NBER WORKING PAPER SERIES

THE REAL EFFECTS OF HEDGE FUND ACTIVISM:
PRODUCTIVITY, ASSET ALLOCATION, AND LABOR OUTCOMES

Alon Brav
Wei Jiang
Hyunseob Kim

Working Paper 17517
http://www.nber.org/papers/w17517

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2011

Previously circulated as "The Real Effects of Hedge Fund Activism: Productivity, Risk, and Product Market Competition." The authors have benefited from comments from and discussions with Lucian Bebchuk, Christa Bouwman, Joan Farre-Mensa, Simon Gervais, Sandy Klasa, April Klein, Dalida Kadyrzhanova, Vikram Nanda, Michael Raith, Adriano Rampini, and seminar and conference participants at Arizona State University, Boston College, Brigham Young University, Cornell University, Duke University, Drexel, Ecole Polytechnique Fédérale de Lausanne, Emory, Erasmus, Fordham, Fudan, HEC Paris, Imperial College, INSEAD, Interdisciplinary Center at Herzlyia, London Business School, Michigan, New York University, University of Oregon, Rotterdam School of Management, Rutgers, SAIF, Seoul National University, Southern Methodist University, Tel Aviv University, Temple, University of Amsterdam, University of Washington, University of Illinois at Urbana-Champaign, University of Oxford, Wharton, Yale, the Annual Corporate Governance Conference at Drexel University, Western Finance Association Annual Meetings, the International Conference on Corporate Governance at Tsinghua University, the HBS Information, Markets and Organization Conference, the Annual Financial Intermediation Society Conference, Jackson Hole Finance Conference, the SFS Finance Cavalcade, and the Annual Conference on Corporate Finance at Washington University in St. Louis. We thank Bert Grider at the Triangle Census Research Data Center for help with data and clearance requests. We also thank Jin Xu and Yinghua Li for help with data collection at an early stage of the paper and Bryan Oh for excellent research assistance. Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

The Real Effects of Hedge Fund Activism: Productivity, Asset Allocation, and Labor Outcomes
Alon Brav, Wei Jiang, and Hyunseob Kim
NBER Working Paper No. 17517
October 2011, Revised January 2015
JEL No. G23,G3,G34

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 in the three years after an activist intervention, and the improvements are most pronounced in those interventions specifically targeting the firm's business strategy. We also find that plants sold post-intervention exhibit a significant improvement in productivity under new ownership, consistent with the view that efficient capital redeployment is an important channel via which activists create value. We further find that employees of target firms experience a reduction in work hours and stagnation in wages despite an increase in labor productivity. Additional tests refute alternative explanations that attribute the improvement to mean reversion, management's voluntary reforms, industry consolidation shocks, or hedge funds' stock picking abilities. The overall evidence is consistent with hedge fund intervention having a real and long-term effect on the fundamental values of target firms.

Alon Brav
Fuqua School of Business
Duke University
One Towerview Drive
Durham, NC 27708
and NBER
brav@duke.edu

Hyunseob Kim
Cornell University
Johnson Graduate School of Management
366 Sage Hall
114 East Avenue
Ithaca, NY 14853
hk722@cornell.edu

Wei Jiang
Graduate School of Business
Columbia University
411 Uris Hall
New York, NY 10027
wj2006@columbia.edu

The Real Effects of Hedge Fund Activism:
Productivity, Asset Allocation, and Labor Outcomes

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 in the three years after an activist intervention, and the improvements are most pronounced in those interventions specifically targeting the firm's business strategy. We also find that plants sold post-intervention exhibit a significant improvement in productivity under new ownership, consistent with the view that efficient capital redeployment is an important channel via which activists create value. We further find that employees of target firms experience a reduction in work hours and stagnation in wages despite an increase in labor productivity. Additional tests refute alternative explanations that attribute the improvement to mean reversion, management's voluntary reforms, industry consolidation shocks, or hedge funds' stock picking abilities. The overall evidence is consistent with hedge fund intervention having a real and long-term effect on the fundamental values of target firms.

JEL Classification: G12, G23, G34
Keywords: Hedge fund activism, Corporate Governance, Productivity, Capital reallocation, Labor outcomes

1. Introduction

A growing literature on hedge fund activism shows that the stock prices of target firms experience significantly positive returns when the market first learns of the presence of the activist. The range of abnormal returns during the short-term announcement window is highly consistent across different studies and markets.[1] A subset of this literature also documents a significant improvement in operating performance in the period following hedge fund interventions. Using our sample of close to 2,000 activism events in the U.S. from 1994 to 2007, we validate and summarize this pattern using return on assets (ROA) as the performance measure. Figure 1 plots the target firms' average ROA in excess of that of a control group—where the control group consists of firms in the same three-digit SIC industry and year, and is adjusted for firm size and age—from three years before to three years after the public announcement of activism. There is a clear "V" shaped pattern centered on the year of intervention, and the level in the third year post intervention is significantly higher than that during the year of intervention or the year prior to intervention.

[1] Average event returns range from five to ten percent. See Brav, Jiang, Partnoy, and Thomas (2008), Klein and Zur (2009), Clifford (2008), Greenwood and Schor (2009) for U.S. companies; and Becht, Franks, Mayer, and Rossi (2009), Becht, Franks, Grant and Wagner (2014) for non-U.S. markets.

While the evidence regarding both stock returns and firm operating performance speaks favorably on the impact of hedge funds activism, several important related questions have yet to be addressed. First, research to date has not explicitly identified how hedge fund activists create value. As a result, little is known about the precise mechanism via which activists are able to improve efficiency and increase shareholder value. In fact, opponents of hedge fund activism often consider hedge fund activists to be "short-term focused" and "financial engineering oriented," and deny that such activists have any meaningful real and long-term impact.[2] Moreover, performance measures at the firm level, such as ROA, do not reveal the underlying channels of improvement. That is, these measures cannot isolate gains from production efficiency of existing assets from those due to capital reallocation, such as the divestiture of underperforming assets, because firm-level analysis cannot trace out the performance of the underlying assets subsequent to the change in ownership.

Second, since previous research is based on databases that cover only public companies at the firm level (such as Compustat), it has been a challenge to address the potential survivorship bias in the post-intervention period. Within two years of activists' intervention, close to 26% of companies targeted by activists disappear from the Compustat database because they were either acquired or delisted, a rate almost twice the normal attrition rate of the Compustat universe. As a result, researchers have not been able to directly assess post-intervention performance based on an uncensored sample. Third, while existing research has focused on the effects of hedge fund activism on shareholder wealth and the overall operating performance of the target firms, little is known about its impact on the firms' other stakeholders, particularly the employees.

The limitations of previous research are due both to the novelty of the topic, and hence the lack of a large sample of post-intervention data, and the reliance on firm-level information of public companies. This paper addresses these important impediments by exploring the U.S. Census Bureau's longitudinal databases of manufacturing establishments (i.e., plants), including the Census of Manufacturers (CMF) and the Annual Survey of Manufacturers (ASM). We match these plant observations to hedge fund activism events from 1994 to 2007 and then examine the dynamics of productive efficiency at firms targeted by activists, measured by total factor productivity (TFP). We assess the relative importance of the gains in efficiency among assets in place and those due to reallocation of the target firms' plants. In addition, we are able to investigate the impact of hedge fund activism on labor by examining changes to labor productivity, work hours, and wages obtained from the Census Bureau datasets.

[2] See, for example, "Hedge Fund Activists Set for Comeback," *Financial Times,* December 8, 2009, and "Current Thoughts about Activism," by Martin Lipton, *The Harvard Law School Forum,* available at: http://blogs.law.harvard.edu/corpgov/2013/08/09/current-thoughts-about-activism/#more-50945.

The following are our key findings on the long-term real effects of hedge fund activism. First, the productivity of plants owned by firms targeted by activists evolves in a pattern similar to the dynamics of ROA shown in Figure 1. Three years prior to the intervention, the productivity of target firms' plants is slightly higher than their control plants with similar size and age in a given industry and year. Target firms' productivity deteriorates thereafter to a level similar to that of the control plants when intervention occurs, but then rebounds within three years post-intervention to a level higher than that of the control plants. Second, we find that the improvement in production efficiency associated with hedge fund activism is more pronounced when the activist targets operational issues, such as business strategies or asset sales, relative to when the activist targets general undervaluation or capital structure issues. Third, one channel through which activists create value is by facilitating efficient reallocation of corporate assets. Focusing on the subsample of plants that were sold after hedge fund intervention, we find that these plants exhibit lower productivity than plants in the control sample prior to the sale, but then experience a significant improvement in productivity under new ownership. Moreover, the improvement is significantly greater than that of plants sold without the involvement of hedge funds. This evidence suggests that the presence of hedge funds is essential for the matching of plants to new owners who can operate the underperforming plants more efficiently. Fourth, while labor productivity improves significantly post-intervention, there is an (insignificant) decline in work hours and stagnation in wages post-intervention. Moreover, the increase in labor productivity is only significant in highly unionized industries. The improvement in labor productivity coupled with relatively stable wages indicates that workers do not fully capture the value of productivity improvements, but instead relinquish most of the surplus to equity investors after hedge fund intervention. Fifth, we find that target plants significantly increase their investment in information technology, which, in turn, is positively associated with the gains in productivity post-intervention.

The combined 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 the popular press.[3] Moreover, the plant observations in our Census data survive changes in ownership (i.e., plant sales) and firm delistings from exchanges, and thus are not subject to a potential selection issue caused by asset sales or firm attrition. Hence, our estimates of higher plant productivity for the targets of hedge fund activism are more accurate than performance analyses based on data from Compustat.

[3] Our evidence that hedge fund activists focus on strategies that impact long-term firm performance is consistent with the finding in McCahery, Sautner, and Starks (2014), who conduct a survey of institutional investors' preferences and decision-making regarding corporate governance. McCahery et al. (2014) find that the two most important factors that tend to trigger activist intervention are disagreement with the firms' strategies, such as planned diversifying mergers or acquisitions, and corporate governance.

An important question remains: Given the nonrandom selection of target firms by hedge funds, to what extent are the documented effects causal? 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 the implications of such changes for target firms. The observed improvement in the target firms' performance post-intervention may therefore just reflect the consequences of these shocks independent of the activists' presence.

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 activist intervention. Activists tend to hold a concentrated equity stake in the target firm until the resolution of their goals, a holding period that averages close to two years (see Brav et al. (2008)). It is hard to argue that activists would willingly hold undiversified positions and be subject to costly engagements (Gantchev (2013)), which typically evolve into shareholder proposals and proxy contests, if these were not necessary means to achieve their goals. We nevertheless conduct additional tests to isolate the effects of hedge fund intervention, vis-à-vis several counterfactuals.

We begin with a placebo test to assess the possibility that target plants, which tend to experience deterioration in performance prior to the intervention, might have recovered on their own simply by the force of mean-reversion. However, when we follow matched plants with a similar magnitude of a decrease in productivity before the arrival of activists, we do not find evidence of mean reversion. We then consider the alternative hypothesis that hedge funds select companies where management would have implemented changes even without influence of or pressure from hedge funds. To this end, we focus on the subsample of openly confrontational events where the hostile nature of hedge fund activism is proof of management's resistance, and it would therefore be difficult to attribute the post-intervention changes to management's voluntary and planned reform. We find, however, that the subsample of hostile engagements actually shows a slightly larger improvement than the rest of the activist interventions. A third specific alternative hypothesis is that hedge funds are sophisticated stock pickers selecting target firms that are best positioned to benefit from an industry shock. We test and refute this alternative explanation by examining the performance of plants that belong to target firms' non-primary business segments.

Next, to address the possibility that hedge funds merely engage in stock picking rather than adding value through intervention, we utilize a legal feature in ownership disclosure as the source of identification. Specifically, we measure the performance of firms for which hedge fund ownership remained constant, but the fund switched from a 13G to a 13D filing,[4] which indicates that the fund switched from a passive to an activist stance. The subsample of 199 such cases provides an ideal setting to test the incremental effect of intervention over stock picking. The significant performance improvement of these firms after the hedge funds' decision to switch their filing relative to the firms for which the hedge funds maintained a 13G filing—combined with results from the other identification tests—suggests that the performance improvement among target firms would not have occurred had the hedge funds been mere passive investors.

The findings of our study should be broadly interpreted as reflective of the real effects of active monitoring by informed outside shareholders. Recent work has analyzed the effect that general outside blockholders have on firm performance (McCahery, Sautner, and Starks (2014); Becker, Cronqvist, and Fahlenbrach (2011); Clifford and Lindsey (2013)), with a particular focus on the governance channel. Based on their incentive structure, investment strategies, and minimal regulation, we expect hedge funds to be among the most effective activists.[5] Moreover, productivity gains, which often occur in conjunction with restructuring activities, have been documented among takeover and private equity transaction targets (Maksimovic, Phillips, and Prabhala (2011); Li (2013); Davis, Haltiwanger, Jarmin, Lerner, and Miranda (2011)). The fact that a form of non-control based shareholder monitoring attains the same outcome indicates that hedge fund activism occupies an important middle ground between internal (via boards) and external governance by corporate raiders.

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 plant-level information from the Census of Manufacturers (CMF) and the Annual Survey of Manufacturers (ASM), based on which we construct measures of productivity. The CMF covers all manufacturing plants in the U.S. for years ending in '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 the applicable number of

[4] A shareholder who acquires more than 5% beneficial ownership is required to disclose in the Schedule 13D within 10 days of crossing 5% if it intends to influence control. If the investment intention is purely passive, the disclosure requirement is a less stringent 13G form. Section 7.3 provides a more detailed discussion of these filing requirements with the SEC.

[5] For a more detailed argument see Gillan and Starks (2007) and Brav, Jiang, and Kim (2009).

employees, which increased from 250 to 1,000 during our sample period,[6] are always included in the ASM, while those with fewer employees are sampled randomly with the probability of inclusion increasing in size. Even though it is called a "Survey," reporting is mandatory if selected and misreporting is subject to legal penalties and fines. Both databases provide operating information at the plant level, including the total value of shipments, capital stock and investment, labor hours, and material and energy costs.

The CMF and ASM data have a few critical advantages over standard firm-level databases of public firms such as Compustat in examining the real effects of activism on target firms. First, because these databases cover plants owned by both private and public firms, they allow us to track the performance of target firms even if they disappear from Compustat due to acquisitions or delistings. Because such events tend to occur more often among firms targeted by hedge fund activists, this feature of the Census data minimizes the potential for attrition bias in estimating the effect of activism. Second, accurate estimation of productivity as well as industry benchmarking requires a reasonable uniformity of production functions, a property that applies to plants but not necessarily to firms. Thus, the CMF and ASM data allow us to identify the gain in production efficiency associated with activism, which is beyond the reach of analyses relying on databases of publicly traded companies.

The second data source that we employ 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 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 1990 to 2009 (the last year of the data coverage). The starting year is determined by the sample period of the hedge fund activism database (1994-2007) and the fact that we examine plant performance beginning three 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 the variables necessary to estimate TFP, including the SIC code,[7] total value of shipments, production worker equivalent hours, beginning-year capital stock, and material and energy costs. Appendix A provides details on the construction of these variables, including adjustments for changes in the prices of inputs and outputs, and depreciation. This sample selection

[6] The threshold was 250 employees before 1999, 500 from 1999 to 2003, and 1,000 after 2003.

[7] The ASM and CMF provide SIC codes until 2002 and provide NAICS codes thereafter. We follow Giroud (2013) and impute SIC codes after 2002.

procedure yields 787,758 plant-years in our sample. Henceforth, we will refer to the collection of sources described in this section as the "Census data."

2.1.2. Hedge fund activism data

The database of hedge fund activism events, covering the period of 1994-2007, is an extension of the sample used in Brav, Jiang, and Kim (2009) and is based on the same sample selection criteria. These events are identified mainly through Schedule 13D filings to the SEC, which are mandatory filings for any shareholder who owns 5% or more of any class of a company's shares and intends to influence corporate control. We also conduct news searches to identify activist events at mid- to large-cap companies (above $1 billion) in which the activist holds an ownership stake between 2% and 5%. We then collect detailed information on key aspects of each event from the initial and amended 13D filings via the SEC's EDGAR system and by news searches.

The target firm-year pairs are then matched to (potentially multiple) plant-year observations in the Census data using a bridge file created by the Census Bureau.[8] Panel A of Table 1 shows that for 368 (out of a total of 1,987) activism events from 1994 to 2007, we are able to find at least one matched plant-year in the Census data with adequate information for estimating TFP, resulting in 14,923 plant-year observations in total. This match rate is somewhat lower than those typically reported in previous research due to two factors. First, close to 70% of the hedge fund activism targets in our sample are in non-manufacturing sectors (similar to the proportion among all publicly listed companies in the U.S.). In fact, the match rate increases to 44% for activism target firms in the manufacturing sector (based on Compustat SIC codes). Second, firms targeted by activists tend to be smaller than the target firms examined in previous research using the Census data (e.g., LBO and M&A targets).[9]

[Insert Table 1 here.]

Both the full sample of events and those matched to the Census data are more concentrated in the 2000s than the 1990s, reflecting the rise of activist intervention as an investment strategy among hedge funds from the early 2000s. Out of the 368 activism events matched to the Census data, 245 took place in or after year 2000. The number of plant-year observations maintains a similar proportion.

---

[8] For the matched target firms, the Census Bureau data covers the majority of sales and employees (63% and 54%) reported in Compustat. In addition, our main results are robust when we exclude target firms with a "small" fraction of sales or employees covered by the Census databases (e.g., in the bottom quartile or 5th percentile) or focus on firms with manufacturing Compustat SIC codes.

[9] For comparison, Lichtenberg and Siegel (1990) match about 50% of their LBO target firms with the Census data. Note that target firms classified as "non-manufacturing" based on the SIC code from Compustat might own manufacturing establishments, and thus can also be matched to the Census data.

Given that only a subset of the firms targeted by hedge funds are matched to the Census data, it is necessary to examine if the matched activism events are representative of the entire sample to ensure that our findings have general implications beyond the manufacturing sector. The distributions of stated objectives and success rates (including partial successes) for the full and matched samples, reported in Table 1 Panel B, indicate that the matched events appear to be nearly identical to the full sample of events along these two important dimensions. For example, the success rates (i.e., the proportion of events in which hedge funds attained, at least partially, their stated goals) for both samples are roughly two-thirds.

2.2 Measurement of Plant Productivity

Our main measure of plant performance is TFP, which is defined as the difference between the actual and predicted output given the 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); Giroud (2013)) and estimate the following log-linear Cobb-Douglas production function using Ordinary Least Squares (OLS) regressions by three-digit SIC industry and year:

$$\ln\left(Y_{ijt}\right) = \alpha_{jt} + \beta_{jt}^{K} \ln\left(K_{ijt}\right) + \beta_{jt}^{L} \ln\left(L_{ijt}\right) + \beta_{jt}^{M} \ln\left(M_{ijt}\right) + \varepsilon_{ijt}. \tag{1}$$

In equation (1), α_{jt} is an 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 the estimate of TFP for plant i in industry j in year t. The coefficients in equation (1) carry *(j,t)* subscripts, which allow factor intensities to vary by industry-year. In addition, given that TFP is the estimated residual of the industry-year specific regressions, we can interpret the TFP of a given plant as a relative productivity rank of the plant within a given industry and year. Finally, following Maksimovic, Phillips, and Yang (2013), we standardize the TFP measure from equation (1) by dividing it by its cross-sectional standard deviation for a given industry-year.[10] Essentially, this adjustment accounts for differences in the precision of TFP estimates among industry-years. As expected, using the non-standardized measure yields qualitatively similar but noisier results.

Though equation (1) is the common method adopted in the finance literature to analyze productivity at the micro-unit level, it is subject to the criticism that the estimated TFP is a regression residual and could therefore be contaminated if ε_{ijt} in equation (1) is positively correlated with one or more inputs. The current state-of-the-art remedy to this issue has been proposed by Levinsohn and Petrin (2003). It controls for unobserved shocks in productivity using an observable intermediate input (in this

[10] We first winsorize the residuals before standardizing in order to maintain the statistical properties of standardized TFP (i.e., N(0,1)).

case, materials) based on the assumption that the intermediate inputs' demand function is monotonic in productivity as long as the market for the input is competitive. The Levinsohn and Petrin (2003) method requires a long panel of plant-year observations to estimate the production function in equation (1) because it relies on estimated within-plant persistent productivity shocks. For reliable estimation of the parameters, we use 20 years of data for each industry-year panel.

2.3 Descriptive statistics

Table 2 reports descriptive statistics comparing the characteristics of the matched target plants with those of all Census plant-year observations used in our analyses and with those of all plant-year observations belonging to public firms (from Compustat).

[Insert Table 2 here.]

On average, plants owned by target firms are significantly smaller than plants affiliated with publicly traded firms, but do not differ significantly from the full Census sample. Specifically, the summary statistics for plants owned by target firms indicate that in the four years before to three years after a hedge fund intervention, these plants have a total value of shipments (TVS) of \$78m and real net capital stock of \$41m (in 2005 dollars) on average, which are (insignificantly) larger than the respective values for the full Census sample, but significantly (at the 1% level) smaller than the average of all plants affiliated with publicly traded firms. 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 unit by construction for the full sample. In comparison, target plants have a significantly positive mean TFP indicating that they are more efficient than the average plant in the full sample. Similarly, target plants show operating profit margins that are higher than that of the full sample of plants on average, but that do not differ significantly from the average operating profit margins of plants affiliated with public firms.

Next, we compare target firms that were matched to the Census sample with all target firms and then all public firms (the Compustat universe) in the year prior to intervention. The summary statistics are reported in Table 3. 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, when comparing the targets matched with the Census data to the full sample of target firms, the former tends? to hold less cash, pay more dividends, have lower valuation ratios (i.e., q), lower sales growth, and lower R&D spending. These characteristics suggest that the firms matched to the Census sample generally have lower growth opportunities but enjoy better cash flows, typical characteristics of firms in mature industries. These differences are largely due to the fact that more than 70% of the Census-matched firms are concentrated in the manufacturing sector. The comparison between target firms and the full Compustat universe is consistent with the findings in Brav et al. (2008). Notably target companies are significantly smaller and have lower valuation ratios than all companies, on average; but target companies also enjoy significantly higher cash flows.

[Insert Table 3 here.]

3. Hedge Fund Activism and Productivity

3.1 Plant and Firm Productivity before and after Activists' Intervention

As a first step, we examine the impact of hedge fund activism on target firms' productivity at the plant level. Our main dependent variable is plant-level TFP computed as the estimated residual from a log-linear Cobb-Douglas production function regression at the SIC three-digit industry-year level as in equation (1).[11] Our TFP measure can be understood as the relative productivity rank of a plant within its industry-year. By construction, the TFP of an industry in a given year, averaged over all plants, is zero. The resulting regression specification is as follows:

$$y_{it} = \sum_{k=-3}^{3} \gamma_k d_{it}[t+k] + \lambda Control_{it} + \alpha_i + \alpha_{jt} + \varepsilon_{it}. \quad (2)$$

The key independent variables in equation (2) are a set of plant-year dummy variables, *d[t-3],…, d[t+3],* corresponding to the plant-year observations from three years before to three years after the firm that owns the plant is targeted by a hedge fund activist. Moreover, we code the dummy variables *d[t+k],* $0 \leq |k| \leq 3$ as one if a given plant is owned by the target firm in year *t+k*. Hence, this specification analyzes performance at plants that remain in the hands of the target companies before and after hedge fund intervention. We require that targeted plants be owned by target firms both in years *t-1* and *t*. This condition reduces the number of events included in the analysis to 318 (from 368 in total). The effect of ownership changes on productivity is an important but separate question which we examine in Section 4.

The 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 birth—identified by the flag for plant birth in the LBD—or its first appearance in the CMF or ASM database, whichever is the earliest. The starting year is censored in 1972 when the coverage of the Census databases begins. This set of control variables

[11] Our main results are robust to a translog functional form, a less popular measure used in the literature.

is standard among research that analyzes plant-level performance using the CMF and ASM data (e.g., Schoar (2002); Giroud (2013)). Finally, the estimation takes into account firm or plant and industry × year fixed effects (α_i and α_{jt}). Given that the dependent variable, TFP, is already an industry-level residual, we use industry × year fixed effects to avoid biases in coefficient estimates (Gormley and Matsa (2014)).

Table 4 reports results from a variety of specifications to ensure robustness. The dependent variable in the first three columns is standardized TFP. The baseline regression, reported in column (1), includes industry × year fixed effects. Columns (2) and (3) add firm and plant fixed effects, respectively. To validate that our results are not driven by the normalization of TFP, the dependent variable in column (4) is the non-standardized TFP. In column (5), the TFP measure is obtained using the Levinshon and Petrin (2003) GMM procedure to address the issue that the residuals and the inputs are potentially correlated in equation (1). Column (6) reports results at the firm level by aggregating plants belonging to the same firm. Finally, column (7) shows results for operating margin, defined as total value of shipments minus labor costs minus material costs, all divided by total value of shipments.[12]

[Insert Table 4 here.]

Note that the level of coefficients on $d[t+j]$, $j = -3,...,3$, is not directly comparable across the different specifications in Table 4. In the absence of plant or firm fixed effects (columns (1), (4), and (5)), these coefficients reveal the productivity of plants at targeted firms relative to peers with similar size and age in a given industry and year. The overall positive coefficients indicate that hedge fund target firms are more productive, which is consistent with the summary statistics in Table 2 and the finding in Brav et al. (2008) that the average target is a mature firm that has relatively strong business fundamentals but that may be subject to agency problems of free cash flows. The corresponding coefficients in columns (2) and (3) become negative around the years of intervention when the regressions incorporate plant or firm fixed effects, indicating that firms tend to underperform relative to their own "normal" levels during that time.

Importantly, all specifications deliver a consistent message: Plant productivity generally deteriorates prior to intervention, probably due to bad governance or mismanagement such as poor adaptation to market changes. The deterioration triggers the activist intervention, but is more or less reversed within the 2–3 year period post intervention. Formal tests, reported at the bottom of Table 4, indicate that the improvement in productivity from the year of intervention to three years afterwards is statistically significant at the 5% level for most of the specifications (the exception is column (2) in which plant fixed effects are included). And in three out of the seven specifications, the improvement is

[12] All dollar values are in 2005 dollars. Shipments and material costs are divided by appropriate deflators from the NBER-CES manufacturing database, and labor costs are deflated using the CPI from the Bureau of Labor Statistics.

significant beginning in year *t+2*. The economic magnitude of the improvement in plant-level TFP associated with activism is sizeable: A typical target plant experiences an increase in TFP of 5.2%–11.8% of the standard deviation from years *t* to *t+3* using the first three specifications where the dependent variable is constructed to be of unit standard deviation. A formal test of the joint significance of deterioration before and improvement post intervention, which amounts to an *F* test for the joint inequality of the coefficients on *d[t]* and *d[t-3]*, and that of the coefficients on *d[t+3]* and *d[t]*, rejects the null hypothesis at the 5% level for five specifications.

Interestingly, both the pattern and the magnitude of TFP around hedge fund intervention echo the pattern in Figure 1 showing an improvement in ROA at target firms after intervention. The improvement in ROA from the trough in year *t* to three years following is about 3 percentage points, which is roughly 10% of the standard deviation of ROA (with the same winsorization at the 1% extremes as we conducted on the TFP estimates) during our sample period. Using the framework of Bosch-Badia (2010), Appendix B shows how this change in ROA is consistent with the documented gain in TFP by decomposing it into the changes in operating profit margin, which in turn is driven by changes in TFP, and asset turnover.

3.2. Conditioning on Hedge Funds' Stated Objectives

We now turn to the evidence provided in Table 1, Panel B, indicating that there is significant heterogeneity in activist "styles," namely that activism campaigns may target a range of corporate policies. The large variation in activists' objectives likely reflects the fact that target firms may face different types of problems prior to intervention. For example, some firms have inefficiencies in operations or asset composition while others have agency problems related to free cash flows or inadequate governance mechanisms. In this section, we exploit this heterogeneity and ask whether there is a link between the stated objectives and the outcomes of activism events as measured by TFP.

[Insert Table 5 here.]

The evidence in Table 5 is consistent with the idea that conditioning on hedge funds' objectives generates significant variation in the dynamics of target firms' TFP. First, the "General" category in column (1) is associated with the smallest (and insignificant) magnitude of TFP improvements two to three years after the intervention, while all categories with specific activist agendas exhibit economically and statistically significant improvements. Moreover, target firms in both the "General" and "Capital structure" categories started with levels of productivity that are significantly higher than those of their industry-year peers in years *t-3* and *t-2*, suggesting that targets in these two categories tend to have strong fundamentals but may suffer from agency problems due to free cash flows. The "Business strategy" and

"Sale" categories in columns (4) and (5) are associated with the largest magnitude of TFP improvements from years *t* to *t+3* (27%-31% of the standard deviation) and the lowest levels of TFP in year *t-3*. Finally, the "Governance" category in column (3) represents the middle ground.

Overall, the heterogeneity in the impact of activism on plant productivity is consistent with the argument that hedge fund activists optimally target firms with different characteristics and problems using different strategies. The evidence in Table 5 suggests that hedge funds tend to target operational issues when the firm's productivity lags behind its industry peers, while they focus on more general issues when target firms' operations are managed relatively efficiently but there is a room to improve their capital structure and governance practices.

4. Capital Reallocation and Attrition Analyses

4.1. Gains Due to Reallocation of Assets: New Insights from the Census Data

To the extent that hedge fund activists help enhance the productive efficiency of the targeted firms, an equally important question is whether such improvements are accomplished through improvements in the efficiency of assets in place, capital reallocation, or both. In fact, efficient redeployment of capital is a commonly stated goal of activist hedge funds. In addition to the roughly 20% of events in which hedge funds explicitly demand the sale of the entire target company, in another 15% of the events the activists push for the divestiture of under-performing or non-core assets in order to strengthen the companies in their core line of business. The case of Pershing Square's engagement with Fortune Brands, described in Appendix C, also points to capital reallocation as an important mechanism for the value added by activist hedge funds.

Prior literature has offered some indirect evidence on the gains from capital reallocation. For example, Brav et al. (2008) 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 for the sale of the target. The scope of these previous findings, however, has been limited by the use of data from CRSP/Compustat. First, performance measures computed using firm-level data (such as ROA) do not separate organic improvement (i.e., productivity gains of existing assets) from gains due to the reallocation of assets (i.e., due to acquisition/disposition of higher/lower performing assets). The Census data, which are recorded at the plant level and hence survive ownership changes and firm delistings, allow us to separate the two effects by tracing performance at plants that change ownership post targeting (i.e., the plants that are spun off).

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., if it goes private). Within two years after intervention, 25.5% of the targets in our sample cease to be covered by Compustat, a rate that almost doubles the average attrition rate of a typical Compustat firm. Therefore, addressing the potential delisting bias is challenging, particularly given that the direction and magnitude of the bias are *a priori* unclear. Firm delistings are 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 firms targeted by hedge fund activists because attrition from the sample may actually represent a successful outcome for the following reasons. First, targeted companies on average have stronger fundamentals (higher productivity, ROA, and liquidity, as shown by prior literature and Table 4 of this paper), and hence the subsequent attrition is less likely to be distress-related 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. Indeed, 70% of the target firms that disappear from Compustat within two years post intervention are acquired. Using trading liquidity as an instrument, Brav, Jiang, and Kim (2009) show that the use of Compustat data causes a negative survivorship bias because of the characteristics of firms that delist from Compustat. That is, firms that will experience greater improvements in performance post intervention are also more likely to disappear from the Compustat database conditional on observable characteristics.

The Census data allow us to make direct inferences on the direction and magnitude of the attrition bias by following targeted plants regardless of the listing status of the firms with which they are affiliated. 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 intervention experience greater productivity gains than plants owned by firms that remain in the database, on average.

4.2 Ownership Changes of Target Firms' 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 activists. In our sample, about 23% of the plants of the targeted companies were sold between the year of intervention and the third year post-intervention. The "sale rate" for non-targeted companies during a three year period is 13%. These numbers validate the stated goals of hedge funds in many activism events and generalize the anecdotes regarding hedge fund strategies. Consider, for example, Trian Fund Management's engagement with Wendy's/Arby's beginning in 2008. The hedge fund pushed Wendy's to jettison the underperforming sandwich chain and to revitalize the company's core menu in order to better compete against rivals McDonald's and Burger King. Appendix C of this paper also provides a detailed description of Pershing Square's engagement with Fortune Brands and its role in the conglomerate's decision to spin off two of its peripheral segments.

To formally assess the impact of asset reallocation, we first analyze the determinants of a plant sale and, in particular, the impact of hedge fund intervention. In Table 6 Panel A, columns (1) and (2), we report results from probit regressions at the plant-year level where the dependent variable is a dummy variable set to 1 if a plant sale occurred in a given year. The plant characteristics with the strongest effect on a plant sale are TFP and the centrality of the specific firm segment to which the plant belongs (as measured by the contribution of the industry segment to the firm's total shipments). As expected, both are significantly negatively associated with the probability of plant sale. Related to hedge fund activism, we find the following significant (at the 5% level) result: plants belonging to targeted firms are more likely to be sold after, but not before, the intervention. Moreover, the negative and significant coefficient on the interaction term *After* × *TFP* implies that low productivity plants are far more likely to be sold post intervention. Finally, column (3) examines the determinants of plant sales using a competing risks model (Fine and Grey (1999)). This specification is particularly suitable in this context because, at a given point in time, the same plant has "competing" risks of being sold or closed (i.e., only one of the events can occur). The evidence in column (3) mirrors that in columns (1) and (2) in that target plants are more likely to be sold after the arrival of activists, especially if these plants underperform. In sum, Panel A provides a clear message that hedge funds' interventions are associated with the sale of poorly performing plants.

The above evidence on plant sales, as well as the case of Pershing Square's targeting of Fortune Brands, suggests that hedge fund activists may push target firms to "refocus" by selling peripheral plants or divisions. In Panel B of Table 6, we examine whether target firms indeed refocus post-activism using the broader Census Bureau's LBD data which covers both manufacturing and non-manufacturing establishments. Specifically, using employment and wage data from the LBD (sales or output-like variables are not available from the LBD), we construct the firm-level segment HHI across all establishments within firms and compare it before and after intervention (as well as for non-event firm-years). Lower levels of this measure indicate higher levels of diversification. We find that the segment HHI increases significantly after intervention. In particular, columns (1) and (3) show that HHI scores at target firms are always below those of industry-year peers, consistent with the view that target firms (and public firms in general) were more diversified but have become "less diversified" after intervention. Estimates in columns (2) and (4), which include firm and year fixed effects (instead of industry × year fixed effects), indicate that target firms were slightly more diversified relative to their own average levels before intervention, but become less diversified afterwards. The change from before to after is statistically significant at the 5% level across different specifications, reassuring the robustness of the result that hedge fund activism is associated with a reduction in diversification at target firms.

[Insert Table 6 here.]

Next, we ask whether productivity improves among plants that were sold and are subsequently under new ownership. A mere divestiture of a negative NPV business unit creates value for a firm; yet the efficiency gain argument in favor of hedge fund intervention could be further strengthened if the performance of plants that are sold post-intervention improves under new ownership. To test this hypothesis, we re-run the TFP regression in equation (2) 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 $t+2$). The results are reported in Table 6, Panel C.

The first column of Panel C shows that plants that are sold post-activism exhibit a "V"-shaped pattern of performance around their sale. In particular, those plants had productivity levels that were statistically equivalent to those of their industry-year-size-age benchmarked peers three years before their sale, but were sold right after their trough in terms of performance. Subsequently, the change in TFP from years t to $t+3$ amounts to 23% of the standard deviation in TFP of the peer group, which is statistically significant at the 10% level. Columns (2) and (3), which use firm and plant fixed effects, respectively, show similar magnitudes of improvements in TFP during the period. Benchmarking from the year before the plant sale (when the performance is at its trough), the magnitude of TFP changes is about 50% larger and statistically significant at the 5% level across columns (1) to (3).

A question remains as to whether the TFP improvement subsequent to the sale of a plant is unique among targeted firms or is equally prevalent among plants sold in the absence of hedge fund intervention. Columns (4) to (6) in Panel C address this issue through what is essentially a placebo test. When we examine all sales of plants that do not belong to firms ever targeted by hedge funds in our sample, we find that the improvement from years t to $t+3$ is 0.040 in column (4) (statistically significant due to a much larger sample of plant sales), or one-sixth of the magnitude experienced by plants sold subsequent to the arrival of hedge fund activists. The difference-in-difference, at 0.187, is short of being statistically significant (t-statistic = 1.58). Again, compared to TFP in year $t-1$, the difference-in-difference estimate is 0.339 and statistically significant at the 5% level (t-statistic = 2.49).

The results in Table 6 illustrate the relative importance of TFP improvement on the intensive margin (i.e., the gain in efficiency for assets retained by the target firms post intervention) and on the extensive margin (i.e., the gain in efficiency due to assets matched to new owners). In all, hedge funds seem to be more effective on the extensive margin by facilitating asset reallocation. Such a role is natural given that hedge funds are outside investors who usually do not possess detailed knowledge about the inner operations of a firm, but may have a comparative advantage in sharing industry-wide best practices and in managing asset portfolios at the industry level. Further analysis on the characteristics of buyers illustrates the role of hedge fund activists in matching buyers with plants to be sold. In particular, we find that the buyers of plants post-activism are more productive, profitable, and larger than the selling target firms (untabulated). Also, the likelihood that the buyers and sellers are in the same two-digit SIC industry is higher by about 9% when hedge fund activists involve in plant sales. These results suggest that hedge fund activists facilitate finding larger and more efficient potential buyers with likely core competencies to operate the sold plants and who may also have "deeper pockets."[13]

Given the active divestiture of under-performing plants after intervention (and their subsequent improvement in TFP), it is interesting to distinguish how much of the improvement in overall firm-level TFP is due to improvements in plants owned by target firms pre- and post-intervention and how much is due to gains from divestitures. Among plants owned by target firms in year t, 81% are retained by target firms ("continuing") and the rest are sold or closed ("divested") by year $t+3$.[14] In addition, the average TFP of the "continuing" and "divested" plants is 1.06% above and 3.78% below that of their industry-year peers in year t, which implies that firm-level average TFP at target firms is about 0.14% (= 0.81×1.06% + 0.19×(−3.78%)) above that of their peers. By year $t+3$, the TFP of the continuing plants increases to 3.66%, which also is the firm-level average TFP in the year. If we assume (hypothetically) that all the divested plants had been retained until year $t+3$ and that the TFP at these plants had increased by the same magnitude as the continuing plants (i.e., by 2.60% = 3.66% − 1.06%), the average TFP of the target firms in year $t+3$ would be 2.74% (= 0.81×3.66% + 0.19×(−1.18%)) instead of 3.66%. Therefore, the divestiture may account for approximately a quarter (0.92% out of 3.52% = 3.66% − 0.14%) of the firm-level TFP gains three years post-activism.

4.3 Delisting from Compustat

Our Census sample includes plants belonging to 368 companies that were targeted by hedge funds between 1994 and 2007. Within this sample, 91 companies disappear from Compustat within two years after intervention because they were sold, taken private, or liquidated. This attrition rate is

[13] In addition, we find that the increase in TFP documented in Table 6 Panel C is more pronounced among the least concentrated industries (measured by the HHI) in which markets for corporate assets are likely "thicker." This result suggests that hedge fund activists may be more effective in facilitating efficient asset sales when a larger number of potential buyers exist for asset redeployment (Williamson (1988)).

[14] Newly opened or purchased plants by targeted companies are negligible during the period so are ignored.

comparable to that for the full sample of Compustat-covered hedge fund targets. Among this "attrition sample," we are able to follow 261 plants owned by 53 firms that are delisted from Compustat post-intervention. These additional observations from the Census data allow us to assess the sign as well as the magnitude of the attrition bias that arises when using the Compustat data. We then discuss the remaining bias caused by plant liquidation.

[Insert Table 7 here.]

In Table 7, we report results from regressions that interact the dummy variables $d[t+k], -3 \leq k \leq 3$ with an indicator variable, *Attrition (Non-attrition),* which is set equal to one if a plant belongs to a company that is targeted by hedge funds and then delisted from (remains in) the Compustat database by the end of year $t+1$. On the right side of the table, we report the t-tests for improvement in performance among the plants of companies remaining in and disappearing from the Compustat database. Interestingly, when we focus on the plants that belong to companies that were delisted from Compustat during the one-year post-intervention period (*Attrition* = *1*), we find a positive improvement in two (three) years with a magnitude of 0.159 (0.367). The improvement from years t to $t+3$ is significant at the 5% level. In comparison, the magnitude of the improvement for the remaining firms (*Non-attrition* = *1*) is reduced to about one-third. The statistical significance for the improvement is higher for the remaining firms due to a much larger sample.

We thus find no support for the conventional positive survivorship bias. The relative magnitude actually suggests an unusual negative survivorship bias. That is, restricting estimation to the sample of target firms surviving in Compustat tends to *underestimate* the change in performance associated with hedge fund activism. This result provides support for the indirect evidence in Brav, Jiang, and Kim (2009), determined using an instrumental variable approach, and is good news for the existing literature using firm-level data: the performance (such as ROA) improvements documented therein are on the conservative side.

Needless to say, the Census data have their own attrition issues. About 16% of target plants and 27% of non-target plants that exist in our sample during the year of intervention disappear within two years. There are two reasons for the attrition. First, although all operating plants are sampled in the CMF for the years ending '2' and '7', "small" plants (with fewer than 250 to 1,000 employees depending on the year) are not sampled every year in the ASM, so they might disappear from the sample (possibly temporarily) although they are in operation. This attrition is due to random sampling and therefore should not contribute to a bias in either direction. Second, the plants that are liquidated drop out of the sample simply because they cease to exist. A formal test, reported in Table 6 Panel A, columns (4)-(6), shows that the difference in the probability of plant closure for plants belonging to target firms after the intervention compared to before is insignificant. This is in contrast with the finding in the first three columns that the probability of a plant sale increases significantly post hedge fund intervention compared to before.

5. Employment, Labor Productivity, and Wages

In this section, we explore the impact of hedge fund activism on the employees of target firms by using an empirical specification analogous to equation (2). In particular, our dependent variables include measures of employment, labor productivity, and wages, all in log scale. We measure labor productivity using output per labor hour and value added (i.e., sales - materials costs) per labor hour. The key independent variables, as described in Section 3.1, are the set of plant-year dummy variables corresponding to plant-year observations from three years before to three years after a firm, to which the plant belongs to, is targeted by a hedge fund activist. The control variables include segment and firm size and plant age.

We report the regression results for these labor outcomes in Panel A of Table 8. Columns (1) to (3) show that target plants experience a decline in employment and work hours relative to their peers within the same industry-year. Both the number of workers and hours per worker decrease post-activism, leading to a 7.3% and 4.3% drop in total labor hours from years t to $t+2$ and t to $t+3$, respectively. These declines, however, are not statistically significant at conventional levels. A reduction in "labor stock" is also evident in column (8), in which we see increases in the capital-to-labor (K/L) ratio of 6.7% and 5.3% during the two and three years following intervention, respectively (the former is significant at the 5% level). Such a pattern is similar to, but entails an even larger magnitude than, that documented by Davis et al. (2011) regarding declining employment at target firms subsequent to private equity (PE) transactions.

Meanwhile, columns (4) and (5) show that labor productivity improves by 8.4% to 9.2% at the target plants during the three-year period post-activism. These estimates are statistically significant at the 1% and 5% levels, and are consistent with the improvements in TFP documented in Section 3. The estimates in columns (6) and (7), however, indicate that worker wages do not keep up with the improved labor productivity—per-hour wages increase (insignificantly) by 1.1% and wages per worker remain flat (largely due to the reduction in total work hours) in the three years after the arrival of activists. These results indicate that the employees of target firms experience a de facto but implicit wage reduction: productivity-adjusted per hour wages decrease by 7.3% (= 8.4% - 1.1%) from years *t* to *t+3*.[15]

[Insert Table 8 here.]

The combined evidence is consistent with a divergence of interests between managers and outside shareholders concerning labor prior to the intervention of hedge funds. As argued in Pagano and Volpin (2005) and Cronqvist et al. (2009), top managers, who usually own a minority share of the target firm but bear the full cost of monitoring workers, are less incentivized to motivate employees or to improve productivity through monitoring. Instead, given the small private cost, managers would be willing to pay employees higher wages to motivate them or improve relations with labor. In contrast, activist hedge funds, who have a stronger financial incentive to improve firm performance as minority blockholders (Shleifer and Vishny (1986)), are more willing to monitor the top managers and promote higher-powered (financial and non-financial) incentives. This change, in turn, likely trickles down to lower-level management, leading to an improvement in productive efficiency while reigning in wages.[16] In fact, this interpretation of the results on labor outcomes is consistent with the popular press' view of hedge fund activism as being unfriendly to the target firm employees.[17] Our findings are inconsistent with models of firm-specific human capital and implicit commitment (e.g., Shleifer and Summers (1988)), or an efficient wage hypothesis (e.g., Shapiro and Stiglitz (1984)). These models would predict that a wage reduction or stagnation after hedge fund intervention leads to a *decrease* in productivity.

Next, in Panel B, we present evidence on the changes in these labor outcomes separately for activism events in low and high unionization industries defined at the median of the annual distribution of collective bargaining coverage (Hirsch and Macpherson (2003)). Columns (1) to (3) show that employment and work hours decrease three years after intervention in industries with strong union presence while they are relatively flat in industries with weak union presence. One plausible explanation

---

[15] In unreported results we find that the average worker at a target plant experiences a significant decrease in 'total supplemental labor costs' (i.e., fringe benefits) by 3.9%, suggesting that the overall compensation package deteriorates after hedge funds' engagement.

[16] In unreported results we attempt to trace the change in incentives following the tests in Bandiera, Barankay, and Rasul (2007). These authors use a field experiment showing that managers under high-powered incentive schemes direct their monitoring effort to more productive workers, which leads to an increase in the dispersion of as well as the average productivity. Hence, to the extent that managerial efforts for monitoring and individual plants' productivity are complementary, better monitoring ought to lead to an increased dispersion of productivity across plants within a given firm as more productive plants improve productivity at a faster pace. Consistent with this prediction, we find that the across-plant standard deviation of productivity increases by about 3-4% post-activism.

[17] See, for example, "How Wall Street Bent Steel," *The New York Times*, December 7, 2014, and "'Shareholder Value' is Hurting Workers," *The Wall Street Journal*, December 9, 2014. These articles report that before targeted by Relational Investors, workers of Timken Corp. were paid $23 an hour, which is "higher than at any of Timken's specially-steel rivals," and that "workers receive the equivalent of another $20 an hour in benefits." However, after the arrival of Relational, the firm's pension fund contributions dropped from nearly a third of cash flows to near zero.

for the result is that highly unionized industries are more likely to employ or keep a surplus of labor prior to hedge fund intervention (Freeman and Medoff (1984)). In addition, unionized labor tends to prefer to restructure operations through layoffs rather than wage cuts partly due to "inverse seniority rules," in which junior workers are laid off before senior (Abraham and Medoff (1984)). Hence, target firms in such an industry may experience more cuts in employment and perhaps fewer cuts in per-hour wages because senior workers who earn higher wages are less likely to be laid off after hedge fund intervention.

Importantly, columns (4) and (5) show that both measures of labor productivity improve significantly in the highly unionized industries, while the increase is insignificant in industries with low unionization rates. This result further supports the argument that hedge fund activists improve the efficiency of target firms with entrenched labor (unions in this case) in part via stricter monitoring. In addition, column (7) shows that within two (three) years after the arrival of activists, per-hour wages increase significantly by 5.2% (3.7%) in highly unionized industries. The formal test for differences at the bottom of the table indicates that the increase in per-hour wages in highly unionized industries is significantly different than that in industries with low unionization. The improvement in productivity in highly unionized industries is, however, not significantly different from that in industries with low unionization. The increases in wages and labor productivity post-activism in highly unionized industries are again consistent with unions relying more on layoffs than wage reductions as a way of restructuring.

We find consistent evidence in an additional analysis examining wage changes separately for "white-collar" (i.e., non-production) and "blue-collar" (i.e., production) workers. Specifically, we find that the average wage of white-collar workers drops by 5.0% post-activism while it is relatively flat for blue-collar workers employed at targeted plants (untabulated). In addition, the average wage of all employees at target firms covered by the LBD[18] decreases by 13.3% post-activism (significant at the 1% level). Given that the LBD is likely to include more white-collar workers (e.g., those in administrative offices) than the ASM and CMF, this result again suggests that non-production workers, who are less likely to be covered by unions (Freeman and Medoff (1984)), suffer larger wage cuts than production workers.

Overall, the results in this section indicate that, on average, workers at target firms do not share in the improvements associated with hedge fund activism. They experience a reduction in work hours and stagnation in wages, while their productivity improves significantly. The reduction in work hours and increase in productivity are especially pronounced in industries with strong labor unions, but the increase in wages partly counters the potentially negative impact of activism on workers' welfare in these

[18] The LBD covers virtually the entire set of manufacturing and non-manufacturing establishments in the U.S. See Section 2.1.1 for details of the database.

industries. The evidence on the average productivity and its dispersion suggests that hedge fund activism helps mitigate inefficiencies through stricter monitoring. Moreover, the reduction in productivity-adjusted wages from above-par levels suggests that hedge fund activism facilitates a transfer of "labor rents" to shareholders, which may account for a portion of the positive abnormal returns associated with the announcement of hedge fund interventions.

6. Technology-related Investment and Productivity

The evidence in the previous section suggests that better monitoring of employees is a potential channel via which target firms experience gains in productivity after activists' intervention. In this section, we turn to another important input to target firms' production process, namely capital investment, as a potential driver of productivity. In particular, motivated by recent research arguing that information technology (IT) and related innovations have significantly contributed to productivity growth in the U.S. since the mid-1990s (e.g., Brynjolfsson and Hitt (2000); Bresnahan, Brynjolfsson and Hitt (2002)), we examine investments in IT, especially computers, and their impact on target firm productivity around hedge fund activism.

We first examine whether firms targeted by hedge funds change their investment in IT capital using a specification similar to equation (2). Given that the ASM and CMF databases do not include variables for 'capital expenditures for computers' until 2001, this analysis focuses on plant observations from 2001 to 2009 (36.6% of the full sample). Column (1) of Table 9, Panel A shows that the target plants begin with a level of IT investment (scaled by lagged capital stock) that is significantly lower than that of their industry-year peers in the year of the intervention. However, this difference relative to the industry-year peers becomes insignificant in the post-intervention period (beginning from year $t+1$). The bottom rows show that the "catch up" in IT investment at target plants from years t to $t+1$ or $t+2$ is statistically significant with an economic magnitude ranging from 8-9% of lagged capital stock. Using the natural log of IT investment as the dependent variable, column (2) shows an increase of similar economic magnitude (but lower statistical significance).[19]

[Insert Table 9 here.]

The significant increase in expenditures in computers at target plants raises the question of whether the investments in IT capital lead to an increase in productivity. At a broad level, to the extent

[19] Recent work by Brav, Jiang, Ma, and Tian (2014) shows that hedge fund activism is associated with less innovative inputs but higher innovative efficiency. Hence, evidence in both studies suggests that hedge funds tend to target mature firms but revive some of their technological edge while reducing investments or overall assets.

that investment in computer equipment represents an improvement in the quality of capital to a newer vintage (e.g., Sakellaris and Wilson (2004)), an increased investment in IT may lead to higher productivity. In Panel B, we estimate equation (2) with TFP and labor productivity as the dependent variables separately for plants with relatively large and small *changes* in computer investment scaled by lagged capital (defined at the median) from years *t* to *t+3*. We control for both plant and industry × year fixed effects. Column (1) of the panel shows that computer-related investments and productivity gains after activism are in fact positively related. For target plants with a change in IT investment above (below) the median, the improvement in TFP over the three years following intervention is 13.4% (4.5%) of the standard deviation. The change in TFP is statistically significant at the 10% level only for the above-the-median group. Column (2) shows a qualitatively similar result for labor productivity: for target plants with a change in IT investment above (below) the median, the improvement in labor productivity is 6.6% (1.6%) during the three-year period, but the change in labor productivity is statistically insignificant for both groups partly due to the smaller sample used in the analysis.

We conclude this section with an attempt to link the changes in labor productivity that we observe to the *level* of IT capital. The literature on IT and productivity (e.g., Bartel et al. (2007)) suggests that investment in technology has a larger impact on productivity when it is more complementary with worker skills (e.g., non-routine, problem-solving skills). Thus, we expect that target firms may experience a larger improvement in labor productivity in industries where IT capital is crucial and thus is more likely complementary with labor. To examine this prediction, Panel C estimates the effect of hedge fund activism on labor productivity and wages conditional on "IT intensity." We measure IT intensity using the share of investments in computers among total capital expenditure at the two-digit SIC level (Stiroh (2002)).[20] We find that increases in both labor productivity and wages (columns (1) and (2)) are more pronounced in industries for which IT is more important (above the median) and thus is more likely to be complementary with labor skills. These results are consistent with Agrawal and Tambe (2014), who argue that IT investments during PE ownership impart IT-related human capital to the employees, which in turn increases their post-PE employment duration and wages. Therefore, while hedge fund activism may not benefit the workers *on average* (Table 8), it may benefit them in sectors where technology-related skills are important (in the form of higher wages). Lastly, column (3) shows that the log capital-to-labor ratio increases significantly only for the more IT-intensive industries, consistent with the idea that productivity gains in these industries may be spurred by IT-related capital investments. As can be seen from the formal tests for the difference at the bottom of the table, only the change in labor productivity is almost significant (at the 10% level) when we compare the high- and low-level IT intensive industries.

[20] The variable is measured at the beginning of the sample period (2001) when the information on computer expenditures becomes available in the Census Bureau's plant-level datasets.

7. Causality

7.1. Overview

Although the evidence reported so far is consistent with hedge fund intervention affecting the plants of target companies, it does not prove such an effect. Before delving into the causality tests, we would like to highlight two different aspects of a treatment effect in our context. The first question is the following: If hedge fund activists were randomly assigned to target firms (i.e., if targeting per se were exogenous to future firm performance), would they have improved the performance? This question addresses the population average treatment effect. The second question asks: Would the same changes have occurred at the target firms without the hedge funds' efforts? This notion represents the treatment effect on the treated.

For the purpose of our research, as well as for relevant policy implications, we are primarily interested in the second notion of the treatment effect and do not attempt to take a stand on the first. We fully acknowledge that hedge funds do not target firms randomly, along either observable or unobservable dimensions. In fact, the selection of targets where the hedge funds can have the biggest impact is an important part of the activists' investment strategy, and no sensible policy should mandate random matching of targets to hedge fund activists. As a result, we are most interested in assessing the real effects from activism relative to passive investments. That is, the counterfactual is the outcome that would prevail had the hedge funds picked the same target firms but remained merely as passive investors.

Current research on hedge fund activism has already provided support for the view that hedge fund intervention, beyond stock picking, is necessary for the observed outcomes. Certain changes, notably a significant increase in CEO turnover as in Brav et al. (2009), are natural outcomes of confrontation, which are unlikely to have occurred but for the persistence of the activists. In our sample, activists tend to hold concentrated stakes in target firms for an average holding period of two years.[21] We observe an even longer duration of ownership by Pershing Square in the Fortune Brands case described in Appendix C. Undiversified positions together with costly engagements, including proxy contests or public campaigns (Gantchev (2013)), cannot be justified by pure stock picking. Moreover, openly hostile activism events generate higher announcement returns than non-confrontational events. And activist stakes, which require the filing of a Schedule 13D, generate higher returns than the revelation of large

[21] The holding period is measured as the length of time between the filing of the initial Schedule 13D and the final amendment to the 13D indicating the stake has dropped below the 5% level. This measure provides a lower-bound for a hedge fund holding period of a significant stake.

passive stakes, which can be disclosed with a longer delay on Schedule 13G (see Klein and Zur (2009), Clifford (2008)).

We conduct several additional tests to complement the evidence summarized above. Each test addresses a particular alternative hypothesis regarding the possibility that the same changes would have occurred even if hedge funds were mere passive investors.

7.2. Specific Alternative Hypotheses

7.2.1. "Self-cure"

The first alternative hypothesis is that the target companies would "self-cure." That is, target companies and their plants experience deterioration in performance prior to hedge fund intervention, but might have recovered on their own just by the force of mean-reversion. To address this concern, we conduct a placebo test where to each of the plants belonging to a target firm, a "pseudo event" is assigned. A pseudo-event plant does not belong to a firm targeted by hedge funds but experiences similar deterioration from years *t-3* to *t*, [22] and is in the same industry and year as the targeted plant. For these pseudo events, we run the same regression as in Table 4 and plot the coefficients on the *d[t+k], k=-3,…,+3,* dummies in Figure 2 on top of the coefficients for the matched sample of "true" events.

[Insert Figure 2 here.]

By construction, the target plants and the pseudo-event plants share similar paths in their productivity from year *t-3* to year *t*. Importantly, the paths diverge right after intervention: The placebo plants do not show any evidence for improvement, whereas the matched target plants experience an improvement beginning from year *t+1*. The changes in TFP for the event plants from years *t* to *t+2* or *t+3* are statistically significant at the 5% level, while those for the pseudo event plants are not significant.

7.2.2. Voluntary reform by the target firm

The next alternative hypothesis is that hedge funds select companies where management was about to implement changes even without influence of or pressure from the hedge funds. To assess this possibility, we focus on the subsample of openly confrontational events where the hostile nature of hedge fund activism, due to management's resistance to the hedge fund's agenda, is publicly known. For this

[22] Specifically, we first require matched plants to have TFP changes from years *t-3* to *t* that are within +/- 0.01 of the TFP change for an "event" plant. If a match is not found using this threshold, we subsequently increase it to 0.05, 0.10, and 0.20 until we find a match.

subsample of hostile events, it is difficult to attribute any changes to management's voluntary and planned reforms, as we know that management in these cases resisted the actions demanded by the activists. We include only those events in which the activist's tactics involve actual or threatened proxy contests or lawsuits, or shareholder campaigns of a confrontational nature (such as public denouncements of management or shareholder proposals aimed at the ouster of the CEO). These events account for about one quarter of our sample. Note that our classification algorithm is conservative: while we might miss events that were hostile behind closed doors, the selected subsample should consist exclusively of hostile events. Results are reported in the first two columns of Table 10 Panel A.

[Insert Table 10 here.]

Repeating the same regression as in Table 4 but restricting the analysis to hostile events, column (1) reveals the same pattern in TFP: Deterioration before and improvement after the intervention. For comparison purpose, coefficients associated with non-hostile events are shown in column (2). Interestingly, TFP improvement between years t and $t+3$ is comparable between hostile and non-hostile events (0.152 vs. 0.107), both of which are significant at the 10% level.

7.2.3. Industry Shocks

The third alternative hypothesis posits that hedge funds are sophisticated stock pickers and identify the firms that are best positioned to benefit from an industry shock (such as winners from consolidation). Under this hypothesis, the real effects associated with hedge fund activism should be concentrated in plants belonging to the target firms' primary industries—which were the reason for the activists' interest in the overall firm—but not in plants belonging to the target firms' non-primary industries.

The key subsample for this analysis consists of target firms that have plants in both their primary and non-primary industries. Following Maksimovic and Phillips (2002), we define a three-digit SIC segment of a target firm as "core" ("peripheral") if the combined shipments of the industry segment is larger than or equal to (less than) 25% of the firm's total shipments. In columns (3) and (4) of Table 10 Panel A, we report the coefficients separately for events involving plants that are part of the core segments of targeted firms and for those that are peripheral. We find that improvements in plants in non-primary industries are just as strong as their primary-industry counterparts. The three-year post intervention TFP improvement is 0.126 (t-statistic = 2.12) for peripheral plants and 0.106 (t-statistic = 2.02) for core plants, and the two numbers are not statistically different from each other (t-statistic = 0.25).

Therefore, riding-the-industry-shock alone cannot explain our main results finding productivity improvements in targeted plants.

7.3. A General Alternative: Stock Selection vs. Intervention

It is difficult to exhaust all specific alternative explanations for our findings. We thus conduct a summary test that aims to separate hedge funds' stock picking abilities from the effects of intervention. In our setting, a "treatment" is a public statement of hedge fund intervention, which necessarily builds on hedge funds' block holding. The challenge is therefore to separate hedge funds' skills in picking stocks and the anticipation of positive changes in the target firm from the actual actions taken by hedge funds to cause or facilitate these changes. Such a separation can be derived from cases where activists change their investment stance from passive to activist without material ownership changes in the target firm. It turns out that a legal feature in the SEC's ownership disclosure rules allows for such an identification strategy.

Investors who hold beneficial ownership of more than 5% (but below 20%) for purely an "investment purpose" and without an intention to exert control are usually eligible to file a shorter form 13G (under Exchange Act Section 13(g) and Regulation 13D-G). To equate a 13D (13G) filing to an activist (passive) stance for identification purposes, we must establish that (i) an investor who files a 13G cannot take actions that could be construed as influencing firm policies and control (including actively "communicating" with management regarding firm strategies), and (ii) an investor with a passive stance does not want to file a 13D. It turns out that (i) is required by law and (ii) is incentive compatible. Regarding (ii), the 13G form not only requires disclosure of less information, but also allows for a longer delay in ownership disclosure.[23] Moreover, 13D filings entail more legal obligations.[24] As such, a true passive investor should not find it appealing to file a Schedule 13D.

Given the above, we attempt to filter out the treatment effect by focusing on changes in firm performance subsequent to a hedge fund's Schedule 13D filing (which involves both stock picking and potential intervention) versus a 13G filing (stock picking only). Since hedge funds may choose to take activist or passive positions in different firms, which may not be comparable even if we control for all observable characteristics, our identification comes narrowly from the same hedge fund-firm paring, that is, when a hedge fund switches from a "G" to a "D." A switch is required by law if a formerly passive investor decides that it may now want to take actions to influence control. Importantly, a switch usually

[23] Passive blocks of more than 5% require disclosure in Schedule 13G within 45 days after the end of the calendar year.

[24] Such legal obligations include instant filing of an amendment if there is any "material" change in the action, including ownership changes of 1% or more in either direction.

does not come with significant ownership changes—the only major change is that the investment stance switches from passive to active.

There are 299 events (out of the roughly 2,000 events) in our sample where activism was initiated by the activists' switch of 13G to 13D filings. Due to the relatively small sample of switching events and the loss of event observations when matching to Census data,[25] we conduct the test both at the plant level using the Census data and at the firm level using data from Compustat. Given that the previous sections establish that target plants' productivity follows a similar pattern with target firms' ROA (Figure 1 and Table 4), and that the attrition of Compustat firms does not introduce a positive survivorship bias for target firms (Table 7), we believe the analysis of firm-level operating performance is informative about the performance of underlying business units.

We construct a new sample where a plant-year or firm-year observation is included if at least one of our 319 sample hedge funds has disclosed 5% or more passive ownership in a Schedule 13G and does not switch the filing (the "G-stayers") and those observations where hedge funds have switched to a Schedule 13D filing from a 13G (the "switchers"). A plant-year or firm-year data point becomes an "event" observation if the 13G filing was switched to a 13D during the year in question. We call the event "*G to D switch*." This sample encompasses 2,983 plant-year observations or 3,954 firm-year observations (including 199 event observations). We then run the following regression:

$$\Delta Performance_{i,t\to t+3} = \beta \cdot G\ to\ D\ switch_{i,t} + \gamma \cdot Control_{i,t} + \alpha_f + \alpha_t + \alpha_{SIC3} + \varepsilon_{i,t}\,, \tag{3}$$

where $\Delta Performance_{i,t\to t+3}$ is the change in TFP or ROA during the three-year period post switch (if there is a "*G to D switch*" in year *t*) or just during a three-year period (for non-events). $G\ to\ D\ switch_{i,t}$ is a dummy variable equal to one if a hedge fund switched a 13G filing in firm *i* (or plant that belongs to firm *i*) to a 13D filing in year *t*. $Control_{i,t}$ represents the same control variables used in previous plant-level regressions, or includes firm market capitalization and firm age from the CRSP database for firm-level regressions. α_f, α_t, and α_{SIC3} are hedge fund, year, and three-digit SIC industry fixed effects.

Results, reported in Table 10 Panel B, are encouraging despite the small sample of events. Compared to the "G-stayers," the "switchers" experience TFP changes amounting to 0.085–0.126 of a standard deviation and ROA changes that are 2.5–3.3 percentage points higher during the three-year period post switch after controlling for year and hedge fund fixed effects. This specification is particularly informative as it controls for fund-specific stock-picking ability. The key coefficients are significant at the 10% (5%) level using plant (firm) regressions. If we further add industry fixed effects,

[25] Recall that we are able to match about one-sixth of the activism event firms to the Census data.

the coefficients are rendered insignificant although the magnitude remains comparable. Due to the small number of switches in the sample, the loss of statistical power is expected with multiple layers of fixed effects.

Table 10 Panel B demonstrates that firm and plant performance improves after a passive hedge fund blockholder turns activist.[26] Given that only the activist's stance, and not his ownership, changes at the switching point, we believe the test provides a clean identification of intervention beyond stock picking. Importantly, the coefficients on *G to D switch* are of comparable magnitude to the overall improvement in TFP and ROA of all target plants and firms (see the differences in the coefficients on *d[t+3]* and *d[t]* as reported in Table 4 and plotted in Figure 1), suggesting that the "treatment effect" (conditional on hedge fund stock picking) underlies the association between hedge fund intervention and improvements in firm performance.

It is important to emphasize that we do not claim that the same improvement would arise if a *randomly* chosen 13G filer is made to switch to a 13D. Our results support a causal effect of intervention among the firms in which the hedge funds have chosen to intervene. In other words, if the hedge funds were disallowed to engage in activism, then the improvement we observe would not have materialized even if the same hedge funds picked the same firms for the purpose of passive investment.

8. Conclusions

Using mostly plant-level observations from the U.S. Census Bureau, we show that hedge fund intervention is associated with productivity gains at the plants of the targeted companies. We also measure the performance of plants that were sold subsequent to intervention and find that they were among the worst performing plants at the time of divesture, but later experience a substantial improvement under new ownership relative to a matched sample. We find that employees of target firms experience a reduction in work hours and stagnation in wages while their productivity improves. These results support the view that hedge fund activists facilitate improvements in productive efficiency by improving the productivity of assets-in-place and by capital re-allocation. Overall, the evidence provided in the paper highlights the real and fundamental effects that hedge fund activists facilitate at target firms.

This study complements earlier and concurrent work on the real effects of other types of blockholders, notably private equity firms; and at the same time differentiates activist hedge funds from

[26] Consistent with this result, using blockholders that switch from a passive to an active investment stance in the Korean market, Kim, Kim, and Kwon (2009) find that the disclosure of the switch is associated with positive stock returns.

other blockholders. The most important difference between the two is that private equity firms usually take control of a portfolio firm while hedge fund activism is "influence" based. The nature of targeting is also very different. The ideal candidates for private equity firms could be fledgling businesses which benefit from financial/managerial nurturing or firms that go through structural changes which are better off being under close scrutiny by concentrated stakeholders. The typical targets for activist hedge funds are relatively mature firms with strong cash flows whose value could be improved with better governance, refocusing of business, and more efficient reallocation of assets. Our analyses demonstrate that hedge fund activism occupies an important middle ground in corporate governance between corporate control and routine monitoring by diversified shareholders.

Appendix A: Construction of Variables to Estimate the Production Function

This appendix describes the construction of the variables required to estimate the production function described in Section 2.2 using variables from the CMF and ASM databases. Output is computed as the sum of the 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 divide output by 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); Kovenock and Phillips (1997)). First, we obtain the initial book value of capital stock for each plant when the plant is born (identified using the LBD) or first appears in the CMF or ASM. Second, we adjust this book value for depreciation by multiplying it by the NAICS-based industry-level capital stock deflator from the Bureau of Economic Analysis (BEA). The deflator is the ratio of industry current value of net capital stock to industry historical value of gross capital stock. Third, we account for changes in the price of capital by deflating the adjusted initial 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:

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

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, 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 wages divided by wages for production workers. The underlying assumption in constructing this measure of labor hours is that the relative wages for production and non-production workers represent the ratio of their marginal products. Lastly, material costs are computed as the costs of materials and parts plus the costs of fuel and electricity, divided by the four-digit SIC level material deflator from the NBER-CES manufacturing database.

Appendix B: Decomposing Changes in ROA into Changes in Operating Margin and Asset Turnover

In this appendix, we formally link the magnitude of the change in ROA to the change in raw TFP from years *t* to *t+3*. In particular, we use a modified version of the decomposition in Bosch-Badia (2010) in which ROA is decomposed into TFP, input and output price changes, and asset turnover. Using the 'DuPont decomposition' of ROA, we obtain the following relation:

$$\text{ROA} = \text{Operating margin} \times \text{Asset turnover}, \qquad \text{(A-2)}$$

where ROA is the ratio of earnings before interests and taxes ("operating profits") to lagged total assets, operating margin is the ratio of operating profits to concurrent sales, asset turnover is the ratio of sales to lagged assets and, as Bosch-Badia (2010) shows, operating margin = 1 – 1/(TFP × price change ratio). The price change ratio = change in output price / change in input price. All price changes are relative to the benchmark year (i.e., year *t*). In addition, we further make the following two assumptions: (i) The baseline operating margin is 24.7% (see Table 2, column (1)), and (ii) the price change ratio is equal to one (i.e., input and output prices change by the same magnitude).

With these assumptions we can link the change in ROA to the changes in TFP and in asset turnover. First, we estimate the change in TFP using the specification in Table 4, column (4). Specifically, we narrow the estimation to only manufacturing firms based on Compustat SIC codes and find average productivity gains of 2.6% from years *t* to *t+3* for plants owned by manufacturing target firms. Second, given the baseline operating margin of 24.7%, the increase in TFP of 2.6% translates into an expansion in operating margin by 1.9 percentage points to 26.6%. Third, the magnitude of the change in ROA also depends on the change in firm-level asset turnover, which is driven by reductions in capital at the plants that are not sold, and by divestitures and/or closures of plants. Using Compustat data, we find that for manufacturing target firms asset turnover increases from 1.07 to 1.20 on average from years *t* to *t+3*. Taking the two changes together, the implied ROA increases by 5.5 percentage points from 26.4% in year *t* (= 24.7% × 1.07) to 31.9% in year *t+3* (= 26.6% × 1.20).

It is worth pointing out that the "operating profits" we compute above using the Census plant-level data does not subtract firm-level overhead costs (i.e., sales, general, and administrative costs; SG&A), and thus is more comparable to the "gross profits" (sales minus cost of goods sold) computed using Compustat data. If we further incorporate the change in the SG&A-to-assets ratio between years *t* and *t+3* (an increase of 1.0 percentage point) into the change in ROA, the implied change in ROA would be 4.5 (= 5.5 − 1.0) percentage points, which remains similar to the actual change in ROA (5.4 percentage points).

Appendix C: Case Study of Pershing Square Capital Management and Fortune Brands

On October 8, 2010, Pershing Square filed a Schedule 13D with the SEC indicating that it owned 10.9% of Fortune Brands' shares and that it also had exposure to cash-settled total return swaps arrangements, thus increasing its economic exposure to a total of 11.3%. At the time, Fortune Brands, a conglomerate, ran three divisions: a home and security business, a spirits business, and a golf related business. With scarce evidence for synergies across the divisions, it was believed that the company would be worth more if one or two of the parts were sold or spun off.

On October 28, 2010, during the conference call for the third quarter earnings results, the CEO, Bruce Carbonari, said that the company was open to constructive talks with all shareholders including Pershing Square. He proceeded, however, to defend the conglomerate's business structure. Shortly afterwards the company reported that Credit Suisse and Centerview Partners were hired for the negotiations with Pershing Square.[27] It is important to note that since the filing of the Schedule 13D Pershing Square had kept its plan for the firm as well as the negotiations with management private.

In mid-November 2010, the *Wall Street Journal* reported that "[s]everal parties could be interested in the different businesses of Fortune and some have expressed an interest already."[28] The article speculated on which of Fortune Brands' competitors might want to acquire its spirits and golf assets and on the possibility that the remaining home and security business could be sold to private equity firms. On December 8th, 2010, Fortune Brands said it would spin off its golf and home and security businesses and retain its higher growth spirits business to be renamed Beam Inc. By then, the company's stock price had risen by 18% since the initial filing by Pershing Square.

In the ensuing period, Pershing Square did not reduce its stake in Fortune Brands. In fact, on August 8, 2011, it was reported that it increased its direct ownership stake to 13.5% (and its economic exposure to 14.8% including the total return swaps). Pershing Square remained the largest shareholder of the spun-off building products business, named Fortune Brands Home and Security, and the spirits business, Beam. In the letter to investors later in November 2011, the fund described Beam's strong competitive position and high growth reflecting "a very scarce asset" with "many strategic alternatives available to the company, including a sale of the business, a merger with another spirits company, and the acquisition of other brands." The fund also described its holding in Fortune Brands Home and Security as an investment that was well-positioned to benefit from an improvement in the housing market.

---

[27] The transcript of the earnings conference call is available at www.SeekingAlpha.com. See also the article in *Reuters*, "Fortune Brands' biggest foe: the Tax Man," October 29, 2010.
[28] "Fortune May Cooperate With Ackman," *The Wall Street Journal*, November 13, 2010.

References:

Abraham, Katherine G., and James L. Medoff, 1984, Length of Service and Layoffs in Unions and Nonunion Work Groups, *Industrial and Labor Relations Review* 38, 87–97.

Agrawal, Ashwini K. and Prasanna Tambe, 2014, Private Equity and Workers' Career Paths: The Role of Technological Change, Working paper, New York University.

Bandiera, Oriana, Iwan Barankay, and Imran Rasul, 2007, Incentives for Managers and Inequality among Workers: Evidence from a Firm Level Experiment, *Quarterly Journal of Economics* 122, 729–73.

Bartel, Ann, Casey Ichniowski, and Kathryn Shaw, 2007, How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills, *Quarterly Journal of Economics* 122, 1721–58.

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

Becht, Marco, Julian Franks, Jeremy Grant, and Hannes Wagner, 2014, The Returns to Hedge Fund Activism: An International Study, ECGI working paper series in Finance.

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, 3093–129.

Becker, Bo, Henrik Cronqvist, and Rudiger Fahlenbrach, 2011, Estimating the Effects of Large Shareholders Using a Geographic Instrument, *Journal of Financial and Quantitative Analysis* 46, 907–42.

Bertrand, Marianne, and Sendhil Mullainathan, 2003, Enjoying the Quiet Life? Corporate Governance and Managerial Preferences, *Journal of Political Economy* 111, 1043–75.

Bosch-Badia, Maria Teresa, 2010, Connecting Productivity to Return on Assets through Financial Statements: Extending the Dupont Method, *International Journal of Accounting and Information Management* 18, 92–104.

Brav, Alon, Wei Jiang, Frank Partnoy, and Randall Thomas, 2008, Hedge Fund Activism, Corporate Governance, and Firm Performance, *Journal of Finance* 63, 1729–75.

Brav, Alon, Wei Jiang, and Hyunseob Kim, 2009, Hedge Fund Activism: A Review, *Foundations and Trends in Finance* 4, 185–246.

Brav, Alon, Wei Jiang, Song Ma, and Xuan Tian, 2014, Shareholder Power and Corporate Innovation: Evidence from Hedge Fund Activism, Working paper, Duke University, Columbia University, and Indiana University.

Bresnahan, Timothy, Erik Brynjolfsson, and Lorin Hitt, 2002, Information Technology, Work Organization and the Demand for Skilled Labor: Firm-Level Evidence, *Quarterly Journal of Economics* 117, 339–76.

Brynjolfsson, Erik and Lorin M. Hitt, 2000, Beyond Computation: Information Technology, Organizational Transformation and Business Performance, *Journal of Economic Perspectives* 14, 23–48.

Clifford, Christopher P., 2008, Value Creation or Destruction? Hedge Funds as Shareholder Activists, *Journal of Corporate Finance* 14, 323–36.

Clifford, Christopher P., and Laura Lindsey, 2013, Getting What You Pay For: Blockholder Monitoring, CEO Compensation, and Firm Performance, Working paper, University of Kentucky and Arizona State University.

Cronqvist, Henrik, Fredrik Heyman, Mattias Nilsson, Helena Svaleryd, and Jonas Vlachos, 2009, Do Entrenched Managers Pay Their Workers More?, *Journal of Finance* 64, 309–39

Davis, Steven J., John C. Haltiwanger, Ron S. Jarmin, Josh Lerner, and Javier Miranda, 2011, Private Equity and Employment, NBER Working Paper 17399.

Fine, Jason P. and Robert J. Gray, 1999, A Proportional Hazards Model for the Subdistribution of a Competing Risk, *Journal of the American Statistical Association* 94, 496-509.

Freeman, Richard B., and James L. Medoff, 1984, What Do Unions Do? Basic Books.

Gantchev, Nickolay, 2013, The Costs of Shareholder Activism: Evidence from a Sequential Decision Model, *Journal of Financial Economics* 107, 610–31.

Gillan, Stuart L., and Laura T. Starks, 2007, The Evolution of Shareholder Activism in the United States, *Journal of Applied Corporate Finance* 19, 55–73.

Giroud, Xavier, 2013, Proximity and Investment: Evidence from Plant-Level Data, *Quarterly Journal of Economics* 128, 861–915.

Gormley, Todd, and David Matsa, 2014, Common Errors: How to (and Not to) Control for Unobserved Heterogeneity, *Review of Financial Studies* 27,617–61.

Greenwood, Robin, and Michael Schor, 2009, Hedge Fund Investor Activism and Takeovers, *Journal of Financial Economics* 92, 362–75.

Hirsch, Barry and David Macpherson, 2003, Union Membership and Coverage Database from the Current Population Survey: Note, *Industrial and Labor Relations Review* 56, 349–54.

Kim, Woochan, Woojin Kim, and Kap-Sok Kwon, 2009, Value of Outside Blockholder Activism: Evidence from the Switchers, *Journal of Corporate Finance* 15, 505–22.

Klein, April, and Emanuel Zur, 2009, Entrepreneurial Shareholder Activism: Hedge Funds and Other Private Investors, *Journal of Finance* 64, 187–229.

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

Levinsohn, James, and Amil Petrin, 2003, Estimating Production Functions Using Inputs to Control for Unobservables, *Review of Economics Studies* 70, 317–41.

Li, Xiaoyang, 2013, Productivity, Restructuring, and the Gains from Takeovers, *Journal of Financial Economics* 109, 250–71

Lichtenberg, Frank R., 1992, *Corporate Takeovers and Productivity*, The 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, 165–94.

Maksimovic, Vojislav, and Gordon M. Phillips, 2002, Do Conglomerate Firms Allocate Resources Inefficiently Across Industries? Theory and Evidence, *Journal of Finance* 57, 721–67.

Maksimovic, Vojislav, Gordon M. Phillips, and Liu Yang, 2013, Private and Public Merger Waves, *Journal of Finance* 68, 2177–217.

Maksimovic, Vojislav, Gordon M. Phillips, and N.R. Prabhala, 2011, Post-Merger Restructuring and the Boundaries of the Firm, *Journal of Financial Economics* 102, 317–43.

McCahery, Joseph A., Zacharias Sautner, and Laura T. Starks, 2014, Behind the Scenes: The Corporate Governance Preferences of Institutional Investors, Working paper, Tilburg University, Frankfurt School of Finance & Management, and University of Texas at Austin.

Pagano, Marco, and Paolo F. Volpin, 2005, Managers, Workers, and Corporate Control, *Journal of Finance* 60, 841–68.

Sakellaris, Plutarchos, and Daniel J. Wilson, 2004, Quantifying Embodied Technological Change, *Review of Economic Dynamics* 7, 1–26.

Schoar, Antoinette, 2002, Effects of Corporate Diversification on Productivity, *Journal of Finance* 57, 2379–403.

Shapiro, Carl, and Joseph E. Stiglitz, 1984, Equilibrium Unemployment as a Worker Discipline Device, *American Economic Review* 74, 433–44.

Shleifer, Andrei, and Robert Vishny, 1986, Large Shareholders and Corporate Control, *Journal of Political Economy* 94, 461–88.

Shleifer, Andrei, and Lawrence H. Summers, 1988, Breach of Trust in Hostile Takeovers, in Allan J. Auerbach, ed.: *Corporate Takeovers: Causes and Consequences* (University of Chicago Press, Chicago).

Shumway, Tyler, 1997, The Delisting Bias in CRSP Data, *Journal of Finance* 52, 327–40.

Stiroh, Kevin J., 2002, Information Technology and the U.S. Productivity Revival: What Do the Industry Data Say?, *American Economic Review* 92, 1559–76.

Williamson, Oliver E., 1988, Corporate Finance and Corporate Governance, Journal of Finance 43, 567–591.

Figure 1: Target Firm Return on Assets (ROA) before and after Activist Intervention

This figure plots the coefficients β_k , k=-3,…, +3, from the following regression at the firm (i) – year (t) level:

$$ROA_{i,t} = \sum_{k=-3}^{+3} \beta_k \; d[t+k]_{i,t} + \gamma \; Control_{i,t} + \alpha_{SIC3} + \alpha_t + \varepsilon_{i,t},$$

where $ROA_{i,t}$ is return on assets, defined as the ratio of earnings before interests and taxes to total assets. $d[t+k]_{i,t}$, k = -3,…,+3 is a dummy variable equal to one if firm i was or will be targeted by hedge funds in year t + j years. $Control_{i,t}$ represents control variables including the logarithms of firm market capitalization and firm age (proxied by the number of years since the firm's first appearance in CRSP). α_{SIC3} and α_t are three-digit SIC and year fixed effects. The solid line plots the coefficients on $d[t+k]$ dummies, which represent industry-year adjusted ROA. The dotted lines represent 95% confidence intervals.

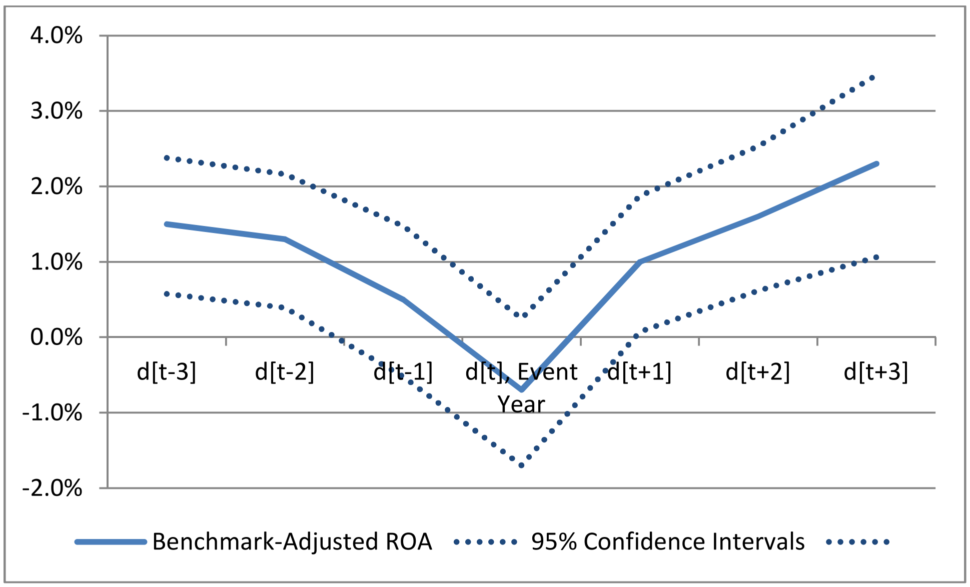

Figure 2. Placebo Test: Target Plants vs. Plants Matched on Pre-Intervention Deterioration

This figure plots two sets of estimated coefficients on *d[t+k]*, $k = -3,\dots,+3$, where *t* is the year of intervention, as in regression (2) (see Table 4). The two graphs represent i) plants in targeted firms that have matched plants (blue, solid line), and ii) non-event plants matched by similar declines in TFP from *t-3* to *t* in the same industry and year as the targeted plants (red, dashed line).

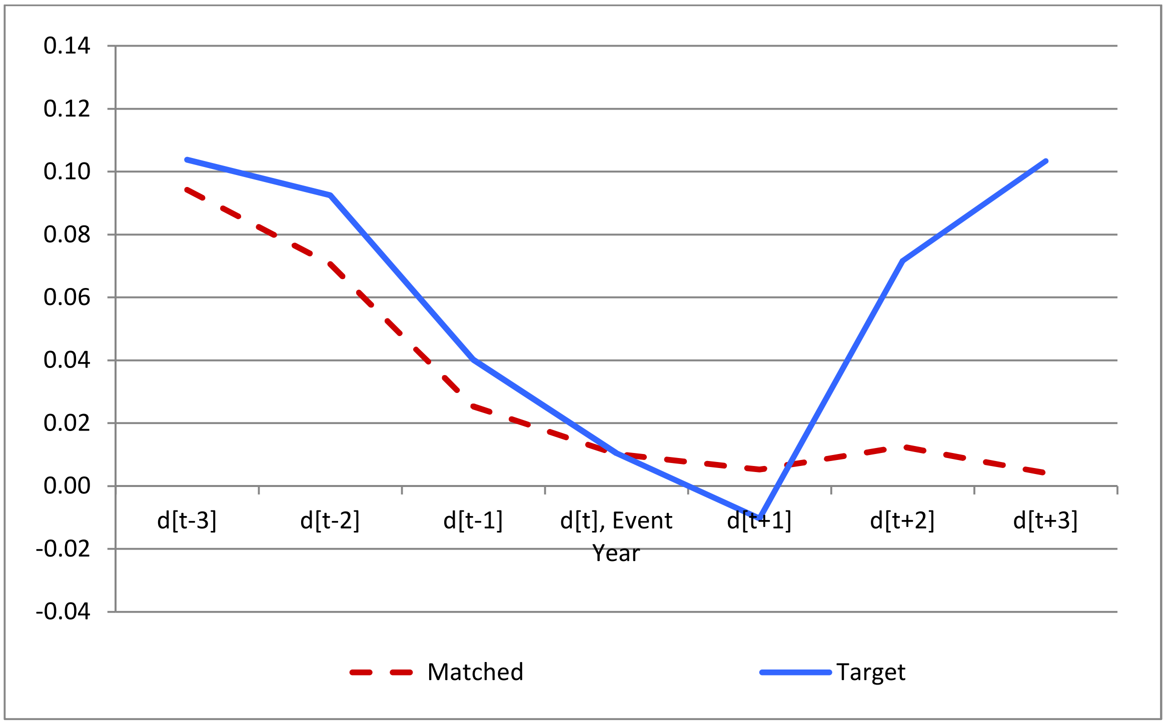

Table 1: Descriptive Statistics on the Census-matched Activism Events

Panel A provides the number of 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. Manufacturing and non-manufacturing target firms, based on Compustat SIC codes, are presented separately. Panel A also shows the number of plant-year observations for the Census-matched events. Panel B provides the distribution of activists' stated objectives and success rates for the Census-matched sample (columns 1-3) and the full sample (columns 4-6) from 1994 to 2007. The objectives are classified into five categories: A "General" category in which the hedge fund did not specify a particular goal other than to maximize shareholder value or stock returns; A "Capital structure" category in which the hedge fund targets capital structure and payout issues; A "Business strategy" category in which the hedge funds proposes or criticizes strategies regarding acquisition, diversification, and/or asset reallocation; A "Sale" category in which the stated goal of the activism is to put the target firm up for sale; A "Governance" category which includes a broad spectrum of governance issues such as board independence, executive compensation, takeover defenses, and disclosure. Columns 1, 2, 4, and 5 report the number and the percentage of events. Columns 3 and 6 list the rate of success, including partial success. Percentages sum up to more than 100% because one event can have multiple objectives. However, the first category ("General") and the other four categories are mutually exclusive. An event is classified as successful if the hedge fund achieves its main stated goal and as 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

Events	Num. of Events	Num. of Plant-years
1. All activism events	1987	-
a. Manufacturing targets	640	-
b. Non-manufacturing targets	1347	-
2. Matched to Census data with Total Factor Productivity (TFP)	368	14923
a. Manufacturing targets	281	12631
b. Non-manufacturing targets	87	2292

Panel B: Summary of Activism Events by Stated Objective

	Census-matched			All		
Stated Objectives	N Events (1)	% of Sample (2)	% Success (3)	N Events (4)	% of Sample (5)	% Success (6)
1. General	237	64.4%	N/A	1212	61.0%	N/A
2. Capital Structure	51	13.9%	64.7%	263	13.2%	62.0%
3. Business Strategy	56	15.2%	58.9%	293	14.7%	58.4%
4. Sales of Target	61	16.6%	65.6%	375	18.9%	62.7%
5. Governance	119	32.3%	73.9%	631	31.8%	72.4%
Specific – Sum [2 to 5]	131	35.6%	64.9%	775	39.0%	65.0%
Total – Sum [1 to 5]	368	-	-	1987	-	-

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

This table presents descriptive statistics on the plant-year observations of firms targeted by activists (column "Targets"), all plant-year observations used in the analysis (column "Universe"), and plant-year observations matched to public firms from Compustat (column "Universe-Public") from the CMF and ASM databases for the period from 1990-2009. We require each observation in these 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, and it is constructed using a perpetual inventory formula following the procedure described in Appendix A; "Total wages" is the sum of wages for production and non-production workers in million dollars; "Total employees" is the number of total employees; "Average wage" is computed as total wages divided by total employees (in thousand dollars); "Wage per hour (production workers)" is total production worker wages divided by total production hours; "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's birth, which is proxied by the flag for plant birth in the Longitudinal Business Database (LBD), or its first appearance in the CMF or ASM database, whichever is the earliest; "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 the within-industry standard deviation; "Operating margin" is defined as (TVS - labor costs - material costs) / TVS; "Num. Industries (SIC3)" is the number of three-digit SIC industries represented in the sample; "Observations" is the number of plant or firm observations. Column 7 (Column 8) shows t-statistics for tests of the difference in means between "Targets" and "Universe" ("Universe-Public").

	Targets		Universe		Universe-Public		t-statistic	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Mean	Stdev	Mean	Stdev	Mean	Stdev	(1) vs. (3)	(1) vs. (5)
Total value of shipment ($m)	78.17	142.81	74.15	340.50	145.32	529.62	0.49	-4.72
Capital stock ($m) – real, net	40.61	102.37	39.33	193.95	83.16	318.49	0.22	-5.39
Total wages ($m)	12.10	17.40	10.38	34.45	19.54	56.97	1.75	-4.26
Total employees	265	324	226	545	385	872	2.27	-4.59
Average wage ($000)	44.12	14.16	41.00	15.13	44.22	15.45	4.29	-0.12
Wage per hour (production workers)	18.82	6.73	17.21	6.81	18.85	7.18	5.06	-0.07
Plants per segment (SIC3)	9.23	12.57	6.52	13.56	12.43	18.02	1.75	-1.79
Plants per firm	28.23	29.23	18.3	33.58	41.66	43.18	2.06	-2.46
Plant age	23.30	8.99	19.93	8.99	20.77	8.55	7.65	5.87
TFP (Standardized)	0.104	0.961	0.000	0.998	0.112	0.934	2.98	-0.86
Operating margin	0.247	0.271	0.229	0.278	0.240	0.312	1.65	0.61
Num. Industries (SIC3)	119	-	134	-	133	-	-	-
Observations (plant-year)	14,923	-	787,758	-	238,846	-	-	-
Observations (unique plant)	2,900	-	125,112	-	31,005	-	-	-
Observations (firm-year)	1,902	-	406,747	-	29,391	-	-	-
Observations (unique firm)	304	-	85,552	-	3,702	-	-	-

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

This table presents descriptive statistics on firms targeted by hedge fund activists that have been 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 from 1994-2007. All variables are retrieved from the year prior to the event year. "MV" is market capitalization in million dollars; "Assets" is total book value of assets in million 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 dividends + preferred dividends)/(market value of common stock + book value of preferred stock); "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; "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 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. All potentially unbounded variables are winsorized at the 1% extremes. *,**, and *** in the column "Census Sample" indicates that the average value of a particular variable is significantly different from that of "All Target Firms" at the 10%, 5%, and 1% levels. *, **, and *** in the column "All Target Firms" indicates the same significance levels regarding the difference with the "Full Compustat Sample."

	Census Sample (#obs = 368)		All Target Firms (#obs = 1,575)		Full Compustat Sample	
	Mean	Stdev	Mean	Stdev	Mean	Stdev
MV	800.50	2071.36	657.81***	1554.44	1677.3	5156.96
Assets	1090.27	2694.02	1128.22***	3498.62	2555.98	8420.64
Leverage	0.288*	0.251	0.26**	0.259	0.284	0.298
Cash	0.109***	0.149	0.173	0.219	0.18	0.231
Div Yld %	0.950**	1.620	0.751***	1.751	1.111	2.295
q	1.671***	1.393	2.066***	1.986	3.86	8.072
Sales growth	0.082***	0.296	0.242	0.905	0.261	0.711
Cash flow	0.044***	0.165	0.009***	0.238	-0.134	0.78
R&D	0.038**	0.062	0.048***	0.117	0.064	0.164
Firm age	21.42***	17.81	12.77*	13.89	12.14	13.73
Capx %	5.01*	4.96	5.54	7.06	5.78	7.55
Total Payout Yld %	2.34	4.54	2.21***	4.62	2.18	4.29
CEO turnover	0.21***	0.41	0.13***	0.34	0.09	0.29
Altman (Ex. Leverage)	1.52***	1.67	-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 from three years before to three years after the hedge fund's intervention. The dependent variable is standardized total factor productivity (TFP), a measure of productivity, as defined in Table 2 for the specifications in columns 1-3 and 6. Column 4 uses non-standardized ("raw") TFP as the dependent variable, and column 5 uses standardized TFP based on the Levinsohn and Petrin (2003) GMM estimates of production functions. Column 7 uses operating margin, defined in Table 2, as the dependent variable. *d[t+k]* (*k=-3,…,+3*) are dummy variables equal to one if the plant belongs to a targeted firm in year *t+k*. Year *t* is the event year. "log(plants per segment)," "log(plants per firm)" and "Plant age (/ 100)" are defined in Table 2. The unit of observation is the plant except for column 6, 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 averaged across segments for a given firm. Industry × year fixed effects are included in all regressions. Columns 2 and 3 additionally include firm and plant fixed effects, respectively. The *t*-statistics based on standard errors adjusted for sample clustering at the firm level are reported below the coefficient estimates. At the bottom of the table we report differences in the coefficients on the dummy variables before and after the event year and the associated *t*-statistics, as well as the statistics from *F*-tests for joint inequality.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unit	Plant	Plant	Plant	Plant	Plant	Firm	Plant
Dep. Var.	TFP	TFP	TFP	Raw TFP	LP TFP	TFP	Margin
d[t-3]	0.067	0.058	0.007	0.018	0.112	0.040	0.009
	1.70	2.23	0.31	1.42	2.94	0.77	0.84
d[t-2]	0.071	0.061	0.017	0.020	0.132	0.015	0.013
	1.52	1.94	0.54	1.34	2.55	0.29	1.06
d[t-1]	0.029	0.013	-0.015	0.006	0.097	-0.026	0.002
	0.74	0.39	-0.52	0.46	2.74	-0.45	0.16
d[t]	-0.001	-0.019	-0.037	-0.002	0.042	-0.049	-0.010
	-0.02	-0.57	-1.20	-0.12	1.01	-0.81	-0.94
d[t+1]	0.010	-0.018	-0.047	0.005	0.045	-0.026	-0.001
	0.23	-0.48	-1.38	0.33	0.95	-0.44	-0.06
d[t+2]	0.055	0.026	-0.007	0.016	0.113	0.067	0.002
	1.28	0.75	-0.23	1.10	2.71	1.09	0.20
d[t+3]	0.118	0.069	0.016	0.036	0.190	0.084	0.012
	2.50	1.80	0.41	2.35	3.95	1.40	0.97
log(plant per segment)	0.015	0.035	0.003	0.007	0.007	0.014	0.003
	1.65	4.40	0.44	2.05	0.74	0.88	1.23

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unit	Plant	Plant	Plant	Plant	Plant	Firm	Plant
Dep. Var.	TFP	TFP	TFP	Raw TFP	LP TFP	TFP	Margin
log(plant per firm)	0.064	-0.073	0.006	0.022	0.046	-0.065	0.007
	10.42	-7.04	1.58	9.60	9.51	-4.67	3.77
Plant age (/100)	-0.608	-0.857	1.385	-0.200	-0.857	-0.971	-0.038
	-16.74	-18.54	0.05	-15.21	-21.13	-9.33	-4.39
Firm fixed effects	N	Y	N	N	N	Y	N
Plant fixed effects	N	N	Y	N	N	N	N
Industry × year fixed effects	Y	Y	Y	Y	Y	Y	Y
Observations	787758	787758	787758	787758	787758	407020	787758
R2	1.31%	33.38%	55.07%	1.45%	1.03%	58.03%	15.35%
Differences and t-statistics:							
d[t] – d[t-3]	-0.068	-0.077	-0.044	-0.020	-0.069	-0.089	-0.020
	-2.20	-2.34	-1.34	-1.78	-1.67	-1.23	-2.43
d[t+2] – d[t]	0.056	0.045	0.029	0.018	0.071	0.116	0.013
	1.74	1.44	0.97	1.54	1.74	1.95	1.37
d[t+3] – d[t]	0.118	0.089	0.052	0.038	0.148	0.133	0.022
	2.87	2.23	1.31	2.65	2.86	1.93	2.07
F test:							
(d[t] – d[t-3] = 0)							
& (d[t+3] – d[t])	5.26	3.91	1.32	4.14	4.56	1.96	3.82
(p-value for F-test)	0.01	0.02	0.27	0.02	0.01	0.14	0.02

Table 5: Hedge Funds' Stated Objectives and Productivity

This table examines the impact of hedge fund activism on the productivity of plants owned by target firms from three years before to three years after the hedge fund's intervention, conditioning on the stated objective of the hedge fund, defined as in Table 1, Panel B. TFP is estimated using the specification described in Table 2. All other independent variables are defined in Table 4. Industry × year fixed effects are included in all regressions. The *t*-statistics based on standard errors adjusted for sample clustering at the firm level are reported below the coefficient estimates. At the bottom of the table we report differences in the coefficients on the dummy variables before and after the event year and the associated *t*-statistics, as well as the statistics from *F*-tests for joint inequality.

	(1)	(2)	(3)	(4)	(5)
Objective:	General	CapStructure	Governance	Strategy	Sale
Dep. Var.			TFP		
d[t-3]	0.103	0.154	0.035	-0.041	-0.143
	1.91	1.98	0.80	-0.58	-2.59
d[t-2]	0.130	0.212	-0.032	0.038	-0.188
	2.50	1.69	-0.62	0.39	-4.68
d[t-1]	0.098	0.049	-0.077	-0.002	-0.148
	1.84	0.59	-1.80	-0.02	-3.15
d[t]	0.037	0.112	-0.109	0.000	-0.166
	0.65	1.10	-2.25	0.00	-2.87
d[t+1]	0.057	0.082	-0.046	-0.008	-0.169
	1.10	1.03	-0.72	-0.07	-1.68
d[t+2]	0.060	0.193	0.027	0.112	-0.069
	1.26	1.61	0.52	0.92	-0.91
d[t+3]	0.085	0.271	0.093	0.309	0.106
	1.46	3.02	1.50	3.17	1.23
log(plant per segment)	0.015	0.015	0.015	0.015	0.014
	1.65	1.66	1.64	1.65	1.62
log(plant per firm)	0.064	0.065	0.065	0.065	0.065
	10.49	10.46	10.54	10.54	10.63
Plant age (/100)	-0.608	-0.607	-0.607	-0.607	-0.606
	-16.77	-16.77	-16.76	-16.77	-16.75
Industry × year fixed effects	Y	Y	Y	Y	Y
Observations	787758	787758	787758	787758	787758
R2	1.31%	1.31%	1.31%	1.31%	1.31%
Differences and t-statistics:					
d[t] – d[t-3]	-0.067	-0.042	-0.144	0.041	-0.022
	-1.64	-0.62	-2.74	0.63	-0.37
d[t+2] – d[t]	0.023	0.081	0.136	0.112	0.097
	0.47	1.03	2.82	1.10	1.53
d[t+3] – d[t]	0.049	0.159	0.201	0.309	0.272
	0.86	2.26	3.36	2.52	3.39
F test:					
(d[t] – d[t-3] = 0) & (d[t+3] – d[t])	1.43	2.62	7.52	5.05	5.80
	0.24	0.07	0.00	0.01	0.00

Table 6: Determinants of Plant Sale and Closure, Firm-level Segment Concentration, and Performance of Plants Sold after Activism

Panel A shows the determinants of plant sales (columns 1-3) and closures (columns 4-6) using probit and competing-risks regressions where Sale (Closure) is the main risk and Closure (Sale) is the competing risk in column 3 (6) . “Segment share” is the ratio of the combined shipments of the industry segment to the firm’s total shipments. “Before” is a dummy variable equal to one for event years *t-3* through *t-1*, and zero otherwise. “After” is a dummy variable equal to one for event years from *t* to *t+3*, and zero otherwise. Panel B shows changes in firm-level segment HHI computed across all divisions of firms using the LBD, which proxies for the degree of focus in firms’ business segments, around hedge fund activism events. Panel C, columns 1-3 provide the productivity pattern of plants owned by target firms prior to intervention and then sold to other firms within two years post- intervention. In these columns, “*d[t - k]” (“d[t + k]*”) are dummy variables equal to one for *k* years before (after) the plant sale, and zero otherwise. “*d[t]*” is defined similarly. Panel C, columns 4-6 provide the pattern of total factor productivity (TFP) for plants sold by firms not targeted by activists. All other independent variables are defined as in Table 4. Industry × year fixed effects are included in all regressions in Panel C. *t*-statistics based on standard errors adjusted for sample clustering at the firm level are reported below the coefficient estimates. At the bottom of each panel we report differences in the coefficients before and after the event year and the associated *t*-statistics. In part of the table, the numbers of observations are rounded to the nearest thousands to follow the Census Bureau’s disclosure rules.

Panel A: Determinants of Plant Sale and Closure

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Probit	Probit	Competing risks	Probit	Probit	Competing risks
Dep. Var.		Sale			Closure	
TFP	-0.021	-0.019	0.050	-0.217	-0.222	-0.521
	-5.08	-4.58	6.70	-43.90	-45.38	-47.02
Segment share	-0.350	-0.365	-0.625	-0.234	-0.265	-0.392
	-9.41	-9.92	-8.61	-10.69	-12.51	-7.11
Before	-0.064	-0.063	-0.145	0.142	0.116	0.257
	-0.92	-0.93	-0.98	2.83	2.32	2.12
After	0.165	0.166	0.318	0.216	0.197	0.403
	2.28	2.31	2.32	4.53	4.64	4.03
Before × TFP	-0.004	-0.005	0.002	-0.054	-0.053	-0.091
	-0.10	-0.13	0.03	-1.05	-0.99	-0.96
After × TFP	-0.090	-0.090	-0.192	0.004	0.004	0.045
	-2.45	-2.44	-2.81	0.10	0.10	0.54
log(plant per segment)	-0.016	-0.026	-0.076	0.040	0.060	0.153
	-1.07	-1.85	-2.73	4.68	7.60	7.29
log(plant per firm)	-0.010	-0.021	-0.024	-0.038	-0.032	-0.066
	-0.64	-1.30	-0.76	-4.55	-3.90	-3.01
Plant age (/100)	0.046	0.028	0.604	-1.378	-1.282	-2.715
	0.98	0.62	6.18	-32.39	-31.25	-29.13
Year dummies	Y	Y	Y	Y	Y	Y
Industry dummies	N	Y	Y	N	Y	Y
Observations	763130	763130	763130	763130	763130	763130
Pseudo-R2	1.46%	2.12%	-	3.11%	4.85%	-

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Probit	Probit	Competing risks	Probit	Probit	Competing risks
Dep. Var.		Sale			Closure	
Differences and p-values:						
After – Before	0.229	0.229	0.463	0.073	0.081	0.146
Chi2	8.16	8.11	7.98	2.05	2.46	1.49
p-value	0.004	0.004	0.005	0.152	0.117	0.222
(After – Before) × TFP	-0.086	-0.085	-0.194	0.059	0.057	0.136
Chi2	2.39	2.36	4.17	1.07	1.01	1.53
p-value	0.122	0.125	0.041	0.301	0.316	0.216

Panel B: Change in Firm-level Segment Concentration

	(1)	(2)	(3)	(4)
Unit	Firm			
Dep. Var.	HHI (employee)		HHI (pay)	
Before	-0.309	-0.010	-0.320	-0.007
	-17.43	-0.99	-18.29	-0.79
After	-0.280	0.017	-0.295	0.013
	-14.05	1.37	-15.05	1.14
Industry × year fixed effects	Y	N	Y	N
Year fixed effects	N	Y	N	Y
Firm fixed effects	N	Y	N	Y
Observations	407020	407020	407020	407020
R2	13.53%	91.21%	13.64%	91.69%
Differences and t-statistics:				
After – Before	0.029	0.026	0.025	0.021
	2.38	2.45	2.00	2.04

Panel C: Change in the Productivity of Sold Plants

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Plants Sold by Target firms			Plants Sold by Non-target Firms		
Dep. Var.	TFP					
d[t-3]	-0.046	-0.015	0.015	-0.015	-0.042	0.001
	-0.75	-0.22	0.25	-1.59	-4.52	0.19
d[t-2]	-0.117	-0.095	-0.060	-0.026	-0.056	-0.005
	-1.61	-1.15	-0.90	-2.53	-5.52	-0.73
d[t-1]	-0.224	-0.211	-0.171	-0.054	-0.086	-0.027
	-2.40	-2.21	-2.15	-5.14	-7.67	-3.47
d[t]	-0.116	-0.112	-0.092	-0.098	-0.116	-0.059
	-1.58	-1.51	-1.54	-8.73	-9.85	-6.41
d[t+1]	-0.126	-0.114	-0.086	-0.063	-0.068	-0.014
	-1.71	-1.38	-1.19	-6.20	-6.14	-1.59
d[t+2]	-0.040	-0.012	-0.022	-0.057	-0.058	-0.008
	-0.43	-0.09	-0.26	-5.57	-5.38	-0.97
d[t+3]	0.110	0.116	0.090	-0.058	-0.059	-0.007
	1.13	0.86	1.00	-5.33	-5.39	-0.78
log(plant per segment)	0.015	0.035	0.003	0.014	0.034	0.002
	1.64	4.42	0.44	1.58	4.40	0.32
log(plant per firm)	0.065	-0.073	0.006	0.064	-0.070	0.005
	10.53	-7.04	1.57	10.67	-6.81	1.33
Plant age (/100)	-0.605	-0.857	1.486	-0.614	-0.846	1.294
	-16.70	-18.52	0.06	-17.37	-18.70	0.05
Firm fixed effects	N	Y	N	N	Y	N
Plant fixed effects	N	N	Y	N	N	Y
Industry × year fixed effects	Y	Y	Y	Y	Y	Y
Observations	786324	786324	786324	816000	816000	816000
R2	1.31%	33.43%	55.08%	1.32%	33.26%	54.93%
Differences and t-statistics:						
d[t] – d[t-3]	-0.071	-0.097	-0.107	-0.082	-0.074	-0.060
	-0.70	-0.89	-1.26	-7.23	-6.30	-6.52
d[t+2] – d[t]	0.076	0.101	0.070	0.041	0.059	0.050
	0.68	0.70	0.70	3.68	5.17	5.01
d[t+3] – d[t]	0.227	0.229	0.182	0.040	0.058	0.052
	1.95	1.58	1.87	3.45	5.01	5.13
d[t+3] – d[t-1]	0.335	0.328	0.261	-0.004	0.027	0.020
	2.49	1.99	2.44	0.33	2.25	2.17
(d[t+3] – d[t]) × (Target – Non-target)	-	-	-	0.187	0.171	0.130
	-	-	-	1.58	1.26	1.46
(d[t+3] – d[t-1]) × (Target – Non-target)	-	-	-	0.339	0.300	0.241
	-	-	-	2.49	1.91	2.38

Table 7: 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 one year post-activism, and zero otherwise. All variables are defined in Table 4. Industry × year fixed effects are included in the regression. The *t*-statistics based on standard errors adjusted for sample clustering at the firm level are reported below the coefficient estimates. On the right hand side of the table we report differences in the coefficients before and after the event year interacted with the attrition status, and the associated *t*-statistics.

	(1)
Dep. Var.	TFP
d[t-3] × Attrition	0.001
	0.02
d[t-2] × Attrition	-0.022
	-0.28
d[t-1] × Attrition	-0.031
	-0.36
d[t] × Attrition	-0.043
	-0.50
d[t+1] × Attrition	0.067
	0.46
d[t+2] × Attrition	0.116
	0.48
d[t+3] × Attrition	0.324
	1.57
d[t-3] × Non-attrition	0.075
	1.73
d[t-2] × Non-attrition	0.083
	1.62
d[t-1] × Non-attrition	0.038
	0.87
d[t] × Non-attrition	0.005
	0.11
d[t+1] × Non-attrition	0.004
	0.09
d[t+2] × Non-attrition	0.051
	1.20
d[t+3] × Non-attrition	0.103
	2.15
log(plant per segment)	0.015
	1.65
log(plant per firm)	0.064
	10.42
Plant age (/100)	-0.608
	-16.74

Differences and t-statistics:	
Industry × year fixed effects	Y
Observations	787758
R2	1.31%
(d[t] – d[t-3]) × Attrition	-0.044
	-0.52
(d[t+2] – d[t]) × Attrition	0.159
	0.83
(d[t+3] – d[t]) × Attrition	0.367
	2.03
(d[t] – d[t-3]) × Non-attrition	-0.070
	-2.12
(d[t+2] – d[t]) × Non-attrition	0.046
	1.35
(d[t+3] – d[t]) × Non-attrition	0.098
	2.26
(d[t+3] – d[t]) × (Att – Non-att)	0.269
	1.45

Table 8: Outcomes for Employees of Target Firms

This table examines the impact of hedge fund activism on outcomes for employees of plants owned by target firms from three years before to three years after the hedge funds' intervention. All dependent variables in this table are in log scale. Panel A estimates the average effects for all targeted plants, and Panel B provides separate estimates for high- and low-unionization industries (defined at the annual median). Annual data on industry-level collective bargaining coverage are obtained from Hirsch and Macpherson (2003). "Hours/worker" is defined as total labor hours divided by the number of employees; "Total hours" is the production worker equivalent man hours as described in Appendix A; "Labor productivity" is defined as total output divided by total labor hours; "Labor VA / hour" is value added per labor hour (another measure of labor productivity) defined as (sales - material costs) / total labor hours; "K/L" is the ratio of capital to total labor hours. All other variables are defined in Tables 2 and 4. Industry × year fixed effects are included in all regressions, and *t*-statistics based on standard errors adjusted for sample clustering at the firm level are reported below the coefficient estimates.

Panel A: Impact on Labor Outcomes

Dep. Var.	(1) Total employees	(2) Hours / worker	(3) Total hours	(4) Labor productivity	(5) Labor VA / hour	(6) Avg. wage	(7) Wage / hour	(8) K/L
d[t-3]	0.417	-0.006	0.411	-0.004	-0.007	0.032	0.023	-0.062
	5.39	-0.50	5.19	-0.08	-0.24	1.91	1.08	-1.09
d[t-2]	0.356	-0.004	0.351	-0.002	0.011	0.035	0.024	-0.075
	4.47	-0.38	4.23	-0.04	0.38	2.39	1.19	-1.49
d[t-1]	0.360	-0.007	0.353	0.002	0.000	0.038	0.031	-0.025
	5.44	-0.59	4.99	0.07	0.00	2.58	1.58	-0.53
d[t]	0.290	-0.013	0.278	-0.009	-0.043	0.031	0.029	-0.010
	4.69	-1.12	4.20	-0.24	-1.50	2.18	1.60	-0.23
d[t+1]	0.289	-0.028	0.261	0.003	-0.028	0.011	0.021	0.041
	4.45	-2.17	4.08	0.09	-1.04	0.66	1.23	0.85
d[t+2]	0.252	-0.047	0.205	0.036	-0.002	0.021	0.047	0.057
	4.35	-2.92	3.56	0.89	-0.06	1.22	2.90	1.18
d[t+3]	0.256	-0.022	0.234	0.075	0.049	0.031	0.041	0.043
	3.47	-1.38	3.19	1.62	1.51	1.88	2.20	0.73
log(plant per segment)	-	-	-	0.056	0.016	-0.014	0.002	0.027
	-	-	-	6.87	2.55	-4.52	0.45	2.35
log(plant per firm)	-	-	-	0.098	0.038	0.025	0.031	0.151
	-	-	-	18.27	9.22	8.92	9.69	16.98
Plant age (/100)	-	-	-	-0.139	-0.013	0.540	0.449	3.364
	-	-	-	-4.39	-0.52	36.48	28.56	55.95
Industry × year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	787758	787758	787758	787758	787758	787758	787758	787758
R2	25.95%	3.84%	25.26%	45.60%	15.75%	30.01%	26.95%	39.14%

Dep. Var.	(1) Total employees	(2) Hours / worker	(3) Total hours	(4) Labor productivity	(5) Labor VA / hour	(6) Avg. wage	(7) Wage / hour	(8) K/L
Differences and t-statistics:								
d[t] – d[t-3]	-0.127	-0.007	-0.134	-0.005	-0.037	-0.001	0.006	0.052
	-2.62	-0.79	-2.74	-0.22	-1.60	-0.11	0.54	1.76
d[t+2] – d[t]	-0.038	-0.034	-0.073	0.045	0.041	-0.011	0.017	0.067
	-0.90	-1.74	-1.39	2.04	1.42	-0.66	1.73	2.03
d[t+3] – d[t]	-0.034	-0.009	-0.043	0.084	0.092	0.000	0.011	0.053
	-0.53	-0.60	-0.63	2.70	2.47	0.00	0.76	1.28

Panel B: Impact on Labor Outcomes across High- and Low-Unionization Industries

Dep. Var.	(1) Total employees	(2) Hours / worker	(3) Total hours	(4) Labor productivity	(5) Labor VA / hour	(6) Avg. wage	(7) Wage / hour	(8) K/L
Plant-level controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry × year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	787758	787758	787758	787758	787758	787758	787758	787758
R2	25.95%	3.85%	25.26%	45.63%	15.77%	30.01%	26.97%	39.17%
Sample	Low Unionization Rate							
d[t] – d[t-3]	-0.149	-0.015	-0.164	-0.022	-0.032	0.002	0.014	0.051
	-2.80	-1.13	-2.95	-0.67	-1.27	0.14	0.81	1.15
d[t+2] – d[t]	-0.037	-0.029	-0.065	0.027	0.015	-0.031	-0.012	0.059
	-0.56	-0.87	-0.78	0.81	0.42	-1.06	-0.73	1.10
d[t+3] – d[t]	0.022	0.008	0.030	0.059	0.048	-0.005	-0.006	0.034
	0.26	0.40	0.32	1.38	1.66	-0.23	-0.28	0.59
Sample	High Unionization Rate							
d[t] – d[t-3]	-0.121	0.004	-0.116	-0.004	-0.048	-0.008	-0.008	0.040
	-1.91	0.36	-1.81	-0.13	-1.21	-0.64	-0.56	1.07
d[t+2] – d[t]	-0.021	-0.043	-0.064	0.084	0.077	0.013	0.052	0.093
	-0.47	-2.95	-1.32	2.74	1.72	1.00	3.59	2.17
d[t+3] – d[t]	-0.062	-0.029	-0.091	0.131	0.144	0.010	0.037	0.091
	-0.89	-1.44	-1.27	3.16	2.18	0.60	2.04	1.62

Dep. Var.	(1) Total employees	(2) Hours / worker	(3) Total hours	(4) Labor productivity	(5) Labor VA / hour	(6) Avg. wage	(7) Wage / hour	(8) K/L
(d[t+3] – d[t]) × (High – Low)	-0.085	-0.036	-0.121	0.072	0.096	0.015	0.042	0.057
	-0.89	-1.48	-1.24	1.31	1.36	0.58	1.76	0.74
(d[t+2] – d[t]) × (High – Low)	0.016	-0.015	0.001	0.058	0.062	0.044	0.064	0.034
	0.22	-0.47	0.01	1.33	1.12	1.44	2.76	0.50

Table 9: Investments in Technology and Productivity

This table examines the impact of hedge fund activism on investments in information technology (IT) and on productivity at target firms. Panel A shows the change in investments in IT capital (i.e., 'capital expenditures for computers') around hedge fund intervention. Information on IT expenditures is available from the ASM and CMF from 2001 to 2009, which determines the sample period. Panel B examines whether investments in IT capital are associated with gains in productivity at target firms. We estimate productivity at plants with relatively high and low changes in computer investment scaled by lagged total capital (defined at the median) from the year of intervention to three years afterwards. Panel C sorts plants on the importance of IT capital in the production process (measured by two-digit SIC level expenditures on computers scaled by total capital expenditures), and estimates the effect of hedge fund intervention on productivity, wages, and the capital-to-labor ratio for the above- and below-the-median groups separately. At the bottom of each panel, we report differences in the coefficients before and after the event year and the associated *t*-statistics. Industry × year fixed effects are included in all regressions in this table, and *t*-statistics based on standard errors adjusted for sample clustering at the firm level are reported below the coefficient estimates. In part of the table, the numbers of observations are rounded to the nearest thousands to follow the Census Bureau's disclosure rules.

Panel A: Investments in Information Technology around Hedge Fund Activism

Dep. Var.	(1) IT investment / lagged capital	(2) log(IT investment)
d[t-3]	-0.055	-0.301
	-0.87	-1.73
d[t-2]	-0.090	-0.310
	-1.85	-2.02
d[t-1]	-0.124	-0.327
	-2.25	-1.66
d[t]	-0.150	-0.285
	-3.78	-1.75
d[t+1]	-0.063	-0.150
	-1.44	-0.91
d[t+2]	-0.056	-0.178
	-1.08	-1.48
d[t+3]	-0.049	-0.193
	-0.64	-0.84
Plant-level controls	Y	Y
Industry × year fixed effects	Y	Y
Observations	288000	288000
R2	10.96%	11.42%
Differences and t-statistics:		
d[t+1] – d[t]	0.087	0.135
	1.73	0.89
d[t+2] – d[t]	0.095	0.107
	1.92	0.82
d[t+3] – d[t]	0.101	0.092
	1.18	0.35

Panel B: Investments in IT and Productivity

Dep. Var.	(1) TFP	(2) Labor productivity
Plant-level controls	Y	Y
Plant fixed effects	Y	Y
Industry × year fixed effects	Y	Y
Observations	476000	476000
R2	59.27%	85.90%
Sample	Low change in IT Investment	
d[t] – d[t-3]	0.022	-0.005
	0.42	-0.17
d[t+2] – d[t]	0.040	-0.002
	0.94	-0.09
d[t+3] – d[t]	0.045	0.016
	0.71	0.61
Sample	High change in IT Investment	
d[t] – d[t-3]	-0.046	-0.034
	-0.67	-0.97
d[t+2] – d[t]	0.009	0.021
	0.14	0.64
d[t+3] – d[t]	0.134	0.066
	1.79	1.58
(d[t+3] – d[t]) × (High-Low)	0.089	0.050
	1.08	1.12

Panel C: Importance of IT and Labor Outcomes

Dep. Var.	(1) Labor productivity	(2) Wage / hour	(3) Log K/L
Plant-level controls	Y	Y	Y
Industry × year fixed effects	Y	Y	Y
Observations	787758	787758	787758
R2	45.62%	26.99%	39.16%
Sample	Low IT Importance - Industries		
d[t] – d[t-3]	0.006	0.018	0.044
	0.22	1.41	1.33
d[t+2] – d[t]	0.050	0.009	0.069
	1.67	0.63	1.49
d[t+3] – d[t]	0.048	-0.001	0.009
	1.12	0.05	0.17
Sample	High IT Importance - Industries		
d[t] – d[t-3]	-0.032	-0.012	0.047
	-0.96	-0.71	1.18
d[t+2] – d[t]	0.045	0.028	0.074
	1.66	1.92	1.97
d[t+3] – d[t]	0.143	0.029	0.129
	3.49	1.47	2.35
(d[t+3] – d[t]) × (High – Low)	0.095	0.030	0.120
	1.65	1.19	1.58
(d[t+2] – d[t]) × (High – Low)	-0.004	0.019	0.005
	-0.11	0.92	0.08

Table 10: Tests for Causality

This table provides evidence on the causal effects of hedge fund activism on the productivity of target firms. Panel A, columns 1 and 2 provide separate estimates of the effect of activism on plant productivity for hostile and non-hostile events. Panel A, columns 3 and 4 estimate the effect of activism separately for plants in peripheral and core segments of the target firm. We define a three-digit SIC industry of a target firm as "peripheral" if the combined shipments of the industry segment are less than 25% of total shipments of the firm (see Maksimovic and Phillips (2002)). At the bottom of panel A, we report differences in the coefficients before and after the event year and the associated *t*-statistics. Industry × year fixed effects are included in all regressions in Panel A. Panel B examines the effects of switches in filing status from Schedule 13G to Schedule 13D. Columns 1 and 2 provide regression results at the plant-year level using the Census data with the change in total factor productivity (TFP) as the dependent variable. Columns 3 and 4 provide regression results at the firm-year level using Compustat data with the change in ROA as the dependent variable. The change is recorded over a three-year period (or a two-year period, if an observation is not available after three years), and for event observations the three-year period begins with the event year. Year and hedge fund fixed effects are included in all regressions in Panel B. In both panels, *t*-statistics based on standard errors adjusted for sample clustering at the firm level are reported below the coefficient estimates.

Panel A: Hostile Events and Target Plants in Non-core Segments

	(1)	(2)	(3)	(4)
Split	Hostile	Non-hostile	Peripheral (<25%)	Core (>=25%)
Dep. Var.	TFP			
d[t-3]	-0.033	0.098	-0.001	0.111
	-0.62	2.03	-0.02	2.23
d[t-2]	-0.057	0.111	0.003	0.117
	-1.06	1.94	0.05	2.22
d[t-1]	-0.062	0.058	-0.071	0.100
	-1.13	1.24	-1.37	2.07
d[t]	-0.082	0.025	-0.078	0.050
	-1.20	0.49	-1.43	0.99
d[t+1]	-0.059	0.033	-0.066	0.057
	-0.64	0.67	-0.83	1.27
d[t+2]	0.034	0.061	-0.032	0.101
	0.50	1.23	-0.51	2.04
d[t+3]	0.071	0.131	0.047	0.156
	0.95	2.41	0.71	2.79
log(plant per segment)	0.015		0.013	
	1.65		1.51	
log(plant per firm)	0.064		0.065	
	10.42		10.54	
Plant age (/100)	-0.608		-0.609	
	-16.75		-16.77	
Industry × year fixed effects	Y		Y	
Observations	787758		787758	
R2	1.31%		1.32%	

Split	(1) Hostile	(2) Non-hostile	(3) Peripheral (<25%)	(4) Core (>=25%)
Dep. Var.		TFP		
Differences and t-statistics:				
d[t] – d[t-3]	-0.049	-0.073	-0.077	-0.062
	-0.72	-2.24	-1.36	-1.56
d[t+2] – d[t]	0.116	0.037	0.046	0.052
	1.64	1.00	0.84	1.19
d[t+3] – d[t]	0.152	0.107	0.126	0.106
	1.96	2.21	2.12	2.02
(d[t+3] – d[t])				
× (Hostile – Non-hostile)	-	0.046	-	0.019
(or × (Peripheral – Core))	-	0.50	-	0.25

Panel B: Schedule 13G to 13D Switchers

Sample	(1) Plant level—Census data	(2)	(3) Firm level—Compustat data	(4)
Dep. Var.	Change in TFP		Change in ROA	
13G to 13D Switch	0.126	0.085	0.033	0.025
	1.73	1.29	2.15	1.59
Controls	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
HF fixed effects	Y	Y	Y	Y
Industry fixed effects	N	Y	N	Y
Observations	2983	2983	3,954	3,954
R2	6.39%	13.14%	8.90%	15.40%