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The Real Effects of Hedge Fund Activism: Productivity, Risk, and Product Market Competition

Alon Brav[a,b], Wei Jiang[c], and Hyunseob Kim[a]

[a] *Duke University, Durham, NC 27708, USA*

[b] *National Bureau of Economic Research, Cambridge, MA 02138, USA*

[c] *Columbia University, New York, NY 10027 USA*

Abstract

This paper studies the long-term effect of hedge fund activism on the productivity of target firms using plant-level information from the U.S. Census Bureau. A typical target firm improves its production efficiency within two years after activism, and this improvement is concentrated in industries with a high degree of product market competition. By following plants that were sold post-intervention we also find that efficient capital redeployment is an important channel via which activists create value. Furthermore, our analyses demonstrate that measuring performance using the Compustat data is likely to lead to a downward bias because target firms experiencing greater improvement post-intervention are also more likely to disappear from the Compustat database. Finally, consistent with recent work in asset-pricing linking firm investment decisions and expected returns, we show how changes to target firms' productivity are associated with a decline in systemic risk, particularly in competitive industries.

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1. Introduction

A growing literature on hedge fund activism identifies a significant stock price reaction (5-10 percent abnormal return) for targeted companies with the announcement of activism (Brav, Jiang, Partnoy, and Thomas (2008a), Klein and Zur (2009), Clifford (2008), Greenwood and Schor (2009)). The range of short-term price impact is highly consistent across different studies and different markets.[1] The current literature on hedge fund activism, however, has not explicitly identified the underlying sources of value creation by hedge fund activists. As a result, little is known about the precise mechanism via which activists are able to increase shareholder value. In fact, opponents of hedge fund activism often blame hedge fund activists as "short-term focused" and "financial engineering oriented,"[2] denying any meaningful real and long-term impact.

The limitation of previous research is due both to the novelty of the topic, and hence the lack of a large sample of post-intervention data, as well as the constraints of databases (such as Compustat) that cover only public companies at the firm level. First, within two years of activists' intervention, close to 20% of companies targeted by activists disappear from the Compustat database since they were either acquired or delisted, doubling the normal attrition rate of the Compustat universe. As a result, researchers have not been able to assess the post-targeting performance based on an unbiased sample. Second, commonly used operating measures such as return on assets (ROA) do not reveal the underlying channels of improvement. In particular, these standard performance measures cannot isolate improvement in the productivity of the going concerns, that is, production efficiency gains, from gains to capital reallocation that are due to divestiture of underperforming assets and refocusing.

This paper addresses both of these important issues by exploring the longitudinal data of manufacturing establishments (i.e., plants) from the Census of Manufacturers (CMF) and the Annual Survey of Manufacturers (ASM) databases maintained by the U.S. Census Bureau. By matching these plant observations to hedge fund activism events from 1994 to 2007, we examine the dynamics of production efficiency for firms targeted by activists, measured by total factor productivity (TFP), and the gains in efficiency due to the reallocation of target firms' plants.

The following key findings on the long-term real effect of hedge fund activism arise from our analyses. First, the productivity of plants owned by the target firms shows a "V"-shaped pattern around the year of the intervention. Two years prior to the intervention, the productivity of target firms' plants is significantly higher than their control plants with similar size and age in a given industry and year. Target firms' productivity deteriorates during the two years leading to the intervention to a level similar to that of

[1] See Brav, Jiang, and Kim (2010) for a survey of these studies.
[2] See, for example, "Hedge Fund Activists Set to Comeback," *Financial Times,* December 8, 2009.

the control plants, but then rebounds to the pre-activism level two years post-activism. Second, we find that this improvement in production efficiency associated with hedge fund activism is concentrated in industries with more intense product market competition.

Third, we document for the first time that there exists a positive "spillover effect" of activism on the industry peers of targeted plants. That is, plants that operate in an industry repeatedly targeted by hedge fund activists also experience a significant improvement in productivity even though they are not direct targets. Again, this spillover effect on industry peers is concentrated in relatively competitive industries. Fourth, we present evidence that one channel through which activists create value is by facilitating efficient reallocation of corporate assets. More specifically, prior to their sales, plants that are eventually sold exhibit lower productivity and profitability compared to plants in the control sample. However, after the sale, the plants experience greater improvement in the hands of the new owners, suggesting that hedge funds facilitate the matching to new owners who can operate the underperforming plants more efficiently.

Overall, these results reveal that hedge fund activism leads to a significant improvement in the production efficiency and profitability for targeted firms, particularly in competitive industries. This evidence refutes the assertion that the effects of hedge fund activism are purely financial (such as extracting payouts to shareholders through leverage) as argued by some policy makers and popular press. Moreover, given that plant observations in our Census data are not subject to the attrition bias related to the public status of the parent firm (which is the case for firm observations in Compustat), our estimates of higher plant productivity for the targets of activism are more accurate than performance analyses based on the Compustat data. Furthermore, the positive externalities of activism on non-target industry peers indicate that estimates based on industry benchmarks are conservative.

Last, we link the significant announcement return for activism and the improvement in underlying plant productivity to the change in the target firms' systematic risk. In particular, building on recent economic theories linking firms' operating efficiency to their expected rates of return, we test for a "discount-rate channel" which posits that higher efficiency brought about by activism leads to a predictable decline in systemic risk and a positive abnormal return. The loading on the Fama-French HML ("value") factor of target stocks around the announcement of activism indeed exhibits an *inverted* "V"-shaped pattern, a mirror image of the pattern we find for the productivity of plants owned by the targets. Furthermore, consistent with our earlier findings regarding target plants' productivity, this change in the factor loading is significant in the competitive industries but not in concentrated industries. Taken together, our study identifies both a "cash-flow channel" (efficiency gains) and a "discount-rate channel" (a decline in systematic risk) that account for positive abnormal returns at the announcement of activism.

We have thus far not discussed the effect of nonrandom selection of target firms by hedge funds on our estimation. Though we make an effort to control for observables such as plant age, size, and industry affiliation, some unobservable and omitted plant or firm characteristics may be correlated with both the decision to intervene and the targets' future performance. It may also be argued that activists are able to anticipate significant industry-level shocks to the structure of the product market and thus anticipate the implications of such changes on target firms. The observed improvement in target firm's performance post-intervention may therefore just reflect the consequences of these shocks independent of the presence of the activists.

We believe that these concerns are justified although it is important to emphasize that the growing literature on activism has shown that many of the changes associated with hedge fund activism are unlikely to have occurred absent activists' actions. First, certain changes in financial and governance polices (such as the significantly higher CEO turnover post-intervention documented by Brav et al. (2008a)) tend to be the outcomes of confrontation and thus are unlikely to have occurred but for the commitment of activists. Second, previous work (e.g., Brav et al. (2008a)) has established that activists tend to hold on to a concentrated equity stake in the target firm until the resolution of their goals, a holding period that averages close to two years. It is hard to argue that activists would willingly hold undiversified positions and be subject to costly engagements (Gantchev (2011)) that typically evolve into shareholder proposals and proxy contests if these were not necessary means to achieve their goals. Third, openly hostile activism generates higher announcement returns than non-confrontational ones (Brav et al. (2008a), which in turn generates higher return than the revelation of large passive stakes (Klein and Zur (2009)). Hence, the market considers intervention necessary for value-enhancing changes.

Overall, we believe that a careful interpretation of the evidence in this paper should balance the view that activists are able to anticipate and act upon changes that may have occurred anyway with the view that activists create value for shareholders by effectively influencing the governance, financial and operating performance of target firms. At the very least, our results indicate that the positive returns to hedge fund activism should not be attributed to purely financial gains, but instead reflect anticipated improvement in the fundamental values of the targets.

The paper proceeds as follows. Section 2 presents the construction of the data and sample used in the analysis. In particular, we describe how we construct our measure of production efficiency and match the Census data to the hedge fund activism events data. Section 3 presents the main results of the paper on the real effect of activism on productivity of plants owned by the target firms. One focus of this section is the interactive effect of product market competition with corporate governance in the form of hedge fund activism. In Section 4 we document the extent to which hedge fund activists create value through efficient reallocation of target firms' assets by examining the dynamics of productivity of plants sold post-activism. This section also examines the extent to which the estimate of the real effect of activism based on Compustat is biased due to sample attrition from the database. Section 5 investigates the link between the onset of activism and subsequent change in plant productivity and the underlying systematic risk of target firms. We conclude in Section 6.

2. Data and Key Variables

2.1 Data sources and sample construction

2.1.1 Plant-level Data

We obtain data on manufacturing establishments (i.e., plants) from two types of databases maintained by the U.S. Census Bureau. The first data source includes the Census of Manufacturers (CMF) and the Annual Survey of Manufacturers (ASM) which provide plant-level information to compute our measures of productivity, profitability, and product market competition. The CMF covers all manufacturing plants in the U.S. with at least one employee for years ending '2' or '7' (the "Census years"), resulting in roughly 300,000 plants in each census. The ASM covers about 50,000 plants for the "non-Census years." Plants with more than 250 employees are always included in the ASM, while those with fewer employees are randomly sampled with the probability increasing in size. Both the CMF and ASM provide operating information at the plant level including total value of shipments, capital stock and investment, labor hours, and material and energy costs.

Compared to standard firm-level databases of public firms such as Compustat, the CMF and ASM have a few critical advantages for our analyses. First, since they cover plants owned by private firms as well as public firms, these databases allow us to track the performance of target firms even if they disappear from the database of public firms due to acquisitions or delistings. Since such events tend to occur more often among firms targeted by hedge fund activists this feature of the Census data helps us minimize the potential attrition bias in estimating the effect of activism (see Brav, Jiang, and Kim (2010) for a discussion of this issue). Second, accurate estimation of productivity as well as industry benchmarking requires a reasonable uniformity of production functions, a property that applies to plants well but not necessarily at the firm level. Thus, the CMF and ASM data allows us to identify the efficiency gain in the production process associated with activism as well as the effect of activism on a targeted industry, both of which are beyond the reach of analyses relying on databases of publicly traded companies such as Compustat.

The second data source is the Longitudinal Business Database (LBD) from which we obtain unique longitudinal identifiers for plants and information on ownership changes. The LBD tracks more than five million (both manufacturing and non-manufacturing) establishments every year, essentially covering the entire U.S. economy. The variables available in the database include the number of employees, annual payroll, industry classifications, geographical location, and ownership status.

We focus on manufacturing plant-year observations in the CMF and ASM from 1992 to 2007 (the last year of the data coverage), which is determined by the sample period of the hedge fund activism database (1994-2007) and the fact that we examine plant performance beginning two years prior to the intervention. We exclude 'miscellaneous manufacturing industries' (i.e., three-digit SIC=399) as this category does not represent a group of plants that share a common production function. We also require each plant observation to have variables necessary to estimate total factor productivity (TFP), including SIC codes, total value of shipments, production worker equivalent hours, beginning-year capital stock, and material and energy costs.[3] Appendix A provides details on the construction of these variables, including adjustments for changes in prices of inputs and outputs, and depreciation. This sample selection procedure yields 633,510 plant-years in our sample.

2.1.2. Hedge Fund Activism Data

The database of hedge fund activism events was collected by Brav, Jiang, and Kim (2010) and Li and Xu (2010), covering the period of 1994-2007.[4] These events are identified mainly through Schedule 13D fillings to the SEC in which hedge funds disclose ownership exceeding 5% with intention to influence corporate control. We collect detailed information on key aspects of each event from the initial and amended 13D filings via the SEC's EDGAR system, supplemented by news searches. We refer the reader to Brav, Jiang, and Kim (2010) for additional details on the data collection.

The target firm-year pairs are then matched to (potentially multiple) plant-year observations in the Census data using a bridge file between a firm identifier in the Census files and a unique public firm identifier created by the Census Bureau staff. Panel A of Table 1 shows that for 305 activism events from 1994 to 2007 (out of 2180 events in total), we are able to find at least one matched plant-year in the CMF and ASM data with adequate information for estimating TFP, resulting in 6,561 total number of plant-

[3] The ASM and CMF provide SIC codes until 2002 and provide NAICS codes only thereafter. We follow Giroud (2011) and impute the SIC codes after 2002 as follows. First, for plants that appear prior to 2002, we assume that the SIC code after 2002 is the same as the last available SIC code before 2002. Second, for plants that appear after 2002, we use a concordance table between the SIC and NAICS codes provided by the U.S. Census Bureau. Given that the concordance is not one-to-one, for NAICS codes with multiple potential SIC matches, we pick the SIC code with the largest employment share among the potential SIC codes, computed using the 2002 LBD data.

[4] We thank Yinghua Li and Jin Xu for generously sharing their hedge fund activism data for the period 1994-2000.

year observations. This match rate is somewhat lower than those typically reported in previous research due to two factors.[5] First, more than 70% of the hedge fund activism targets in our sample are in non-manufacturing sectors. Second, activism targets tend to be smaller than sample firms examined in previous research using the Census data (e.g., LBO and M&A targets). Indeed, the matching rate is much higher for the target firms in the manufacturing sector.[6]

[Insert Table 1 here.]

Panel B of Table 1 shows that both the full sample of events and those matched to the Census data are more concentrated in the 2000s compared to the 1990s, consistent with the rise of activist intervention as a viable investment strategy among hedge funds from the early 2000s (Brav et al., 2008a, 2008b). Given that not all of the targets of hedge fund activists are matched to the Census files it is necessary to examine if the matched activism events are representative of the entire sample.[7] The comparison of the distribution of stated objectives and success rates (including partial successes) between the full sample and matched sample, reported in Table 1 Panel C, indicates that the matched events appear to be very similar to the full sample of events. For example, the success rate (i.e., the proportion of events in which hedge funds at least partially attained their stated goals) for the matched sample is 50%, almost identical to that for the full sample. Given the similarities between the full and matched sample of activism events the results in this study are likely to be generalizable to the larger universe of hedge fund activism events.

2.2 Key Variables

2.2.1 Productivity

Our main measure of plant performance is total factor productivity (TFP), which is defined as the difference between the actual and predicted output given inputs. In order to compute the predicted output for each plant, we follow the literature (e.g., Lichtenberg and Siegel (1990), Lichtenberg (1992), Schoar (2002), Bertrand and Mullainathan (2003), and Giroud (2011)) and estimate a log-linear Cobb-Douglas production function using Ordinary Least Squares (OLS) regressions by three-digit SIC industry and year:

$$\ln(Y_{ijt}) = \alpha_{jt} + \beta_{jt}^{K} \ln(K_{ijt}) + \beta_{jt}^{L} \ln(L_{ijt}) + \beta_{jt}^{M} \ln(M_{ijt}) + \varepsilon_{ijt}, \qquad (1)$$

[5] For example, Lichtenberg and Siegel (1990) report a matching rate of about 50% for their LBO target firms with the Census data.

[6] Note that target firms classified as "non-manufacturing" based on the SIC code from Compustat might own manufacturing establishments, and thus could also be matched to the ASM and CMF data.

[7] We are in the process of collecting detailed information on hedge fund activism events from 1994 to 2000. We therefore perform this "representative analysis" for events from 2001 to 2007 only. We plan to update the analysis to include the pre-2001 events in the next draft of this paper.

where α_{jt} is industry-year specific intercept, Y_{ijt} is output, K_{ijt} is net capital stock, L_{ijt} is labor input, M_{ijt} represents material costs. ε_{ijt} is the residual and the estimate of the TFP for plant *i*, in industry *j* in year *t*. The coefficients in (1) carry *(j,t)* subscripts, which allows for factor intensities that are industry-year specific. In addition, given that TFP is the estimated residual of the industry-year specific regressions, we can interpret TFP of a given plant as a relative productivity rank of the plant within a given industry and year. Finally, we "standardize" the TFP measure from (1) by dividing it by its cross-sectional standard deviation for a given industry-year. Essentially, this adjustment accounts for differences in the precision of TFP estimates among industry-years (following the practice of Maksimovic, Phillips, and Yang (2010)).[8]

Since one of our goals is to examine the effect of activism on industry peers of the target firms (see Section 3.2), we compute *industry-level TFP* by estimating a log-linear Cobb-Douglas production function using OLS regressions at the three-digit SIC level for each year:

$$\ln(Y_{jt}) = \alpha_t + \beta_t^K \ln(K_{jt}) + \beta_t^L \ln(L_{jt}) + \beta_t^M \ln(M_{jt}) + \varepsilon_{jt}, \tag{2}$$

This specification is very similar to that in equation (1), except that dependent and independent variables in the regression are aggregated at the industry level (indexed by *j*) as sums of plant-level variables. Similar to in equation (1), we take the residual of the OLS regression (ε_{jt}) as our estimate of TFP for each industry-year pair.

As a complementary measure of performance, we also employ operating profit margin in our analysis, defined as total output minus material and labor costs divided by total output. More specifically, total output is total value of shipments plus the net increase in inventories (of both finished goods and work in progress), labor costs are total payroll, and material costs are costs of materials and parts plus energy costs, all adjusted for changes in prices. One advantage of this performance measure relative to TFP is that it does not rely on particular structural assumptions for production functions. In addition, it is comparable to the operating margin constructed using Compustat variables (except for the fact that our Census-based measure excludes overhead costs), allowing for a comparison of the results with those for the Compustat sample. Unless otherwise specified, all potentially unbounded variables are winsorized at the 1% tail.

[8] As Lichtenberg and Siegel (1990) point out if each industry is perfectly competitive the constructed measure of output does not reflect pricing power and the TFP measure captures only production efficiencies. However, to the extent that the product market is not perfectly competitive, the measure of TFP could reflect pricing power or markup, as well as efficiency. However, as we show later, the gains in efficiency associated with activism are actually driven by target plants in competitive industries.

2.2.2 Product Market Competition

Our main measure of the degree of product market competition is the Herfindahl-Hirschman Index (HHI). Specifically, we compute the HHI using the Census data as follows:[9]

$$HHI_{jt} = \sum_{f=1}^{N_j} S_{fjt}^2, \tag{3}$$

where HHI_{jt} is the Herfindahl-Hirschman index for industry *j* in year *t*, and S^2_{fjt} is the squared market share of firm *f* in industry *j* in year *t*. Market shares are measured using total value of shipments aggregated at the firm level (i.e., sales), and industry is defined at the three-digit SIC level. In our robustness checks in Section 3.3, we also compute the HHI based on an alternative industry classification scheme.

While the HHI is well-articulated in the theory of industrial organization (see Tirole (1994)) and widely used in the empirical literature, we use industry net profit margin (or the "Lerner Index") as an alternative measure of product market competition for robustness check. Following Domowitz et al. (1986), the industry net profit margin for industry *j* in year *t* is computed as:

$$NPM_{jt} = \left[\frac{\sum_{i=1}^{N_j}(TVS_{ijt}+\Delta inv_{ijt}-wage_{ijt}-mat_{ijt})}{\sum_{i=1}^{N_j}(TVS_{ijt}+\Delta inv_{ijt})}\right], \tag{4}$$

where TVS_{ijt} is total value of shipments, Δinv_{ijt} is the net change in inventories, $wage_{ijt}$ is total payroll (labor costs), and mat_{ijt} is material costs for plant *i* in industry *j* in year *t*. Industry is defined at the three-digit SIC code level.

2.2.3 Descriptive Statistics

Table 2 reports the descriptive statistics comparing the characteristics of target plants and those of all plant-year observations used in our analysis. On average, plants owned by target firms have a total value of shipments (TVS) of \$93m, real net capital stock of \$44m, and total wage of \$14m (in 2005 dollars), which are larger than the respective values for the full sample. Moreover, the workers in the target plants are paid more in terms of average wage per worker and hourly wage for production workers.

In addition, the average firm in the target (full) sample operates seven (six) plants in its three-digit SIC segment and 18 plants within the firm across segments. These statistics on firm size are

[9] Since the CMF covers a much larger number of firms compared to that in a typical ASM sample, the HHI computed using the CMF tends to be significantly smaller than that using the ASM. We therefore compute the HHI using the ASM data only (rather than both the ASM and CMF data) and impute the previous year's value of the HHI for the "Census years" for the consistency of the measure over years. Our results are robust qualitatively if we construct the HHI using the CMF instead, and impute the latest Census year's value of the HHI for the non-Census years.

generally larger than those reported in previous research using the CMF and ASM databases (e.g., Schoar (2002), Giroud (2011)), which is not surprising given that our sample period begins in 1991 while those of previous research usually begin in an earlier year (e.g., 1977).

[Insert Table 2 here.]

Since our main measure of production efficiency, standardized TFP, is constructed as the residual of a production function regression scaled by its standard deviation, it has a mean of zero and a standard deviation close to 1.00 by construction for the full sample (due to the winsorization at 1% tails the standard deviation is slightly less than 1.00). In comparison, target plants have a positive mean TFP indicating that they are more productive than the average plant in the full sample. Similarly, target plants show a higher profit margin than the full sample of plants, on average. Finally, the HHI computed using all plant observations in the ASM database with a positive value of shipments has a mean of 0.04 and a standard deviation of 0.04. Notably, the mean industry HHI for target plants is larger than that for the full sample (0.052 vs. 0.040) indicating that hedge fund activists are more likely to target firms operating in concentrated industries. The mean HHI for our sample is much smaller than a commonly reported mean HHI of around 0.15 based on Compustat data because the Census data covers a wider range of firms including both private and public firms compared to Compustat which covers public firms only. In this sense, our measure of product market competition (HHI) based on the Census data is likely to be more accurate.

[Insert Table 3 here.]

Table 3 provides descriptive statistics for firms targeted by activists that are matched to the Census plant-level data as well as all target firms for the 1994-2007 period. First, Census-matched target firms are similar to all target firms in terms of size (measured by market equity and book assets) and leverage. However, targets matched with the Census data tend to hold less cash, pay more dividends, have lower valuation ratios (i.e., q), lower sales growth rates, spend less on R&D, and are more profitable than the full sample of activism target firms. These characteristics suggest that firms that are matched to the Census databases generally have worse growth opportunities but enjoy better cash flows. In addition, we note that these differences in firm characteristics should reflect the difference in industry composition between the two samples: A great majority of the Census-matched firms are concentrated in the manufacturing sector whereas less than 30% of all targets are in the sector.

3. Hedge Fund Activism, Productivity, and Product Market Competition

3.1 Plant and Firm Level Analyses

As a first step, we examine the impact of hedge fund activism on target firms' productivity and profitability at the plant level. Our main dependent variable is plant-level total factor productivity (TFP) computed as the estimated residual of a log-linear Cobb-Douglas production function regression at the SIC three-digit industry-year level as in equation (1).[10] Our TFP measure can be understood as the relative productivity rank of a plant within its industry-year. Moreover, by construction, the TFP of an industry in a given year, averaged over all plants, is zero. The second dependent variable is plant-level operating profit margin, defined as total output minus material and labor costs scaled by total output. The resulting regression specification is as follows:

$$y_{it} = \sum_{k=-2}^{2} \gamma_k d_{it}[t+k] + \lambda Control_{it} + \alpha_j + \alpha_t + \varepsilon_{it}. \tag{5}$$

The key independent variables in equation (5) are a set of year-plant dummy variables, *d[t-2], d[t-1], d[t], d[t+1], d[t+2],* corresponding to plan-year observations from two years before to two years after a firm, to which the plant belongs to, is targeted by a hedge fund activist. A plant is necessarily part of the target company during year *t* if the observation has *d[t]* equal to one. Similarly, we require that the plant is owned by the target in year $t+k$, $0 < |k| \leq 2$ for *d[t+k]* to be coded one. Hence this specification analyzes the dynamics of performance of plants that remain in the hands of the target companies before and after hedge fund targeting. Section 4 will separately examine the effects of ownership changes on productivity.

Control variables include segment and firm size, measured by the log number of plants in a given industry segment of a given firm and the log number of all plants of a given firm, respectively. Plant age is defined as the number of years since a plant's first appearance in the CMF or ASM database. The starting year is censored in 1972 when the coverage of Census databases begins.[11] This set of control variables is standard among research that analyzes plant-level performance using the CMF and ASM data (e.g., Schoar (2002), Giroud (2011)). Finally the estimation takes into account industry and year fixed effects (α_j and α_t).[12]

[10] While this specification is a standard in the literature (see e.g., Lichtenberg and Siegel (1990), Lichtenberg (1992), Schoar (2002), Bertrand and Mullainathan (2003), Giroud (2011)), we also examine the robustness of our main results to an alternative specification (i.e., a translog functional form) in Section 3.3.

[11] The CMF database is also available in 1963 and 1967, but the ASM is not available in the "non-Census years" between 1964 and 1972. Hence, it is possible to track each plant *continuously* only from 1972 and onwards.

[12] Industry fixed effects are excluded when the dependent variable is TFP given that the computation of TFP already accounts for industry fixed effects.

Table 4 reports regression results at the plant-year level (columns 1 and 2) as well as at the firm level (columns 3 and 4). In columns 3 and 4, plant-level TFP is aggregated to the firm level using beginning-year capital stock as a weight and the number of plants per segment is the average across segments for a given firm. All four specifications in the table demonstrate a "V"-shaped dynamics of performance for plants owned by firms targeted by activists. That is, the productivity and profit margin of targets of hedge fund activism experience a deterioration prior to targeting and then rebound steadily afterwards. In particular, column 1 shows that the improvement in productivity from the year of targeting to two years afterwards is statistically significant at the 10% level. Column 2 shows that changes in operating margin are not significant at a conventional level. Firm-level changes in columns 3 and 4 are qualitatively similar to the plant-level changes, although the statistical significance is generally weaker for the firm-level results. The economic magnitude of the improvement in plant-level TFP due to activism is sizeable: a typical target plant experiences an increase in TFP of 0.056 from year t to year t+2, which amounts to 6.3% of the standard deviation (0.90). This pattern echoes the findings in Brav et al. (2008a) of improved performance at target firms after the intervention based on return on assets and profit margin as dependent variables.

[Insert Table 4 here.]

In addition, the positive coefficients on the targeting dummies suggest that plants owned by target firms are generally more productive and profitable than their industry-size-age matched peers, consistent with Brav et al.'s (2008a) finding that hedge funds tend to target mature firms with relatively strong cash flows but may be subject to agency problems of free cash flows. These firms experience deterioration due to bad governance or mismanagement such as poor adaptation to market changes. The deterioration triggers activist targeting, and is more or less reversed within the two-year period post targeting. The dynamics of plant-level productivity is hard evidence for changes in the fundamental value of firms associated with hedge fund targeting. In addition, it refutes the assertion that the positive returns to hedge fund activism can be attributed solely to financial gains (such as extracting payouts to shareholders through leverage).[13]

A growing body of recent work highlights the interactive effects of product market competition and corporate governance. Bauer, Braun, and Viehs (2010) show that lack of industry competition in combination with managerial entrenchment increases the likelihood of activist shareholder proposals. Kadyrzhanova and Rhodes-Kropf's (2010) theoretical model concludes that industry concentration affects the trade-offs of governance for shareholders. Giroud and Mueller (2010, 2011) show that anti-takeover laws have a more negative impact on shareholder value in non-competitive industries; and relatedly, firms

[13] See, for example, "Hedge Fund Activists Set for Comeback," *Financial Times,* December 8, 2009.

in noncompetitive industries benefit more from good governance as measured by the Gompers, Ishii, and Metrick (2003) governance index.

The body of work reviewed above has not uncovered the relation between product market competition and governance in the form of hedge fund activism. To this end, we extend the analysis in Table 4 to incorporate the interactive effects of product market competition, proxied by the Herfindahl-Hirschman Index (*HHI*) of output value computed at the SIC three-digit level as described in equation (3). Results are reported in Table 5 where the interactive terms $d[t+k] \times HHI$, $-2 \leq k \leq 2$ are added to the baseline regression.

[Insert Table 5 here.]

The key message of Table 5 is conveyed in the last six rows where we test whether the difference between the coefficients on *d[t+2]* and *d[t]*, for example, and the differences between the interaction terms with *HHI* are significantly different from zero. The first difference captures the plant-level productivity and profitability gain in year *t+2* over year *t* for the most competitive industries (where *HHI* is close to zero). For the target firms in the most competitive industries, production efficiency and operating profitability improve by 0.100 and 0.010, respectively, in the two-year period post-activism compared to the level in the year of activism. The second difference assesses the slope of the first difference along varying levels of *HHI*. While not statistically significantly at a conventional level, these negative differences between dummies interacted with HHI indicate that the gain in plant performance deteriorates as industries become less competitive. In other words, hedge fund activism is more effective in improving production efficiency in competitive industries, suggesting that product market competition and corporate governance are complements in this context. The result for the difference between the coefficients on *d[t+2]* and *d[t-1]*, and the difference between interaction terms with *HHI* shows a qualitatively similar pattern.

One natural question that arises from this result is: Why do hedge fund activists target firms in non-competitive industries given that the effect of activism on productivity appears to generate insignificant efficiency gains? In fact, and perhaps surprisingly, we find that hedge funds are slightly more likely to target less competitive industries using Compustat as well as Census data (see also Giroud and Mueller (2011) for similar evidence). One possible explanation for this result is that hedge fund activists create value in different ways in competitive versus concentrated industries. In particular, Raith's (2003) theoretical model shows that the benefit of improved efficiency (due to better governance or incentives) is higher in competitive industries in which the firm-level demand function is relatively elastic, and thus a marginal improvement in efficiency leads to a large increase in output and profits ("business stealing effect"). Therefore, activists might want to focus on improving productivity in competitive industries. In concentrated industries, however, the benefit of productivity gains is not as large due to relatively inelastic demand curves, and so activist hedge funds could instead focus on allocational, financial and governance-related improvements.

Consistent with this hypothesis, we find that hedge fund activism leads to a larger increase in dividend payout, CEO turnover rates, and leverage ratios in concentrated industries compared to competitive industries using the Compustat data (unreported). This evidence supports the view that in concentrated industries, activists *optimally* focus on aspects of target firms other than production efficiency, such as capital structure and corporate governance.

Our results offer a different perspective on Giroud and Mueller (2010) who find that the passage of business combination laws (which delay takeovers) led to a larger drop in the operating performance of firms in non-competitive industries. While Giroud and Mueller (2010) support substitutability between competition and takeover pressure in mitigating managerial slack, we uncover a complementary effect between product market competition and governance in the form of hedge fund activism. It is worth noting that the theory in this context is ambiguous. While competition requires high effort to avert failure (Schmidt (1997)) and leads to strong managerial incentives because outcomes are more informative (Hart (2003)), it also reduces profits which makes effort less attractive (Schmidt (1997) and Raith (2003)). Therefore, this relation is ultimately an empirical question. Our results indicate that efficiency gains due to good governance and incentives are more beneficial in more competitive industries, suggesting that the "business stealing effect" as in Raith (2003) dominates.

Our findings also highlight the difference between control driven (e.g. takeovers) and non-control driven (e.g. activism) forms of market-based governance, especially in their interaction with product market competition. In fact, the role of takeover defenses (which underlie common governance measures) is quite different in the context of hedge fund activism. While they are meant to deter takeovers, firms with more of these defenses stand a higher chance of being targeted by hedge fund activists (Brav, Jiang, and Kim (2010)).

3.2 The Industry Impact of Hedge Fund Activism

The previous section illustrates the differential effects of hedge fund activism on target firms sorted by the competitiveness of the industries that the target firms' plants belong to. The analysis invariably benchmarks event firms against their industry peers in order to filter out the common shocks to an industry. However, to the extent that the hedge funds' impact spills over to the rest of the industry, the effect on the target firms that we find above might be under- (or over-) estimated if the spillover effect on non-target industry peers is positive (or negative), on average.

We therefore attempt to estimate the association between hedge fund activism and changes in industry-level productivity and profit margin, excluding the targets themselves, using the following regression specification:

$$\Delta y_{j,t-1:t+2} = \beta_1 TargetShare_{j,t} + \beta_2 HHI_{j,t} + \beta_3 TargetShare_{j,t} \cdot HHI_{j,t} + \gamma Control_{j,t} + \alpha_j + \alpha_t + \varepsilon_{j,t} . \quad (6)$$

In equation (6), the unit of observation is the three-digit SIC industry (*j*) -year (*t*) pair, where plants belonging to firms targeted by activists in each year are excluded from their industry portfolios. For each activism industry-year, we track the changes in performance (productivity or profit margin) of the industry (excluding target companies) that the targets belong to from one year before to two years after the targeting. The resulting $\Delta y_{j,t-1:t+2}$ is the dependent variable.

The independent variable of interest is $TargetShare_{j,t}$, a proxy for the intensity of hedge fund targeting in a given industry and year, defined as the market share (measured by sales in dollars) of companies targeted in year *t* in industry *j*. Conditional on targeting, the market share of targeted companies in an average industry-year is 2.29%, with a standard deviation of 4.73%. The unconditional (i.e., including industries with no hedge fund activist presence) mean is 0.25%.

Following the discussion in Section 3.1, we further interact $TargetShare_{j,t}$ with *HHI*, the industry Herfindahl-Hirschman index of sales, to explore the effect of product market competition. The control variables that we include which are common practice in the literature (Schoar (2002), Giroud (2011)) are the average segment and firm sizes (measured by the log mean numbers of plants per segment and firm, respectively), and the average plant age. The exact specification of the control variables is not crucial since they are mostly insignificant in the regression. Finally, α_j and α_t are industry and year fixed effects, respectively. Results are reported in Table 6.

[Insert Table 6 here.]

Columns 1 and 3 show a negligible effect of $TargetShare_{j,t}$ on the performance of non-target industry peers. That is, the presence of hedge fund activists in a given industry has no significant impact on the non-targeted companies unconditionally. However, interacting the market share of targeted companies with the product market competition yields a negative cross-sectional effect, which is significant at the 5% (10%) level using productivity (operating margin) as the dependent variable (tabulated in columns 2 and 4). This result indicates that the effect of hedge fund activism on non-targets in the same industry increases with the degree of product market competition. For example, the spillover effect increases more than two-fold when we move from the typical industry (0.509 = 1.238 - 18.232 × 0.04, at the mean of HHI) to an industry that is one standard deviation (0.04) more competitive than the mean industry (1.238 = 1.238 - 18.232 × (0.04-0.04)).

Relatedly, the coefficient on $TargetShare_{j,t}$ is significantly positive in the productivity regression in the presence of its interaction with the HHI, revealing a positive spillover effect of hedge fund targeting on non-targets among the most competitive industries (where *HHI* is close to zero). This result echoes the previous result that supports a complementary relation between product market competition and governance in the form of hedge fund activism. The analogous effect on the operating margin turns out to be insignificant (albeit of the same sign), possibly reflecting the difficulty to improve operating margin for a whole industry that is highly competitive. In addition, the direct effect of *HHI* is significantly negative both in columns 2 and 4, consistent with the common understanding that competition promotes performance growth (see Nickell (1996) and references therein).

The results in Table 6 offer some new insights into those of Table 5, and into event studies of hedge fund activism based on industry benchmarks in general. To the extent that activism exerts disciplinary effects on untargeted peer firms in competitive industries, the *overall* impact on the targeted firms is larger than the estimated improvements benchmarked to their counterparts in the same industry. Our results also corroborate the study by Fos (2011) who finds that the mere increase in the *likelihood* of a proxy contest has a positive performance consequence for ex post non-targets, and that by John and Kadyrzhanova (2009) who emphasize the importance of governance standards at the industry level as a determinant of managerial entrenchment at the individual firm level.

Anecdotes confirm this industry spillover view. In 2008 Wendy's and Arby's were pushed by Trian Fund Management to jettison underperforming brands and focus on better assets. Following these developments several other fast-food companies openly announced that they were seeking to reposition themselves. Notably Yum Brands Inc. sought to spin off its Long John Silver's and A&W All-American Food Restaurants in order to focus on Pizza Hut, Taco Bell and KFC. Non-targets took such actions not only to preempt future attacks by activists, but also to compete with targets which were now presumably leaner and stronger (i.e., more efficient).

In light of the results in Table 6, we should therefore view the estimates reported in Table 5 for the productivity gain of targeted companies in the most competitive industries as being conservative.

3.3 Robustness Checks

In this section, we examine the robustness of the baseline results demonstrating the impact of hedge fund activism on the productivity of plants owned by target firms as well as their non-target industry peers. First, we examine the robustness to an alternative specification of a production function to estimate TFP. In particular, we estimate the production function using a translog functional form that allows second-order terms of inputs including interactions between them. This specification is a generalization of the Cobb–Douglas production functional form used in our baseline model in equation (1) and a second-order approximation to any arbitrary production function (Maksimovic et al., (2010)). Specifically, we estimate the following production function using Ordinary Least Squares (OLS) regressions by three-digit SIC industry and year:

$$\begin{aligned}\ln(Y_{ijt}) = \\ & \alpha_{jt} + \beta_{jt}^{K}\ln(K_{ijt}) + \beta_{jt}^{L}\ln(L_{ijt}) + \beta_{jt}^{M}\ln(M_{ijt}) + \beta_{jt}^{KK}\ln(K_{ijt})\ln(K_{ijt}) + \\ & \beta_{jt}^{LL}\ln(L_{ijt})\ln(L_{ijt}) + \beta_{jt}^{MM}\ln(M_{ijt})\ln(M_{ijt}) + \beta_{jt}^{KL}\ln(K_{ijt})\ln(L_{ijt}) + \\ & \beta_{jt}^{KM}\ln(K_{ijt})\ln(M_{ijt}) + \beta_{jt}^{LM}\ln(L_{ijt})\ln(M_{ijt}) + \varepsilon_{ijt}, \qquad (7)\end{aligned}$$

where α_{jt} is industry-year specific intercept, Y_{ijt} is output, K_{ijt} is net capital stock, L_{ijt} is labor input, M_{ijt} represents material costs, and ε_{ijt} is the residual, and hence our estimate of TFP for plant *i*, in industry *j* in year *t*.

[Insert Table 7 here.]

Panel A of Table 7 shows the estimation results. The basic patterns that emerge from this panel are very similar to those from our baseline results in Tables 4 and 5. The productivity of target plants shows a "V"-shaped pattern around the year of hedge fund intervention, and this effect is more pronounced for more competitive industries. In particular, the increase in TFP from years t to t+2 is statistically significant at the 10% level in column 1. In addition, the economic magnitude of these results is comparable to that in Tables 4 and 5.

Next, in Panel B we employ alternative measures of product market competition, in addition to the HHI for the three-digit SIC industry used in our main analysis. Specifically, we use a dummy for concentrated industries which is equal to one if an industry has an HHI within the largest quartile and zero otherwise (column 1), the HHI computed at the Fama-French 48 industry level (column 2), and industry-level net profit margin (column 3). The results across all specifications confirm our main results though the overall significance is lower.

4. Capital Reallocation and Attrition Analyses

4.1 Identifying Gains Due to Reallocation of Assets: Compustat versus the Census Data

To the extent that hedge fund activists help enhance production efficiency of the targeted firms (and industries), an equally important question is whether such improvements are accomplished through improving the efficiency of assets in place or through capital reallocation. In fact, efficient redeployment of capital is a commonly stated goal of activist hedge funds. In addition to the events in which hedge funds explicitly demand sales of the entire target company (about 20% of the events), in another 15% of the events the activists push for the divestiture of under-performing or non-core assets in order to strengthen and refocus on the companies' core lines of business. Anecdotal evidence (such as the one referenced in Section 3.2) also points to capital reallocation as an important mechanism for the value added by the activist hedge funds.

Prior literature has offered some indirect evidence for the extent of the gain from capital reallocation. Brav et al. (2008a) and Greenwood and Schor (2009) show that announcement returns of hedge fund activism are largest among events in which the stated goal is to push the sale of the targets. Brav et al. (2008a) also document a significant positive correlation between target firms' industry-adjusted changes in assets and their industry-adjusted changes in ROA post intervention. Both results suggest that activist hedge funds help create shareholder value through efficient reallocation of capital.

However, the analyses in the previous literature are limited by the scope of CRSP/Compustat data. First, performance measures computed using Compustat firm-level data do not isolate organic improvement (i.e., productivity gains of existing assets) from re-allocational gains (i.e., due to acquisition/disposition of better/worse performing assets). The Census data, which is recorded at the plant level and hence survives ownership changes and firm delisting, allows us to separate the two effects. Indeed, we are able to show that plants that change ownership post targeting (i.e., are spun off) performed worse than their industry peers one year prior to their sale, suggesting that hedge funds are effective at facilitating the divestiture of underperforming assets.

Second, a Compustat firm will drop out of the database if it is acquired by another company (public or private), or is delisted (i.e., going private). Brav, Jiang, and Kim (2010) document a non-random distribution of target firms' attrition from the Compustat database: Within two years after being targeted by hedge funds, 18.6% of the targets cease to be covered by Compustat (a proxy for delisting), a rate that almost doubles the average attrition rate of typical Compustat firm. Therefore, addressing the potential delisting bias is challenging, particularly given that the direction and magnitude of the bias is a priori unclear.

Firm delisting is usually associated with negative reasons (Shumway (1997)). Accordingly, analyses based on the surviving sample tend to carry a positive bias. However, such an intuition might not apply to the hedge fund activism target firms because attrition from the sample may actually represent a successful outcome for the following reasons. First, targeted companies tend to have stronger fundamentals (higher productivity, ROA, and liquidity, as shown by Brav et al. (2008a) and Table 4 of this paper), and hence the subsequent attrition is less likely due to distress compared to firms delisted without the intervention of hedge fund activists. Moreover, the "sale of the company" objective category experiences the highest attrition rate (31.0%), where the ex post sale of a target firm reflects a successful execution of the stated goal of the hedge fund. In fact, using analyst coverage and trading liquidity as instruments, Brav, Jiang, and Kim (2010) uncover a negative survivorship bias due to delisting from Compustat. That is, firms that will experience greater improvement in performance post intervention are also more likely to disappear from the Compustat database conditional on observable characteristics.

The Census data allows us to pin down the direction and magnitude of the attrition bias by following targeted plants regardless of the listing status of the firms they are affiliated with. The analyses that follow provide direct evidence consistent with a negative survivorship bias. That is, plants belonging to firms that were delisted from Compustat post targeting experience greater productivity gains than those that remain in the database.

4.2 Ownership Change of Plants

By focusing on plants that belong to targeted companies prior to activism but were later spun off, we attempt to identify gains in efficiency via asset redeployment facilitated by the activists. In Table 8 Panel A, we re-run the regression presented in equation (5) but do not restrict the ownership of plants by the targeted companies in the two years before and after targeting. Instead, the dummy variable $d_{i,t}$ $[t+k]$, $k = -2, -1, +1, +2,$ assumes the value of one as long as the plant is owned by the target company during the year of targeting (year t). In contrast, the analysis in Table 4 requires the ownership of the plant by the target company in *each* of the years for the corresponding plant-year event dummy to be coded as one.

[Insert Table 8 here.]

It is apparent from Panel A that the post-targeting performance change for these broadly defined event plants is worse than those reported in Table 4 for plants owned by target firms in each year from t-2 to t+2. Specifically, plants owned by targeted firms in the year of activism show a deterioration in performance (measured by both TFP and operating margin) until one year after the intervention (i.e., t+1). The negative change from t-1 to t+1 is statistically significant at the 5% level for TFP. The difference between the results in Table 4 and Table 8 Panel A is due to plants that were owned by the target companies in the year of targeting but then sold over the subsequent two years. Thus, this contrast in results suggests that worse-performing plants were more likely to be sold after hedge fund intervention. However, to make the efficiency gain argument in favor of hedge fund intervention, one must also observe an improvement in the performance of sold plants in the hands of new owners. To this end, we re-run the regression in equation (5) but redefine an event as the sale of a plant by a firm that was targeted by hedge fund activists in the year of activism or within two subsequent years (i.e., from t to $t+2$). Usually an event of plant sale in this specification lags the corresponding event of hedge fund targeting by two years.

Table 8, Panel B shows that plants that are sold post-activism exhibit a sharp "V"-shaped pattern of performance around their sales. In particular, those plants had productivity that is statistically equivalent to that of their industry-size-age benchmarked peers two years before their sale, but were sold at their trough in terms of performance. Subsequently, both the efficiency and profitability of the plants experience a statistically and economically significant improvement in the hands of the new owners: The change in TFP (operating margin) from years t to $t+2$ is statistically significant at the 5% (1%) level, and this improvement is equivalent to 19% (36%) of its standard deviation. Taken together, the patterns in both panels of Table 8 are consistent with the view that firms divest underperforming assets after hedge funds' intervention, and that the sold plants are passed along to owners who can operate them in a more efficient and profitable manner. These results help validate the stated goals of hedge funds in many activism events and generalize the anecdotes of Trian Fund and Wendy's/Arby's mentioned in Section 3.2.

4.3 Delisting from Compustat

Our Census sample includes plants belonging to 305 companies that were targeted by hedge funds between 1994 and 2007. Within this sample, 91 companies disappear from Compustat within two years after being targeted because they were sold, taken private, or liquidated. Among this sample of attrition firms which posts challenges on any analyses using the Compustat data, we are able to follow 191 plants owned by 53 firms that delisted from Compustat post-targeting. These additional observations from the Census data allow us to assess the sign as well as the magnitude of the attrition bias associated with using the Compustat data.

[Insert Table 9 here.]

In Table 9, we report results from regressions that interact the dummy variables $d_{it}[t+k]$, $-2 \leq k \leq 2$ with an indicator variable, *Attrition (Non-attrition),* which is equal to one if a plant belongs to a company targeted by hedge funds and then is delisted from (remains in) the Compustat database during the two years afterwards. The bottom of the table reports the test for performance improvement among the plants of companies remaining in the Compustat database (e.g., H_0: *(d[t+2] – d[t]) × Non-attrition) = 0*). While the changes are generally positive, we cannot reject the hypotheses that there is no improvement from one year before targeting to two years post-targeting. Interestingly, when we focus on the plants that belong to companies that were delisted from Compustat during the two-year post-targeting period (e.g., H_0: *(d[t+2] – d[t]) × Attrition) = 0*), we find a significantly positive improvement at the 5% level. The economic magnitude of this change is significant compared to that for the non-attrition targets: The improvements in TFP and profit margin are four to five times larger for the attrition target plants than those for the non-attrition targets (e.g., the change in TFP from *t* to *t+2* is 0.169 vs. 0.036).

The combination of the two tests in Table 9 for performance changes suggests an unusual negative survivorship bias. That is, restricting the measurement of performance to the sample of surviving firms in Compustat tends to underestimate the change in performance of target firms. This result is consistent with the analysis of non-random attrition of hedge fund activism targets in Brav, Jiang and Kim (2010) using an instrumental variable approach. Moreover, given this result, the performance (such as ROA) improvement documented in Brav et al. (2008a) and Klein and Zur (2009) should be viewed as a lower bound.

Needless to say, the Census data have their own attrition issues. About 35% of the plants that appear in our sample before hedge fund targeting disappear afterwards. There are two reasons for the attrition. First, "small" plants (with fewer than 250 employees) are not sampled every year in the ASM (but, all operating plants are sampled in the CMF for the years ending '2' and '7') so that they might disappear from the sample (possibly temporarily), but in fact could still operate. This attrition bias is purely due to random sampling and therefore should not bias results in either direction. Second, the plants that are liquidated drop out of the sample simply because they cease to exist. The two-year attrition rate for target plants is 16%, while it is 27% for all other plants in the sample (i.e., control plants). This finding is consistent with the result in Section 3.2 that target plants tend to be larger, older, and more productive than the full sample of plants.

5. Efficiency and Time Varying Systematic Risk Around Hedge Fund Activism

The announcement of hedge fund activism, which is typically observed at the time hedge funds file a Schedule 13D with the SEC, leads to a large positive price reaction of approximately 6% (Brav et al. (2008), Klein and Zur (2009), Clifford (2008) and Greenwood and Schor (2009)). This revision in beliefs is consistent with the idea that market participants anticipate that intervention will benefit the target firm's shareholders. This benefit, however, can accrue through two channels. The first – the "cash flow channel" - links the activist's stated goals to the firm's operating performance. The combined evidence from earlier work based on changes in operating profitability (Becht et al. (2009), Brav et al. (2008), Boyson and Mooradian (2007) and Clifford (2008)), and the more detailed plant-level analysis in the preceding sections, is consistent with the market's positive reaction to the intervention.[14]

In this section we consider the possibility that the positive price reaction at the time the market learns of a new activist intervention reflects anticipated changes in future discount rates – a "discount rate channel." Specifically, we ask whether the activist's intervention is also associated with a decline in target firms' systematic risk in the post-intervention period. Here we lean on the idea that changes in firm investment decisions are linked to time-variation in expected rates of returns (Carlson, Fisher, and Giammarino (2004), Zhang (2005), Li, Livdan and Zhang (2009)). For example, Novy-Marx (2011) argues that the return premia earned by "value" firms relative to "growth" firms is driven by the former's relative inefficiency as low margin producers and thus their higher sensitivity to negative economic shocks. To the extent that activists' intervention leads to improved margins at underperforming target firms, we should observe a decline in expected rates of return post-event. Similarly, Imrohoroglu and Tuzel (2011) find that the annual return spread between high and low productivity firms is 6.3%. They conclude that low productivity firms that tend to be small value firms (as our target firms) with low asset growth and profitability, are riskier and thus command a risk premium. They propose a mechanism whereby low productivity firms bear higher costs relative to high productivity firms due to their inability to quickly adjust to negative aggregate shocks and thus have a lower valuation and higher expected return. Since the evidence that we have presented in section 3 is consistent with an increase in firm productivity post-activism the prediction from Imrohoroglu and Tuzel's (2011) framework is that expected returns should decline post-activism. This is indeed what we observe below.

The analysis in section 3.1 also shows that changes in firm efficiency occur predominantly in competitive industries. Interestingly, Imrohoroglu and Tuzel's (2011)) findings are much stronger in low concentration industries as well; in fact, their main result turns insignificant in high concentration

[14] An alternative "cashflow" channel by which shareholders might benefit from activists' actions is the potential wealth transfer from other stakeholders. Brav et al. (2008a) examine two important groups of stakeholders: creditors and senior management represented by the CEOs. They find little evidence to support the view that shareholders of the target company gain at the expense of the creditors by increasing leverage and lowering the debt rating. Aslan and Maraachlian (2009) reach a similar conclusion. Brav et al. (2008a) do find support for the view that some of the positive price reaction may be driven by changes in governance that lead to better monitoring of senior management. They find that activists are successful in forcing out entrenched CEOs, reduce the pay of the ones that stay, and alter their compensation to have higher pay-for performance sensitivity.

industries.[15] We therefore ask in the second part of this section whether the documented changes in systematic risk are indeed concentrated in competitive industries.

5.1 Changes in systematic risk

The empirical setup underlying our tests of the hypothesis that systematic risk declines in the post-activism period is based on changes in factor loadings estimated from calendar-time portfolio regressions around the Schedule 13D filing month. We employ the full sample of 1,141 activism events over the period 2001-2007 and form four portfolios as follows. The first portfolio is formed by buying all firms that will be targeted by a hedge fund in three-year's time and hold these target firm shares until one year prior to the activism. This portfolio is labeled as (-36, -13) in Table 10.

[Insert Table 10 here.]

A second portfolio, labeled (-12, -1), is formed by buying all firms that will be targeted by hedge funds in one year's time and these target shares are held for eleven months up to one month prior to the targeting. The remaining two portfolios, (+1,+12) and (+13,+36) are formed similarly. For example, the portfolio with holding period (+1,+12) continually adds target firms that have had an activist event in the preceding month and holds these firms through a year after their respective activism events. For each of these four portfolios we estimate a regression of the portfolio excess returns on the Fama-French RMRF, SMB, and HML factors and the momentum factor, MOM.[16] We then focus on changes in the slopes on the risk factors and, in particular, the factor loading on HML, as evidence for possible changes in systematic risk. Clearly, all portfolios in the pre-event windows do not represent a tradable strategy. They are presented for an ex post analysis of the stock return patterns of target companies in the pre-targeting period. We present results in Panel A of Table 10 using four-factor models with equal and value-weighting of firms' returns. "Alpha" is the estimate of the regression intercept. "Beta" is the factor loading on the market excess return (the Fama and French RMRF). "SMB," "HML," and "MOM" are the estimates of factor loading on the Fama-French size and book-to-market factors, and the Carhart momentum factor, respectively. "R2" is the adjusted R2 from the regressions and "N" is the number of monthly observations. We set a minimum of ten firms per month for all portfolios.

Several key patterns emerge from the estimates reported in panel A. First, the positive factor loadings on both SMB and HML indicate that targeted companies commove with small value firms, consistent with their characteristics (Brav et al. (2008a)). Second, targeted firms underperform in the pre-event period. The negative alphas are large and significantly negative when we value-weight during the

[15] Private correspondence with the authors.
[16] We obtain these factor returns and monthly risk-free rates from Ken French's web site at Dartmouth College.

entire three-year period preceding the intervention. We observe lower magnitude of underperformance when we equal weight and only in the year preceding the activism. Importantly, there is no abnormal return drift in the three-year post-event period (Schedule 13D filing or the first announcement of activism for non-13D events) consistent with an unbiased market reaction to the announcement of hedge fund activism.

Third, the portfolios' market beta and slopes on both SMB and MOM show little systematic variation moving from left to right across the four portfolio specifications. However, the factor loadings on HML show a clear "inverted-U" pattern. In the value-weight regressions the factor loading on HML for portfolio (-36, -13) is 0.203, reaching a high of 0.524 in the year preceding the intervention. The HML factor loading then decline to an insignificant low of 0.104 by three years post-intervention. The equal weight regressions yield a similar pattern although the highest HML slope of 0.636 is reached in the first year post-activism and then declines to an insignificant 0.158. The magnitude of this reversion is economically large. The sample average annual return on the Fama and French HML portfolio over the period 1927-2010 is 4.9 percent and is only slightly lower at 4.6 percent for the most recent decade. Hence, a decline in slopes of roughly 0.3-0.4 translates into a decrease of 1.5% - 2% in the target firm expected annual rate of return – clearly, a large enough change that could drive some of the event-day price reactions.

The preceding evidence is consistent with the idea that target firms turn more "value" prior to being targeted and by the time activists choose to intervene their sensitivity to the systematic variation in HML is close to its peak. This sensitivity then declines over the ensuing three years post-activism. However, it may very well be the case that these changes reflect the evolution of systematic risk that is shared by other non-target firms and thus perhaps is driven by non-activism related economic forces. To examine this possibility we next present in panel B tests that are designed to compare the dynamics of the HML slopes of targeted and non-targeted matched samples. We form two matched benchmark portfolios. The first is an industry benchmark formed by matching each target firm to one of the corresponding Fama and French 48 value-weight industry portfolios. The second is an industry, size, and book-to-market-based benchmark portfolio.

Consider first the Fama-French industry benchmark. To test whether the evolution of the factor loadings on HML mimic those of the corresponding industry we proceed as follows. For each of the four time frames considered earlier, (-36, -13), (-12, -1), (+1,+12) and (+13,+36), we form a zero-cost portfolio that is long in target firms and short in the industry benchmark portfolio. The long side of each of the zero-cost portfolios is just a portfolio that was used earlier in panel A. The short side is formed by first matching each target firm to one of the corresponding Fama and French 48 value-weight industry portfolios and then either equal- or value-weighting the benchmark industry returns. We test for differences in factor exposures between target firms and their respective industries by asking whether the estimates of the portfolios' factor loadings are significantly different from zero.

The evidence in panel B highlights several differences that are worth noting. First, target firms underperform relative to their industry in the period preceding the activism and as in panel A the underperformance is stronger in the value weight regressions. Second, target firms have a much higher exposure to SMB for all four portfolios. This is of course not surprising given that targets are typically small firms whereas our benchmark is a value-weight industry portfolio. We control for size differences with the characteristic-based benchmark below. Third, an examination of the slopes on HML shows that the inverted-U shape pattern observed in panel A is not driven by industry-wide effects. In the value-weight specification the factor loading is 0.114 and insignificant in the period (-36, -13) but then peaks at 0.416 in the first year post-activism. The difference declines back to 0.157, a level similar to the one prior to the activism, in the post-event period (+13,+36) and remains significant. In the equal weight regressions we observe a similar pattern. Future targets have a higher loading of 0.226 on HML in the period (-36, -13) and this difference peaks at 0.658 in the first-year post-activism. We then see, again, a decline in the zero-cost portfolios' exposure on HML to 0.225 – essentially the level observed at the outset in the period (-36, -13).

Since the industry-wide benchmark does not control for firm specific characteristics that may better capture the time-variation in factor loading, we next proceed in panel C and form zero-cost portfolios that are long in target firms and short in an industry and characteristic-based benchmark portfolio. The benchmark is formed by first matching each target firm with non-target replacement firms with the same 3-digit SIC code. We retain firms whose market capitalization is within 50%−150% of the target firm's market capitalization. Next, we further narrow down the list of benchmark firms to those whose book-to-market ratio within 75%−125% of the target firm's book-to-market ratio, measured in the year preceding the hedge fund activism. The last step is to value weight the remaining benchmark firms. As in panel B we form both equal- and value-weight zero-cost portfolios that are long in the target firms and short in the matched non-target firm returns. Panel C provides the calendar-time regression results.

As before, we observe that target firms underperform relative to their benchmark in the pre-event period in the value-weight specification. The equal-weight regressions show little evidence of underperformance. In addition, the matching by market capitalization now generates no significant differences in loadings on SMB throughout the four periods we examine in both equal- and value-weight specifications. More notably, although we control for book-to-market, we can still observe how target firms' slope on HML is significantly higher than the matched firms in the years before and after the targeting. This evidence suggests that target firms' reversion in sensitivity to the information captured by HML contains a component that is not shared by other non-targets. This difference turns insignificant by the second and third year post-activism.

5.2 Risk changes conditioned on the degree of product market competition

The results in Section 3.1 show that changes in firm efficiency occur predominantly in competitive industries. We now ask whether a matching industry pattern could be observed in the changes in target firms' systematic risk.[17]

[Insert Table 11 here.]

The estimation strategy mimics that in Table 10. However, we now also condition on the degree of competitiveness of the target firm's industry using its Herfindahl-Hirschman Index ("HHI"). The HHI index is formed as in the previous analysis at the 3-digit SIC level. Table 11 reports regression estimates from equal- and value-weighted calendar-time portfolio regressions by sorting target firms into "competitive" and "non-competitive" industries. An industry is classified as competitive (non-competitive) if its HHI index is lower (higher) than the 25th percentile of industry HHIs in a given year. HHI classifications are lagged by one year. The choice of this 25th percentile is driven by the need to have a sufficient number of observations in both portfolios, as we are now adding one more conditioning variable to our regressions. Panel A provides results for competitive industries (low HHI) while panel B provides results for targets in non-competitive industries (high HHI). Within each panel and weighting scheme we report target firm long only portfolio regression results and results in which we take a long position in a target firm portfolio and short a value-weight portfolio of benchmark firms formed by matching based on 3-digit SIC code, size and book-to-market ratio as in panel C of Table 10. We set a minimum of ten firms per month for all portfolios.

Several key results on factor loading are worth noting. In the zero-cost regressions in which we go long in target firms and short the benchmark portfolio, the slopes on the market portfolio, SMB and MOM are economically small with no discernible pattern across the four time-periods both for competitive and non-competitive industries. However, it can be seen that the inverted-U shape pattern on HML in these regressions is economically large and significant only when we consider the competitive industries in panel A. In the value weight regressions the zero-cost HML slope peaks at 0.526 in the year leading up to the activism and in the equal-weight specification the slope peaks at 0.478 in the first year

[17] Most theoretical work linking optimal firm investment and risk dynamics does not condition on the extent of industry concentration. An exception is Aguerrevere (2009). In his model, when demand is low, firms in more competitive industries earn higher returns since their assets in place are riskier than their growth options whereas when demand is high firms in more concentrated industries earn higher returns since their growth options are riskier.

post-activism, a pattern similar to that observed in the preceding table. The reversion in HML slopes is hard to detect when we look at targets compared to their benchmark firms in non-competitive industries. The value-weight specification yields HML slopes that are all economically very small while in the equal-weight regression we do see some degree of mean-reversion although all slopes on HML are insignificant.

We conclude from this analysis that activism in competitive industries is fundamentally different than that in more concentrated industries as it is associated with both higher target firm efficiency and a decline in expected rate of return in the post-event period.

6. Conclusions

Using plant-level observations from the U.S. Census Bureau we show that hedge fund intervention is associated with both productivity and profitability gains at the plants of the targeted companies and that this effect is stronger in more competitive industries. This outperformance is notable since we find that benchmark plants, those managed by non-targeted peers in the competitive industries, share some of this improvement as well. We also measure the performance of plants that were sold subsequent to the intervention and find that they were among the worst performing at the time of divesture but later experience a substantial improvement in the hands of new owners relative to a matched sample. These results support the view that hedge fund activists facilitate improvements in terms of both production efficiency and capital re-allocation.

We also show how the use of Compustat data to measure the performance of targeted firms is likely to lead to a downward bias in estimates of performance since target firms that experience greater improvement in performance post-intervention are also more likely to disappear from the Compustat database. Finally, we link the real effects to the target firms' expected return by empirically testing whether the positive price reaction at the time of the announcement of activism reflects an anticipated decline in future discount rates, building on the idea that the target firm's higher efficiency implies a decline in its sensitivity to negative economic shocks and thus lower systemic risk. Consistent with this view we find that target firms' sensitivity to HML-related factor risk peaks around the time of intervention and then declines predictably to that of matched control firms. This mean reversion is, again, mostly concentrated in competitive industries. Overall, the evidence provided in the paper highlights the real and fundamental effects brought about by hedge fund activists to their target firms as well as their industry peers.

Appendix A – Construction of Variables to Estimate Production Function

This appendix describes the construction of variables required to estimate the production function described in Section 2.2 using variables in the CMF and ASM databases. Output is computed as the sum of total value of shipments (TVS) and the net increase in inventories of finished goods and works in progress. To account for industry-level changes in output price, we deflate output using the four-digit SIC level output price deflator from the NBER-CES manufacturing database constructed by Bartelsman, Becker, and Gray (2000).

Capital stock is constructed using a recursive perpetual inventory formula (Lichtenberg (1992), Kovneck and Phillips (1997)). First, we obtain the initial value of nominal capital stock for each plant when the plant is born (identified using the LBD) or first appears in the CMF or ASM. Second, we translate this initial *historical* value of *gross* capital stock into a *constant* value of *net* capital stock using a NAICS-based industry-level capital stock deflator from the Bureau of Economic Analysis (BEA). Third, we account for changes in the price of capital by deflating the computed real, net capital stock using the four-digit SIC level investment deflator from the NBER-CES manufacturing database. Fourth, beginning with the constructed initial net capital stock in constant dollars for each plant, we accumulate capital stock going forward using the following recursive formula:

$$K_{it} = K_{it-1} \times (1 - \delta_{it}) + I_{it}, \qquad \text{(A-1)}$$

where K_{it} is net capital stock, δ_{it} is a two-digit SIC level depreciation rate from the BEA, and I_{it} is investment for plant i in year t. The measure of investment is deflated using the four-digit SIC level investment deflator from the NBER-CES manufacturing database. Before 1997, variables for investment were available separately for equipment and structure, and we thus construct capital stock separately for each category and then sum the two capital stock measures to obtain total capital stock. After 1997, only variables for total capital are available, and so we only construct total capital stock.

We use "production-worker equivalent hours" as our measure of labor input. Specifically, labor input is constructed as the total production worker hours times total wage bills divided by wage bills for production workers. The underlying assumption to construct this measure of labor hour is that the per-hour wage rates for production and non-production workers are similar. Lastly, material costs are computed as the costs of materials and parts plus the costs of fuel and electricity.

References:

Aguerrevere, Felipe, 2009, Real Options, Product Market Competition and Asset Returns, *Journal of Finance* 64:2, 957 – 983.

Bartelsman, Eric J., Randy A. Becker, and Wayne B. Gray, 2000, NBER-CES Manufacturing Industry Database.

Bauer Rob, Robin Braun, and Michael Viehs, 2010, Industry Competition, Ownership Structure and Shareholder Activism, 2010, Working paper, Maastricht University.

Becht, Marco, Julian Franks, Colin Mayer, and Stefano Rossi, 2009, Returns to shareholder activism: Evidence from a clinical study of the Hermes UK Focus Fund, *Review of Financial Studies* 22:8, 3093–3129.

Bertrand, Marianne and Sendhil Mullainathan, 2003, Enjoying the Quiet Life? Corporate Governance and Managerial Preferences, *Journal of Political Economy* 111, 1043-1075.

Boyson, Nicole and Robert M. Mooradian, 2007, Hedge funds as shareholder activists from 1994–2005. Working Paper, Northeastern University.

Brav, Alon, Wei Jiang, Frank Partnoy, and Randall Thomas, 2008a, Hedge fund activism, corporate governance, and firm performance, *Journal of Finance* 63:4, 1729-1775.

Brav, Alon, Wei Jiang, Frank Partnoy, and Randall Thomas, 2008b, The returns to hedge fund activism, *Financial Analyst Journal* 64, 45–61.

Brav, Alon, Wei Jiang, and Hyunseob Kim, 2010, Hedge Fund Activism: A Review, *Foundations and Trends in Finance*, 4:3, 185-24.

Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2004, "Corporate Investment, growth options, and security returns," *Journal of Finance* 54, 1153-1607.

Domowitz, Ian, R. Glenn Hubbard, Bruce C. Petersen, 1986, Business Cycles and the Relationship between Concentration and Price-Cost Margins, *RAND Journal of Economics* 17, 1-17.

Fos, Vyecheslav, 2011, The Disciplinary Effects of Proxy Contests, Working paper, University of Illinois.

Gantchev, Nickolay, 2011, The Cost of Shareholder Activism: Evidence from a Sequential Decision Model, Working paper, University of North Carolina.

Giroud, Xavier, 2011, Soft Information and Investment: Evidence from Plant-level Data, Working paper, MIT Sloan School of Management.

Giroud Xavier, and Holger Mueller, 2010, Does Corporate Governance Matter in Competitive Industries, *Journal of Financial Economics* 95, 312-331.

Giroud Xavier, and Holger Mueller, 2011, Corporate Governance, Product Market Competition, and Equity Prices, *Journal of Finance* 65, 563-660

Gompers, Paul, Joy Ishii, and Andrew Metrick, 2003, Corporate governance and equity prices, *Quarterly Journal of Economics* 118, 107–155.

Greenwood, Robin and Michael Schor, 2009, Hedge fund investor activism and takeovers, *Journal of Financial Economics* 92:3, 362-375.

Hart, Oliver D., 1983, The market mechanism as an incentive scheme, *Bell Journal of Economics* 14, 366–382.

Imrohoroglu, Ayse and Selale Tuzel, 2011, Firm Level Productivity, Risk, and Return, Working paper, University of Southern California.

Kadyrzhanova, Dalida and Matthew Rhodes-Kropf, 2010, Concentrating on Governance, Forthcoming Journal of Finance.

Klein, April and Emanuel Zur, 2009, Entrepreneurial shareholder activism: Hedge funds and other private investors, *Journal of Finance* 64:1, 187-229.

Kovenock, Dan and Gordon Phillips, 1997, Capital Structure and Product Market Behavior: An Examination of Plan Exit and Investment Decisions, *Review of Financial Studies* 10, 767-803.

Li, Erica, X.N., Dmitry Livdan, and Lu Zhang, 2009, Anomalies, *Review of Financial Studies* 22:11, 4301-4334.

Li, Xiaoyang, 2011, Productivity, Restructuring, and the Gains from Takeovers, Working paper, Ross School of Business.

Li, Yinghua, and Jin Xu, 2010, Hedge fund activism and bank loan contracting, Working paper, Purdue University.

Lichtenberg, Frank R., 1992, Corporate Takeovers and Productivity, MIT Press, Cambridge, MA.

Lichtenberg, Frank R. and Donald Siegel, 1990, The effects of leveraged buyouts on productivity and related aspects of firm behavior, *Journal of Financial Economics* 27, 165-194.

Maksimovic, Vojislav, Gordon M. Phillips, and Liu Yang, 2010, Private and Public Merger Waves, Working paper, University of Maryland.

Nickell, Stephen J., 1996, Competition and corporate performance, *Journal of Political Economy* 104, 724-746.

Novy-Marx, Robert, 2011, Operating leverage, *Review of Finance* 15, 103-134.

Raith, Michael, 2003, Competition, risk, and managerial incentives, *American Economic Review* 93, 1425-1436.

Schmidt, Klaus M., 1997, Managerial incentives and product market competition, *Review of Economic Studies* 64, 191–213.

Schoar, Antoinette, 2002, The effect of diversification on firm productivity, *Journal of Finance* 62:6, 2379-2403.

Shumway, Tyler, 1997, The delisting bias in CRSP data, *Journal of Finance* 52:1, 327-340.

Tirole, Jean, 1994, The Theory of Industrial Organization, MIT Press, Cambridge, MA.

Zhang, Lu, 2005, The value premium, *Journal of Finance* 60:1, 67-103.

Table 1: Sample Construction and Descriptive Statistics on the Census-matched Sample

Panel A shows the numbers of all hedge fund activism events and the events matched to the Census of Manufacturers (CMF) and Annual Survey of Manufacturers (ASM) databases from 1994 to 2007, separately for manufacturing and non-manufacturing target firms based on the Compustat SIC code. The panel also shows the number of plant-year observations for the Census-matched events. Panel B breaks down the numbers of the Census data-matched events and plant-year observations, and all events by decade. Panel C shows the distribution of activists' stated objectives, the percentage among the sample, and success rates for the full sample (columns 1-3) and the Census-matched sample (columns 4-6) of events from 2001 to 2007. Columns 1, 2 and 4, 5 report the number of events, and the percentage among all events, of each category. Columns 3 and 6 list the rate of success (including partial success). Percentages sum up to more than 100% since one event can have multiple objectives (However, the first category and the other four categories are mutually exclusive.) An event is classified as successful if the hedge fund achieves its main stated goal and a partial success if the hedge fund and the company reach some settlement through negotiation that partially meets the fund's original goal.

Panel A: Sample Selection for Activism Events Matched to Census Data from 1994 to 2007

Events	Num. events	Num. plant-years
1. All activism events	2180	-
a. Manufacturing targets	649	-
b. Non-manufacturing targets	1531	-
2. Matched to Census data with TFP	305	6561
a. Manufacturing targets	275	6028
b. Non-manufacturing targets	30	533

Panel B: Hedge Fund Activism Events Matched to Census Data by Decade

Decade	Census-matched	Num. plant-years	All events
1990s	126	2685	956
2000s	179	3876	1224
Total	305	6561	2180

Panel C: Summary of Activism Events by Stated Goals from 2001 to 2007

	Census-matched			All		
Stated Objectives	N events (1)	% of Sample (2)	% Success (3)	N events (4)	% of Sample (5)	% Success (6)
1. General	107	59.8%	N/A	646	52.8%	N/A
2. Capital Structure	24	13.4%	50.0%	162	13.2%	52.5%
3. Business Strategy	31	17.3%	48.4%	206	16.8%	51.9%
4. Sales of Target	31	17.3%	48.4%	254	20.8%	54.3%
5. Governance	47	26.3%	53.2%	333	27.2%	60.7%
Specific – Sum [2 to 5]	72	40.2%	50.0%	578	47.2%	53.6%
Total – Sum [1 to 5]	179	-	-	1224	-	-

Table 2: Summary Statistics on Plant Observations from the CMF and ASM Sample

This table presents descriptive statistics on the plant-year observations targeted by activists (column "Targets") and all plant-year observations used in the analysis (column "Universe") from the CMF and ASM databases for the period 1991-2007. We require each observation in both samples to have all variables necessary to compute total factor productivity (TFP). "Total value of shipments" is TVS in the CMF and ASM databases and a measure of sales from plants in million dollars; "Capital stock" is the sum of real net stock of equipment and structures in 2005 constant million dollars. It is constructed using a perpetual inventory formula following the procedure described in Appendix A; "Total wage" is the sum of wages for production and non-production workers in thousand dollars; "Total employees" is the number of total employees; "Average wage" is computed as total wage divided by total employees; "Wage per hour (production workers) is total production worker wage divided by total production hour; "Plants per segment" is the number of plants in a given industry segment (defined at the three-digit SIC level) of a given firm; "Plants per firm" is the total number of plants of a given firm; "Plant age" is the number of years since a plant first appears in the CMF or ASM database; "TFP (Standardized)" is total factor productivity computed by estimating a log-linear Cobb-Douglas production function by three-digit SIC industry and year, divided by its within-industry standard deviation; "Operating margin" is defined as (output – labor costs – material costs) / output; "HHI (Census)" is the Herfindahl–Hirschman Index computed at the three-digit SIC level using all observations with positive total value of shipments in the ASM database. "Num. industries (SIC3)" is the number of three-digit SIC industries represented in the sample; "Observations" is the number of plant or firm observations.

	Mean	STD	Mean	STD
	Targets		Universe	
Total value of shipment ($m)	93.46	237.95	73.13	323.54
Capital stock ($m)	44.02	109.52	39.91	198.2
Total wage ($000)	13.72	25.61	10.74	34.94
Total employees	291	399	233	555
Average wage ($000)	44.54	14.29	41.07	15.11
Wage per hour (production workers)	18.96	6.79	17.16	6.76
plants per segment (SIC3)	7.46	9.39	6.24	12.93
plants per firm	17.84	16.73	17.73	32.46
Plant age	24.89	7.71	20.21	8.76
TFP (Standardized)	0.097	0.94	0.002	0.899
Operating margin	0.257	0.278	0.221	0.281
HHI (Census)	0.052	0.054	0.04	0.043
Num. Industries (SIC3)	113	-	134	-
Observations (plant-year)	6561	-	633510	-
Observations (unique plant)	1708	-	99792	-
Observations (firm-year)	1085	-	334555	-
Observations (unique firm)	258	-	72287	-

Table 3: Summary Statistics on Firm Observations from the Compustat Sample

This table presents descriptive statistics on targets of hedge fund activists matched to the Census plant-level data (column "Census Sample") and all target firms (column "All Target Firms"), benchmarked with the full sample of Compustat firms (column "Full Compustat Sample") for the event period 1994-2007. All variables are retrieved from years prior to the event year. "MV" is market capitalization in millions of dollars; "Assets" is total book value of assets in millions of dollars; Leverage is defined as debt/(debt + book value of equity); "Cash" is defined as (cash + cash equivalents)/assets; "Div Yld %" is dividend yield, defined as (common dividend + preferred dividends)/(market value of common stocks + book value of preferred); "q" is defined as (book value of debt + market value of equity)/(book value of debt + book value of equity); "Sales growth" is the growth rate of sales over the previous year; "Cash flow" is defined as (net income + depreciation and amortization)/lagged assets; "R&D" is R&D scaled by lagged assets; "Firm age" is the number of years since a firm's first appearance in Compustat; "HHI" is the Herfindahl-Hirschman index of industry competition defined as the industry-level (SIC3) squared sum of firm market shares measured by sales; "Capx %" is capital expenditures scaled by lagged assets; "Total Payout Yld %" is defined as the sum of common dividends and common share repurchases, scaled by the lagged market capitalization; "CEO Turnover" is equal to one if the name of the current CEO is different than that of previous year's CEO, and zero otherwise; "Altman (Ex. Leverage)" is Altman's Z-Score computed excluding the leverage ratio.

	Census Sample (#obs = 305)	All Target Firms (#obs = 1,575)		Full Compustat Sample	
	Mean	Mean	Std	Mean	Std
MV	828.90	657.81	1554.44	1677.30	5156.96
Assets	1094.50	1128.22	3498.62	2555.98	8420.64
Leverage	0.276	0.260	0.259	0.284	0.298
Cash	0.119	0.173	0.219	0.180	0.231
DivYld %	1.975	0.751	1.751	1.111	2.295
q	1.739	2.066	1.986	3.860	8.072
Sales Growth	0.056	0.242	0.905	0.261	0.711
Cash flow	0.047	0.009	0.238	-0.134	0.780
R&D	0.038	0.048	0.117	0.064	0.164
Firm Age	NA	12.77	13.89	12.14	13.73
HHI	NA	0.15	0.14	0.14	0.14
Capx %	NA	5.54	7.06	5.78	7.55
Total Payout Yld %	NA	2.21	4.62	2.18	4.29
CEO Turnover	NA	0.13	0.34	0.09	0.29
Altman (Ex. Leverage)	NA	-0.19	3.97	-1.55	5.33

Table 4: Hedge Fund Activism and Productivity

This table examines the impact of hedge fund activism on the productivity of plants owned by target firms in each year from two years before to two years after the hedge fund's intervention. Our measures of productivity are standardized total factor productivity (TFP) and operating margin as defined in Table 2. "d[t - k]" ("d[t + k]") is a dummy variable equals to one for k years before (after) activism, and zero otherwise. "d[t]" is defined similarly. "log(plants per segment)," "log(plants per firm)" and "Plant age (× 100)" are defined in Table 2. The unit of observation is the plant in columns 1 and 2, and the firm in columns 3 and 4, in which plant-level TFP is aggregated at the firm level using beginning-year capital stock as a weight and the number of plants per segment is the average across segments for a given firm. Industry fixed effects are excluded (included) when the dependent variable is TFP (Operating margin) given that our computation of TFP already accounts for industry fixed effects. Year fixed effects are included in all regressions. t-statistics based on standard errors adjusted for sample clustering at the plant (firm) level are reported below the coefficient estimates in columns 1 and 2 (columns 3 and 4).

	(1)	(2)	(3)	(4)
Unit	Plant	Plant	Firm	Firm
Dep. Var.	TFP	Op margin	TFP	Op margin
d[t-2]	0.074	0.008	0.106	0.032
	2.92	1.04	**1.91**	**1.91**
d[t-1]	0.042	-0.005	0.070	0.023
	1.62	-0.68	1.40	1.42
d[t]	0.041	0.000	-0.005	0.024
	1.49	0.07	-0.11	1.62
d[t+1]	0.032	0.002	0.003	0.015
	0.98	0.21	0.05	0.81
d[t+2]	0.096	0.009	0.096	0.041
	2.82	0.95	1.42	**1.99**
log(plant per segment)	-0.001	0.002	-0.017	-0.011
	-0.26	1.54	-1.23	-2.52
log(plant per firm)	0.057	0.008	0.069	0.021
	19.53	**8.74**	**7.08**	**6.51**
Plant age (x100)	-0.700	-0.027	-0.544	-0.014
	-20.66	**-2.94**	**-14.44**	-1.37
Year fixed effects	Y	Y	Y	Y
Industry fixed effects	N	Y	N	Y
Observations	633510	633510	334631	334631
R2	1.19%	13.24%	0.36%	15.27%
d[t+1] – d[t-1]	-0.010	0.007	-0.068	-0.009
	0.35	0.79	1.42	0.46
d[t+2] – d[t]	0.056	0.009	0.101	0.017
	1.78	0.93	**1.72**	0.89
d[t+2] – d[t-1]	0.055	0.014	0.026	0.018
	1.65	1.35	0.41	0.82

Table 5: Hedge Fund Activism, Product Market Competition, and Productivity

This table presents the interactive effect of hedge fund activism with product market competition on the productivity and profitability of plants owned by target firms in each year from the two years before to two years after the hedge fund's intervention. Our measure of product market competition is the Herfindahl–Hirschman Index (HHI) defined in Table 2 lagged by one year relative to the dependent variable. TFP is estimated using the specification described in Table 2 and operating margin is defined as in Table 2. All other independent variables are defined in Table 4. Industry fixed effects are excluded (included) when the dependent variable is TFP (Operating margin) given that our computation of TFP already accounts for industry fixed effects. Year fixed effects are included in all regressions. t-statistics based on standard errors adjusted for sample clustering at the plant level are reported below the coefficient estimates.

	(1)	(2)
Unit	Plant	Plant
Dep. Var.	TFP	Op margin
d[t-2]	0.119	0.004
	3.43	0.36
d[t-1]	0.038	-0.026
	1.04	**-2.58**
d[t]	0.051	-0.023
	1.35	**-2.47**
d[t+1]	0.062	-0.013
	1.38	-1.21
d[t+2]	0.151	-0.013
	3.19	-1.00
d[t-2] × HHI	-0.880	0.097
	-1.75	0.57
d[t-1] × HHI	0.091	0.426
	0.16	**2.86**
d[t] × HHI	-0.184	0.472
	-0.34	**3.77**
d[t+1] × HHI	-0.501	0.251
	-0.83	1.55
d[t+2] × HHI	-0.893	0.365
	-1.38	**2.04**
HHI	-0.187	0.404
	-3.45	**9.55**
log(plant per segment)	-0.001	0.002
	-0.28	1.45
log(plant per firm)	0.058	0.008
	19.67	**8.75**
Plant age (×100)	-0.698	-0.027
	-20.58	**-2.92**
Year fixed effects	Y	Y
Industry fixed effects	N	N
Observations	633510	633510

R2	1.20%	13.28%
d[t+1] – d[t-1]	0.024	0.013
	0.61	1.14
d[t+2] – d[t]	0.100	0.010
	2.24	0.78
d[t+2] – d[t-1]	0.113	0.013
	2.42	0.92
(d[t+1] – d[t-1]) × HHI	-0.592	-0.175
	1.20	1.16
(d[t+2] – d[t]) × HHI	-0.708	-0.107
	1.27	0.65
(d[t+2] – d[t-1]) × HHI	-0.983	-0.060
	1.57	0.32

Table 6: Hedge Fund Activism and Productivity of Industry Peers

This table presents the effects of hedge fund activism on changes in productivity from one year before to two years after the intervention for plants that are in the target firms' industries but not directly targeted by an activist hedge fund (i.e., "non-target industry peers"). The unit of observation is the three-digit SIC industry, excluding plants targeted by activist hedge funds in a given year. TFP is estimated using the specification described in Table 2 at the three-digit SIC industry level. Operating margin and the HHI are defined in Table 2. "Target share" is the share of output commanded by activists' target plants in a given industry one year prior to activism, and hence is a measure of targeting intensity of the industry. Other control variables are computed based on the industry-level means of the control variables defined in Table 4. Industry and year fixed effects are included in all regressions. t-statistics based on standard errors adjusted for sample clustering at the industry level are reported below the coefficient estimates.

	(1)	(2)	(3)	(4)
Unit	SIC3 industry	SIC3 industry	SIC3 industry	SIC3 industry
Dep. Var.	d(TFP) (t-1 to t+2)	d(TFP) (t-1 to t+2)	d(Op margin) (t-1 to t+2)	d(Op margin) (t-1 to t+2)
Target share	0.078	1.238	-0.008	0.114
	0.20	**2.29**	-0.15	1.26
Target share × HHI	-	-18.232	-	-2.063
	-	**-2.01**	-	**-1.67**
HHI	-	-0.998	-	-0.265
	-	**-1.82**	-	**-2.57**
log(mean plants per segment)	-0.013	-0.002	-0.007	-0.004
	-0.14	-0.02	-0.45	-0.27
log(mean plants per firm)	-0.085	-0.092	-0.019	-0.021
	-0.90	-0.99	-0.92	-1.01
Mean plant age (× 100)	2.774	2.809	0.286	0.291
	0.99	1.00	0.65	0.69
Year fixed effects	Y	Y	Y	Y
Industry fixed effects	Y	Y	Y	Y
Observations	1603	1603	1603	1603
R2	14.68%	15.79%	25.22%	27.16%

Table 7: Robustness Check

Panels A and B examine the robustness of baseline results in Tables 4 and 5 to an alternative production functional form and measures of product market competition, respectively. Specifically, in Panel A we use a translog production function which allows second-order terms of inputs and interactions between them to estimate TFP. In Panel B, we use a Cobb-Douglas production functional form as in Tables 4 and 5. “High HHI dummy” is equal to one if the HHI of an industry is larger than the 75th percentile, and zero otherwise. “HHI (FF48)” is the HHI computed using firm-level total value of shipments based on the Fama-French 48 industry classification; “Net profit margin” is industry-level net profit margin defined as (output – labor costs – material costs) / output. Operating margin is defined as in Table 2. All other independent variables are defined in Table 4. In Panels A and B, industry fixed effects are excluded given that our computation of TFP already accounts for industry fixed effects. Year fixed effects are included in all regressions. t-statistics based on standard errors adjusted for sample clustering at the plant (industry) level are reported below the coefficient estimates in Panel A (Panel B).

Panel A: Alternative Form of Production Function

Unit Production func. Dep. Var.	(1) Plant Translog TFP	(2) Plant Translog TFP
d[t-2]	0.067	0.072
	2.61	**2.08**
d[t-1]	0.020	-0.006
	0.78	-0.17
d[t]	0.004	0.014
	0.15	0.39
d[t+1]	0.002	-0.011
	0.08	-0.24
d[t+2]	0.066	0.083
	1.86	**1.67**
d[t-2] × HHI	-	-0.188
	-	-0.19
d[t-1] × HHI	-	0.445
	-	0.44
d[t] × HHI	-	-0.235
	-	-0.23
d[t+1] × HHI	-	0.249
	-	0.25
d[t+2] × HHI	-	-0.265
	-	-0.27
HHI	-	-0.113
	-	-0.11
log(plant per segment)	0.000	0.011
	-0.03	**2.47**
log(plant per firm)	0.045	0.048
	15.51	**15.76**
Plant age (×100)	-0.474	-0.457
	-14.21	**-13.46**
Year fixed effects	Y	Y
Industry fixed effects	N	N
Observations	633510	633510
R2	0.71%	0.85%
d[t+1] – d[t-1]	-0.018	-0.005
	0.59	0.10
d[t+2] – d[t]	0.062	0.069
	1.91	1.46
d[t+2] – d[t-1]	0.046	0.089
	1.31	**1.82**
(d[t+1] – d[t-1]) × HHI	-	-0.196
	-	0.32
(d[t+2] – d[t]) × HHI	-	-0.031
	-	0.00
(d[t+2] – d[t-1]) × HHI	-	-0.710
	-	1.12

Panel B: Alternative Measures of Product Market Competition

	(1)	(2)	(3)
Unit	Plant	Plant	Plant
Concentration measure	High HHI dummy	HHI (FF48)	Net profit margin
Dep. Var.	TFP	TFP	TFP
d[t-2]	0.113	0.101	0.191
	4.08	**3.25**	**2.58**
d[t-1]	0.058	0.046	0.164
	1.99	1.47	**2.02**
d[t]	0.058	0.060	0.125
	1.90	**1.84**	1.46
d[t+1]	0.073	0.050	0.304
	1.95	1.31	**2.97**
d[t+2]	0.146	0.131	0.370
	3.70	**3.20**	**3.38**
d[t-2] × Concentration	-0.058	-1.093	-0.396
	-1.00	-1.50	**-1.70**
d[t-1] × Concentration	-0.008	-0.167	-0.406
	-0.14	-0.24	-1.59
d[t] × Concentration	-0.017	-0.687	-0.278
	-0.29	-1.04	-1.05
d[t+1] × Concentration	-0.071	-0.606	-0.911
	-1.17	-0.78	**-2.81**
d[t+2] × Concentration	-0.015	-1.143	-0.917
	-0.22	-1.32	**-2.62**
Concentration	-0.014	-0.172	-0.018
	-2.27	**-2.21**	-0.74
log(plant per segment)	-0.001	-0.001	-0.001
	-0.28	-0.28	-0.22
log(plant per firm)	0.057	0.057	0.057
	19.59	**19.59**	**19.50**
Plant age (×100)	-0.699	-0.700	-0.700
	-20.62	**-20.66**	**-20.66**
Year fixed effects	Y	Y	Y
Industry fixed effects	N	N	N
Observations	633510	633510	633510
R2	1.20%	1.19%	1.19%
d[t+1] – d[t-1]	0.016	0.004	0.139
	0.46	0.10	1.40
d[t+2] – d[t]	0.088	0.071	0.245
	2.37	**1.85**	**2.44**
d[t+2] – d[t-1]	0.088	0.085	0.206
	2.30	**2.10**	**1.90**
(d[t+1] – d[t-1]) x Concentration	-0.063	-0.440	-0.505
	1.06	0.68	1.62
(d[t+2] – d[t]) x Concentration	0.002	-0.456	-0.639
	0.00	0.67	**1.98**
(d[t+2] – d[t-1]) x Concentration	-0.007	-0.976	-0.511
	0.10	1.31	1.47

Table 8: Ownership Changes of Plants and Performance of Plants Sold After Activism

Panel A shows the productivity pattern of plants owned by target firms in the year of activism regardless of their owners pre- or post-activism. In Panel A, "d[t - k]" ("d[t + k]") is a dummy variable equal to one for k years before (after) the targeting by an activist, and zero otherwise. Panel B shows the productivity pattern of plants owned by target firms prior to activism and then sold to other firms within two years post-activism. In Panel B, "d[t - k]" ("d[t + k]") is a dummy variable equals to one for k years before (after) the sale of plants, and zero otherwise. "d[t]" is defined similarly. All other independent variables are defined as in Table 4. TFP, operating margin and the HHI are defined as in Table 2. Industry fixed effects are excluded (included) when the dependent variable is TFP (Operating margin) given that our computation of TFP already accounts for industry fixed effects. Year fixed effects are included in all regressions. t-statistics based on standard errors adjusted for sample clustering at the plant level are reported below the coefficient estimates.

Panel A: Productivity of Plants Owned by Target in the Year of Intervention

	(1)	(2)
Unit	Plant	Plant
Dep. Var.	TFP	Op margin
d[t-2]	0.124	0.023
	4.65	**3.07**
d[t-1]	0.061	0.003
	2.35	0.35
d[t]	0.043	0.000
	1.58	0.02
d[t+1]	0.002	-0.010
	0.07	-1.27
d[t+2]	0.023	-0.003
	0.75	-0.31
log(plant per segment)	-0.001	0.002
	-0.24	1.55
log(plant per firm)	0.057	0.008
	19.51	**8.72**
Plant age (×100)	-0.700	-0.027
	-20.65	**-2.91**
Year fixed effects	Y	Y
Industry fixed effects	N	Y
Observations	633147	633147
R2	1.19%	13.24%
d[t+1] – d[t-1]	-0.059	-0.013
	2.44	1.64
d[t+2] – d[t]	-0.020	-0.003
	0.71	0.35
d[t+2] – d[t-1]	-0.038	-0.005
	1.33	0.57

Panel B: Productivity of Plants Sold to Other Firms after Activism

	(1)	(2)
Sample	1	1
Unit	Plant	Plant
Dep. Var.	TFP	Op margin
d[t-2]	-0.046	-0.018
	-0.63	-0.83
d[t-1]	-0.156	-0.017
	-2.29	-0.77
d[t]	-0.202	-0.069
	-2.63	**-2.86**
d[t+1]	-0.149	-0.049
	-1.74	-1.56
d[t+2]	-0.034	0.033
	-0.43	1.20
log(plant per segment)	-0.001	0.002
	-0.27	1.55
log(plant per firm)	0.057	0.008
	19.61	**8.78**
Plant age (×100)	-0.698	-0.027
	-20.61	**-2.89**
Year fixed effects	Y	Y
Industry fixed effects	N	Y
Observations	632802	632802
R2	1.19%	13.24%
d[t+1] – d[t-1]	0.007	-0.033
	0.10	1.09
d[t+2] – d[t]	0.168	0.102
	2.11	**3.41**
d[t+2] – d[t-1]	0.121	0.050
	1.52	**1.81**

Table 9: Survivorship Bias due to Sample Attrition from Compustat

This table provides estimates of the extent to which firm attrition from the Compustat database induces biases in the measurement of the effect of hedge fund activism on target firms' performance. "Attrition" ("Non-attrition") is a dummy variable equal to one if the target firm that owns a plant disappears (does not disappear) from Compustat within two years post-activism, and zero otherwise. All other independent variables, and TFP and operating margin are defined in Table 4. Industry fixed effects are excluded (included) when the dependent variable is TFP (Operating margin) given that our computation of TFP already accounts for industry fixed effects. Year fixed effects are included in all regressions. t-statistics based on standard errors adjusted for sample clustering at the plant level are reported below the coefficient estimates.

	(1)	(2)
Unit	Plant	Plant
Dep. Var.	TFP	Op margin
d[t-2] × Attrition	0.032	0.020
	0.65	1.32
d[t-1] × Attrition	0.002	-0.008
	0.03	-0.54
d[t] × Attrition	0.022	0.003
	0.43	0.20
d[t+1] × Attrition	0.094	0.006
	1.27	0.30
d[t+2] × Attrition	0.191	0.044
	2.07	**1.79**
d[t-2] × Non-attrition	0.089	0.004
	3.07	0.43
d[t-1] × Non-attrition	0.056	-0.004
	1.94	-0.48
d[t] × Non-attrition	0.048	-0.001
	1.52	-0.06
d[t+1] × Non-attrition	0.017	0.001
	0.47	0.08
d[t+2] × Non-attrition	0.084	0.004
	2.28	0.43
log(plant per segment)	-0.001	0.002
	-0.27	1.55
log(plant per firm)	0.057	0.008
	19.53	**8.74**
Plant age (×100)	-0.700	-0.027
	-20.66	**-2.94**
Year fixed effects	Y	Y
Industry fixed effects	N	Y
Observations	633510	633510
R2	1.19%	13.24%
(d[t+1] – d[t-1]) × Attrition	0.092	0.014
	1.37	0.69

(d[t+2] – d[t]) × Attrition	0.169	0.041
	1.95	**1.67**
(d[t+2] – d[t-1]) × Attrition	0.190	0.052
	2.10	**1.91**
(d[t+1] – d[t-1]) × Non-attrition	-0.040	0.005
	1.25	0.51
(d[t+2] – d[t]) × Non-attrition	0.036	0.005
	1.09	0.50
(d[t+2] – d[t-1]) × Non-attrition	0.027	0.009
	0.77	0.75

Table 10: Time variation in factor exposures around hedge fund activism

The table reports statistics on time-variation in factor loadings associated with firms targeted by hedge fund activists over the period 2001-2007. In panel A we report regression estimates and *t*-statistics from equal- and value-weighted calendar-time portfolio regressions. The "portfolio holding period," indicates the holding period in months relative to the month of the hedge fund intervention. For example, the portfolio with holding period +1,+12, continually adds target firms that have had an activist event in the preceding month and holds these firms through a year after their respective activism events. In Panel B we form zero-cost portfolios that are long in target firms and short an industry benchmark portfolio. The benchmark is formed by matching each target firm to one of the corresponding Fama and French value-weight industry portfolios. We present results based on both equal- and value-weighting the matched industry returns. In Panel C we form zero-cost portfolios that are long in target firms and short an industry and characteristic-based benchmark portfolio. The benchmark is formed by first matching each target firm with replacement firms with the same 3-digit SIC code. We retain firms whose market capitalization is within 50% of the target firm's market capitalization. Next, we further narrow down the list of benchmark firms to those whose book-to-market ratio within 25% of the target firm's book-to-market ratio, measured in the year preceding the hedge fund activism. The last step is to value weight the remaining firm returns. Results are presented based on both equal- and value-weighting these benchmark returns. "Alpha" is the estimate of the regression intercept. "BETA" is the factor loading on the market excess return (the Fama and French RMRF). "SMB," "HML," and "MOM" are the estimates of factor loading on the Fama-French size and book-to-market factors, and the Carhart momentum factor, respectively. "R2" is the adjusted R^2 from the regressions and "N" is the number of monthly observations. We set a minimum of ten firms per month for all portfolios.

Panel A: Target firm four-factor model regressions								
	Value-Weight portfolios Holding period in months relative to the event-month				Equal-Weight portfolios Holding period in months relative to the event-month			
	-36,-13	-12,-1	+1,+12	+13,+36	-36,-13	-12,-1	+1,+12	+13,+36
Alpha	-1.366	-1.590	-0.192	0.180	-0.053	-0.745	-0.398	0.097
	-6.229	-4.544	-0.628	0.784	-0.201	-2.828	-1.684	0.417
BETA	1.083	1.066	1.118	1.044	0.895	0.937	1.048	0.984
	19.118	11.018	13.425	18.331	13.146	12.871	16.267	17.072
SMB	0.616	0.449	0.521	0.467	0.846	0.701	0.723	0.851
	10.900	4.625	4.569	4.833	12.447	9.600	8.195	8.707
HML	0.203	0.524	0.515	0.104	0.266	0.392	0.636	0.158
	2.928	4.681	4.025	1.135	3.187	4.657	6.428	1.710
MOM	-0.016	-0.087	-0.022	-0.038	-0.278	-0.281	-0.112	-0.248

	-0.432	-1.379	-0.289	-0.844	-6.151	-5.912	-1.886	-5.394
R2	0.878	0.665	0.786	0.854	0.838	0.823	0.871	0.886
N	106	94	94	106	106	94	94	106

Panel B: Zero-cost four-factor model regressions. Long target firm and short matched Fama and French Value-Weight 48 industries

	Value-Weight portfolios Holding period in months relative to the event-month				Equal-Weight portfolios Holding period in months relative to the event-month			
	-36,-13	-12,-1	+1,+12	+13,+36	-36,-13	-12,-1	+1,+12	+13,+36
Alpha	-1.239	-1.435	-0.164	0.028	-0.132	-0.725	-0.458	0.117
	-5.495	-4.267	-0.608	0.149	-0.503	-2.904	-1.772	0.479
BETA	0.060	-0.007	0.172	-0.004	-0.152	-0.101	0.087	-0.014
	1.035	-0.077	2.336	-0.078	-2.251	-1.463	1.233	-0.224
SMB	0.533	0.512	0.339	0.461	0.785	0.717	0.554	0.657
	9.172	5.488	3.368	5.824	11.613	10.360	5.737	6.376
HML	0.114	0.381	0.416	0.157	0.226	0.264	0.658	0.225
	1.600	3.541	3.680	2.096	2.724	3.307	6.066	2.306
MOM	0.019	-0.077	-0.028	-0.078	-0.208	-0.154	-0.055	-0.210
	0.493	-1.268	-0.419	-2.101	-4.629	-3.422	-0.849	-4.321
R2	49.5	22.0	26.3	34.0	55.9	52.7	43.6	44.8
N	106	94	94	106	106	94	94	106

Panel C: Zero-cost four-factor model regressions. Long target firms and short industry and size and book-to-market matched portfolio

	Value-Weight portfolios Holding period in months relative to the event-month				Equal-Weight portfolios Holding period in months relative to the event-month			
	-36,-13	-12,-1	+1,+12	+13,+36	-36,-13	-12,-1	+1,+12	+13,+36
Alpha	-1.007	-0.885	-0.284	0.252	0.249	0.461	-0.683	-0.209
	-3.661	-2.491	-0.946	0.947	1.068	1.804	-2.891	-1.003
BETA	0.053	-0.066	0.083	0.097	-0.117	-0.097	-0.025	0.012

	0.738	-0.671	1.009	1.481	-1.928	-1.377	-0.393	0.239
SMB	0.095	0.129	-0.082	-0.130	-0.055	0.028	-0.161	-0.041
	1.351	1.240	-0.734	-1.154	-0.917	0.373	-1.819	-0.464
HML	0.097	0.468	0.270	-0.002	0.320	0.208	0.439	0.050
	1.115	4.070	2.094	-0.018	4.347	2.519	4.326	0.610
MOM	0.050	-0.032	-0.035	0.114	-0.109	0.040	-0.063	-0.137
	1.055	-0.489	-0.470	2.182	-2.721	0.860	-1.059	-3.344
R2	-0.2	17.0	1.9	1.5	39.6	14.1	16.5	10.5
N	105	93	93	105	105	93	93	105

Table 11: Time variation in factor exposures around hedge fund activism conditional on industry competitiveness

The table reports statistics on time variation in factor loadings associated with hedge fund activism over the period 2001-2007 conditional on the competitiveness of the target firm's industry. Competitiveness is measured using the Herfindahl-Hirschman ("HHI") index calculated at the industry 3-digit SIC code. An industry is classified as competitive (non-competitive) if its HHI index is lower (higher) than the 25th percentile of industry HHIs in a given year. HHI classifications are lagged by one year. We report regression estimates and *t*-statistics from equal- and value-weighted calendar-time portfolio regressions based on target firms from "competitive" and "non-competitive" industries. Within each panel and weighting scheme we report target firm long only portfolio regression results and results in which we long target firm portfolio and short a value-weight portfolio of benchmark firms formed by matching based on 3-digit SIC code, size and book-to-market ratio. In Panel A we report results for targets in competitive industries whereas in Panel B we report regression results for targets in non-competitive industries. The "portfolio holding period," indicates the holding period in months relative to the month of the hedge fund intervention. "Alpha" is the estimate of the regression intercept. "BETA" is the factor loading on the market excess return (the Fama and French RMRF). "SMB," "HML," and "MOM" are the estimates of factor loading on the Fama-French size and book-to-market factors, and the Carhart momentum factor, respectively. "R2" is the adjusted R^2 from the regressions and "N" is the number of monthly observations. We set a minimum of ten firms per month for all portfolios.

Panel A: Target firms in competitive industries (low HHI) four-factor model regressions																
	Value-Weight portfolios								Equal-Weight portfolios							
	Long targets				Long targets, short industry and characteristics-matched firms				Long targets				Long targets, short industry and characteristics-matched firms			
From:	-36	-12	+1	+13	-36	-12	+1	+13	-36	-12	+1	+13	-36	-12	+1	+13
To:	-13	-1	+12	+36	-13	-1	+12	+36	-13	-1	+12	+36	-13	-1	+12	+36
Alpha	-1.016	-1.654	0.132	0.324	-0.863	-0.816	0.030	0.221	0.151	-0.366	-0.283	0.076	0.644	0.966	-0.579	-0.247
	-3.195	-3.292	0.373	0.913	-2.436	-1.684	0.079	0.646	0.503	-1.116	-0.970	0.290	2.168	2.911	-2.196	-1.083
BETA	1.076	1.064	1.163	1.146	-0.073	-0.127	0.139	0.187	0.973	0.939	1.044	0.982	-0.155	-0.257	-0.021	-0.024
	13.013	7.691	12.015	13.044	-0.785	-0.905	1.338	2.165	12.434	10.412	13.115	15.068	-1.985	-2.679	-0.297	-0.420
SMB	0.562	0.593	0.497	0.276	0.087	0.114	-0.246	-0.314	0.857	0.829	0.725	0.881	-0.052	0.164	-0.284	-0.035
	6.873	4.026	3.736	1.848	0.962	0.712	-1.738	-2.070	11.086	8.631	6.630	7.945	-0.684	1.489	-2.902	-0.355
HML	-0.049	0.416	0.355	-0.019	-0.022	0.526	0.283	-0.276	0.121	0.117	0.564	-0.002	0.306	0.037	0.478	0.001
	-0.486	2.562	2.342	-0.134	-0.199	3.341	1.725	-2.002	1.271	1.106	4.518	-0.015	3.253	0.344	4.217	0.006

MOM	-0.019	-0.075	-0.016	-0.005	0.063	-0.082	0.055	0.071	-0.284	-0.295	-0.236	-0.262	-0.186	0.010	-0.149	-0.152
	-0.340	-0.815	-0.176	-0.071	1.041	-0.925	0.580	1.052	-5.508	-4.905	-3.221	-5.055	-3.644	0.167	-2.275	-3.370
R2	79.9	52.7	74.2	71.5	0.2	13.2	2.8	6.3	83.2	79.9	83.2	85.7	33.7	7.7	21.3	7.8
N	105	93	92	104	103	92	91	101	105	93	92	104	104	92	91	103

Panel B: Target firms in non-competitive industries (high HHI) four-factor model regressions																
	Value-Weight portfolios								Equal-Weight portfolios							
	Long targets				Long targets, short industry and characteristics-matched firms				Long targets				Long targets, short industry and characteristics-matched firms			
From:	-36	-12	+1	+13	-36	-12	+1	+13	-36	-12	+1	+13	-36	-12	+1	+13
To:	-13	-1	+12	+36	-13	-1	+12	+36	-13	-1	+12	+36	-13	-1	+12	+36
Alpha	-1.170	-1.407	-0.168	-0.023	-0.823	-1.156	-0.047	-0.317	-0.119	-1.158	0.020	0.163	-0.544	-1.308	-0.344	0.033
	-3.838	-3.608	-0.528	-0.092	-1.593	-2.397	-0.101	-0.753	-0.409	-3.435	0.069	0.495	-1.458	-3.130	-0.676	0.078
BETA	1.152	1.083	0.973	0.946	0.269	0.414	0.044	0.116	0.825	0.871	0.888	0.969	0.104	0.101	-0.115	-0.023
	14.446	9.609	11.364	15.339	1.964	3.017	0.298	1.009	10.846	8.939	11.371	11.846	1.051	0.852	-0.710	-0.204
SMB	0.525	0.372	0.691	0.600	0.025	-0.090	0.361	-0.079	0.806	0.709	0.799	0.812	0.015	0.256	-0.196	0.238
	6.733	2.900	5.908	5.480	0.192	-0.546	1.903	-0.417	10.843	6.388	7.488	5.604	0.165	1.783	-0.940	1.246
HML	0.681	0.755	0.655	0.225	-0.068	0.076	0.092	0.140	0.570	0.712	0.493	0.440	0.106	0.211	0.424	0.055
	7.085	5.892	4.649	2.255	-0.434	0.410	0.377	0.763	6.216	6.431	3.838	3.322	0.945	1.308	1.591	0.310
MOM	-0.088	-0.093	-0.264	-0.078	-0.126	0.127	-0.450	0.081	-0.253	-0.158	-0.007	-0.302	0.188	-0.037	0.133	-0.192
	-1.683	-1.287	-3.375	-1.606	-1.513	1.239	-3.975	0.964	-5.100	-2.548	-0.105	-4.680	3.123	-0.419	1.072	-2.333
R2	74.9	60.3	78.9	83.8	8.7	5.8	20.8	-2.2	75.6	66.9	76.9	81.8	6.5	1.5	4.3	5.4
N	103	90	90	101	91	78	78	88	103	90	90	101	91	78	78	92