Firm by Inst. Investor	0.661	0.658	0.000 $t = 0.347$
Fraud Firm's Inst. Ownership	64.424	64.415	0.000 $t = 0.067$
Treatment Indicator	1	0	0.499

	[0,0] (1)	[0,+1] (2)	[-1,0] (3)	[-1,+1] (4)	[-2,+2] (5)
Treatment	-0.064^{***}	-0.113^{***}	-0.111^{***}	-0.158^{***}	-0.267^{***}
	(0.014)	(0.029)	(0.023)	(0.036)	(0.053)
Matched	-0.002^{*}	-0.010^{***}	-0.004^{*}	0.011^{***}	-0.020^{***}
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
Difference	-0.062^{***}	-0.103^{***}	-0.107^{***}	-0.147^{***}	-0.247^{***}
	(0.015)	(0.029)	(0.025)	(0.037)	(0.055)
N	47,504	47,504	47,504	47,504	47,504

Panel B - Poor Profitability Counterfactual

	Treatment	Matched	OLS Coefficient
N	40,023	40,023	
Same Institutional Investor	Yes	Yes	
Fraud Firm's Portfolio Weight	0.249	0.252	-0.000 $t = -0.511$
Ownership % in Fraud Firm by Inst. Investor	0.462	0.460	0.000 $t = 0.307$
Fraud Firm's ROA	0.043	-7.385	NA
Treatment Indicator	1	0	0.500

	[0,0] (1)	[0,+1] (2)	[-1,0] (3)	[-1,+1] (4)	[-2,+2] (5)
Treatment	-0.061^{***}	-0.104^{***}	-0.107^{***}	-0.149^{***}	-0.256^{***}
	(0.012)	(0.023)	(0.022)	(0.032)	(0.047)
Matched	-0.006^{**}	-0.010^{**}	-0.005	0.009^{*}	-0.025^{***}
	(0.003)	(0.004)	(0.004)	(0.005)	(0.008)
Difference	-0.055^{***}	-0.094^{***}	-0.102^{***}	-0.140^{***}	-0.231^{***}
	(0.012)	(0.022)	(0.021)	(0.030)	(0.044)
N	40,023	40,023	40,023	40,023	40,023