Internet Appendix

(Not for Publication)

The Product Market Effects of Hedge Fund Activism

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Appendix A. Computation of price markups and TFP

We give a brief description of our estimation process for price-cost markups, specifically Model 4 in Table A.1, which forms the basis of the analysis in Section 6. We assume Hicks-neutral technological progress and model the production process by a translog production function. (For notational ease, we exclude organizational capital.) Expressed in natural logarithms, this production function can be written as (Christensen, Jorgenson, and Lau, 1973):

$$q_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \omega_{it} + \eta_{it} \tag{A.1}$$

where l_{it}, k_{it} are log values of labor and physical capital of the firm and q_{it} is a value-added log output for firm i in period t. ω_{it} is the productivity and η_{it} is an error term not known by the firm or the econometrician. Productivity shocks anticipated by the firm are represented by ω_{it}, while η_{it} consists of measurement error and output shocks that are not taken into account by the firm when making its input decisions.[1] Utilizing the coefficients on labor and capital, the output elasticity of labor can be computed as:

$$\xi_i^L = \beta_l + 2\beta_{ll} l_{it} + \beta_{lk} k_{it} \tag{A.2}$$

Whereas Olley and Pakes (1996) rely on an investment demand function to proxy for productivity, Levinsohn and Petrin (2003) introduce a material demand function. However, data on investment are readily available at the firm level, which is often not the case with data on materials. Hence, we follow Olley and Pakes (1996) to estimate firm level productivities.[2]

Our procedure consists of two steps. First, we estimate the labor coefficients and separate the

[1] A Cobb-Douglas production function is nested in the above representation and can be obtained by restricting the higher order term parameters β_{ll}; β_{kk} and β_{lk} to be equal to zero. Obviously, with a Cobb-Douglas production function, there exists no variation in the output elasticities across firms or over time. With a translog production function, while production function coefficients are the same for all producers, output elasticities differ across firms depending on their input use.

[2] Olley and Pakes (1996) provide the main IO approach to endogeneity problems. Assuming that investment is a monotonic function of productivity and capital, they replace productivity with the inverted function of capital and investment. Since the endogeneity problem is thereby addressed, they can estimate the labor coefficient and remove measurement errors in output. Assuming that productivity is first order Markov, a set of timing assumptions on when input decisions are made imply that observed variables or their lags are uncorrelated with the innovation in

productivity term ω_{it} from the i.i.d. error term η_{it}. In Olley and Pakes (1996), ω_{it} is a state variable that affects firms' decision making such that firms with a positive productivity shock in period t will invest more in physical capital, i_{it}, and hire more labor, l_{it}, in that period. The solution to the firm's optimization problem results in the equations for i_{it}, $i_{it} = i(\omega_{it}, k_{it})$, which is strictly increasing in ω. The inversion of this equation yields $\omega_{it} = h(i_{it}, k_{it})$. Consequently, we run the following regression:

$$q_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + h_t(i_{it}, k_{it}) + \eta_{it} \tag{A.3}$$

In the estimation, we approximate the $h(.)$ function by a second order polynomial. Clearly, the capital coefficients are not separately identified from the $h_t(.)$ function, but we can retrieve an estimate $\hat{\phi}_{it}$ for the composite function containing the capital terms and productivity, $\phi_{it} \equiv \beta_k k_{it} + \beta_{kk} k_{it}^2 + h(i_{it}, k_{it})$.[3] In the second step, we identify the capital coefficients. We follow the standard assumptions that productivity follows an AR(1) process; that is, $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$, where ξ_{it} represents a shock to productivity in period t (unexpected at period t-1), and that it takes firms one period to order, receive and install new capital. In particular, the timing assumption on capital provides the moment conditions to identify the capital coefficients:

$$E\begin{bmatrix} \xi_{it} | k_{it} \\ \xi_{it} | k_{it}^2 \end{bmatrix} = 0 \tag{A.4}$$

We now describe the process for computing the markups by using our estimates and data on firm-level input expenditures and revenues. The key variables for estimating the firm level productivity in our benchmark case are the firm level value added, employment, physical capital, and organization capital. The firm level data are obtained from Compustat and supplemented by industry level data from the NBER-CES, BLS and BEA. Value added (q_{it}) is computed as Sales–Materials, deflated by the price deflator for the value of shipments for the matching industry. Sales

productivity. A GMM estimator from these moments identifies the capital coefficient.

[3] Although the presence of log labor provides sufficient variation to identify the coefficient β_{lk} on the interaction term $l_{it} k_{it}$, we also experimented with a specification where we identify β_{lk} in the second stage. The main results did not change.

are net sales. Materials are measured as total expenses minus labor expenses. Total expenses are approximated as [sales - operating income before depreciation and amortization]. Labor expenses are calculated by multiplying the number of employees from Compustat by wages for the matching industry. The labor stock (l_{it}) is measured by the number of employees. Capital stock (k_{it}) is given by gross plant, property & equipment, deflated by the price deflator for investment for the matching industry following the methods of Hall (1990) and Brynjolfsson and Hitt (2003). Since investment is made at various times in the past, we need to calculate the average age of capital at every year for each company and apply the appropriate deflator (assuming that investment is made all at once in year [current year - age]). Average age of capital stock is calculated by dividing accumulated depreciation (gross PPE - net PPE) by current depreciation. Age is further smoothed by taking a 3-year moving average. The resulting capital stock is lagged by one period to measure the available capital stock at the beginning of the period.

In our estimations, we also include organizational capital as an input in some of the models. Following Eisfeldt and Papanikolau (2013), we construct the organizational capital from the Sales, general, and administrative expenses from Compustat by using the perpetual inventory method. These expenses are considered as investment in organizational capital, deflated by the price deflator for investment for the matching industry. Investment is assumed to depreciate by 20% per year. Estimated production function parameters and markups are reported in Table A.1.

Appendix B. IV Estimation of the Real Effects of HFA on Rival Firms by Full Information Maximum Likelihood (FIML)

To address the possibility that hedge funds are strategically choosing firms that are proactively undertaking operational improvements and strategy reforms in response to HFA threats or industry shocks, we use an instrumental variable (IV) approach estimated through full information maximum likelihood (FIML). We first simultaneously model the direct and indirect effects of HFA on industry rivals while endogenizing target selection by hedge funds in a manner that is (arguably) unrelated to the performance of the targets. Specifically, for each target firm *k* in industry *m*, let *i* be a rival firm (i.e., be in the same 4-digit industry). We denote by $y_{i,k,t}$ the year *t* performance measure of rival firm *i* of target *k*: Then we estimate:

$$y_{i,k,t} = \delta_0 + \delta_1 ' A_{i,k,t-1} + \sum_{j=0}^{3} \delta_k HFA_{k,t-j} + \psi_m + \xi_t + \varepsilon_{i,k,t} \quad \text{(B.1)}$$

$$HFA^{*}_{k,t} = \gamma_0 + \gamma_1' B_{k,t-1} + \gamma_2 C_{k,t-1} + \upsilon_{k,t} \quad \text{(B.2)}$$

Where

$$HFA_{k,t} = \begin{cases} 1 \text{ if } HFA^{*}_{k,t} > 0 \\ 0 \text{ if } HFA^{*}_{k,t} \leq 0 \end{cases} \quad \text{(B.3)}$$

Here, ψ_m and ξ_t represent industry and year fixed effects, respectively. The inclusion of these fixed effects ensures that our estimates are robust to industry- and time-specific unobservable (or omitted) variables that might otherwise confound our analysis. Meanwhile, $HFA_{k,t-j}$ is a dummy variable that takes a value of 1 if year *t-j; j = 1, 2,3* is the HFA event year for a target firm *k* (that is pseudo-event year for rival firm *i*. $A_{i,k,t-1}$ is the vector of control variables for the performance of rival firm *i* at time *t-1*. $C_{k,t-1}$ is an instrumental variable that influences the decision to target firm *k* in year *t*; but affects the performance of rival firms only indirectly through the spillover effects of activist intervention. Finally, $B_{i,k,t-1}$ is the vector of control variables for the HFA of target *k* at time *t-1*.

Our estimator for equations (B.1) and (B.2) is closely related to that employed by Keane, Moffit, and Runkle (1988), as well as by Clerides, Lach, and Tybout (1998). To begin, we write these equations in shortened form by collapsing their right-hand-side variables to the vectors Z^1 and Z^2 respectively:

$$y_{i,k,t} = \alpha^1 + \beta^1{}' Z^1_{i,k,t-1} + \varepsilon^1{}_{i,k,t} \qquad \text{(B.4)}$$
$$HFA^*_{k,t} = \alpha^2 + \beta^2{}' Z^2_{i,k,t-1} + \varepsilon^2{}_{i,k,t} \qquad \text{(B.5)}$$

where (B.3) also holds. Then for a given target event *k,* the likelihood function, conditioned on Z^1, Z^2, α^1 and α^2 may be written as:

$$L\left(y, HFA, Z^1, Z^2, \alpha^1, \alpha^2, \theta\right) = \prod_i^I \prod_t^T \left[f\left(y_{i,k,t} \middle| HFA_{kt} = 1\right) \Pr\left(HFA_{kt} = 1\right)\right]^{HFA_{kt}} \left[f\left(y_{i,k,t} \middle| HFA_{kt} = 0\right) \Pr\left(HFA_{kt} = 0\right)\right]^{1-HFA_{kt}}$$
$$= \prod_i^I \prod_t^T \left[f\left(y_{i,k,t} \middle| HFA^*_{kt} \geq 0\right) \Pr\left(HFA^*_{kt} \geq 0\right)\right]^{HFA_{kt}} \left[f\left(y_{i,k,t} \middle| HFA^*_{kt} < 0\right) \Pr\left(HFA_{kt} < 0\right)\right]^{1-HFA_{kt}}$$

where $\theta = \left(\beta^1, \beta^2, \sigma_{\varepsilon^1}, \sigma_{\varepsilon^2}, \sigma_{\varepsilon^1 \varepsilon^2}\right)$.

To simplify the conditional density functions, note that:

$$f\left(y_{i,k,t} \middle| HFA^*_{kt} \geq 0\right) \Pr\left(HFA^*_{kt} \geq 0\right) = \int_0^\infty f\left(y_{i,k,t}, HFA^*_{kt}\right) dHFA^*_{kt} = \int_0^\infty f\left(HFA^*_{kt} \middle| y_{i,k,t}\right) f\left(y_{i,k,t}\right) dHFA^*_{kt}$$
$$= f\left(y_{i,k,t}\right) \int_0^\infty f\left(HFA^*_{kt} \middle| y_{i,k,t}\right) dHFA^*_{kt} = f\left(y_{i,k,t}\right) \left[1 - \int_{-\infty}^0 f\left(HFA^*_{kt} \middle| y_{i,k,t}\right) dHFA^*_{kt}\right]$$
$$= f\left(y_{i,k,t}\right)\left[1 - G(0)\right].$$

where $G(.)$ is the cumulative distribution for $\left(HFA^*_{kt} \middle| y_{i,k,t}\right)$. Similarly,

$$f\left(y_{i,k,t} \middle| HFA^*_{kt} \leq 0\right) \Pr\left(HFA^*_{kt} \leq 0\right) = f\left(y_{i,k,t}\right) G(0)$$

Assuming that, $\left(\varepsilon^1{}_{i,k,t}\ ,\ \varepsilon^2{}_{i,k,t}\right)$ is jointly normal, we have:

$$HFA_{kt}^{*}, \left| y_{i,k,t} \sim N\left(Z_{i,k,t}^{2}\beta^{2} + \alpha^{2} + \left(\frac{\sigma_{\varepsilon^{1}\varepsilon^{2}}}{\sigma_{\varepsilon^{1}}^{2}}\right)\left(y_{i,k,t} - Z_{i,k,t}^{1}\beta^{1} - \alpha^{1}\right), \sigma_{\varepsilon^{2}}^{2} - \frac{\sigma_{\varepsilon^{1}\varepsilon^{2}}}{\sigma_{\varepsilon^{1}}^{2}} \right)\right.$$

So the conditional likelihood can be written as

$$L(.) = \prod_{i}^{I} \prod_{t}^{T} f\left(y_{i,k,t}\right)\left[1 - G(0)\right]^{HFA_{kt}} G(0)^{1-HFA_{kt}}$$

where

$$G(0) = \Phi\left(-\left[Z_{i,k,t}^{2}\beta^{2} + \alpha^{2} + \left(\frac{\sigma_{\varepsilon^{1}\varepsilon^{2}}}{\sigma_{\varepsilon^{1}}^{2}}\right)\left(y_{i,k,t} - Z_{i,k,t}^{1}\beta^{1} - \alpha^{1}\right) \right]\left[\sigma_{\varepsilon^{2}}^{2} - \frac{\sigma_{\varepsilon^{1}\varepsilon^{2}}}{\sigma_{\varepsilon^{2}}^{2}} \right]^{-1/2} \right)$$

$$f(y_{i,k,t}) = \phi\left(\frac{y_{i,k,t} - Z_{i,k,t}^{1}\beta^{1} - \alpha^{1}}{\sigma_{\varepsilon^{1}}} \right)$$

where Φ and ϕ are the standard normal cdf and pdf functions, respectively. We report the results in Table A.3 below. Note that each column in this table corresponds to a different outcome (performance) variable that is simultaneously modeled through the system (B.1)-(B.3). Our outcome variables are ROA, CashFlow, CAPEX, TFP, market shares and markups. FIML estimation considers all information regarding the joint distribution of the HFA selection system (B.2)-(B.3) and the outcome equation (B.1) simultaneously.[4]

As a robustness check, to address the fact that lagged endogenous variables appear in Z^1 and Z^2, we also followed Heckman's (1981) suggestion of adding equations to the system that

4 It is computationally difficult to estimate a likelihood that has so many layers of fixed effects. Fortunately, algorithms have recently been developed to handle such high-dimensional fixed effect regressions. Following Gormley and Matsa (2014), we use the iterative algorithm of Guimaraes and Portugal (2010). Alternatively, we also did not include fixed effects but demeaned the control and dependent variables at the industry and year level (e.g. Gormley and Matsa, 2014) before maximizing the likelihood function.

represent the dependence of $\left(HFA_{k,1}, HFA_{k,1}, ..., HFA_{k,t-1}\right)$ on α^1 and the dependence of

$\left(y_{i,k,1}, y_{i,k,2}, ..., y_{i,k,t-1}\right)$ on α^2:

$$
\begin{aligned}
y_{i,k,t} &= \rho^1\alpha^1 + \Psi^{1\,\prime} Z^{1*}_{i,k,t-1} + \zeta^1{}_{i,k,t} \\
HFA^*_{k,t} &= \rho^2\alpha^2 + \Psi^{2\,\prime} Z^{2*}_{i,k,t-1} + \zeta^2{}_{i,k,t}
\end{aligned}
$$

Here $Z^{2*}_{i,k,t-1} \subset Z^2_{i,k,t-1}$ is the vector of strictly exogenous determinants of HFA^*_{kt}, $Z^{1*}_{i,k,t-1} \subset Z^1_{i,k,t-1}$ is the vector of strictly exogenous determinants of $y_{i,k,t}$, and $\left(\zeta^1{}_{i,k,t}, \zeta^2{}_{i,k,t}\right)$ is a serially uncorrelated bivariate normal random vector. The likelihood then becomes:

$$
L(.) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\prod_{i}^{I}\left(\prod_{t}^{T}\tilde{f}\left(y_{i,k,t}\right)\left[1-\tilde{G}(0)\right]^{HFA_{kt}}\tilde{G}(0)^{1-HFA_{kt}}\right)\left(\prod_{t=1}^{T-1} f\left(y_{i,k,t}\right)\left[1-G(0)\right]^{HFA_{kt}} G(0)^{1-HFA_{kt}}\right) h\left(\alpha^1,\alpha^2\right) d\alpha^1 d\alpha^2
$$

where

$$
\begin{aligned}
\tilde{G}(0) &= \Phi\left(-\left[Z^{2*}_{i,k,t}\psi^1 + \rho^2\alpha^2 + \left(\frac{\sigma_{\zeta^1\zeta^2}}{\sigma^2_{\zeta^1}}\right)\left(y_{i,k,t} - Z^{1*}_{i,k,t}\beta^1 - \rho^1\alpha^1\right)\right]\left[\sigma^2_{\zeta^2} - \frac{\sigma_{\zeta^1\zeta^2}}{\sigma^2_{\zeta^1}}\right]^{-1/2}\right) \\
\tilde{f}(y_{i,k,t}) &= \phi\left(\frac{y_{i,k,t} - Z^{1*}{}_{i,k,t}\psi^1 - \rho^1\alpha^1}{\sigma_{\zeta^1}}\right)
\end{aligned}
$$

Our results based on the likelihood function above are very robust.

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Table A.1
Estimated production parameters and markups.

This table presents the estimated production function parameters and markups where estimation relies on a method developed by Olley and Pakes (1996). In Model 1 the production function is assumed to have a Cobb-Douglass form between labor and physical capital. In Model 2 (5) with organization capital, the production function is assumed to have a Cobb-Douglass (Translog) form between labor, physical capital and organization capital and without endogenous productivity. In Models 3 and 4 the production function is Translog with and without organizational capital, production functions as described in the main text. The sample is an unbalanced panel. Standard errors are presented in parentheses.

	Model 1: Cobb-Douglas		Model 2: Cobb-Douglas		Model 3: Translog		Model 4: Translog		Model 5: Translog	
	Estimate	S.E	Estimate	S.E	Estimate	S.E	Estimate	S.E	Estimate	S.E
Labor	0.680	(0.002)	0.705	(0.002)	0.576	(0.003)	0.775	(0.001)	0.692	(0.002)
Capital	0.124	(0.005)	0.113	(0.003)	0.166	(0.004)	0.152	(0.002)	0.135	(0.000)
Organizational Capital			0.126	(0.000)	0.118	(0.002)			0.158	(0.005)
Autocorrelation	0.695	(0.000)			0.667	(0.005)	0.789	(0.000)		
Markup	1.389	(0.000)	1.455	(0.004)	1.549	(0.001)	1.544	(0.001)	1.590	(0.005)
No. of observation	48,224		45,107		45,107		48,224		48,224	
Endogenous productivity	yes		no		yes		yes		no	
Organizational capital	no		yes		yes		no		yes	

Table A.2
Estimation results for likelihood of activist investor intervention

This table presents the probit estimation results for the HFA, where the dependent variable is a binary variable that equals one if a firm is subject to HFA and zero otherwise. All variables are retrieved from the year prior to the event. All explanatory variables are measured as of time *t–1*. *InstOwner* is the percentage of firm shares held by institutional investors; *Past campaigns* is the logarithm of the number of HFA campaigns at the firm in the past 3 years. *Stock Return* is a dummy equal to one if a firm's return exceeds the industry median. *Credit spread* is the difference between the yields of BB- versus AAA-rated corporate bonds obtained from Bloomberg. All other variables are defined in the main text. Standard errors are White heteroskedasticity-adjusted and are clustered for the same industry. *F*-tests for the difference between the coefficients for the year+3 and the event year for the whole sample are also provided. We report *t*-statistics in parentheses. *, ** and *** mean the coefficient is significant at the 10%, 5%, or 1% level, respectively.

Dependent variable: Prob(HFA)			
	(1)	(2)	(3)
lnMV of Equity	-0.090**	-0.085**	-0.107***
	(-2.20)	(-2.22)	(-2.57)
Leverage	-0.028**	-0.039**	-0.044**
	(-2.22)	(-2.17)	(-2.05)
Cash	0.030***	0.027***	0.049***
	(2.99)	(2.96)	(3.25)
lnHHI	-1.004**	-1.026**	-1.435**
	(-2.12)	(-2.28)	(-2.33)
InstOwner	0.075**	0.079**	0.080**
	(2.36)	(2.10)	(2.11)
Stock return	-0.226***	-0.425***	-0.307***
	(-3.08)	(-3.16)	(-3.59)
Past campaigns	0.679***	0.825***	0.292***
	(3.14)	(3.78)	(3.08)
Market-to-Book	-0.018*	-0.017*	-0.007
	(-1.76)	(-1.87)	(-1.59)
Tobin's Q	-0.012	-0.014	-0.027*
	(-1.50)	(-1.62)	(-1.80)
Credit spread	-0.013	-0.019*	-0.014*
	(-1.52)	(-1.71)	(-1.65)
Industry fixed effects	yes	no	yes
Year fixed effects	no	yes	yes
No. of Observations	48,006	48,006	48,006
Pseudo R-squared	0.059	0.062	0.074

Table A.3

Real effects on rivals after hedge fund activism: Full information maximum likelihood.

This table presents the full-information maximum likelihood (FIML) estimation results of the real effects of hedge fund activism on the rivals of target firms. Panel A presents the coefficients of outcome equation. For brevity, we only report the coefficients on the *HFA* dummies and unreported controls are same as those used in Panel B. Panel B presents the coefficient estimates of the selection equation where the dependent variable equals one if a firm is subject to HFA in year *t.* All explanatory variables are measured as of time *(t–1). InstOwner* is the percentage of firm shares held by institutional investors; *Past campaigns* is the logarithm of the number of HFA campaigns at the firm in the past 3 years. *Stock Return* is a dummy equal to one if a firm's return exceeds the industry median. *Credit spread* is the difference between the yields of BB- versus AAA-rated corporate bonds obtained from Bloomberg. We also use instrumental the expected annual selling (*Exp.InstSell)* and buying *(Exp.InstBuy)* volumes in stock *s*, conditional only on institutional trading in firms other than stock *s* as in Gantchev et al. (2014). All other variables are defined in the main text. Standard errors are White heteroskedasticity-adjusted and are clustered for the same industry. *F*-tests for the difference between the coefficients for the year+3 and the event year for the whole sample are also provided. We report *t*-statistics in parentheses. *, ** and *** mean the coefficient is significant at the 10%, 5%, or 1% level, respectively.

Table A.3 (continued)
Real effects on rivals after hedge fund activism: Full information maximum likelihood

Panel A. Outcome model						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	*ROA*	*CashFlow*	*CAPEX*	*TFP*	*Market Shares*	*Markups*
Year0 (event year)	0.003	0.004	-0.000	0.001	0.003	-0.002
	(1.19)	(1.48)	(-1.22)	(1.49)	(1.16)	(-1.19)
Year+1	-0.007	0.000	0.001	-0.008*	-0.009*	-0.010*
	(-1.33)	(-1.26)	(-1.30)	(-1.69)	(-1.71)	(-1.80)
Year+2	-0.008*	-0.014*	-0.009*	-0.018**	-0.017**	-0.029**
	(-1.76)	(-1.95)	(-1.75)	(-2.06)	(-2.04)	(-2.51)
Year+3	-0.013**	-0.011*	-0.008*	-0.014**	-0.016*	-0.022**
	(-1.90)	(-1.85)	(-1.77)	(-1.97)	(-1.99)	(-2.34)
Panel B. Selection model: Prob(HFA)						
lnMV of Equity	-0.102**	-0.059**	-0.75***	-0.098*	-0.066**	-0.116**
	(-2.24)	(-2.07)	(-2.66)	(-1.95)	(-2.18)	(-2.05)
Leverage	-0.057**	-0.030**	-0.045*	-0.076**	-0.034*	-0.050**
	(-2.02)	(-2.00)	(-1.82)	(-2.07)	(-1.90)	(-2.14)
Cash	0.077**	0.068**	0.059**	0.085**	0.080*	0.101**
	(-2.45)	(-2.40)	(-2.07)	(-2.11)	(-1.94)	(-2.08)
lnHHI	-0.706**	-0.667*	-0.605*	-0.844**	-0.715*	-0.569*
	(-2.12)	(-1.99)	(-1.71)	(-2.32)	(-1.86)	(-1.70)
InstOwner	0.019**	0.045***	0.052**	0.071**	0.034**	0.022***
	(2.48)	(2.64)	(2.43)	(2.27)	(2.39)	(2.51)
Past campaigns	0.015***	0.029**	0.030**	0.019**	0.015**	0.024**
	(2.34)	(2.27)	(2.44)	(2.28)	(2.30)	(2.09)
Stock return	-0.228*	-0.179*	-0.302*	-0.176*	-0.305*	-0.219*
	(-1.88)	(-1.92)	(-1.76)	(-1.88)	(-1.72)	(-1.90)
Tobin's Q	-0.026*	-0.019*	-0.033*	-0.025	-0.030*	-0.019
	(-1.95)	(-1.78)	(-1.90)	(-1.57)	(-1.68)	(-1.69)
Credit spread	-0.009*	-0.008	-0.010*	-0.007	-0.006	-0.008
	(-1.92)	(1.33)	(-1.88)	(1.26)	(1.35)	(-1.44)
Exp.Inst Buy	-2.529***	-2.804***	-3.355***	-2.027**	-3.306***	-3.029***
	(-2.72)	(-2.88)	(-3.12)	(-2.11)	(-3.10)	(-2.84)
Exp.Inst. Sell	2.166**	2.290**	3.128***	2.007**	2.775**	2.226**
	(-2.38)	(-2.44)	(-3.00)	(-2.19)	(-2.06)	(-2.15)
Industry fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Pre-event dummies (Year-1,Year-2,Year -3)	yes	yes	yes	yes	yes	yes
Hansen-J Chi2 *p*-value	0.505	0.429	0.276	0.680	0.149	0.325
No. of Observations	48,880	47,219	50,115	46,002	49,138	46,002
F-test *p*-value: (Year+3 –Year0)	0.007	0.000	0.036	0.000	0.028	0.000
Joint test of excluded instruments	0.000	0.000	0.004	0.000	0.000	0.000