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Positive Externalities Of The Dodd-Frank Act: How The SEC Is Helping Rather Than Harming Activist Hedge Funds

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Abstract

This study researches the effects of the Dodd-Frank-Act (DFA) on the effectiveness of Hedge Fund Activism (HFA). Using Total Factor Productivity (TFP) as proxy for target firm value creation, I show that the DFA significantly increases (+5.2%) HFA effectiveness for all targets, although less (-7%) for manufacturing targets. After the DFA, the channels and strategies through which HFA creates value (Brav et al., 2015) are changed: higher capex investments and increased labor productivity are no longer the primary HFA value creation channels, and pushing for the sale of the target is not the most dominant HFA strategy anymore. The increases in firm TFP targeted by DFA-subjected hedge funds relative to the not DFA-subjected hedge funds imply that the SEC is unintendedly stimulating HFA effectiveness. Possible explanations are that the improved risk management brought about by the DFA causes positive spillover effects (e.g., improved target firm selection) in activist hedge funds or as the DFA is not shortening the 10-day non-disclosure window it is not effectively targeting HFA (Coffee & Palia, 2014).

Keywords: Total Factor Productivity, Hedge Fund Activism, Dodd-Frank Act, U.S. Securities and Exchange Commission, U.S. Regulation, Corporate Governance, Shareholder Activism, Regression Discontinuity Design

JEL Classification: G34, G28, J24

Contents

Introduction

Background

Hedge Fund Activism (HFA)

HFA, and especially its feuds with the target firm management, has been increasingly visible to the public. Recent examples include Gamestop (Umar, Gubareva, Yousaf & Ali, 2021) and Herbalife (LaPolla, 2018) where in both cases HFA faced revolts, by retail investors (Gamestop) and by another hedge fund investor (Herbalife). Both hedge fund feuds got their own Netflix show, which was for the ordinary citizen their first introduction to HFA. The Gamestop case is interesting, since this was the first time that retail investors collaborated in an organized manner through social media platforms like Reddit in trying to undermine the performance of hedge funds. The hedge fund with one of the largest short positions in Gamestop, Melvin Capital, faced losses up to 49% of its investments in the first months of 2021, requiring a three billion USD bailout. But, the Reddit forum /WallStreetBets was not done yet: in the months after successfully 'saving' Gamestop, the forum encouraged each other to take on long-only stakes (Business Insider, 2021) in stocks like Bed Bath & Beyond, AMC, BlackBerry, and Clover Health that were shorted by major US hedge funds, causing these hedge funds to lose up to six bln. USD. Besides retail investors, internal stakeholders also revolt (Harvard Law School Forum on Corporate Governance, 2020) against HFA using corporate governance protection mechanisms like monitoring trading and shareholder compositions, relationship management with major investors to avoid hostile activism, and avoiding proxy contests (i.e., external stakeholders advocating for changes in C-suite management) by hiring trusted CEOs.

In short, hedge funds in general and its activism, are under increased scrutiny. However, HFA campaigns have tripled over the past decade (S&P Global Market Intelligence, 2024), and HFA is expected to maintain as one of the major features of Corporate Governance (Armour & Cheffins, 2009). It is important to split HFA in negative and long-activism. Both examples of Gamestop and Herbalife are negative, i.e. short activism: hedge funds betting that the target firm is overpriced and will go bankrupt soon, and engage in aggressive short selling to drive the stock price to zero. Although this topic is interesting given its dynamic nature, existing literature (Molk & Partnoy, 2021; Boyson & Pichler, 2019) already has found concise evidence on its effects: negative activism works effectively as target firm share prices are significantly brought down, increasing hedge fund alphas. This study focuses on long-activism, i.e., positive activism, and will from now on be the only type of activism implicated when using 'HFA'. Long-activism involves acquiring a significant stake in a publicly traded company with the goal of influencing the company's management and operations to enhance shareholder value. This strategy is often employed by hedge funds seeking to unlock unrealized value in the target company and generate positive returns for their investors. Examples include Starboard Value that urges News Corp's breakup, advocating for a spin-off of its online property business, estimating a $7bn value unlock. News Corp shares rise 5% following the announcement (Financial Times Editorial Board, 2023). Another recent example includes Starboard Value that acquired a stake in Salesforce, and started urging the cloud software giant to boost margins, citing an underperformance relative to peers and market indices. Salesforce shares rise over 4% (Financial Times Editorial Board, 2022).

From unregulated to regulated: the brief history of US regulation of hedge funds

“A seismic boom”. These are the words (Bloomberg, 2002) of the former SEC chairman Harvey L. Pitt in May 2002, who referred to the explosive growth in hedge funds that began in the 2000s. The loosening of investor eligibility rules for hedge funds and the ability of hedge funds to operate primarily outside of federal securities regulation in the United States, was made possible by utilizing exemptions granted to private investment companies. The starting point was Section 3(c)(1) of the Investment Company Act of 1940, which exempts funds that do not issue securities to more than 100 investors and do not conduct a public offering of their securities from the legislation's purview. Furthermore, the SEC enlarged the private investment firm exemption in 1982 with the introduction of a "safe harbour," which released fund managers from the obligation to assess investors' appropriateness based only on their accredited status. Although policy makers were looking for increased private markets regulations after the increasing hedge funds scandals and its role in the 2007 Subprime mortgage crisis, the SEC struggled with designing an effective law that had no negative externalities. Lead by the Democratic Party, the first major banking and hedge fund regulation in the past decades got introduced: the Dodd-Frank Act (DFA) (SEC, 2024). It got accepted in Congress in October 2010 and fully enacted in March 2012. The DFA reduced the anonymity of hedge funds by making them obliged to register themselves much more in detail to the SEC, as prior to the DFA hedge funds were in most cases exempt from reporting or they only had to report basic information (office address, number of employees, etc.) to the SEC that was not significantly affecting their performance. The new requirements of SEC registration after the DFA implied significant reporting requirements (‘Form PF’) for a large number of hedge funds on the following items: assets under management, leverage utilization, trading and investment positions, type of assets owned, and more. As all these items had to be publicly disclosed, the DFA caused the Federal Reserve to have the same level of supervision over hedge funds as it has over a bank holding company. Also, the DFA introduced the Volcker rule, restricting banks from making speculative investments together with alternative investment firms like hedge funds that do not benefit its clients. To ensure the SEC's workload remained manageable and to ensure that only hedge funds with the biggest market impact are affected, the disclosure and reporting requirement discussed are solely applicable for hedge funds with an AUM exceeding 150 mln. USD. Funds below this threshold are not subject to the significantly increased reporting requirements. Until the Republican Party regained control of Congress in 2016, the DFA encountered little pushback in the congress or the senate. However, in 2016 significant policy shifts occurred in the U.S: restrictions on border control, local manufacturing, and increased ‘free market’. Given the latter, there were motivated efforts to quickly change or remove the DFA. The first attempt entailed introducing the Financial CHOICE Act (United States Congress, 2017), that attempted to return to the regulatory environment that existed prior to the 2008 financial crisis. The bill was supported by banking lobbyists (NPR, 2017) and aimed to repealing almost all DFA provisions, like scrapping the requirement to put their clients' interests ahead of their own (The Volcker Rule). The bill was criticized by the executive director of Americans for Financial Reform: "It is bad for consumers, it is bad for investors, and it is bad for the stability of the American economy" (NPR, 2017). However, the bill was dropped as it did not make it out of the Senate and thus the DFA was not repealed. However, the Republican party did not want to give up and continued its efforts: after it already repealed Obamacare, it made the revoking the DFA their next mission, and introduced a less drastic version of their 2017 bill. The adjusted bill and was aimed at improving conditions for SMEs and consumers – rather than improving the conditions for hedge funds and banks. Although the bill restored some parts of hedge fund secrecy like increasing the threshold to be obliged to disclose information and increased communication requirements exemptions, the bill ultimately represented a diluted version of their 2017 bill and did not repeal the DFA. Therefore, the 2018 bill is not expected to significantly influence hedge fund activity as the DFA did.

Literature review

The direct effects of the Dodd-Frank-Act on hedge funds

The DFA seemed to affect larger hedge funds (Hofstra, 2012): 51.5% of hedge fund managers polled stated that the DFA is a “significant concern” for its future performance. Furthermore, these worries are stated in an article of the Hedge Fund Journal (2012) shortly after the implementation of the DFA: *“It’s undeniable that hedge funds are bearing an unusual burden as a result of Dodd Frank legislation. The large number of new information requirements (…) have brought (…) higher costs for hedge funds.”*. Moreover, the direct effect of the DFA on hedge fund performance is adverse (Cumming, Dai & Johan, 2020), as fund alphas of DFA-subjected hedge funds significantly decrease compared to non-DFA-subjected hedge funds. Furthermore, Shelby (2017) reports that increased transparency requirements brought about by the DFA are expected to be effective against hedge fund risk taking that is causing its higher alphas. Restrepo (2024) also notes a decrease in the net profits for investors in DFA-subjected hedge funds due to higher compliance costs and its collateral effects, like managerial attention diversion and changes in financial valuation and its reporting practices. It seems obvious that the DFA is a significant blow for hedge funds – and potentially its activism.

However, Kaal (2013) researched the expectations of hedge fund managers the first year after the implementation. Conversely to the negative expected outcome researched before its implementation, it appeared that hedge fund managers expected that one year after implementation the

DFA will be considerably less harming to hedge funds: the paper polled that 76% of the hedge fund managers stated that their investors' rate of return was not affected by the registration and disclosure requirements. Kaal (2016) extended its research by analysing the DFA three years after its implementation and finds similar results: the DFA is not impacting hedge funds significantly. Furthermore, findings include that after the DFA, hedge funds have changed and increased their communications about its AUM and reporting structure with investors.

However, it appears that DFA is possibly affecting hedge funds in a way that might be hard to detect: an increasing amount of hedge funds are closing funds to new investors as they do not want to adhere to the new reporting requirement and are changing funds' legal structures, both indicating potential survivorship bias as these funds are not analysed in performance analyses post-DFA. Besides these indicators of rapid responses to the DFA, it showed that hedge funds' compliance costs doubled three years after the DFA compared to the year before the DFA, as well as finding that hedge funds largely absorbed the increased reporting and compliance expenses by using pass-through expenses, i.e. letting their clients pay for the higher costs incurred by the DFA. Thus, Kaal (2016) confirms the outcomes of its previous study; the DFA is probably not affecting hedge funds significantly, as hedge funds are adjusting efficiently to new regulatory demands. Similarly, Partnoy (2015) finds that the DFA might not capture all hedge funds, as some might have restructured as family offices in order to attempt to avoid the increased regulatory burden and thus expects that the DFA impacts hedge funds less severe as expected by Cumming, Dai and Johan (2020), Restrepo (2024) and Shelby (2017). Furthermore, Kidd (2018) is not expecting the DFA to impact hedge funds significantly, as the regulators are not understanding the drivers of hedge fund risk taking and argues that the DFA is rather an easy and quick piece of legislation than an effective one.

Thus, the effect of the DFA on hedge funds is probably ambiguous, and less harming than first thought. As only approximate 1% (Lipton, 2015) of all US hedge funds are activist, it is interesting to analyse whether the DFA affects these activist funds differently than the DFA effects discussed on all hedge funds. Although few academic papers are directly linking DFA to HFA instead of to hedge funds in general, Shelby (2016) argues that although the DFA was a 'drastic' change to the regulatory landscape as it decreases its desired secrecy, the DFA is not as effective as it could be as HFA specifically should be targeted more. Furthermore, Coffee and Palia (2014) predict a minimal negative effect of the DFA on HFA as HFA is most effectively targeted when shortening the Williams Act ten-day window. This window is a requirement for hedge funds to file a disclosure with the SEC (Harvard Corp Gov, 2011) within ten days after purchasing a stake higher than 5% in a target firm, enabling hedge funds to trade in secrecy for ten days. As this ten-day window enables HFA to engage in asymmetric trading that harms other investors by reducing overall market liquidity and widening the bid-ask spread, shortening this window would potentially lower the effectiveness of HFA and its risk taking. Although the Willim Act ten-day window was originally reduced to five days in the DFA, the SEC later repealed its plan (Harvard Law School Forum on Corporate Governance, 2019) as it feared negative externalities on private markets. Besides shortening the Willim Act ten-day window, Coffee and Palia (2014) argues that private governance solutions like a window-closing poison pill is perhaps more effective than public regulation in achieving the goals of the DFA.

The short-term and long-term effects of HFA

The immediate positive impact of hedge fund activism on target firms' stock prices during the announcement period reveal (Brav, Jiang, Partnoy, & Thomas, 2008) positive abnormal returns ranging from 5% to 10% in the first few months, indicating the market perception of increased shareholder value after HFA. Furthermore, several studies (Clifford, 2008; Bebchuk, Brav, & Jiang, 2015; Greenwood & Schor, 2009) show that target firm performance, return on assets (ROA), increases following hedge fund interventions. This suggests that besides the initial market reaction, HFA contributes to tangible operational efficiencies and value creation within target companies. However, Baker (2021) and Coffee & Palia (2014) find no evidence that HFA is increase firm operating performance or significant long-term returns when comparing the targets to similar targets.

Furthermore, Lipton (2015) finds that HFA is only profitable for the firm and not for its employees: the positive changes observed in firm productivity do not translate back into better labour outcomes for these employees, as HFA often causes mass layoffs (DesJardine & Durand, 2020; Kim, 2020). Also, as employees are aware of these potential layoffs, leave the firm and thus HFA causes (Chen, Doyle & Shi, 2021) a flight of human capital even prior to actually laying off employees. Although HFA causes increased work-related stress (Kim, 2020), Park (2020) finds that employees are actually more satisfied with management and their work-life balance after HFA. Altogether, although the overall empirical evidence supporting the positive short-term and medium-term effects of hedge fund activism is significant, questions persist regarding the long-term mechanisms of these improvements. Thus, the preconception of hedge fund activists as creators of long-term value should be analysed bilaterally: are the post-HFA observed changes applicable to both the firm and its employees?

Brav, Jiang & Kim (2015): The Real Effects of Hedge Fund Activism: Productivity, Asset Allocation, and Labor Outcomes

Brav, Jiang & Kim (2015) research the long-term effects of Hedge Fund Activism (HFA) on labour outcomes, firm productivity and firm performance. By using plant-level industry data from the US census bureau Annual Survey of Manufacturers, Brav et al. (2015) initially refute the questions raised about HFA being not effective for the firm long-term, and destructive for labour outcomes: HFA increases long-term (three years) firm performance and productivity and increases labour outcomes (productivity and the number of employees). Brav et al. (2015) start their analysis by observing that prior to interventions plant productivity often drops, possibly because of inadequate governance. However, productivity significantly increases two to three years following the hedge fund activist action and thus a ‘V-shaped pattern’ is observed. The productivity gain is consistent with the overall increase in the firm's financial performance, indicating that hedge fund activism has a long-term positive impact on the operational effectiveness and productivity of the target business. Also, the study finds a notable variation in activist "styles": HFA is the most effective when using the HFA strategy to improve the business strategy of the firm of sell the of target.

Although labour productivity increases (+8.4%) and the decline in the number of employees is reduced from -12.7% to -3.4%) in the three years after HFA, worker wages fail to rise in line with these gains: earnings per worker stagnate, causing productivity-adjusted per-hour wages from the following years to decrease by 7.3%. Also, the average salary remains unchanged, particularly for white-collar workers. The results indicate that employees’ salaries remain unchanged despite firm and labour productivity increases in firm targeted by HFA, suggesting a transfer of labour rents to the shareholders of firms rather than to its employees. Thus, although there is no layoff of employees as expected (DesJardine and Durand, 2020 & Kim, 2020), the findings still indicate that not all stakeholders profit in the same way from HFA. The increases in labour productivity imply that activists improve efficiency in labour-intensive enterprises by enforcing stricter oversight like monitoring, indicative of one of the strategies hedge funds use to obtain the observed gains that improves asset efficiency.

Also, findings indicate that gains in firm productivity are achieved through capital reallocation as HFA increases capital expenditures (from now on, ‘capex’) in its target firms, especially in IT investments. Results show that HFA target firms with the highest IT expenditures also had the most gains in firm and labour productivity, indicative of increased capex or IT spend in target firms as a HFA strategy used to achieve the firm productivity growth observed

Relevance

Contribution to Brav. et al (2015) and other existing literature

As Brav et al. (2015) only research events in a timeframe (1994-2007) absent of significant hedge fund regulation, this study tests the robustness of the overall positive effectiveness of HFA in a timeframe with increased regulation, particularly the DFA (2012-2018). As the DFA is the most significant financial legalisation in the U.S. in the past decades and given its ambiguous implications on hedge funds implied by the literature discussed, this study provides a deeper analysis that sparks the debate of the direct effects of the DFA by researching the externalities, i.e. indirect effects, of the DFA. Furthermore, this study builds on the increased societal relevance of HFA in recent years: the lower success rate of HFA campaigns in recent years, the recent decade being the worst decade for hedge fund returns, increased hedge fund scandals and the public revolt against HFA (Gamestop). In doing this, it sparks the debate concerning the controversies and scandals resulting from the increasing presence of HFA as a corporate governance feature and provides insights to investors considering alternative investments.

However, the direct and indirect effects of the DFA are two separate research fields. This study is not estimating the direct effect, i.e. the effect of the DFA on (activist and non-activist) hedge fund risk management, returns and operations, but its indirect effect on the effectiveness of HFA, i.e. the externalities of the DFA. As discussed, the direct effect of DFA has already been researched with ambiguous implications on hedge funds, while the indirect effects on activist hedge funds specifically and its externalities on activist targets are not researched yet. Thus, this study fills this gap in the literature by investigating the robustness of HFA effectiveness, and its strategies and value channels, after the DFA. This study focuses on its key stakeholders affected: shareholders, company management and regulators, and tests how they are impacted by HFA under the new regulatory environment brought about by the DFA. More specifically, it compares HFA target firm productivity, performance and labour outcomes between firms targeted by hedge funds subjected to (AUM above 150 mln. USD) the DFA and those who are not (AUM below 150 mln. USD). Analysing the effectiveness of HFA is generally done using an Event Study Analysis and a Difference-in-Differences (DiD) design (Brav et al., 2015), as well seen in studies investigating the direct effect of the DFA on hedge fund performance (Cumming, Dai & Johan, 2020).

By using a Regression Discontinuity Design (RDD), this analysis aims to better capture the effects observed by Brav et al. (2015) and Cumming, Dai, and Johan (2020). Unlike a DiD design, which most often lacks precision at the cutoff point (150 mln. USD AUM) and assumes a parallel trend that probably does not hold in the context of this study due to the DFA affecting all firms in a different way, a RDD gives a more accurate estimation by exploiting the cutoff as a quasi-random assignment mechanism. The RDD assumes that hedge funds just below and above the cutoff (150 mln. USD AUM) are comparable, that there is no manipulation around the cutoff and that the relationship between the running variable (hedge fund AUM) and outcome variable (target firm TFP) is modelled correctly. Given there is no reason to believe hedge funds manipulate their AUM size to be just below or above the threshold, and that small hedge funds are probably comparable to those slightly above the threshold, the RDD assumptions discussed meet the goal of this study better, allowing for a more reliable estimation of the causal effects of the DFA on HFA.

Thus, the goal of this study is to causally analyse the impact of the DFA on the successful long-term effects of HFA for target firms and labour productivity. However, readers should not confuse the goal of this research with assessing the effectiveness of DFA as a regulatory measure, as this would be beyond the scope of this research and is impossible to conclude after this research given the goal of the DFA is not lower hedge fund returns and change target firm outcomes, but to lower risk taking and ensure financial crises and scandals are mitigated (SEC, 2024). The effectiveness of the DFA can only be assessed when researching the changes in direct risk-taking behaviour by hedge funds, to analyse whether systemic risk has actually gone down.

Research structure

Like Brav et al. (2015) and Şeker & Saliola (2018), this study uses Total Factor Productivity (TFP) as proxy for firm outcomes as it captures improvements in productivity directly, as well as its underlying value channels. By using different proxies for TFP inputs than the Annual Survey of Manufacturers of the US Census Bureau, this research allows to analyse all industries rather than only manufacturing industries like Brav et al. (2015). As TFP is not indicating firm performance and valuation, this study adds an extra layer to existing research by including indirect firm-level performance metrics (Return on Invested Capital and Return on Assets) and market-level performance metrics (stock prices) and serve as robustness checks to the changes observed in TFP in each analysis. Finally, labour productivity and the number of employees are used as proxies for labour outcomes, to analyse whether firm-level gains or losses are translated back in the same way into labour outcomes and the real and long-term effects of HFA are researched.

The first hypothesis studies the impact of the DFA on HFA effectiveness by using a RDD to compare target firms just above and below the DFA threshold. This research focuses on the overall effects of the DFA, including increased disclosure requirements and compliance costs for target firms, to determine if these factors decrease the effectiveness of HFA in firms around the regulatory cutoff. This directly addresses the main research question of this paper: How does the DFA, through the increased DFA provisions mentioned, affect the HFA effectiveness? Building on these results, the effect of the DFA is analysed more granularly by testing the robustness of the secondary research questions of Brav et al. (2015), including the differences in the effect of the DFA between all targets and manufacturing targets, and its value channels and effective HFA types. As these research questions are analysed using a RDD, this study is able to causally test the effect of the DFA on HFA effectiveness. Hence, this study tests whether the observed by Brav et al. (2015) increases in target firm and labour productivity after HFA, and its underlying value creating channels and most effective strategies, remain robust after the largest piece of U.S. hedge fund regulation in decades.

Main findings

The RDD analysis shows that the DFA increases HFA effectiveness by 5.2% but the effect is significantly lower (-7%) for manufacturing targets relative to all targets. Thus, Coffee & Palia (2014) projected correctly that the DFA does not negatively impact HFA, possibly because the DFA is not shortening the 10-day non-disclosure window and thus it is not effectively targeting HFA. The increases in firm TFP targeted by DFA-subjected hedge funds relative to the not DFA-subjected hedge funds imply that the SEC is unintendedly stimulating HFA effectiveness. Furthermore, this study refutes Brav et al. (2015) by indicating that higher capex investments and increased labor productivity are no longer the HFA value channels after the DFA. Also, the sale of the target firm is not the most effective HFA strategy anymore post-DFA.

Hypothesis development

To answer the main research question of this study, the effect of the DFA on HFA effectiveness, and to test the secondary research questions posed by Brav et al. (2015) regarding industry differences, value channels, and dominant HFA strategies, I specify four hypotheses that align with the predictions of the relevant literature. HFA effectiveness is defined as the changes in firm outcomes (TFP and performance), as well as labor outcomes (labor productivity and the number of employees), after the firm receives an activist hedge fund as a shareholder. The more positive these changes, the more effective the activist campaign is considered.

Hypothesis 1

Although empirical studies suggest that HFA may not significantly boost worker wages compared to firm performance and productivity (Brav et al., 2015), economic theory (Kaal, 2020; Nofsinger, 2014) states that HFA improves short-term and medium-term firm and labor productivity by increasing efficient management and better operational practices. Identically, while the goal of the DFA is to reduce hedge fund secrecy through increased reporting requirements, economic theory suggests that its overall effect on the hedge fund industry is rather ambiguous. Although certain economic theories predict a negative effect on hedge fund returns due to increased regulatory burdens (Restrepo, 2024; Shelby, 2017), other studies predict hedge funds to quickly adapt to regulatory changes like the DFA, which would minimize the impact of the DFA (Kaal, 2016; Kaal, 2013; Partnoy, 2015; Kidd, 2018). When testing the exact relationship between the DFA and HFA rather than hedge funds in general, economic theory suggests that the DFA probably does not negatively affect HFA effectiveness (Coffee & Palia, 2014), as the DFA fails to shorten the ten-day window of the Williams Act. Hence, economic theory implies little adverse effects from the DFA on HFA effectiveness.

The goal of this hypothesis is to assess the potential economic implications of regulatory changes, particularly the DFA, on HFA effectiveness. The hypothesis determines whether the DFA has altered the effectiveness of HFA by analysing the significance and direction of the Local Average Treatment Effect (LATE), using a RDD approach. This approach causally tests the hypothesis by comparing similar hedge funds (AUM) and controls for confounding variables. The 'local' part of the LATE is present as the effect applies only to the subgroup (DFA-subjected hedge funds) and 'average' as it measures the average effect of the treatment in this subgroup, instead of the total population. The hypothesis is rejected if a negative treatment effect is found, as this suggests that HFA effectiveness has decreased as a result from the DFA. Thus, the hypothesis is specified as follows:

H1: HFA effectiveness is not negatively influenced despite the implementation of the DFA, as the DFA's regulatory changes do not fundamentally disrupt the mechanisms through which HFA operates.

Hypothesis 2

According to lifecycle theory, younger firms with higher growth opportunities are significantly more likely to benefit from external interventions aimed at improving target firm performance and productivity. This is because these type of firms usually face much more flexible production possibilities and have higher marginal returns on investment compared to firms that are more mature, which probably already are operating near their optimal efficiency (Mueller, 1972). In this context, Brav et al. (2008) shows a broader view that increases in firm outcomes post-HFA are observable across all targets – irrespective of industry. However, this view is challenged as manufacturing firms, given that they are more mature, experience lower growth opportunities and thus lower potential gains from HFA (Brav et al., 2015). From an economic standpoint following generic corporate governance mechanisms (Jensen & Meckling, 1976; Penrose, 1959; Barney, 1991), it is anticipated that the effects of HFA are expected to be more pronounced in less mature firms due to its increased elasticity of productivity relative to its managerial and operational improvements.

Thus, this hypothesis tests whether HFA is more effective in less mature firms with more growth opportunities (all targets) compared to more mature (manufacturing targets), and tries to interpret the underlying reasons if a significant difference is observed. A significant difference implies that manufacturing firms are a biased subsample and that the results of Brav et al. (2015) can not be extrapolated to firms with different maturity levels and growth opportunities. The hypothesis is tested through a RDD analysis by comparing the means of the LATE increases seen between the two groups using t-tests, representing the effectiveness of HFA. This leads to the following hypothesis:

H2: The increases in target firm and labour outcomes after HFA are significantly higher in less mature firms with more growth opportunities compared to manufacturing targets.

Hypothesis 3

The relationship between capex expenditures, labor and firm productivity is well-researched in economic theory studies: the theory of capital allocation states that firms that invest a lot in capital assets are expected to experience higher productivity due to the enhancement of their production capabilities and efficiency (Solow, 1956; Romer, 1990). Moreover, labor productivity is apparently an essential determinant of overall firm productivity and competitiveness, as proposed by (neo-)classical economic theories (Smith, 1776; Marshall, 1890). Economic theories of Corporate Governance and Agency suggest that (activist) hedge funds often influence firm behaviour and resource allocation, thus driving improvements in firm outcomes (Jensen & Meckling, 1976; Shleifer & Vishny, 1986). These theories suggest that HFA enhances firm value by enforcing better capital allocation and improving operational efficiencies.

Building on these theoretical foundations, I hypothesize that firms with higher capex spend and labor productivity experience more significant gains in firm outcomes (productivity and performance), because these investments are aligned with the core value creation mechanisms observed in economic theories: asset efficiency and the optimalisation of capital reallocation. The value channels through which hedge funds operate, as highlighted by these theories, suggest that increased capex and labour productivity are critical levers for enhancing firm value. These theories are understated by the results of Brav et al. (2015), as they show that these two dynamics are driving value creation in companies after HFA involvement. Thus, it is expected that the strategies employed by HFA to create target firm value are effective even under new regulatory environments like the DFA. This leads to the following hypothesis:

H3: For target firms subject to the DFA, increases in capex spend and labor productivity are positively associated with improvements in firm performance and productivity (TFP, ROIC, ROA and Stock Prices) similar to those observed by HFA prior to the DFA implementation.

Hypothesis 4

HFA interventions often involve restructuring the target firm through asset sales or by adjusting strategic capital allocation plans, both are aligned with the theory of optimal resource allocation (Coase, 1937) and corporate control (Williamson, 1985). The resource allocation theory includes that reallocating resources to their most productive uses significantly improves firm outcomes (Coase, 1937; Williamson, 1985), and the corporate control theory underscores the role of strategic changes in improving firm outcomes by aligning managerial incentives with shareholder, like HFA (Fama & Jensen, 1983).

Building on these theoretical foundations, I hypothesise that HFA strategies that involve advocating for the sale of the assets target and changes in long-term capital structure remain robust after the regulatory constraints introduced by the DFA. The are first signs the theory is correct, given the findings of Brav et al. (2015) that indicate that changes in capital structure and advocating for the sale of the target firm are the most successful HFA strategies. However, these findings are in a timeframe absent of significant regulation. This hypothesis is tested by comparing the mean effects of DFA on firm outcomes using a RDD estimation. Thus, this leads to the following hypothesis:

H4: Hedge funds subjected to the DFA that use the HFA strategies sale of target and changes in long-term capital allocation, experience greater improvements in firm outcomes (measured by TFP, ROIC, ROA, and Stock Prices) compared to these target firms employing other strategies (like advocating for changes in governance).

Data

Research design

First, I discuss the process of data matching and dataset construction. As this is relatively straightforward for the indirect firm measures, this part is considerably more comprehensive for TFP, given its long academic history of different estimation methods and adjustments to correct for biases, as well as the importance of choosing the accurate proxies that directly capture firm-level changes. Next, summary statistics of all outcome variables are discussed to analyse differences between samples and proxies of productivity and performance. I choose a three years treatment period for HFA, as the dataset shows that hedge funds hold on to its stake for 794 days, or approximately 2.2 years.

Thus, given that the effects of HFA do not immediately stop after the end of the stake, and given that three years is also the most comparable to Brav et al. (2015), three years are used to capture all of the effects of HFA. To establish causal relationships between HFA and the DFA, I test all hypotheses using a RDD design that accurately analyses the cutoff point (150 mln AUM USD), as well simulating a natural experiment setting. It is expected that the DFA is not impacting (Coffee & Palia, 2014) HFA negatively, although there are signs of the DFA negatively impacting (Cumming, Dai & Johan, 2020, Restrepo, 2024; Shelby, 2017) the hedge fund industry in general (non-HFA and HFA).

Data sources

Using cross-sectional time series (panel) data, the dataset combines characteristics of both cross-sectional data (the comparison of firm and labour outcomes across different firms at the same time) and time series data (the progress of firm and labour outcomes across multiple time periods (t0 until t+3). Thus, I analyse changes over time while controlling for differences between firms, and thus controls the unobservable heterogeneity (time constant but firm varying factors). The dataset is structured in a way that statistical software understands it is panel data: each event has seven observations, structured in seven rows with the same event code going from 0 to +3. As there are considerable outliers in the data that caused skewed results, all potential unbounded variables are winsorized at 5% extremes, to ensure that extreme values do not deter the analysis while retaining the majority of the data distribution.

Data is collected for four different types of variables: hedge fund characteristics, firm productivity and performance data (TFP, ROIC, ROA, Stock prices), labour outcomes data (Labour productivity and employees) and control variables data. The data is collected from seven databases: the US Edgar system, Execucomp, the TASS Lipper Database, the Bloomberg Hedge Fund Long-Activism Database, CapitalIQ, Compustat & Bloomberg Everywhere. By automatically gathering US hedge fund activism event (‘Bloomberg’s activism database tracks all global shareholder activist campaigns – situations where outside shareholders seek to influence a company, such as requesting replacement of management, board seats, share repurchases, proxy fights, etc.') the Bloomberg Hedge Fund Long-Activism Database suits the purpose of this research. The SEC EDGAR System provides detailed information on public (investment) companies filings submitted to the SEC, including annual reports (10-Ks), quarterly reports (10-Qs), and similar financial statements. The TASS Lipper Database is a comprehensive dataset on hedge funds and similar alternative investments, offering performance, AUM data and more comprehensive info on fund strategies and fund management. The Bloomberg Everywhere terminal is a service provided by Bloomberg that offers detailed financial data, analytics, and performance data. Compustat and Execucomp are widely used dataset for company performance and executive compensation, respectively.

Dataset 1: all target firms

TFP

Mathematically, TFP equals the difference between actual and predicted output, given the observed inputs Capital (K), Labour (L), Material (M) and Output (Y). In practical terms, this implicates TFP is measuring its observed internal firm efficiency and thus represents how well the firm converts its observed inputs into outputs, given the technology (or production process) it employs. The adjective 'observed' is important; as TFP equals the delta of actual and predicted output, the TFP figure represents the firm-specific productivity or efficiency shocks not explained by its observed inputs (M, K, L), i.e. the unobserved, unquantifiable or unexplained part of its productivity. Thus, TFP can be thought of as representing the "net outcome" of both observed contributions (which are explicitly modelled) and unobserved influences (captured implicitly through omega). Examples of unobserved factors are variables that directly affect a firm's production technology or efficiency but are difficult to measure. Although Abramovitz (1956) is unsure of the unobserved drivers, recent literature (Wolff, 1991) suggests that sector wide technological efficiency advancements or other industry-wide macro trends and labour outcomes like managerial expertise and worker skill levels represent the unobserved part of TFP that directly impacts firms.

Thus, TFP inputs Labour (L), Capital (K) and Materials (M) need to capture all of the firms observed internal efficiency and should directly affect firms operations. As most balance sheet, income and cash flow statement items like leverage, cash, working capital, etc. reflect the indirect financial structure, investment efficiency and market valuation of a firm rather than serving as direct measures of internal firm efficiency. More accurately, surveys like Annual Survey of Manufacturers (ASM) and Census of Manufacturers (CMF) conducted by the US Census Bureau provide direct inputs measuring firm inputs: employee hours, total value of shipments, detailed inventory items, etc. Brav et al. (2015) uses this survey to construct its TFP. Brav. et al. (2015) gained access to the Longitudinal Business Database (LBD) through RDCs and were able to match the confidential US

Census Bureau industry-level data to firm-level observations. To access the LBD, researchers must submit proposals detailing their study's scope (Census, 2023), the data they want, and how they will maintain the confidentiality of the data. When approved, they have access to detailed microdata not available in public releases, and thus are able to match the ASM data to LBD data using unique firm identifiers. To get similar restricted-use microdata access through the Standard Application Process (SAP) of the US census bureau, it appears that 'all members of the project team must have resided in the United States for at least three of the past five years.'. Thus, given that the LBD is not accessible to users outside the US, matching the industry-level US Census Data to firm-level observations is not possible for the dataset containing all firms.

Given the US Census Bureau data limitations described in the section 3, this study follows Van Beveren (2007) and Bournakis & Mallick (2017) in its direct proxies of TFP inputs: raw materials as a proxy for material input (M), fixed assets as a proxy for capital input (K), number of employees as a proxy for labour input (L) and total revenue minus material costs as a proxy for output (Y). As some firms have diverse or complex production processes where inventory levels are influenced by factors other than production efficiency, like demand fluctuations and supply chain strategies, it is valuable to look at raw materials consumed directly as it quantifies the input cost of materials. The Compustat Inventory items Raw Materials & Work In Progress are used as proxy for M, as the Finished Goods segment of inventories is not contributing directly to output and is already processed in the revenue. As the proxy of Capital Stock (K) should capture the age, condition, or technological level of capital assets directly, the book value of fixed assets (e.g., machinery, equipment, buildings), provides a direct snapshot of the capital available for production purposes and thus fits the purpose as direct measure of the firm's investment in its productive capacity.

The direct measure of labour input should capture either quantity (hours worked, employees, etc.) or quality (skill levels) and should account for variations in the workforce composition, thus the firm-level analysis uses the number of (FTE) employees as proxy for L. As last, the direct proxy for the actual output Y is equal to total revenue – material input, as this isolates value added by the production process itself, excluding the cost of intermediary goods that do not directly contribute to final revenue. Although the proxies of the firm-level are arguably less direct (TVS versus revenue) and granular (hours versus employees) than the TFP input proxies of the ASM used by Brav et al. (2015), the proxies are still legitimate and commonly used (Van Beveren, 2007; Bournakis & Mallick, 2017) direct proxies of the inputs discussed. Also, as the different proxies of TFP allow for all industries to be analysed rather than only manufacturing industries like Brav et al. (2015), this analysis is perhaps less downward biased as most firms in the manufacturing industry are mature firms with lower growth opportunities (Brav et al., 2015) that because of that perhaps underestimated the effect of HFA on TFP.

ROIC, ROA Stock Prices and labour outcomes

ROA – expected to increase due to increased asset efficiency after HFA (Brav et al., 2015) – is calculated as net income / average book value of assets. ROIC - expected to increase due to increased capital efficiency after HFA– is calculated by dividing invested capital over NOPAT. Stock prices – indicative of market sentiment and expected to increase (Brav et al., 2008) after HFA– are the recorded stock prices is USD on the given observation date. Labour outcomes are composed by labour productivity – dividing the total number of employees over total sales - and the number of employees (in thousands) and are both expected to increase after HFA (Brav et al., 2015). The variables used in the calculations of the performance measures and labour outcomes are taken from Compustat while the stock prices are obtained using the 'Bloomberg Everywhere' dataset.

HFA event data

The TASS Lipper Database is used, like Cumming, Dai & Johan (2020), to obtain the AUM of hedge funds and the Bloomberg Hedge Fund Long-Activism Database for identification of events, type of activism and how large the stake is in the company. All events collected by the database have been checked by web searches and several events of the database have been omitted (~10%) as they were not HFA but only passive types of activism; these hedge funds only obtained a stake in the target company and restrained from governance proxy wars, media campaigns, etc., thus not being an HFA. This ensures campaigns are legitimately classified as 'active', as Brav et al. (2015) already showed the significance of this split, as 'Schedule 13D filers' (S.E.C. filing requirement of hedge funds when acquiring a stake in the target company), i.e. HFA, are better in achieving gains in target firm and labour outcomes compared to 'Schedule 13G filers', i.e. passive hedge funds. In the event treatment period, 2012-2015, the Bloomberg Hedge Fund Long-Activism Database collected 465 HFA events, and these events were matched between the Bloomberg Hedge Fund Long-Activism Database and TASS Lipper Database as the latter complemented the event data with hedge fund AUM. However, not all the hedge fund names were instantly matched; as the TASS Lipper Database sometimes used abbreviations, or ''the'' was in either source not used in the name or similar issues that obstructed the data matching. If the hedge fund of the Bloomberg Hedge Fund Long-Activism Database was not present in the TASS Lipper Database, manual lookups in the SEC Edgar database often resulted in the desired annual AUM of the hedge funds.

However, in transforming the dataset to a balanced panel, this research only uses 221 (47%) of the 465 events, as there were either events with a hedge fund with no matching name in the Lipper database and thus its AUM could not be assigned, duplicate HFA events were recorded in the Bloomberg Hedge Fund Long-Activism Database, or a target company that got delisted or acquired somewhere in the three year before or after the event date and thus no data was available in the Compustat and Capital IQ database. The latter could impose positive survivorship bias (Brav et al. 2015; Brav, Jiang, and Kim 2009; Shumway, 1997), as delisting implies HFA events that have led to a nefarious end are now omitted from the research, and the dataset is thus is potentially suffering from positive bias if this research is showing effects of HFA. However, disappearance from the Compustat database could as mentioned as well imply that the target firm is acquired and thus indicating that rather a successful HFA event is omitted from the data set, indicating negative bias. In fact, the negative bias is stronger that the positive bias (Brav et al., 2009), meaning that the survivorship bias in this research is underestimating the results of HFA on firm productivity: if the effects of HFA turn are positive, they are likely even more positive in practice. However, the magnitude of survivorship bias in this study is marginal: of the 53% disappearance rate of this sample, most (78%) is driven by AUM missing data, 8% by duplicate events and only 16%, thus ~8% of the complete dataset, is omitted due to possible acquiring/delisting of HFA targeted firms. Compared to the Compustat 26% disappearance rate of companies targeted by HFA and the overall average attrition rate of all firms in Compustat (12%), the survivorship bias seems to be less of a problem in this study, although the results should be analysed taking the negative biased caused by this into account. As the full research consists of 221 unique HFA events, and an event is treated two years before and after the event date, the total amount of observations this research uses for analysing firm and labour outcomes after HFA equals 1547. The 221 events contain of 83 unique hedge funds, indicating a diverse set of hedge funds engaged in HFA, have on average a stake of 5.9% and hold on to this stake for approximately two years and two months (794 days).

Besides AUM, the TASS Lipper Database offered other hedge fund characteristics to potentially serve as control variables: fund leverage, fund strategy (long/short, multi-strategy, etc.) and management fee (Cumming, Dai & Johan, 2020). However, all the variables mentioned had many missing datapoints in the TASS Lipper database, or were by default set to zero, and thus these variables are not included in this research to maintain meaningful outcomes. The dataset contains of four dummy variable groups: AUM, type of activism, SIC industry codes and the CEO turnover dummy. As main independent variable and variable of interest, the RDD analysis uses this dummy as treatment variable, where AUM is divided into the treatment group (_>150 million USD AUM results in ‘1’) and control group (<150 million USD AUM results in ‘0’), as the latter is not affected by the DFA new reporting and disclosure regulations. There is no significant impact of the DFA on HFA effectiveness, and thus on firm and labour outcomes, expected (Coffee & Palia, 2014). The dummy for type of activism is first collected by the Bloomberg Activism Database, showing sometimes multiple strategies: ‘Cost Cutting; Remove Poison Pill; Break Up; Board Representation; Board Control’. To simplify comparing between activism types, five dummy variables are created for the type of activism, aligning with structure of Brav et al. (2015): General (no clear purpose defined), Capital Structure (changes in capitalization), Business Strategy (pushing for acquiring targets or breaking up the company), Sales for target (selling the company) and Governance (asking for board seats, pushing to fire management). If the event has multiple strategies, the bracket with most observations of activism is chosen as type of activism, thus per event only one type of activism is chosen. For the example discussed, Governance is chosen. Six-digit NAICS codes, taken from Compustat, are divided into six dummy variables: Manufacturing, Trade & Transportation, Wholesale Trade, Retail Trade, Services, and Agriculture, Mining and Construction. CEO turnover, taken from Execucomp, is a dummy variable that equals ‘1’ if in the calendar year of the observation a new CEO joins the management team. The likelihood of the variable equalling ‘1’ is expected to increase as HFA increases, as hedge funds often participate in proxy wars with existing management and are advocating for management changes (Harvard Law School Forum on Corporate Governance, 2020).

To complement the performance measures ROIC, ROA and Stock Prices, the same firm-specific control variables as Brav et al. (2015), except for R&D and Atman’s Z-score, are collected from Compustat and CapitalIQ. The variables are balanced and exhaustive, as they are indicators for valuation (Tobins Q), size (Market Cap and Book Value of Assets), financial structure and investments (Capex% (capital expenditures scaled by lagged assets) and leverage), liquidity (cash scaled by assets and dividend yield), profitability (sales growth and FCF), maturity (firm age) and management stability (dummy for CEO turnover). Vatavu (2015) and Bayaraa (2017) find similar determinants of performance metrics like ROA, ROIC and Stock Prices: leverage, size (market cap), profitability (FCF), sales growth, dividend yield and investments. The summary statistics of these variables serve as a first indication of the differences in performance and valuation between manufacturing targets, all targes and non-targets.

Dataset 2: Manufacturing targets, firm-level

For the firm-level TFP of manufacturing targets, the 221 unique HFA events got reduced to 73, as these were the only target companies in the manufacturing sector based on its six-digit NAICS 31-33 code. As the dataset differentiates firms using six-digit NAICS codes, it allows for a granular analysis, as is shown in the data: about 70% of the 73 manufacturing HFA events have a have a unique six-digit NAICS code. To indicate the granularity of the NAICS codes it is indicative to zoom in some individual events. In 2013 Icahn Enterprises became HFA (Marketwatch, 2016) by publicly intervening with Apple’s management. This event is coded in the data with NAICS code 334220, as Apple belongs to the manufacturing subindustry group ‘Radio and Television Broadcasting and Wireless Communications Equipment Manufacturing’. The event of Viex Capital Advisors (Reuters, 2015) publicly intervening in 2014 with Axcelis Technology’ board belongs to NAICS 333242: ‘Semiconductor Machinery Manufacturing’. The effectiveness of HFA on the firm and labour outcomes of manufacturing targets are expected to be lower than on other targets, given that the manufacturing industry is more mature and experiencing lower productivity growth (Brav et al., 2015).

Dataset 3: all Compustat industries

Only used to compare non-targets to targets, this dataset contains of 865,866 observations and contains of 123,695 U.S. listed companies. For these companies, only the indirect firm-level control variables discussed are gathered.

Dataset 4: RDD

Given the theory that sharp RDD models should only compare outcome variables similar to each other and close to the treatment variable, it is not indicative to include the largest funds in this part of the analysis. Furthermore, larger hedge funds often have diseconomies of (Busse, Chordia, Jiang & Tang, 2014) compared to smaller funds and have less market impact when trading. Of all 221 events, the highest hedge fund AUM is 93 bln. USD and the lowest 0.04 bln. USD, indicating significant outliers between HFA events, e.g. Elliott's (71 bln. USD AUM in 2012) governance activism in 2015 (WSJ, 2016) in CDK Global and Bulldog Investors's (0.2 bln. USD AUM in 2012) governance activism in BDCV Venture **(SEC, 2015)** are included in the dataset. Generally, hedge funds below 1 bln. USD are considered small- or mid cap (Aurum Research, 2019), and thus the range 0-600 mln is chosen given the high number of remaining events (128 or 58% of the 221 original events of all targets of dataset 1) while having a considerably more comparable dataset. Given that larger hedge funds most likely target larger companies given its abundant resources, the target firms investigated in the RDD could be biased towards small or mid cap companies and thus the analysis is slightly different than the dataset used for table 3 and 5. The bias indeed seems to be present when analysing the average market cap of all targets in both datasets: the companies in the RDD dataset are about 15% smaller than the companies in the complete dataset, and thus the results of the RDD analysis should be analysed bearing this in mind. As RDD only investigates event years, only periods 0 until 3 are included in this dataset, resulting in 508 observations due to the omitted larger hedge funds and only including event years.

Summary statistics per dependent variable

Indirect performance measures and labour outcomes

ROA is calculated as net income divided by the average book value of assets. ROIC is calculated by dividing invested capital over NOPAT. Stock prices are the recorded stock prices is USD on the given observation date. Labour outcomes are composed by labour productivity, dividing the total number of employees over total sales, and the number of employees (in thousands). Table 1 shows the summary statistics of firm-specific control variables collected from Compustat and Capital IQ. Market cap and total assets are expressed in mln. USD, while the relative values of leverage (d/e) and Tobins Q representing the proxies of risk and valuation. The relative independent values dividend yield, Sales growth, FCF/LA, Capex/LA are expressed as decimal fractions, the relative dependent values ROA and ROIC are transformed to percentages (x100) to make interpretation of the results easier. Stock prices are expressed in USD, and employees in thousands. Column '(1) vs (3)' shows the differences between the manufacturing subindustry sample of target companies and all targets, and all targets to all listed companies (non-target and target) in the relevant years (2012-2018) that are recorded in Compustat (column '(1) vs (5)').

When comparing column (1) vs (3), it shows that manufacturing targets are similar in size compared to all targets (indicated by MV and Assets). However, manufacturing targets have higher leverage, pay out more dividends and spend more on Capital Expenditures compared to all target firms, but have considerably lower cash flows, valuations (as indicated by Tobins Q) compared to all target firms. These findings are for the biggest part in line with the findings of Brav. et al. (2015), except for leverage that they found to be virtually the same between manufacturing target and all target firms and Capex% being lower in their census sample. The similar findings when comparing the two groups indicates that the conclusion Brav et al. (2015) seems correct: firms matched to the Census sample generally have lower growth opportunities but enjoy better cash flows, indicative that firms in the Census sample are in more mature industries – which is the type of industries most manufacturing companies are in. When comparing the statistic of all targets to the full Compustat (column (3) vs (5)) sample, it is evident that the target firms are considerably smaller and are lower valued, although target firms enjoy higher cash flows. These findings are in line with Brav et al. (2015) and Brav et al. (2008), but are contrary to (DesJardine & Durand, 2020; Kim, 2020), that expect higher valuations after HFA due to the focus of HFA on short-term profitability. Also, target firms have considerably lower leverage and sales growth, and are much younger (firm age) compared to the full Compustat sample.

As HFA generally (Baker, 2021) increases shareholder dividend payouts, the findings of target firms enjoying lower dividend yields than non-target firms is unexpected. Also, the observed lower levels of investments is as expected (Baker, 2021; DesJardine & Durand, 2020; Kim, 2020) but contrary to the findings of Brav et al. (2015) as increased capex should be one of the strategies that HFA creates value by. As last, the performance metrics are compared: manufacturing target firms do not differ significantly (1 vs 3) in its stock prices, ROA and ROIC compared to all target firms, but are significantly higher compared to no-target firms (1 vs 5) in the first three years of the DFA, in line with literature (Brav et al., 2015) of the positive effects of HFA on firm performance.

TFP

Unlike the indirect performance metrics, TFP first needs to be estimated before being able to be used in regression analyses. Meaning, the production function first needs to be derived and afterwords needs to be analysed in different estimation types. Equation (1) shows a standard Cobb-Douglas production function, which is the starting point (van Beveren, 2007) in deriving TFP from the production function.

$$Y_{it} = A_{it} K_{it}^{\beta^k} L_{it}^{\beta^l} M_{it}^{\beta pt^m} \quad (1)$$

Table 1: comparing indirect firm metrics and labour outcomes across samples

	(1)	(2)	(3)	(4)	(5)	(6)	(1) vs. (3)	(3) vs. (5)
	Manufacturing targets (n = 511)		All targets (n = 1547)		Full Compustat Sample (n=123,695)		T-statistics of mean differences	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.		
Market cap	4894.49	9923.65	5481.54	11306.98	12350.78	21189.78	-1.05	-12.75***
Total assets	6797.22	13854.97	6908.32	15379.89	15265.39	26874.27	-0.15	-12.23***
Leverage	1.94	2.46	1.43	1.77	3.53	3.93	5.12**	-21.04***
Cash/assets	637.7	1424.2	709.48	1642.43	578.91	1215.26	-0.88	4.22**
Div yld %	0.01	0.02	0.01	0.01	0.01	0.02	3.48**	-5.79**
Tobins Q	3.16	2.26	3.71	2.58	4.94	3.52	-4.32**	-13.72***
Sales growth %	0.05	0.28	0.06	0.31	0.08	0.37	-0.72	-1.77
FCF/LA	0.01	0.02	0.02	0.02	0.00	0.01	-5.53*	28.37***
Firm age	47.15	45.82	46.56	44.62	80.92	79.87	0.26	-16.92***
Capex/LA	0.07	0.11	0.05	0.09	0.06	0.10	0.00	-2.40*
CEO turnover (dummy)	0.09	0.29	0.09	0.28	0.13	0.37	0.12	-4.46**
ROA	0.31	12.94	0.31	11.42	0.04	0.46	0.00	171.97***
ROIC	-1.26	22.30	-0.16	19.07	-0.18	10.02	1.11	5.15***
Stock prices	32.33	29.13	32.87	29.53	28.61	32.63	-0.366	5,669*

Labour productivity	1571.23	5076.21	2055.78	7842.48	936.35	3300.00	-1.614	5,613*
Number of employees	0.01	0.01	0.01	0.02	0.01	0.0	1.033	-0.698

*Table 1 presents descriptive statistics on firms targeted by HFA, segregated between manufacturing targets and all targets, benchmarked to the full sample of Compustat firms for the event period from 2012 until 2018. Significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.*

Using the discussed proxies for Capital input (K), Labour input (L) and Material input (M), this production function indicates that all variables are observable – except for A_{it}, as this represents the Hicksian neutral efficiency level of firm i in period t. The variable is important, as it captures the unobserved productivity shocks (Y_{it}) unaffected by K,L and M. As unobserved values are unmeasurable – equation (1) is transformed to equation (2) by taking natural logs to be able to still estimate productivity results, while not having to measure the unobserved productivity shocks.

$$\log Y_{it} = \beta 0 + \beta_k \log k_{it} + \beta_l \log l_{it} + \beta_m \log m_{it} + \varepsilon_{it} \quad (2)$$

Thus, equation (2) shows that the unobservable effect is now omitted from the regression and is captured instead in the sum of the intercept (β0 measures the average efficiency level across firm i over time t) and standard error ε_{it}. However, although β0 measures a small part of the baseline unobserved shocks, ε_{it} captures the total effect of variation in productivity not explained by K, L and M and thus ε_{it} is used as proxy of unobserbved shocks. Next, ε_{it} is divided into an observable and unobservable component: $\omega_{it} + u_{it}^q$, where ω_{it} represents firm-level productivity, i.e. predicted TFP and thus is the observable component and u_{it}^q is the unobservable component, indicating unexpected deviations from the mean.

$$\log Y_{it} = \beta 0 + \beta_k \log k_{it} + \beta_l \log l_{it} + \beta_m \log m_{it} + \omega_{it} + u_{it}^q \quad (3)$$

Equation (3) is a TFP model that will be estimated using Ordinary Least Squares (OLS), and is the first form of the TFP production function this research uses, from now on called ‘OLS TFP’. However, this method requires that the inputs in the production function are exogenous, an assumption that is perhaps incorrect (Marschak & Andrews, 1944) as the inputs in the production function discussed are not independently chosen but determined by firm characteristics, thus not being exogenous. This causes the coefficients of labour and material to be biased upwards (van Beveren, 2007) in OLS TFP models, and the capital coefficient to be biased downwards, and the model is prone to simultaneity (not accounting for unobservable productivity shocks) and selection bias (negative effects of using a balanced sample). As a first solution, this research uses the TFP method standard fixed effects estimation (‘FE TFP’) model (xtreg), as this method partially solves (Van Beveren, 2007) the simultaneity and selection biases of ‘OLS TFP’ described as it controls for time fixed effects. Equation (4) shows the model of FE TFP and illustrates that the only change relative to equation (3) is the ‘time’ component, as time is now held constant and thus omitted from ω_i, and thus the ω_i, or the observed productivity, only changes when the firm is changed.

$$\log Y_{it} = \beta 0 + \beta_k \log k_{it} + \beta_l \log l_{it} + \beta_m \log m_{it} + \omega_i + u_{it}^q$$

(4)

Although the TFP FE model is better at handling unobserved heterogeneity than the TFP OLS model, it cannot estimate the effects of time-invariant variables due to the within-transformation that eliminates these effects and empirical findings show (Ackerberg, Benkard, Berry & Pakes, 2007) that FE TFP often result in unreasonably low estimates of the capital coefficient and Olley and Pakes (1996) argues that the assumptions underlying the FE TFP model are invalid and thus is model is not accurately capturing TFP, although more accurately than OLS TFP. The Olley and Pakes (1996) model, ‘OP TFP’, and the Levinsohn (2003) model, ‘LP TFP’, are semi-parametric models that account for the described simultaneity and selection biases of OLS TFP that by using proxies controls for unobserved shocks in productivity. OP TFP use investment as proxy, while LP TFP uses materials, thus one of the three inputs used, as proxy. As Levinsohn and Petrin (2003) observed that OP TFP outcomes can easily become biased as firms do not always have positive values for investment expenditures reported, materials is used as proxy as it is more likely for firms to report positive values of materials (inventories, energy costs, etc.). LP assumes that firms adjust their usage of a flexible input (M, materials) in response to productivity shocks. By observing how M varies with output, holding capital (K) constant, the LP method infers in this way the level of productivity. This research uses LP TFP, similarly to (Brav et al., 2015), as the usage of materials as proxy allows for the lowest chance of biased results and the OP method has unrealistic invertibility condition (van Beveren, 2007) and signs of obtaining an unidentified labour coefficient (Ackerberg, Caves and Frazer, 2006). As materials are the proxy, they are expressed as a function of productivity and capital: $\log m_{it} = m_t(k_{it}, \omega_{it})$. To obtain unobserved productivity (ω_{it}) again so that equation (2) can be rewritten to the LP TFP method, the expression is inverted to $\omega_{it} = s_t(k_{it}, m_{it})$, where s_t represents the inverted term. Thus, equation (3) is transformed to the LP TFP estimation method in equation (5):

$$\log Y_{it} = \beta 0 + \beta_k \log k_{it} + \beta_l \log l_{it} + \beta_m \log m_{it} + s_t(k_{it}, \log m_{it}) + u_{it}^q$$

(5)

For FE TFP and LP TFP, both models hold the same expectations (Van Beveren, 2007) given they are solving the simultaneity and selection bias: both models are expected to provide lower estimates of M and L compared to OLS TFP, as the estimates in L and M are overstated due to the endogeneity problem of OLS TFP. For LP TFP specifically, higher K compared to OLS TFP is expected given that K is quasi-fixed in LP TFP. Thus, a total of three different TFP models (OLS, FE, LP) are estimated. Estimating OLS and FE TFP is done using regressions (5) and (6), and after predicting the residuals of each observation, the newly generated variable is used as proxy for predicted output (TFP) that represents the part of output unexplained by quantifiable inputs. Then, the relevant variables are regressed on TFP, discussed in the next section.

However, the estimation method of LP TFP is different as it analyses both actual output and compares it to each other. Obtaining LP TFP is done in three steps; first, predicted output is estimated using regression (7) through the 'prodest' Stata package, as this package involves the LP method of TFP estimation. The 'prodest' package uses a semi-parametric estimation model to estimate the amount of materials conditional on the observed productivity and the other TFP inputs, to eventually obtain a proxy for the unobservable productivity shocks. Next, it uses the materials proxy in the production function estimation to control for the endogeneity problem (simultaneity bias), and regresses the output on inputs, including the constructed proxy for productivity shocks. Thus, while using the 'prodest' package, it allows for using materials as the proxy variable to control for unobserved shocks in productivity (TFP) calculated based on the estimated coefficients of K, L and M. To obtain the predicted TFP as the first step of LP TFP estimation, the prodest function is specified so that L is treated as an endogenous variable ('free') that doesn't require a control function, K is the state variable and fixed input ('state'), and M is the proxy ('proxy') for unobservable productivity shocks. The second step, obtaining actual TFP (output), is straightforward: actual revenue is the proxy of firm output and represent the actual firm-TFP values while Total Value of Shipments represent actual TFP for industry-TFP values. The third step involves obtaining the differences between the predicted and actual TFP, 'omega', and serves as the LP TFP estimate that represents the portion of output not explained by traditionally measured inputs, but probably by external factors like technological progress, efficiency improvements, and economies of scale. Like Maksimovic, Phillips and Yang (2013) and Brav et al. (2015), the OLS, FE and LP TFP models are standardized by dividing each log TFP value by its yearly cross-sectional standard deviation.

Table 2 compares productivity and its determinants between manufacturing targets, all targets and non-targets. When comparing all targets to non-targets (3 vs 5) it shows that HFA targets are significantly smaller and have fewer employees than non-targets. Also, targets are significantly more productive. While the difference in productivity and lower size of targets is in line with the findings of Brav et al. (2015), the decrease in employees after HFA is rather unexpected, following Brav et al. (2015) but in line with DesJardine and Durand (2020) and Kim (2020) as HFA often causes mass layoffs. The higher average TFP and performance (table 2) of targets compared to all firms signal possible positive effects of HFA, underscoring the findings of Brav et al. (2015) that HFA creates value. Also, it seems that manufacturing targets are more productive than other targets, underscoring the notion of Brav et al. (2015) as manufacturing firms experience lower growth opportunities given that their current level of productivity is already high.

Table 3 shows the relationship between the direct firm inputs and TFP. According to the expectations of van Beveren (2007), the coefficients on L and M of FE-TFP and LP-TFP are expected to be lower compared to the OLS result, given the biased specification of OLS. Looking at table 2.5, this is only correct for M and L: the coefficient of M is slightly smaller (5.6% and 2.4%, respectively) in both models, L is smaller and even negative (-20.1%) in the FE-TFP estimation and smaller but positive (0.4%) in the LP-TFP model. L, or any of the inputs, being negative indicates diminishing marginal returns and is contrary to the properties of the Cobb-Douglas Production Function, as a greater labour input, i.e. increasing the marginal productivity of labour, always leads to the production of more output and thus the value of any input can only be between 0 and 1.

Table 2: comparing TFP between manufacturing and other (non)-targets

	(1)	(2)	(3)	(4)	(5)	(6)	(1) vs. (3)	(3) vs. (5)
	Manufacturing targets (n = 511)		All targets (n = 1547)		Full Compustat Sample (n=123,695)		T-statistics of mean differences	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.		
LP TFP	2.52	0.14	2.27	0.10	1.99	0.16	44.03***	104.9***
Y	1,531	2,636	1,480	2,586	3,265	16,104	0.4	68.3***
L	0.58	1.71	0.70	1.91	1.23	1.02	-1.26	-19.1***
K	3,919	8,669	3,816	9,371	13,079	121,624	0.2	-3.0**
M	332	487	214	417	45	418	5.35***	15.7***

*Table 2 presents descriptive statistics of TFP its output (Y) and inputs Labour (L), Capital (K) and Material (M) on firms targeted by HFA, segregated between manufacturing targets and all targets, benchmarked to the full sample of Compustat firms for the event period from 2012 until 2018. Significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.*

Table 3: comparing the marginal productivity of labour, capital and material

	Material Input (M)		Capital Input (K)		Labour Input (L)	
	Coefficient	St. dev.	Coefficient	St. dev.	Coefficient	St. dev.
FE TFP	0.06*	0.03	0.08***	0.03	-0.20***	0.04
OLS TFP	0.09***	0.02	0.55***	0.02	0.26***	0.02
LP TFP	0.02***	0.00	0.00**	0.00	0.00**	0.00

*Table 3 presents descriptive statistics of the estimated coefficients and standard errors of the TFP inputs total employees (L) fixed assets (K) and material costs (M) using the method described. Significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.*

Thus, the negative slope of L in the FE-TFP model is unexpected, although the assumptions of the fixed effects model (Olley and Pakes, 1996) are possibly explaining the unexpected results. When looking at the main TFP specification, LP TFP, the coefficients are positive for all inputs and statistically significant at a 5% confidence level (like the OLS and FE estimators), as well as following the expectations of L and M being lower coefficients compared to the OLS results. However, for K the results are contrary to expectation, as Van Beveren (2007) predicts that the coefficient of K is expected to be higher in LP-TFP compared to the OLS results due to the exogeneity assumption of the OLS model. This unexpected lower result of K of LP-TFP, and expected lower results of L and M, are as well encountered by Van Beveren (2007) and Bournakis & Mallick (2017) when estimating the coefficients of the three inputs. Also, like Van Beveren (2007), table 3 shows that the changes in fixed assets (K) change TFP the most, compared to L (employees and M (inventories). Thus, interpreting LP-TFP results is as follows; the marginal productivity of K (2.4%), L (0.4%) and M (0.4%) increase productivity, in line with the properties of the Cobb-Douglas Production function. Practically, this means that higher valuations of a firms fixed assets, inventories, and more employees generally increase total firm productivity through the increased marginal productivity due to economies of scale.

This research controls TFP for the external macroeconomics factors the firms investigated are subject to: sector specific inflation and GDP changes. This is often done in firm productivity and performance studies (Van Beveren, 2007; Brav et al. 2015; Bournakis & Mallick, 2017; Schoar, 2002 by deflating the four TFP inputs. Meaning, the ratio of the industry current value of K, L, M and Y to the industry historical value of each of the corresponding inputs, is transformed to real values using index numbers to determine the growth or decline of all of the inputs in a specific industry. Unfortunately, a more granular analysis using the three- or four-digit NAICS deflation is not possible given the two-digit NAICS code data structure of the Bureau of Economic Analysis (BEA).

Empirical results

RDD: Testing the causal effect of the DFA on HFA effectiveness

Now, the specified regressions are used to estimate the effect of the DFA on HFA effectiveness. Using an RDD, I analyse whether the DFA is negatively impacting HFA effectiveness (hypothesis 1). Although the findings of the first hypothesis already answers the research question, the changes brought about by the DFA are analysed more thorough: the differences between all targets and manufacturing targets (hypothesis 2), the robustness of the value channels (hypothesis 3) and strategies (hypothesis 4) of HFA, after the DFA. Hence, I evaluate the robustness of both the baseline findings regarding HFA effectiveness and its subsidiary research questions concerning industry, value channel, and strategy differences identified by Brav et al. (2015).

The DiD framework versus the RDD

As the DFA is affecting hedge funds above 150 mln USD AUM, but not below this threshold, the changes brought about by the DFA should be analysed in a counterfactual framework. This allows to accurately analyse what would have happened to hedge funds in the absence of the DFA by comparing the actual outcome with a "counterfactual" outcome (if the DFA did not affect the DFA-subjected hedge funds). One of the methods to test this is a difference-in-difference (DiD) design like Cumming, Dai and Johan (2020) did. They found that hedge funds with AUM above 150 mln USD are experiencing lower fund alphas, indicating negative effects on hedge fund returns from the DFA. As their research is only using hedge fund returns as dependent variable and not firm and labour productivity and performance, their research is not estimating the direct effect on firm outcomes, as well as not focussing on HFA specifically.

Furthermore, the two major DiD assumptions, no spillover effects and no parallel tends present, are problematic given the goal of this study. The control (hedge funds having AUM higher than 150 mln. USD) and treatment group (lower than 150 mln. USD) most likely have parallel trends in the absence of the intervention, as hedge funds have significant differences across sizes (Busse, Chordia, Jiang & Tang, 2014). Larger hedge funds experience diseconomies of scale as smaller funds are more lean, have less market impact when trading, and are able to exploit niche strategies that are not scalable to larger sized hedge funds. The differences described potentially cause different growth trajectories or risk profiles, contrary to the parallel trends assumption. Furthermore, spillover effects probably significantly differ between larger and smaller hedge funds. As smaller hedge funds are not subjected to the DFA directly, they are still part of the broader U.S. regulatory and economic landscape: changes in macro or regulatory factors aimed at larger hedge funds likely indirectly influences smaller hedge funds as well, e.g. bigger hedge funds that change their investment strategy that affects macro conditions and subsequently impacting smaller hedge funds.

Although using a DiD research model in a counterfactual framework gives stronger results compared to a RDD model, it falls short in precisely isolating the impact of the 150 mln. USD DFA threshold. However, as a DiD model requires random assignment to the treatment, this is not possible for this specific study: hedge fund AUM is endogenous as it is influenced by internal characteristics and decisions of the hedge funds themselves, rather than being randomly assigned. Hence, as this specific DiD requirement cannot be satisfied, a RDD model is used to analyse the DFA cutoff of 150 mln. USD hedge fund AUM that examines the immediate impact on target firm productivity and performance and labour outcomes. The RDD focusses on observations that are located close to this cutoff and assumes these similar (in size) observations are comparable, and thereby mimics a randomized experiment.

Altogether, RDD captures the changes between different firms – while DiD and other event study designs capture rather within firm deviations, enabling this research to capture the treatment effects of the DFA more randomly compared to (Cumming, Dai & Johan, 2020). Thus, to capture the effects of the DFA on the findings found in tables 4 and 5, a RDD design is used to analyse the discontinuity at the threshold (150 mln USD AUM) by comparing values around the cutoff. The goal is to obtain the LATE, representing the causal effect of DFA on firm and about outcomes. Events are organized with the EUR 150 million AUM mark as threshold value (like Cumming, Dai & Johan, 2020). The fundamental element of RDD is that the units immediately below and over the threshold are identical in every way, except for the treatment, simulating a randomized experiment in the vicinity of the cutoff point.

Between the two types of RDD, fuzzy and sharp, the sharp RDD is more applicable to the specific research question of this study, given that the treatment assignment is perfectly determined by AUM crossing the regulatory 150 mln AUM cutoff, i.e. there are no exemptions (SEC, 2024) or allowances of a few mln. USD below or above 150 mln USD that cause some firms to not be affected. Thus, as every hedge fund with an AUM above 150 mln. USD is considered "treated", and every fund below that threshold is "untreated" without any exception, a sharp RDD design is used in this research that compares firm and labour outcomes, i.e. HFA effectiveness, slightly below and above this threshold and in that way the causal influence is tested. To ensure the credibility of the results, sensitivity tests are performed to test the robustness of the LATE to provide insights into how HFA affects firm and labour outcomes after an intervention.

RDD assumptions

Before estimating the RDD, four RDD assumptions for causal inference (Schochet et al., 2010) are analysed: the assignment rule is clearly defined and strictly adhered to (fidelity), AUM must be an ordinal measure with sufficient density on either side of the cutoff, hedge funds must not have the ability to manipulate the running variable, and AUM must be the sole source of observed outcome differences, not confounded by other mechanisms. The first step involves coding in Stata what the cutoff point (c) is: 150 mln. USD AUM. Subsequently, of each event the treatment status (Di) is coded: 1, i.e. treated, if the AUM is above 150 mln. USD, 0, i.e. controlled, if it is below 150 mln. USD. In figure, the scatter plot between AUM and the treatment variable is shown where it is seen that at 150 AUM, treatment of DFA (0 to 1) happens. To make the analysis more indicative and adhere to the fidelity assumption of the RDD, the AUM variable of graph 1 is centered in figure 2: the AUM values of each observation are subtracted by the cutoff point, and thus the new variable 'treatment' turns 1 when ''aumcentered'' equals 0. The second assumption states that RDD should be balanced on both sides of the cutoff. However, this does not mean that the sample should be perfectly equally distributed – just that neither side should see an extreme difference compared to the other – as shown in graph 2 : about 2/3rd of all observations are in the treatment group and 1/3rd in the control group. Thus, the first two assumptions are now accounted for.

Figure 1: RDD: DFA as treatment variable

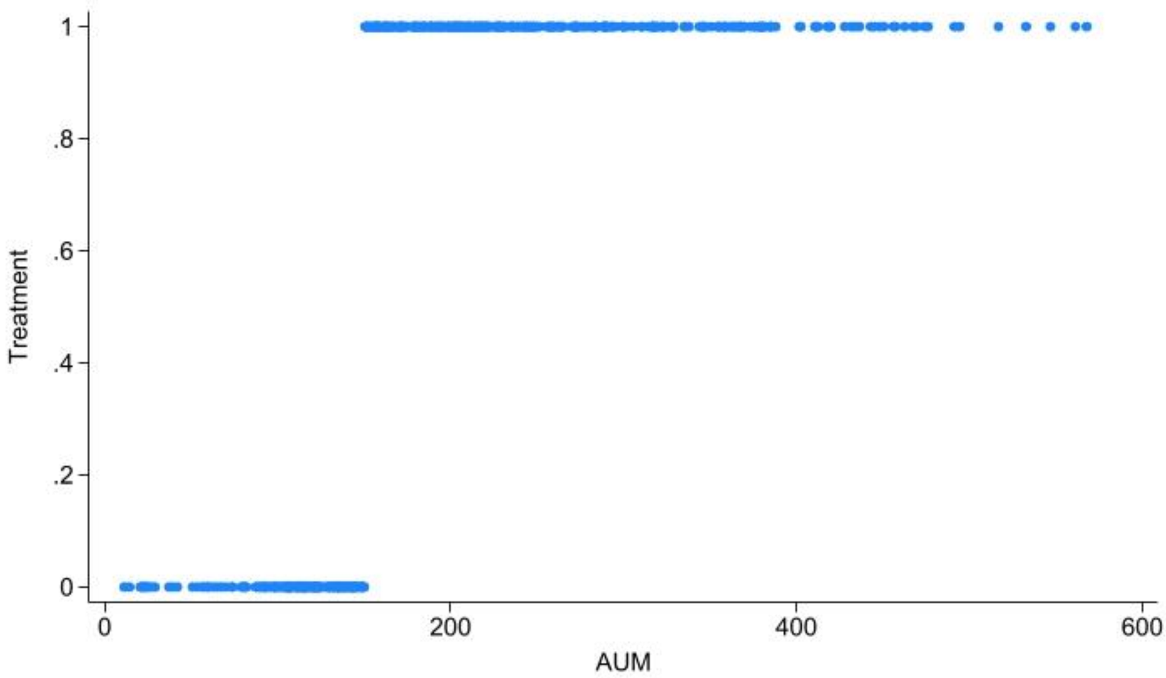

Figure 1 presents the results of coding the treatment (DFA) effect: 1 when hedge funds have AUM over 150 mln. USD, and thus are DFA-subjected.

The third assumption involves checking for potential manipulation around the threshold. Signs of hedge funds manipulating their reported AUM so that they would not be subject to DFA means observing a significant spike in the number of observations around the cutoff, i.e. the RDD is biased due to self-sorting and self-selection indicating that hedge funds were aware of the threshold and its (dis)advantages. Figure 3 shows that, by performing the manipulation test of Cattaneo, Jansson & Ma (2017) using the 'rddensitty command', there are no first indications manipulation: the number of observations is rather constant around the cutoff. Although the width of the aumcentered density line appears to change only minimally at the cutoff indicator low signs of manipulation, the shaded areas around the density line represent the confidence intervals and thus show high variability around the cutoff. The result of the manipulation T test (-0.0292) has a p value of 0.9767, thus the null hypothesis of no manipulation is not rejected, indicating no significant manipulation around the threshold

Figure 2: RDD: centering the treatment variable

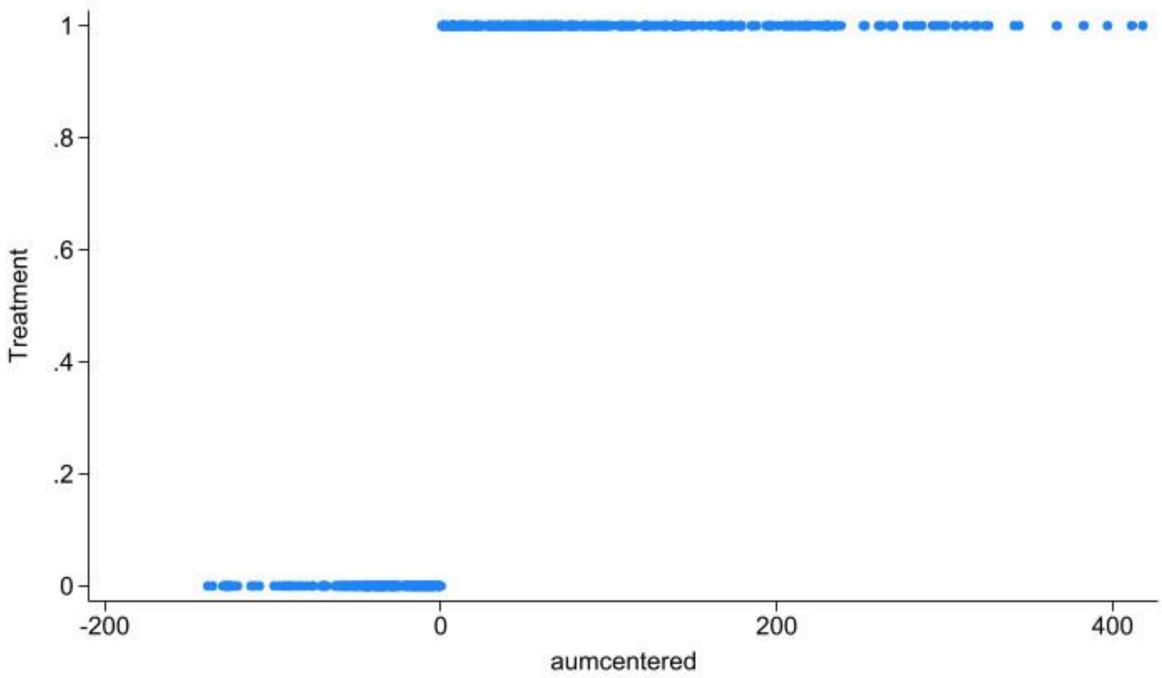

Figure 2 presents the results of centering the running variable.

To test the robustness of the indication of no manipulation around the threshold, the McCrary (2008) test is performed using the Stata package ‘DCdensity’. This test checks for manipulation around the DFA AUM threshold by testing the density of observations – and differs in allowing to set parameters of the test manually rather than having predetermined settings, like the Cattaneo, Jansson & Ma (2017) manipulation test. If manipulation is present, a significant jump in the density and discontinuity at the cutoff is expected. Figure 4 shows such a drop in the density function at the breakpoint which potentially indicates manipulation. Also, increased variance at the threshold is observed, represented by the two lines surrounding the thick black line of the estimated density function. However, statistically testing the results indicates that the drop is not statistically significant as the t-value equals -1.55 (-0.3/0.19), less than the critical value of 1.96 at the 95% confidence level. This means there is no strong evidence of manipulation around the cutoff point, as the observed change is not statistically different from zero, suggesting that the visually observed drop is only random variation.

Figure 3: RDD: the Cattaneo, Jansson & Ma (2017) manipulation test

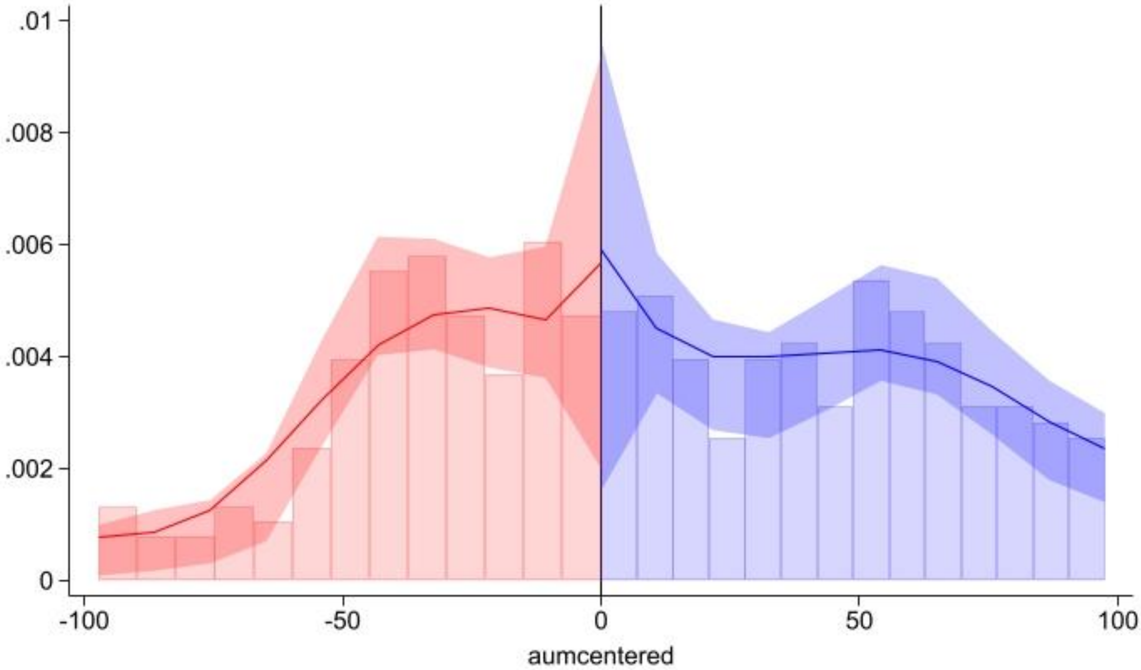

Figure 3 analyses the distribution of the hedge funds around the AUM cutoff (150 mln. USD) of the DFA. An unusual high number of observations just below the cutoff implies manipulation of AUM.

Hence, the RDD results discussed in the next steps most likely display correctly that differences in target firm TFP observed are only due to the DFA, as the third assumption of RDD is accounted for.

Figure 4: RDD: the McCrary (2008) manipulation test

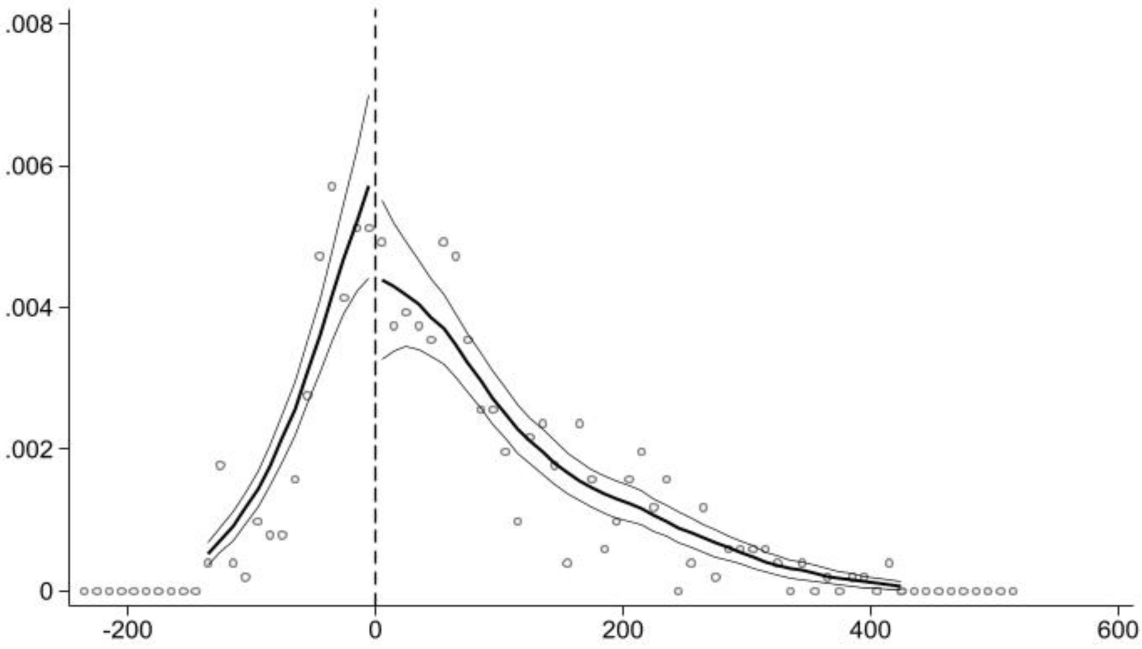

Figure 4 analyses the distribution of the hedge funds around the AUM cutoff (150 mln. USD) of the DFA. An unusual jump at the cutoff implies potential manipulation of the AUM reporting of hedge funds.

The fourth RDD assumption states that units on either side of the cutoff are comparable and that any discontinuity at the cutoff can be attributed to the treatment effect alone, and not to any other confounding explanatory variables, meaning that the RDD estimate may not accurately reflect the causal effect of the regulation. Thus, this assumption checks that there is no other mechanisms besides the treatment status itself affecting AUM changes. Similarly to Bach & Metzger (2017), potentially related variables are tested for being confounding variables, which is the case if a similar jump as in the main firm and labour variables of interest is observed. First, the effect of treatment on productivity and performance is analysed, and the pattern observed is subsequently checked with several explanatory variables. To obtain the RDD plots of both the performance and productivity measures, and of the explanatory variables, the bandwidth needs to be selected given that observations should be as close to the cutoff as possible. The bandwidth selection is done through the 'rdbwselect' command, and the graph is plotted by assigning equal weights to all points to ensure a smoothing function (kernel is set to 'uniform'), a linear function (p(1)) while minimizing the mean squared error of the density estimates ('msed') and checking for mass points given that the data seems to be in a few places concentrated around specific values, possibly due to hedge funds reporting the exact same AUM in some years. While only the optimal bandwidth provided for each variable (ranging from 20 – 35 million USD AUM above and below the cutoff, and are almost always equal on both sides) is showing the causal effect of the DFA, graph 5-8 shows the full range of individual observations of aumcentered. Thus, when analysing the graphs, most emphasis is on the dots close to the threshold as these are indicating causality. However, to analyse the relationship beyond the cutoff, all values are shown as it gives context and validates the RDD assumptions across the whole sample dataset. The optimal bandwidth values obtained are used by dividing the respective bandwidth sizes over the corresponding minimum (-139) side or maximum (+418) of aumcentered to estimate the bins of the RDD plots. I choose the `rdbwselect` command over the more manual approach described by Calonico, Cattaneo, and Titiunik (2014) and used by Bach & Metzger (2014), as the method used in this study automates the optimal bandwidth selection process which creates robust, unbiased and statistically strong estimates, and are not prone to manual errors in the parameter selection and formulation.

Figure 5 shows a negative jump in TFP when hedge funds are DFA-subjected (when aumcentered equals '0'), indicating negative effects of the DFA on activist hedge funds performance, and on its HFA effectiveness, and is unexpected when following Coffee & Paia (2014). However, the negative jump is possibly explained as mandatory increased transparency requirement (Cumming, Dai & Johan, 2020; Restrepo, 2024; Shelby, 2017) has high costs for hedge funds, lowering its returns and thus potentially its HFA effectiveness. Labour productivity and employee see a virtually identical negative jump and slope change at the cutoff, indicating lower HFA effectiveness after the DFA. Thus, DFA seems to indirectly affect target labour productivity negatively in the same way as it does firm productivity. The effect of DFA is less pronounced when looking at performance: only ROIC sees a jump at the cutoff, and no visual change in the slope. However, the jump at the cutoff is positive, contrary to firm and labour productivity outcomes: DFA-affected hedge funds seem to have higher effectiveness in its HFA campaigns compared to non-DFA affected hedge funds. The unexpected positive jump in ROIC, and unaffected ROA and stock prices, are perhaps explained by interdependence of the outcomes: changes in TFP occur first, as it directly captures firm changes. Perhaps, only afterwords it lead to changes in indirect firm metrics like ROA and ROIC, which could in turn influence stock prices. Thus, figure 5 showed that when the treatment affects one firm outcome, it does not mean it will affect all other outcome variables.

Now that a there is a significant jump observed at the cutoff for the firm productivity (TFP), performance (ROIC) and labour outcomes (LP and employees), the explanatory variables are analysed in the same manner. However, they are not expected to show a jump, since correlated variables to firm and labour outcomes should not be impacted by the DFA: if a similar jump to TFP is observed at the cutoff it implies that this is either a random walk or the DFA is actually affecting the explanatory variable. If the latter holds, the variable is included in the estimation of RDD to better isolate the effect of hedge fund AUM size on target firm TFP. Thus, the pre-treatment (t-3 until t-1, to prevent reverse causality) correlation between firm-specific potential covariates (table 1) and firm and labour outcomes are analysed to determine the strongest correlated variables to the firm outcomes, as these are analysed to determine whether a similar jump is observed.

As the inputs of the ratios are also used in the pre-treatment correlation analysis, the variables highly correlated ($p>0.5$) to the firm and labour outcomes are common shares outstanding, total equity, market cap, net sales, fcf/LA and total assets. The logarithm of firm age, although not strongly correlated to firm and labour outcomes (0.05-0.1), is also analysed as is also included in every regression given its direct measurement of firm changes. Thus, similar RDD bandwidth tests and plots are as well used for to the explanatory variable discussed, treating them as outcome variables for the moment. When analysing figure 6, only firm age, net sales, fcf/LA and market cap show a minimal jump at the cutoff, perhaps indicating that they are somehow also affected by the DFA. Although the magnitude of all jumps seems to be considerably smaller than the jump of TFP, the pattern of the graph of market cap and fcf/LA does show a similar pattern as TFP (DFA causes productivity deterioration), although net sales and firm age showing rather the inverse pattern. This might indicate that a companies' net sales has a lagged effect, or is positively affected by the DFA, while fcf/LA and market cap experience a direct negative impact similar to TFP. For the other three variables strongly correlated to the dependent variables, common shares outstanding, total equity and total assets, no significant jump is observed at the threshold, thus no indications of being influenced by the DFA. As the jumps observed in fcf/LA, netsales market cap and firm age seems to be substantial, the variables are included as covariates in the estimation of the treatment effect in the RDD, thereby ensuring that the treatment effect observed in the six firm and labour outcomes is most likely due to the DFA and not due to other confounding mechanisms. Thus, also the fourth assumption of valid causal inference is now met.

Figure 5: RDD: visually observing discontinuities

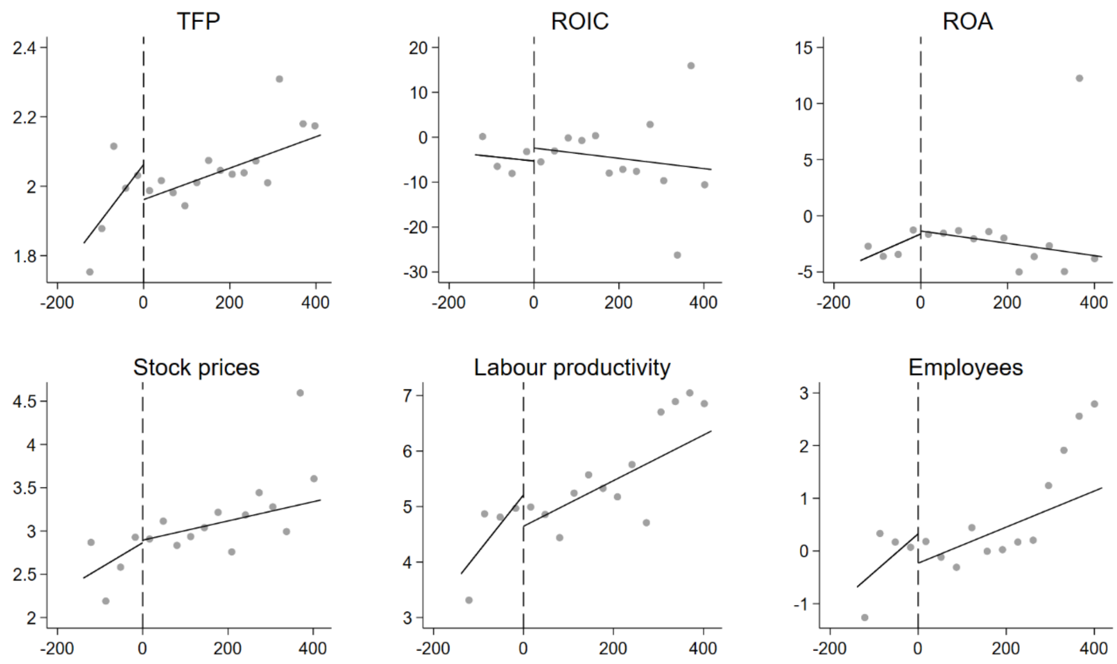

Figure 5 shows the visual relationship between firm and labour outcomes and hedge fund sizes (AUM) and analyses the discontinuity at the centered AUM cutoff (150 mln USD) and its corresponding effect on each outcome. If a jump is observed, this means that there are strong signs DFA is affecting this outcome variable, although the effect still needs to be estimated.

Figure 6: RDD: analysing discontinuities in covariates

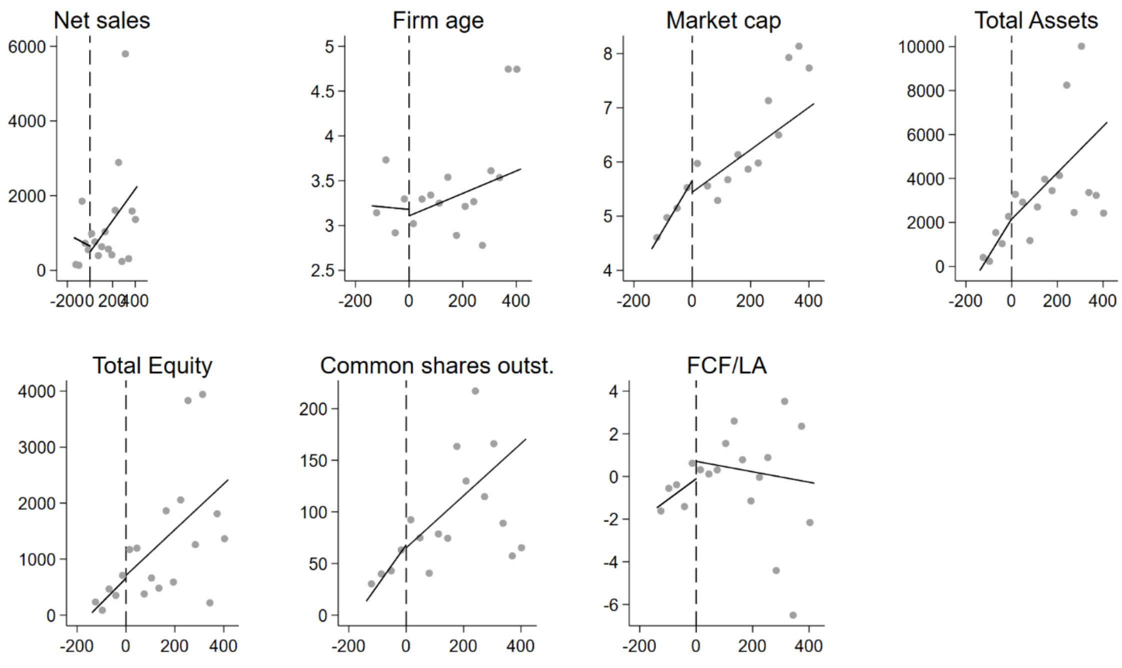

Figure 6 shows the visual relationship between potential covariates of firm and labour outcomes and hedge fund sizes (AUM), and analyses the discontinuity at the centered AUM cutoff (150 mln USD) and its corresponding effect on each covariate. If a jump is observed, the covariate should be controlled for as it is potentially also influenced by the DFA.

Estimating the effect of DFA and AUM on HFA effectiveness, using a parametric model

Now, the jumps observed of the firm and labour outcomes (HFA effectiveness) in figure 5 are estimated on its statistical significance and causality. Since the treatment (DFA) is a policy change that is consistent over time, it’s essential to note that a RDD is inherently cross-sectional as it focuses on comparisons just below and above the cutoff at a given point in time. Thus, using a fixed effects regression, although the dataset is considered panel data and used in fixed regressions models in previous sections, is in this section not suitable (Lee & Lemieux, 2010) for the RDD estimations as it could eliminate the stable treatment effect by controlling for time-invariant factors. This would impose unnecessary restrictions on the model, complicating it without enhancing identification in any way. Furthermore, as TFP already has been estimated using the LP method, which is specifically designed to control for simultaneity bias that accounts for unobservable factors, and then a fixed effects regression is applied to this TFP (and ROIC, ROA, and Stock Prices) measure, firm-specific and time-invariant characteristics are already controlled for. Thus, when analysing the treatment effect using a RDD design, only the discontinuity at the policy threshold is of interest and applying fixed effects again within the RDD framework would not only be redundant but could also distort the identification strategy by over-controlling for firm effects that are already controlled for.

As this potentially causes the RDD analysis to inaccurately capture the causal impact of DFA at the cutoff by distorting it with other firm-specific and time-invariant factors, the next sections do not use fixed effects regressions to estimate the direct impact (LATE) of crossing the threshold of the DFA. By including time-variant covariates this research still accounts for within-panel differences but without absorbing the treatment effect, ensuring that the analysis is adhering to the RDD's cross-sectional principles and is still capturing the causal inference at the cutoff. The next section first estimates the LATE parametrically – and afterwords nonparametrically to test the robustness of the findings of the parametric model.

Estimating RDD parametrically

Nonlinear model

Using a non-linear model that incorporates quadratic terms, instead of a linear model, most likely better fits the plots of TFP, ROIC, labour productivity and employees discussed (figure 5), given the suspected change in the slope and curvature at the cutoff as well as the high variance shown. The six firm and labour outcomes regressions will only be within this optimal bandwidth (h) discussed in the previous section, i.e. the estimation is a weighted regression of the six firm and labour outcomes on hedge fund AUM.

(6)

$$\mathrm{Y_i} = \alpha + \beta\mathrm{X_i} + (\beta\mathrm{X_i})^2 + \beta\mathrm{Z_i} + \beta\mathrm{S_i} + \beta\mathrm{R_i} + \beta\mathrm{T_i} + \tau\mathrm{D_i} + \gamma\mathrm{X}_i\mathrm{D_i} + \gamma\mathrm{X}_i^2\mathrm{D_i} + \varepsilon_\mathrm{i}$$

Equation (6) shows the regression specification where $\mathrm{Y_i}$ equals either TFP, ROIC, ROA, stock prices, labour productivity or employees, α the intercept, $\beta\mathrm{X_i}$ representing the slope coefficient for the running variable $\mathrm{X_i}$ (aumcentered) measures the change in $\mathrm{Y_i}$ for a one million USD change in hedge fund AUM, the changes in $\mathrm{Y_i}$ after changes in covariates market cap, net sales, fcf/LA and firm age ($\beta\mathrm{Z_i}, \beta\mathrm{S_i}, \beta\mathrm{R_i}, \beta\mathrm{T_i}$, respectively), ε_i is the error term for each observation (i) that captures unobserved factors and the treatment effect $\tau\mathrm{D_i}$. The latter is indicative of the 'LATE', where τ is the treatment effect showing differences in TFP due to hedge funds being either DFA-subjected ($\mathrm{D_i}$ =1) or non-DFA-subjected ($\mathrm{D_i}$ =0), and is used to test hypothesis 1. $\gamma\mathrm{X}_i\mathrm{D_i}$ represents the right side of the TFP graph shown in figure 5, i.e. the treatment side, and thus the interaction term tests whether the slope is significantly different after the DFA, making the model more flexible as it accounts for changes in the curvature. The squaring aumcentered $(\beta\mathrm{X_i})^2$ and squaring the coefficient of the interaction term analysing the slope $\gamma\mathrm{X}_i^2\mathrm{D_i}$ is indicative of the nonlinear nature of the model, as it tries to capture complex relationships and interactions between variables better compared to a linear model. As these squared terms allow the model to examine the impact of variable growth rates and acceleration, non-squared terms cannot capture this as they only provide the linear association between these variables. Thus, equation (6) is estimated for all six firm and labour outcome variables within the optimal bandwidth using standard errors that are robust for heteroskedasticity.

Table 4: RDD nonlinear model estimation: comparing the causal effect (LATE) of DFA between firm and labour outcomes

Dependent variable	(1) TFP	(2) ROIC	(3) ROA	(4) Labour productivity	(5) Stock price	(6) Stock price	(7) Employees	(8) Employees
Dataset	All Targets	All Targets	All targets	All targets	All targets	All targets	All Targets	All Targets
Optimal bandwidth	26.5	26.5	31.57	34.92	33.52	134.08	32.89	-
βX_i	-0.00263	-0.839	-0.720	-0.0344	-0.0300	0.0126*	0.000179	-0.0232**
	(0.00460)	(0.972)	(0.467)	(0.0551)	(0.0284)	(0.00718)	(0.0590)	(0.0102)
$(\beta X_i)^2$	-2.62e-05	-0.0197	-0.0208	-0.000592	-0.000590	0.000105	0.000455	-0.000213***
	(0.000168)	(0.0301)	(0.0143)	(0.00142)	(0.000920)	(7.14e-05)	(0.00175)	(7.80e-05)
τD_i	0.0769*	15.63	6.076	0.0557	-0.251	-0.352*	0.0530	0.284
	(0.0454)	(9.625)	(6.243)	(0.724)	(0.329)	(0.206)	(0.613)	(0)
$\gamma X_i D_i$	-0.00720	-0.870	0.338	0.00250	0.0985**	-0.00524	-0.0586	0.0191*
	(0.00783)	(1.436)	(0.835)	(0.0875)	(0.0497)	(0.00880)	(0.0927)	(0.0105)
$(\gamma X_i D_i)^2$	0.000347	0.0672	0.0303	0.00196	-0.00155	-0.000152*	0.00174	0.000229***
	(0.000256)	(0.0419)	(0.0222)	(0.00226)	(0.00150)	(8.29e-05)	(0.00240)	(7.85e-05)
Net Sales	1.55e-05***	-0.00212**	-0.00114**	0.000382***	-3.32e-05	1.15e-06	0.000309***	0.000203***
	(4.22e-06)	(0.000915)	(0.000543)	(7.40e-05)	(3.25e-05)	(2.35e-05)	(5.79e-05)	(5.34e-05)
Log Market Cap	0.0456***	5.089***	3.085***	0.413***	0.375***	0.365***	0.554***	0.484***
	(0.00571)	(1.141)	(0.663)	(0.0838)	(0.0445)	(0.0293)	(0.0640)	(0.0536)
fcf/la	-0.00147	0.837***	0.553***	0.0113	0.0150	0.00434	0.0210*	0.00373
	(0.00109)	(0.282)	(0.164)	(0.0151)	(0.0101)	(0.00623)	(0.0108)	(0.00985)
Log Firm Age	0.0224***	3.032*	0.571	-0.405***	-0.0659	0.00671	0.0918	-0.195***
	(0.00698)	(1.778)	(1.058)	(0.107)	(0.0683)	(0.0398)	(0.115)	(0.0623)
Constant	1.634***	-47.38***	-24.23***	-1.468*	0.812*	1.026***	1.262*	-2.421***
# obsv.	95	144	149	160	146	146	135	135
R2	0.758	0.226	0.267	0.564	0.415	0.415	0.624	0.624

*Table 4 shows the relationship between AUM and target firm outcomes in the absence of the DFA (βX_i), The enhanced effect of βX_i as the term grows $(\beta X_i)^2$, the treatment effect of the DFA (τD_i), the change in slope after the DFA ($\gamma X_i D_i$), the enhanced effect of $\gamma X_i D_i$ as the term grows $(\gamma X_i D_i)^2$ and the impact of the covariates on firm and labour outcomes. Robust standard errors in parentheses and significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1. Column (6) and (8) show the effect of increasing the bandwidth for employees and stock prices.*

When analysing the results of the nonlinear model in table 4, it shows there is a statistical significant effect of the DFA (i.e. LATE) found in TFP (column (1)): firm TFP is 7.7% higher if the firm is targeted by DFA-subjected hedge funds compared to non-DFA, i.e. smaller, hedge funds, statistically significant at a 10% level. Stock prices (column (5)) is the first outcome variable to show a significant relation between DFA and firm performance: the positive change in the slope ($\gamma X_i D_i$) is statistically significant at a 5% level, i.e. hedge funds being DFA-affected (treatment group) is associated with an approximate 9.9% increase in stock prices of the target firm. $\gamma X_i^2 D_i$ indicates that DFA-subjected hedge funds slightly decrease (-0.2%) target firm stock prices as the AUM of a hedge fund increases relative to hedge funds not DFA-subjected, although not statistically significant (p-value of 0.36). However, the other performance measures (ROA and ROIC) and labour outcomes (columns (4) and (7)) show no significant differences in their outcomes, when comparing DFA-subjected and non-DFA-subjected firms.

Although the used optimal bandwidth through the Cattaneo, Jansson & Ma (2017) method is a thorough method for establishing the actual optimal bandwidth, it is indicative (Lee & Lemieux, 2010) to estimate equation (2) using different bandwidth to test the robustness of the results and to analyse whether the models get more or less accurate as the bandwidth in- or decreases. Table 5 analyses the leading variable of this research (TFP) by estimating the nonlinear model of equation (6) using zero, half, the same, twice, four times the optimal bandwidth used in table 5. The findings indicate that as the bandwidth increases and thus the number of observations increase, the model's explanatory power decreases.

Table 5: RDD estimation: robustness tests of the TFP LATE to different bandwidths

	(1) 0.5* Bandwidth	(2) 1* Bandwidth	(3) 2* Bandwidth	(4) 4* Bandwidth
Dataset	All Targets	All Targets	All targets	All targets
βX_i	-0.00124	-0.00263	-0.00205	-0.000187
se	(0.0122)	(0.00460)	(0.00176)	(0.000996)
τD_i	0.0839	0.0769*	0.0188	0.00878
se	(0.0555)	(0.0454)	(0.0305)	(0.0231)
Observations	55	95	194	287
R-squared	0.765	0.758	0.708	0.680

*Table 5 shows the sensitivity of the treatment effect (τD_i) of the DFA on TFP to different bandwidths. Significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.*

Although the significant causal treatment effect (+7.7%) discussed in the last section is positive and statistically significant, it shows that when the bandwidth increases, the effect of the DFA on HFA effectiveness is rather harmful (-0.2%) for a firms TFP, although not statistically significant. Thus, the less accurate model explains the literature that found that DFA decreases hedge fund alphas (Cumming, Dai & Johan, 2020; Restrepo, 2024; Shelby, 2017). However, as the positive LATE that is underscoring the expectations of hypothesis 1 in the optimal bandwidth model is statistically significant, this model is the best fit. For all firm and labour outcomes, standard errors decrease when the bandwidth is increased, indicating more precise estimates as more data is included. As no improved treatment effects are found when increasing the bandwidth for TFP ROA, ROIC and labour productivity, the best fit is the model using the optimal bandwidth and thus the results of table 4 are similar.

However, table 4 shows that for stock prices (column (6)) and employees (column (8)) the outcomes improved when increasing the bandwidth: although the originally established bandwidth for stock prices resulted in a positive insignificant treatment effect, when increasing the bandwidth to four times the original bandwidth, it showed a significant negative causal treatment effect (-35.2%). Thus, targets are experiencing a decrease of more than a third in its stock price, significant at a 10% level, when being targeted by a DFA-subjected hedge fund, indicating that hypothesis 1 should be rejected when focusing on stock prices. However, the treatment effect diminishes (-0.02%) significantly ($p< 0.1$) for larger hedge funds, indicated by the cubed term of the slope coefficient. The large negative jump is not seen at the cutoff of the stock prices model in figure 5, and thus it is indicative of the differences between statistically testing causal relationships and visual observations. Although neither bandwidth showed a significant effect of the DFA on employees in target firms, when using no bandwidth, it shows that larger hedge funds are significantly (at a 5% level) decreasing (-2.3%) the number of employees at a firm if the hedge fund is subjected by the DFA, underscored by the negative squared AUM term. Moreover, the slope indicates that a DFA-subjected hedge fund is significant (at a significance level of 10%) increasing the number of employees in a firm after the DFA relative to before the DFA, and at an increasing rate for larger funds. This finding is underscored by the LATE: DFA-subjected hedge funds increase the number of employees by 28.4%, although not statistically significant. Although HFA in general decreases the number of employees by imposing mass layoffs (DesJardine & Durand, 2020; Kim, 2020), the increase in employees after the DFA is intuitive, as the that the increased reporting and compliance burden of the DFA needs more manpower and thus the number of employees increases. The explanation is underscored by Kaal (2016) that finds that hedge funds are directly increasing its staffing expenses to adhere to the increased reporting requirements of the DFA.

Altogether, the impact of using different bandwidths matters: the treatment effect's magnitude and significance changes, improves precision (reduced SE), and reflects the sensitivity of the LATE to different bandwidths as shown in the model of stock prices and employees. So, a trade-off between bias and precisions is created: the further away from the optimal bandwidth and thus the more biased the model becomes, the more precise the model becomes (more observations, lower SE). However, as the goal of RDD is to estimate the causal effect the treatment at the exact threshold, the most statistically significant and precise estimates of that treatment effect is prioritized over a slightly lower fit of the model, given that the decreases in the Rsquared of most models are only 5-10%. As seen in most outcome variables, the optimal bandwidth is generally the best fit for the model, as the most terms are significant and the R-squared is high, except for stock prices and employees that use adjusted bandwidths resulting in a better fitted model.

Estimating RDD nonparametrically

Testing hypothesis 1

To test the robustness of the findings of the nonlinear regression model, the parametric models are transformed to a non-parametric model using the Stata package `rdrobust`. This nonparametric estimation method is not as heavily reliant on specific assumptions like (non)-linearity and the homoscedasticity of error terms as the parametric estimators (OLS and nonlinear models). These assumptions are potentially overly restrictive or less effective in capturing the true relationship around the RDD cutoff, as the functional form can vary significantly from what is predicted by these models. Thus, by using the nonparametric model this research is more accurately estimating to treatment effect close at the cutoff (LATE), indicated in the regression output by the coefficient of 'Conventional'. This is done through using local polynomial regressions, automatic bandwidth selection and robust bias correction to estimate the relationship around and at the cutoff, and thus this research tries to capture a more complex relationship that is less likely to be visible using linear or prespecified nonlinear models. The method involves analysing a repeated sequence of isolated small windows, allows more curviness in the data and thus is independent of a prespecified linear or nonlinear line. Using the adjusted optimal bandwidths used in the nonlinear model in table 4, as well the same covariates, the average effect of the DFA on target firm TFP compared to the hedge funds unaffected by the DFA is investigated. Given that the nonparametric local polynomial regression does not use a prespecified functional form, the model does not have a specific equation like equation (6) had.

Using the 'rdrobust' command, the effect DFA (c(0)) on HFA effectiveness is analysed by allowing for different polynomial fits on either side of the cutoff (p(1) and q(2)) to capture the significant nonlinearity shown in the parametric models, specifying each corresponding bandwidth using (h) using the same covariates (market cap, net sales, fcf and firm age) as the parametric models. As hypothesis 1 is only focusing on firm outcomes, only columns (1) – (4) of table 6 for all targets should be analysed. Table 6 illustrates that TFP, ROIC and ROA have a positive LATE (the coefficient of 'Conventional' in the 'rdrobust' regressions) and thus imply that the DFA is increasing firm performance (+2.7% until +9%) and firm productivity (+5.2%), while Stock Prices (-16%) imply negative effects from the DFA. Although Coffee & Palia (2014), Kaal (2013, 2016), Kidd (2018) and Partnoy (2015) predict no adverse effects from the DFA, the statistically significant (at a 10% level) increase (+5.2%) in TFP is unexpected, as no literature supports the notion of DFA increasing hedge fund performance or target firm outcomes. However, when comparing the significant LATE (+5.2%) to the significant LATE (+7.7%) of TFP obtained in the parametric nonlinear model, the findings seem robust and correct. Furthermore, although the negative LATE observed of stock prices is in line with expectations of the effect of DFA on hedge funds in general (Cumming, Dai & Johan, 2020, Restrepo, 2024; Shelby, 2017), the finding is unexpected (Coffee & Palia, 2014) when looking at HFA specially. However, the leading outcome variable of this research (TFP) indicates that the DFA has a statistically significant positive impact (5.2%) on firm productivity implies that the DFA is not harming HFA effectiveness, but rather stimulating it and thus hypothesis 1 is not rejected, although the significant positive effect remains surprising.

Thus, larger (AUM above 150 mln. USD) hedge funds are not being outcompeted by their smaller counterparts due to the DFA; rather the opposite. Further studies could investigate the robustness of the positive effects of DFA on HFA, and why the effect is positive: does the increased reporting and disclosure requirements brough about by the DFA cause hedge funds to become more structured in general as it is now mandatory, and the increased thus improve overall hedge fund performance and HFA effectiveness? Or did the increased transparency brought about by the DFA cause more investor and market confidence and thus hedge funds faced less restraints from target companies while performing its activism? Other possible explanations are that the reduced systemic risk cause hedge funds to focus less on short-term gains and more on long-term value or the mandatory increased risk management processes increased the investments due diligence processes of HFA when analysing new targets.

Table 6: RDD estimation empirical results: hypothesis 1

	(1) TFP	(2) ROIC	(3) ROA	(4) Stock price	(5) Employees	(6) Labour productivity
Manufacturing targets	-0.02 (-0.57)	12.50 (1.21)	8.490 (1.30)	-0.32 (-1.56)	-1.03 (-1.05)	-0.75 (-1.81)
All targets	0.05* (0.03)	9 (6.74)	2.69 (4.36)	-0.16 (0.15)	-0.34 (0.46)	-0.19 (0.41)
T test	-2.51**	6.84***	17.3***	-2.28*	-11.76***	-6.44***

*Table 6 shows the results of testing hypothesis 1 (DFA on TFP) and 3 (effect of DFA on all targets versus manufacturing targets). Robust standard errors in parentheses and significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.*

Testing hypothesis 2

To test the robustness whether the manufacturing sample of Brav et al. (2015) is a biased sample, hypothesis 2 is tested using the same 'rdrobust' commands discussed in the previous section and using the 'if Manufacturing == 1' command in Stata after each command to obtain the results for manufacturing firms. As seen in the t tests of table 6, DFA causes significant changes for all six outcome variables between manufacturing and all targets, indicating DFA is impacting HFA effectiveness differently across the two samples. Firm TFP, stock prices and labour outcomes are significantly lower for manufacturing firms after the DFA, indicating lower HFA effectiveness compared to all targets. As TFP is the leading variable in this research and being the only statistically significant outcome variable of both target groups, most emphasis should be on this result. Thus, hypothesis 2 is not rejected, as activist hedge funds in manufacturing industries are significantly less successful in capturing the gains in productivity brought about by the DFA compared to the other industries activist hedge funds are in. The findings imply that either the DFA is targeting the manufacturing industry less effective, or manufacturing targets are less effective in its HFA. As there is no evidence for the first explanation, the second explanation makes more sense: when following Brav et al. (2015), it shows that manufacturing targets are more mature and experience significant lower growth opportunities.

Testing hypothesis 3

Brav et al. (2015) showed that HFA create value through capital reallocation and asset efficiency, brought about by increased IT investments (capex) and increased labour productivity, as their findings showed that by increasing these two variables target firm outcomes increased. Thus, firms that have high amounts of labour productivity or capex spend, are expected to have higher gains in firm productivity and should be experiencing more gains from the DFA compared to firms having lower relative capex spend and lower labour productivity. To analyse capex intensity and the level of labour productivity of a firm, both variables are divided into quartile groups, 1 being the lowest relative (to Lagged Assets) spend of capex or least labour productive, and 4 the highest. Using the Stata 'if capex/LA or labour productivity == <quartile value of 1/2/3/4>' command, in table 7 shows that the most capex-intensive firms (fourth quartile) experience lower (+4.6%) effects on TFP from the DFA than capex-light (first quartile) firms (+25%, statistically significant at a 10% level) contrary to expectations (Brav et al., 2015), as well as lower than the average effect of DFA on firm productivity when not differentiating between capex intensity ('Overall LATE', +5.2%).

For firm performance, results are ambiguous when comparing the extremes in capex spend (first vs fourth quartile), but the pattern observed in TFP is similarly seen when analysing the second quartile: For DFA-subjected hedge funds, HFA targets with lower capex spend are experiencing significantly higher (24.8%, significant at a 5% level) increases ROIC compared to targets in capex heavy industries (6-10%), as well as to the (although insignificant) overall LATE of 9%. Although results are less pronounced for ROA and stock prices, there is certainly no clear pattern of capex-heavy (quartile 3 and 4) target firms experiencing more gains in productivity and performance brought about by DFA-subjected hedge funds relative to the capex-light target firms. Most emphasis is on the pattern observed in the leading firm variable TFP and most significant findings shown in TFP and ROIC, that does not support the notion of capex-heavy firms creating more value relative to capex-light firms or even to the average.

A similar reversed pattern of the expectations is shown when comparing firms with the relative lowest and highest labour productivity: for TFP and ROIC, it shows that the lowest (first quartile) labour productivity experience the highest increases in TFP (13%, significant at a 5% level) compared to an increase of 0.7% in TFP for firms with lowest (first quartile) labour productivity and to the overall LATE (5.2%), when analysing DFA-subjected hedge funds. Similarly for ROIC and ROA, target firms has the highest gains when firms are the least labour productivity (+36% and 13% respectively, both statistically significant) compared to the most labour productive firms (-13.9% and -20.2% respectively, the latter statistically significant), as well as comparing it to the overall LATE of ROIC and ROA (+9%, and +2.7%). Only for stock prices, the pattern is as expected (Brav et al., 2015): when analysing the targets of DFA-subjected hedge funds, more labour productive firms are experiencing higher gains in firm outcomes compared to both the average and lower productive firms, although neither of the observed changes in stock prices are statistically significant. Thus, both channels that should (Brav et al., 2015) create value (higher relative capex send and labour productivity) are not present when analysing DFA-subjected hedge funds and hypothesis 3 is rejected.

The findings imply that either the DFA is affecting these value channels more pronounced than average or these value channels are simply not creating value for HFA, and other mechanism are now at play. Although the first explanation seems unlikely, since no known study is investigating the effect of DFA on HFA value channels it could be an avenue for further research: what are the value channels of HFA, for DFA-subjected hedge funds? The second explanation is more likely, given the magnitude and statistically significant findings that both refute the findings of Brav et al. (2015): due to unknown reasons, increased capex spend, and labour productivity are not the channels that HFA create value anymore. As the underlying mechanisms of these findings remain unclear in this study - further research could, after testing the robustness of the findings, investigate the explanations behind it – perhaps firms are more risk-averse and consequently lower their capex spend given the changes in the new timeframe of the study, as the period of 2012-2018 is characterised by rising interest rates and increased uncertainty of the U.S. political climate.

Table 7: RDD estimation empirical results: hypothesis 2, 3 and 4

	(1)	(2)	(3)	(4)

Dependent variable	TFP	ROIC	ROA	Stock prices
Dataset	All Targets	All targets	All targets	All targets
LP-intesnity				
Q1 (Lowest)	0.13* (2.07)	25.65 (1.79)	8.7 (1.10)	-0.16 (-0.44)
Q2	0.00 (0.16)	35.91** (2.74)	12.94* (2.08)	-0.42 (-1.42)
Q3	-0.04 (-1.24)	2.21 (0.55)	2.007 (0.73)	-0.19 (-0.90)
Q4 (Highest)	0.01 (0.20)	-13.89 (-1.22)	-20.23* (2.26)	0.20 (0.70)
Capex-intensity				
Q1 (Lowest)	0.25* (2.06)	-10.01 (-1.04)	-14.62 (-1.96)	-0.27 (-0.85)
Q2	-0.04 (-1.49)	24.77** (2.95)	7.73 (1.47)	-0.44 (-1.57)
Q3	-0.03 (-0.99)	10.28 (0.79)	9.85 (1.31)	0.48 (1.64)
Q4 (Highest)	0.05 (1.55)	6.060 (0.53)	-0.34 (-0.07)	-0.33 (-1.71)
Governance type				
Capital structure	0.01 (0.29)	18.22 (1.85)	9.69 (1.50)	-0.43 (-1.42)
Sales of target	0.03 (0.71)	-31.11* (-2.40)	-21.45*** (-3.59)	-0.05 (-0.10)
Governance	0.11* (2.20)	0.951 (0.10)	-0.79 (-0.11)	-0.14 (-0.66)
Overall LATE	0.05* (0.03)	9 (6.7441)	2.69 (4.36)	-0.16 (0.151)

*Table 7 shows the results of analysing hypotheses 2, 3 and 4 as it analyses the differences in HFA effectiveness across HFA value channels and activism types. Robust standard errors in parentheses and significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.*

Testing hypothesis 4

Brav et al. (2015) showed that when activist hedge funds sells (parts of) the target firm (‘sale of target’), or when it changes the long-term strategic plans of the target firm (‘business strategy’), HFA effectiveness is the highest: firm productivity increased the most compared to the other HFA strategies that involves changing the board or leadership team (‘governance’), changes in financing decisions (’capital structure’) or when having no clear singular strategy (‘general’). To allow compare which type of activism is the most effective for DFA-affected hedge funds, the Stata command ‘’if activism type == <1/2/3/4/5>’’ is used: 1 representing the dummy variable for the HFA strategy governance, 2 for business strategy, 3 for capital structure, 4 for sale of target and 5 for governance. However, activism type governance and ‘business strategy’ are automatically omitted by the RDD as the strategies have too few observations (5 and 12, respectively) for the RDD to showcase meaningful results, as the introduction already discussed the unbalanced distribution of the five activism types (more than 50% of the HFA strategies is ‘governance’). When focusing on TFP in table 7, findings are that DFA-subjected hedge funds using activism type ‘’Governance’’ increase (+10.5%) target firm productivity and is statistically significantly at a 10% level, larger than the average effect (+5.2%) and compared to other activism strategies. For ROIC and ROA, ‘capital structure’ is the most effective strategy for activist DFA-subjected hedge funds, contrary to the findings of Brav et al. (2015) that argue that changing the capital structure of the target firm is the least effective HFA strategy, although the increase is not statistically significant. Contrary to the expectations, ‘sale of target’ is the least effective strategy for DFA-subjected hedge funds in achieving its HFA goals: performance (ROA and ROICC) deteriorates by -21% and -31% respectively using that HFA strategy, and both decreases are statistically significant at a 10% level. Although stock prices show that ‘sale of target’ is the most effective strategy, the finding is not statistically significant. Altogether, TFP, ROIC and ROA do not support Brav et al. (2015) in ‘sale of target’ being the most effective HFA strategy for hedge funds. Thus, hypothesis 4 is rejected as the HFA strategy ‘sale of target’ is rather the least effective in improving firm productivity, than the most. However, readers should interpret the results bearing in mind that the other effective HFA strategy ‘business strategy’ is not researched due to the low number of observations. Thus, it seems that either the DFA has changed the effectiveness of HFA strategies, a spurious trend in the same timeframe as the DFA is causing changes in effectiveness of HFA strategies that is uncontrolled for in the RDD analysis or hedge funds are using sub strategies within the five HFA strategy brackets and thus using five brackets is not accurately capturing the HFA strategies. While there is no evidence for the first explanation, further researchers can include the HFA strategy analysis in their value channel analysis discussed in the previous section, to research the underlying mechanisms behind the DFA changing both the value channels and most effective HFA strategies of hedge funds. Moreover, as the DFA imposed stricter corporate governance standards that made it harder for hedge funds to enforce radical changes like selling (parts) of a target firm, this perhaps explains why ‘sale of target’ is not the most effective HFA strategy anymore. However, capital structure being the most effective strategy for ROIC and ROA is surprising given that Brav et al. (2015) find this strategy to be the least (excluding campaigns with no clear HFA strategy; ‘general’) effective compared to all strategies. Furthermore, the rises in interest rates of the past decade are expected to negatively impact the strategy as financing costs increased, as well as the fact that the DFA (SEC, 2024) introduced tighter leverage ratios and liquidity ratios requirement for hedge funds. The second and third explanation, a spurious trend and more granularity in HFA strategies, are also potential avenues for further research: if a spurious trend is found, does controlling for it improve outcomes? And, do outcomes change when using e.g. ten instead of five brackets, differentiating sale of target in sale of parts, sale of plant, sale of whole firm, sale of subsidiary, etc.

Conclusion

Discussion of findings

Using Total Factor Productivity (TFP) as proxy for value creation, I causally test the impact of the DFA (hypothesis 1) on HFA effectiveness, the differences of the effect of the DFA between target industries (hypothesis 2), the robustness of HFA value channels observed by Brav et al. (2015) (hypothesis 3) and the dominant HFA strategies observed by Brav et al. (2015) (hypothesis 4). Findings indicate that firm productivity is increased after the DFA by 5.2% (not rejecting hypothesis 1), HFA effectiveness is significantly lower (-7%) for manufacturing targets relative to all targets (not rejecting hypothesis 2) and the channels and strategies by which HFA used to create value are not the same anymore (rejecting hypothesis 3 and 4). Although the RDD shows that the DFA causes significant improvement in (+5.2%) in HFA effectiveness (TFP), this is only a comparison between hedge funds who are subjected by the DFA and those that are not, and thus this finding is not indicating whether HFA in general is effective. Furthermore, this study refutes the findings of Brav et al. (2015) that higher capex investments and increased labour productivity are the channels how HFA create value, as well as the sale of a target being the most effective HFA strategy. Furthermore, the higher increase in target firm TFP of DFA-subjected hedge funds relative to the smaller, not DFA-subjected hedge funds imply that the SEC is unintendedly stimulating HFA effectiveness, perhaps due to the spillover effects of the mandatory improved risk management department that results in better selection of HFA targets.

Limitations

Although the effect of the DFA on HFA is statistically significant and causal, this does not directly mean that the research setup is the most accurate. Perhaps, researchers achieve different results when using different proxies for TFP, as the proxies used are, although direct, less accurately measuring firm-level changes compared to the data from the U.S. Census Bureau. Furthermore, the interpretation of the results of the RDD are potentially biased for larger firms, as the RDD sample excludes the largest hedge funds that more often target larger firms. Furthermore, the positive effect of DFA on HFA effectiveness is potentially biased upwards due to the survivorship bias discussed by Partnoy (2015), that argues some hedge funds have restructured to family offices to avoid the increased regulatory burden, as well hedge funds closing because of the DFA. Thus, the remaining sample of hedge funds is potentially biased upwards given that funds that would experience the most negative effects of the DFA are excluded from the sample. However, as the sample of firms taken from Compustat is likely biased downwards (Brav, Jiang, & Kim, 2009) given that more productive (acquired) firms are omitted from the sample, the positive effect of DFA on HFA (5.2%) observed in this study are probably realistic, as it is biased in both directions.

Implications

Although the effect of DFA on firm TFP is statistically significant, it is not for firm performance and labour outcomes. As the theoretical and academic base of DFA potentially affecting (Cumming, Dai & Johan, 2020; Restrepo, 2024; Shelby, 2017) hedge funds in general and labour outcomes of HFA targets (DesJardine & Durand, 2020; Kim, 2020) is strong enough to encourage further researchers to test the robustness of the insignificant findings of this study. Possible changes to the research structure are increasing the years observed, choosing different proxies for the variables or having a different set of covariates. Also, further researchers could test the robustness of the positive effect of the DFA on alternative investments in general by researching the effect of the DFA on the effectiveness of its counterpart; private equity. Also, there could be concerns whether HFA is the only cause of the changes in the firm and labour outcomes observed, although chances of spurious trends are low given the causality tests conducted by Brav et al. (2015). As they find no evidence for the pattern observed being driven by mean reversion since manufacturing non-target peers did not experience a similar V-shaped pattern, the changes observed in the RDD after HFA are believed to be causal. Also, Brav et al. (2015) showed that switching from a passive (SEC Form 13G) to an activist (SEC Form 13D) investor significantly increased firm and labour outcomes, furthermore indicating that the changes observed in this study are caused by HFA.

As expected (Coffee & Palia, 2014), the testing of hypothesis 1 showed that HFA is not negatively (+5.2%) impacted by the DFA as the SEC is not shortening the 10-day non-disclosure window and thereby not effectively targeting HFA. However, the fact that HFA is not negatively impacted by the DFA does not mean the DFA is not effective – as the goal of the DFA is not to lower hedge fund returns or target firm and labour outcomes, but its goal (SEC, 2024) is to lower systemic risk and retail investor harming practices, regardless of how much return the hedge fund generates. To conclude whether the DFA has been effective – a new study should focus on assessing the changes in systemic risk carried by hedge funds before and after DFA. The results of this study only investigate the externalities of the DFA, as the DFA did not intend to alter the returns of hedge funds, and certainly not target firm or labour outcomes. Thus, although this study finds that HFA caused significant higher firm productivity, questions remain whether the desired decreased systemic risk caused by the DFA achieved. A new study building on this research could also investigate whether there are different positive or negative externalities of the DFA on HFA, besides its increased effectiveness. If there are negative externalities, the SEC faces a trade-off: are the intended consequences significant enough to make up for the negative externalities it is causing?

Furthermore, researchers building on this study could look for externalities caused by other SEC policies related to HFA, as it e.g. is indicative to test whether the size of the stake acquired is causally impacting HFA effectiveness by using a similar RDD design as this research uses for the DFA. As HFA are required to file SEC Form 13D if their stake exceeds 5% and thus are publicly disclosing their activist position, the impact of this disclosure on firm and labour outcomes is potentially indicative. The treatment group would be activist hedge funds having a stake just above the 5% threshold, the control group activist hedge funds just below the 5% threshold, and the running variable the stake percentages of hedge funds in target firms. By using this RDD, researchers investigate HFA more granularly as it splits disclosed and non-disclosed HFA effectiveness and builds on the findings of this study by analysing the externalities observed in this study more thorough.

References

Abramovitz, M. (1956). Resource and output trends in the United States since 1870. American Economic Review, 46, 5-23.

Ackerberg, D. A., Caves, K., & Frazer, G. (2006). Structural identification of production functions. Unpublished manuscript.

Ackerberg, D., Benkard, C. L., Berry, S., & Pakes, A. (2007). Econometric tools for analyzing market outcomes. In J. Heckman & E. Leamer (Eds.), Handbook of Econometrics, 6(1) (pp. 4171-4276). Amsterdam: North-Holland.

Armour, J., & Cheffins, B. R. (2009). The rise and fall (?) of shareholder activism by hedge funds. ECGI - Law Working Paper No. 136/2009. Available at SSRN: https://ssrn.com/abstract=1489336 or http://dx.doi.org/10.2139/ssrn.1489336

Bach, L., & Metzger, D. (2014). Why Do Shareholder Votes Matter? Working Paper. Available at SSRN: https://ssrn.com/abstract=2247084

Bach, Laurent, and Daniel Metzger. "How Do Shareholder Proposals Create Value?" Journal of Financial Economics, vol. 123, no. 3, 2017, pp. 621-649.

Baker, A. C. (2021, October). The effects of hedge fund activism.

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99-120.

Bayaraa, B. (2017). Financial performance determinants of organizations: The case of Mongolian companies. Journal of Competitiveness, 9(3), 22-33. https://doi.org/10.7441/joc.2017.03.02

BBC. (2020, June 8). US recession: What can the 2008 recession teach us about this one?

Bebchuk, L. A., Brav, A., & Jiang, W. (2015). The Long-Term Effects of Hedge Fund Activism. Columbia Law Review, 115, 1085-1156. Retrieved from https://ssrn.com/abstract=2291577

Becht, M., Franks, J., Mayer, C., & Rossi, S. (2009). Returns to shareholder activism: Evidence from a clinical study of the Hermes UK Focus Fund. Review of Financial Studies, 22, 3093–3129. https://doi.org/10.1093/rfs/hhp022

Bloomberg. (2002, July 21). Commentary: Don't bother calling the hedge fund cops. Bloomberg. Retrieved from https://www.bloomberg.com/news/articles/2002-07-21/commentary-dont-bother-calling-the-hedge-fund-cops

Bloomberg. (2023, October 10). Activist hedge funds get less time to disclose 5%-plus stakes under SEC rule. https://www.bloomberg.com/news/articles/2023-10-10/activist-hedge-funds-get-less-time-to-disclose-5-plus-stakes-under-sec-rule

Bournakis, I., & Mallick, S. (2018). TFP estimation at firm level: The fiscal aspect of productivity convergence in the UK. Economic Modelling, 70(C), 579-590.

Boyson, N. & Pichler, P. (2019). The Review of Financial Studies, 32(2), 771-817. https://doi.org/10.1093/rfs/hhy058

Brav, A., Jiang, W., & Kim, H. (2009). Hedge fund activism: A review. Foundations and Trends in Finance, 4, 185–246.

Brav, A., Jiang, W., & Kim, H. (2009). Hedge fund activism: A review. Foundations and Trends in Finance, 4, 185–246.

Brav, A., Jiang, W., & Kim, H. (2015). se. The Review of Financial Studies, 28(10), 2723–2769. https://doi.org/10.1093/rfs/hhv037

Brav, A., Jiang, W., Partnoy, F., & Thomas, R. (2008). Hedge fund activism, corporate governance, and firm performance. Journal of Finance, 63, 1729–1775. https://doi.org/10.1111/j.1540-6261.2008.01381.x

Bureau of Economic Analysis. (2024). GDP price deflator. Retrieved from https://www.bea.gov/taxonomy/term/796

Business Insider. (2021). 2 of the biggest hedge fund victims of GameStop's short squeeze suffered more losses in May, report says. Retrieved from https://www.businessinsider.in/stock-market/news/2-of-the-biggest-hedge-fund-victims-of-gamestops-short-squeeze-suffered-more-losses-in-may-report-says/articleshow/83432988.cms

Busse, J., Chordia, T., Jiang, L., & Tang, Y. (2017). Mutual Fund Trading Costs and Diseconomies of Scale. Retrieved from [URL of where the document is hosted, if available online]

Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs. Econometrica, 82(6), 2295-2326. https://doi.org/10.3982/ECTA11757

Cattaneo, M. D., Jansson, M., & Ma, X. (2017). Manipulation testing based on density discontinuity. Stata Journal, 17(4), 916-946.

Census (2023). Restricted-Use Data Application Process. Retrieved from https://www.census.gov/StandardApp

Chen, G., Doyle, P. M., & Shi, W. (2020). Hedge fund investor activism and human capital loss. Strategic Management Journal. First published November 26, 2020. https://doi.org/10.1002/smj.3257

Clifford, C. (2008). Value creation or destruction? Hedge funds as shareholder activists. Journal of Corporate Finance, 14, 323–336. https://doi.org/10.1016/j.jcorpfin.2008.03.001

Coase, R. H. (1937). "The Nature of the Firm." Economica, 4(16), 386-405.

Coffee, J. C., & Palia, D. (2014). The Impact of Hedge Fund Activism: Evidence and Implications. European Corporate Governance Institute (ECGI) - Law Working Paper No. 266/2014, Columbia Law and Economics Working Paper No. 489. Available at SSRN: https://ssrn.com/abstract=2496518 or http://dx.doi.org/10.2139/ssrn.2496518

Cumming, D. J., Dai, N., & Johan, S. A. (2017). Dodd-Franking the Hedge Funds. Journal of Banking and Finance, Forthcoming. Available at SSRN: https://ssrn.com/abstract=3038171

Day Pitney Generations Newsletter. (2022, September 7). The Archegos scandal: The SEC responds. Retrieved from https://www.daypitney.com/insights/publications/2022/09/fog4-the-archegos-scandal-the-sec-responds/

DesJardine, M. R., & Durand, R. (2020). Disentangling the effects of hedge fund activism on firm financial and social performance. Strategic Management Journal, 41(6), 1054-1082. https://doi.org/10.1002/smj.3134

Editorial Board. (2022, October). Activist Starboard urges Salesforce to lift margins after taking stake. Financial Times. Retrieved from https://www.ft.com/content/0bae75af-deb1-4f03-b79e-e1aa95b3e044

Editorial Board. (2023, October). News Corp break-up would unlock $7bn in value, says activist Starboard. Financial Times. Retrieved from https://www.ft.com/content/d8afff13-ddc0-4e3b-a741-71de75c8351c

Fama, E. F., & Jensen, M. C. (1983). "Separation of Ownership and Control." Journal of Law and Economics, 26(2), 301-325.

Federal Reserve Bank of Chicago. (2016). The role of hedge funds in the financial crisis. Chicago Fed Letter, (370). Retrieved from https://www.chicagofed.org/publications/chicago-fed-letter/2016/370

Federal Reserve. (2023). Industrial Production and Capacity Utilization - G.17. Retrieved from https://www.federalreserve.gov/releases/g17/related_data/manuf_invest_capital.htm

Financial Times Editorial Board. (2008, October). Fuld says Lehman victim of short sellers. Financial Times. https://www.ft.com/content/f59fdd00-93b0-11dd-9a63-0000779fd18c

Financial Times Editorial Board. (2011, October). Rajaratnam sentenced to 11 years in jail. Financial Times. https://www.ft.com/content/19bf5730-f4eb-11e0-ba2d-00144feab49a

Financial Times Editorial Board. (2015, September 30). Old engine of Wall Street is sputtering. Financial Times. https://www.ft.com/content/be194ffc-688c-11e5-a57f-21b88f7d973f

Financial Times Editorial Board. (2021, April 15). Hedge funds rethink after GameStop pain. Financial Times. https://www.ft.com/content/f7ddacb6-dc07-4142-adb2-f7eedf3a2272

Financial Times Editorial Board. (2021, April). Madoff: three lessons from the world's greatest Ponzi scheme. Financial Times. https://www.ft.com/content/055bf6d2-70fb-4ed0-b97a-36f412e1aff7

George, B. C., & Dymally, L. V. (2013). The end of an era of limited oversight: The restructured regulatory landscape of private investment funds through the U.S. Dodd-Frank Act and the E.U. Alternative

Investment Fund Managers Directive. Florida Journal of International Law, 25(2), Article 2. Available at: https://scholarship.law.ufl.edu/fjil/vol25/iss2/2

Greenwood, R., & Schor, M. (2009). Hedge fund investor activism and takeovers. Journal of Financial Economics, 92, 362–375. https://doi.org/10.1016/j.jfineco.2008.05.003

Harvard Law School Forum on Corporate Governance. (2019, June 23). The Timing of Schedule 13D. Retrieved from https://corpgov.law.harvard.edu/2019/06/23/the-timing-of-schedule-13d/

Harvard Law School Forum on Corporate Governance. (2020). 2020 Activist Investor Report. Retrieved from https://corpgov.law.harvard.edu/2020/08/01/2020-activist-investor-report/

Hedge Fund Journal. (2012). Hedge funds and Dodd-Frank. Retrieved from https://thehedgefundjournal.com/hedge-funds-and-dodd-frank/

Hirst, S. (2011, October 22). The Williams Act: A Truly “Modern” Assessment. Harvard Law School Forum on Corporate Governance. Retrieved from https://corpgov.law.harvard.edu/2011/10/22/the-williams-act-a-truly-modern-assessment/

Hofstra. (2012). Reporting concerns among hedge fund managers. ROTHSTEIN KASS Report, 18.

Institutional Investor. (2019, December 13). Why the 2010s have been a ‘Lost Decade’ for hedge funds. Retrieved from https://www.institutionalinvestor.com/article/2bsw43jnxobb1k6qkr8jk/portfolio/why-the-2010s-have-been-a-lost-decade-for-hedge-funds

Investment Executive. (2023, August). SEC ramps up hedge fund regulation. https://www.investmentexecutive.com/news/from-the-regulators/sec-ramps-up-hedge-fund-regulation/

Investopedia. (2019). Buffett's bet with the hedge funds: And the winner is…. Retrieved from https://www.investopedia.com/articles/investing/030916/buffetts-bet-hedge-funds-year-eight-brka-brkb.asp

Jensen, M. C., & Meckling, W. H. (1976). "Theory of the Firm: Managerial Behavior, Agency Costs, and Ownership Structure." Journal of Financial Economics, 3(4), 305-360.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs, and ownership structure. Journal of Financial Economics, 3(4), 305-360.

Kaal, W. A. (2013). Hedge Fund Manager Registration Under the Dodd-Frank Act. San Diego Law Review, 50(2), 243. Available at: https://digital.sandiego.edu/sdlr/vol50/iss2/2

Kaal, W. A. (2020). Disentangling the effects of hedge fund activism on firm financial performance. Strategic Management Journal.

Kaal, W. A., Luppi, B., & Paterlini, S. (2014). Did the Dodd-Frank Act Impact Hedge Fund Performance?. Retrieved from https://ssrn.com/abstract=2389416

Katelouzou, D. (2013). Myths and Realities of Hedge Fund Activism: Some Empirical Evidence. Virginia Law & Business Review, 7, 459. Available at SSRN: https://ssrn.com/abstract=2152351

Kidd, J. (2018). Quacks or Bootleggers: Who’s Really Regulating Hedge Funds? Washington & Lee Law Review, 75, 367. Available at: https://scholarlycommons.law.wlu.edu/wlulr/vol75/iss1/5

Kim. (2020). Financial Capital and Human Capital in American Corporations: How Ownership by Activist Hedge Funds and Index Investors Affects Employee Satisfaction.

Krishnan, C., Partnoy, F., & Thomas, R. (2015). Top hedge funds and shareholder activism. Working Paper, Case Western Reserve University, University of San Diego, and Vanderbilt University. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2658251

LaPolla, S. (2018, February 28). Bill Ackman ends 5-year battle against Herbalife. Forbes. Retrieved from https://www.forbes.com/sites/gurufocus/2018/02/28/bill-ackman-ends-5-year-battle-against-herbalife/

Lee, D. S., & Lemieux, T. (2010). Regression Discontinuity Designs in Economics. Journal of Economic Literature, 48(2), 281–355. https://doi.org/10.1257/jel.48.2.281

Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. The Review of Economic Studies, 70(2), 317-341. https://www.jstor.org/stable/3648636

Lipton, M. (2015, June 2). Dealing with Activist Hedge Funds. Harvard Law School Forum on Corporate Governance. Retrieved from https://corpgov.law.harvard.edu/2015/06/02/dealing-with-activist-hedge-funds-4/

López, P. (2023, November 6). The gradual extinction of the wolves of Wall Street and their hedge funds. El País. Retrieved from https://english.elpais.com/economy-and-business/2023-11-06/the-gradual-extinction-of-the-wolves-of-wall-street-and-their-hedge-funds.html

Lysandrou, P. (2011). The primacy of hedge funds in the subprime crisis. Journal of Post Keynesian Economics, 34(2), 225-253. https://doi.org/10.2307/23119503

Maksimovic, V., Phillips, G., & Yang, L. (2013). Private and public merger waves. The Journal of Finance, 68(5), 2177-2217.

MarketWatch. (2016, June 7). Carl Icahn's $2 billion Apple stake was a prime example of investment inequality. Retrieved from https://www.marketwatch.com/story/carl-icahns-2-billion-apple-stake-was-a-prime-example-of-investment-inequality-2016-06-07

Marschak, J., & Andrews, W. H., Jr. (1944). Random Simultaneous Equations and the Theory of Production. Econometrica, 12(3/4), 143-205. https://doi.org/0012-9682(194407/10)12:3/4<143:RSEATT>2.0.CO;2-O

Marshall, A. (1890). Principles of Economics. London: Macmillan and Co., Ltd.

McCrary, J. (2008). "Manipulation of the running variable in the regression discontinuity design: A density test." Journal of Econometrics, 142(2), 698-714.

Molk, P., & Partnoy, F. (2021, March 26). The long-term effects of short selling and negative activism. University of Florida; University of California Berkeley

Mueller, D. C. (1972). A life cycle theory of the firm. The Journal of Industrial Economics, 20(3), 199-219.

Netflix. (2022). Eat the Rich: The GameStop Saga. Retrieved from https://www.netflix.com/nl/title/81424332

Nofsinger, J. R. (2014). A capability theory of the firm: an economics and (Strategic ...). Journal of Economic Theory.

NPR. (2017, June 8). House passes bill aimed at reversing Dodd-Frank financial regulations. Retrieved from https://www.npr.org/2017/06/08/532036374/house-passes-bill-aimed-at-reversing-dodd-frank-financial-regulations

Olley, S. G., & Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. Econometrica, 64(6), 1263-1297.

Park, R. J. (2020). Social Impact of Activist Hedge Funds: Evidence from Employee Satisfaction and Emission. October 2020.

Partnoy, F. (2015). U.S. Hedge Fund Activism. In Research Handbook on Shareholder Power (Elgar Press, Forthcoming). San Diego Legal Studies Paper No. 15-187. Available at SSRN: https://ssrn.com/abstract=2585290

Penrose, E. T. (1959). The Theory of the Growth of the Firm. Oxford University Press.

Pitt, H. L. (2002, May 24). Remarks before the Investment Company Institute, 2002 General Membership Meeting. Retrieved from http://www.sec.gov/news/speech/spch462.htm

Restrepo, F. (2022). The economic consequences of hedge fund regulation: An analysis of the effect of the Dodd-Frank Act. Journal of Legal Studies. [Forthcoming]. Available at SSRN: https://ssrn.com/abstract=3541916 or http://dx.doi.org/10.2139/ssrn.3541916

Reuters. (2015). Axcelis makes changes to board ahead of likely proxy fight

Romer, P. M. (1990). "Endogenous Technological Change." Journal of Political Economy, 98(5, Part 2), S71-S102.

S&P Global Market Intelligence. (2023). Investor activism activity increase again in H1 2023 but campaign success rates are falling. Retrieved from https://www.spglobal.com/marketintelligence/en/news-insights/blog/investor-activism-activity-increase-again-in-h1-2023-but-campaign-success-rates-are-falling

S&P Global Market Intelligence. (2023). Investor activism activity increase again in H1 2023 but campaign success rates are falling. Retrieved from https://www.spglobal.com/marketintelligence/en/news-insights/blog/investor-activism-activity-increase-again-in-h1-2023-but-campaign-success-rates-are-falling

S&P Global Market Intelligence. (2024). Investor activism surges as companies react to proposed changes. Retrieved from https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/investor-activism-surges-as-companies-react-to-proposed-changes-80689296

S&P Global Market Intelligence. (2024). Investor activism surges as companies react to proposed changes. Retrieved from https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/investor-activism-surges-as-companies-react-to-proposed-changes-80689296

Schoar, A. (2002). Effects of Corporate Diversification on Productivity. The Journal of Finance, 68(5), 2177-2217. https://doi.org/10.1111/1540-6261.00500

Schochet, P. Z., Cook, T., Deke, J., & Imbens, G. (2010). Standards for Regression Discontinuity Designs. October 2010

SEC (2011, June 22). SEC Adopts Dodd-Frank Act Amendments to Investment Advisers Act. Retrieved from http://www.sec.gov/news/press/2011/2011-133.htm

SEC (2015). Corporate governance issues, including executive compensation disclosure and related SRO rules. Retrieved from https://www.sec.gov/spotlight/dodd-frank/corporategovernance.shtml

SEC (2024). Implementing the Dodd-Frank Wall Street Reform and Consumer Protection Act. Retrieved from https://www.sec.gov/securities-topics/dodd-frank-act

Şeker, M., & Saliola, F. (2018). A cross-country analysis of total factor productivity using micro-level data. Central Bank Review, 18(1), 13-27. https://doi.org/10.1016/j.cbrev.2018.01.001

Shelby, C. M. (2016). Are Hedge Funds Still Private? Exploring Publicness in the Face of Incoherency. SMU Law Review.

Shelby, C. M. (2017). Closing the hedge fund loophole: The SEC as the primary regulator of systemic risk. BCL Review, 58, 639.

Shleifer, A., & Vishny, R. W. (1986). "Large Shareholders and Corporate Control." Journal of Political Economy, 94(3, Part 1), 461-488.

Shumway, T. (1997). The delisting bias in CRSP data. Journal of Finance, 52, 327–340. Available at: https://www.jstor.org/stable/41952062

Smith, A. (1776). An Inquiry into the Nature and Causes of the Wealth of Nations. London: W. Strahan and T. Cadell.

Solow, R. M. (1956). "A Contribution to the Theory of Economic Growth." The Quarterly Journal of Economics, 70(1), 65-94.

Thistlethwaite, D. L., & Campbell, D. T. (1960). Regression-discontinuity analysis: An alternative to the ex post facto experiment. Journal of Educational Psychology, 51(6), 309–317. https://doi.org/10.1037/h0044319

Umar, Z., Gubareva, M., Yousaf, I., & Ali, S. (2021). A tale of company fundamentals vs sentiment driven pricing: The case of GameStop. Journal of Behavioral and Experimental Finance, 30, Article C.

United States Congress. (2017). H.R.10 - Financial CHOICE Act of 2017. https://www.congress.gov/bill/115th-congress/house-bill/10

United States Congress. (2018). S.2155 - Economic Growth, Regulatory Relief, and Consumer Protection Act. https://www.congress.gov/bill/115th-congress/senate-bill/2155

Van Beveren, I. (2007). Total factor productivity estimation: A practical review. Journal of Economic Surveys, 26(1), 98-128. https://doi.org/10.1111/j.1467-6419.2007.00500.x

Vatavu, S. (2015). Determinants of return on assets in Romania: A principal component analysis. Timisoara Journal of Economics and Business, 8(1). DOI: 10.1515/tjeb-2015-0003

Williamson, O. E. (1985). The Economic Institutions of Capitalism: Firms, Markets, Relational Contracting. New York: Free Press.

Wolff, E. N. (1991). Productivity growth, capital intensity, and skill levels in the U.S. insurance industry, 1948-86. The Geneva Papers on Risk and Insurance, 16(59), 173-190.