On Dynamic Risk Management

Investigating the Theory of Collateral Constraints

Abstract

This paper investigates the theory of collateral constraints developed by Rampini, Sufi, and Viswanathan in their paper *Dynamic Risk Management* published in 2014. In this theoretical framework, firms are faced with a trade-off between using scarce cash holdings to finance investments and engaging in risk management. Using an updated dataset covering a tumultuous time-period in which oil prices fell dramatically, we employ a wide range of statistical models, including difference-in-differences estimations, to test the validity of this theory in the North American oil and gas industry. Our results are not completely unanimous, but after having analyzed them in detail we can conclude that more financially unconstrained firms tend to hedge more than constrained firms. In addition, as oil prices fell dramatically in the last months of 2014 resulting in widespread financial distress, constrained firms generally responded by decreasing their hedging even more. Ultimately, based on the results from the statistical models and the subsequent analysis, we are in a position to support, though not completely, the theory of collateral constraints.

Key words: Collateral, Financial Constraints, Oil and Gas Industry, Risk Management

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1. Introduction

Since the emergence of the modern corporation, risk management has become increasingly complex and today's hedging activities can take on a multitude of shapes and forms. Various hedging strategies have come to play a crucial part in many firms, especially those heavily susceptible to fluctuations in world commodity prices. In addition, as the legal and economic framework in which firms operate have developed and changed over time, other motivations for conducting risk management have emerged. Most notably, the idea of tax convexity, bankruptcy costs, and managerial risk aversion have played an increasingly important role as determinants of risk management (Smith and Stulz, 1985). This progress and variability of risk management motivations for the last decades have attracted the attention of academia, resulting in numerous papers being published on the subject. One cornerstone in the jungle of risk management literature is the paper by Froot et al. (1993), setting the stage for several subsequent papers. In their paper, the authors assert that capital market imperfections can warrant the implementation of risk management by pointing to a difference in costs between acquiring funds externally and relying on internally generated funds. In essence, information asymmetry between managers who run the firm and outside investors makes external funding more costly since investors require additional compensation on account of inferior information. In other words, firms that are more financially constrained should hedge more to limit the need to acquire costly external funding whereas less financially constrained firms should hedge less (Tufano, 1996).

However, as Rampini et al. (2014) point out, a number of the succeeding papers that empirically investigate this theory have produced contradicting results. Naturally, this contradiction has induced researchers to explore the underlying factors causing the discrepancy between theory and practice. The paper by Rampini et al. (2014) emphasizes the unrealistic assumptions in the model setup by Froot et al. (1993). Most notably, the paper assumes no collateral constraints on hedging and no investment outlays in the model time frame. This setting, argues Rampini et al. (2014), overlooks one important element in the model: *the trade-off between financing and risk management*. In essence, if the assumptions of no collateral constraints on hedging and no investment outlays are relaxed, firms are faced with a decision between using scarce funds to exploit investment opportunities and depositing collateral required to enter into derivative contracts. According to Rampini et al. (2014), this dynamic trade-off serves an important role in explaining the discrepancy between theory and practice in hedging activities.

The paper by Rampini et al. (2014) and the contradiction above form the building block of this paper in which we aim to test the theory of collateral constraints by investigating the hedging

activities of American oil and gas companies. In line with Rampini et al. (2014), we use several proxies to capture the effects of financing constraints on firms' hedging activities and extend our study by employing various models in order to improve statistical robustness. We replicate the panel data tests conducted by Rampini et al. (2014), and since our dataset covers a period between Q1 2013 and Q2 2016, our tests capture the dramatic fall in oil prices during the later part of 2014. In addition, the sample period is well-suited for employing a difference-in-differences (DID) model, which provides basis for an insightful time-dimensional analysis. The DID model is especially useful for testing hedging activities when financially constrained firms enter financial distress - Rampini et al. (2014) show that "Risk management drops substantially as airlines approach distress and recovers only slowly after airlines enter distress." (p. 1). To this end, the DID model is an excellent setup in order to investigate how oil and gas companies change their hedging decisions as they approach or enter financial distress.

Hence, the sample period in combination with the DID model provide a well-suited foundation with varying levels of financial constraints, allowing us to take advantage of the distinct time-dimensional heterogeneity in our data set. In the context of hedging, the DID model is largely overlooked; to the best of our knowledge, the only risk management paper employing this statistical approach is that by Bakke et al. (2016). Therefore, it forms the key method in this paper to expand the hedging literature and to effectively test the validity of the theory of collateral constraints. As a result, by using the DID model we explore how an exogenous shock (the fall in oil prices starting in Q2 2014) affects hedging activities of firms with different ex-ante financing constraints. Also, the benefit of the DID model is that instead of looking at the levels of hedging we study the relative changes in hedging before and after the exogenous shock.

2. Literature review

The objective of this section is to present and contrast the most relevant existing papers that investigate the relationship between financing constraints and risk management. Even though the primary interest of this paper is to explore the underlying factors affecting output hedging, with a designated emphasis on financing constraints, the section still highlights the most important papers focusing on input hedging. The paper by Rampini et al. (2014), which serves as a key reference point in this study, states that there is no conceptual difference between output and input hedging in their model. Also, providing a broad foundation is necessary to familiarize inexperienced readers with and help them navigate through the jungle of risk management literature. Ultimately, by presenting previous papers we strive to legitimize and support the decision to conduct this study so as to highlight our contributions to the extant literature.

Before presenting relevant risk management papers, it is worth pointing out that entering into a derivative contract is a financial transaction. Consequently, in a Miller and Modigliani world with perfect financial markets, risk management is not desirable as investors are better positioned to form cheaper portfolios on their own (Ogden et al. 2003). However, when markets are imperfect as a result of frictions, firms can warrant the implementation of risk management in an attempt to increase firm value (Haushalter, 2000). As will become evident shortly, all papers below are based on one or more of these market imperfections when discussing the hedging behaviour of firms in different industries. Naturally, the extent to which these market frictions are present can vary substantially based on firm characteristics and type of industry.

2.1 Froot et al. (1993)

At the center of risk management literature is the seminal paper by Froot et al. (1993), which provides a theoretical foundation on which numerous subsequent papers are based (Rampini et al. 2014). It presents and briefly discusses the conventional rationales for firms to engage in hedging activities including taxes, managerial motives, and costs of financial distress. However, the most relevant contribution of the paper is the development of a model that can guide firms to hedge optimally in various settings. This framework is based on the assumption that externally generated funds are more expensive than internal funds. The logic behind the cost discrepancy can be attributed partly to different levels of information asymmetry associated with acquiring internal and external funds. Unlike employing internally generated funds, raising outside capital gives rise to information asymmetry since investors, who provide the capital, possess inferior information about a firm's operations than managers do. As a result, investors require additional compensation on their invested funds, thereby increasing the cost of capital of the recipient firm. Therefore, given

that this line of reasoning is sound, and several papers corroborate the difference in cost between internal and external funds, information asymmetry can warrant the implementation of risk management. In other words, firms that are more financially constrained should, in theory, hedge more since obtaining external funds are typically more expensive for these firms. In contrast, conglomerates and larger firms in general should engage in less risk management, following the same rationale.

The motivation for risk management in this framework is also related to the variability of cash flows. The underlying notion, presented by Froot et al. (1993), is that fluctuating internal cash flows must give rise to either a variability in external financing or a variability in investments. Variability in investments is not desirable given that there are diminishing marginal returns to investments. Also, not being able to finance its investments can be harmful to a firm for strategic reasons while also increasing the uncertainty for managers. Since the extent and attractiveness of investment opportunities are hard to predict beforehand, volatile internal cash flows may imply foregone investments in bad times due to lack of available funds. At the same time, marginal costs of external financing tend to increase as the amount of borrowed funds increase. As firms become increasingly leveraged, investors require additional compensation to offset the risks induced by higher leverage ratios. These higher costs to generate outside capital inevitably reduce the residual amount available to pursue investment opportunities. Consequently, minimizing the variability of internally generated cash flows from the firm's operations can ensure more stable investment expenses through time and ultimately decrease deadweight loss arising from external financing. Understanding the consequences of volatile cash flows, argues Froot et al. (1993), can help financially constrained firms to proactively limit the need to acquire costly external financing by implementing risk management.

2.2 Papers investigating the theoretical framework developed by Froot et al. (1993)

Similarly to Froot et al. (1993), Mello and Parsons (2000) develop a model for assessing the extent to which firms should hedge when faced with various levels of financing constraints. Embedded in the model is an intertemporal element that can guide firms to hedge optimally over time as their financial conditions change. The applied model demonstrates that the optimal value of hedging is contingent on a firm's marginal value of cash flows. A firm should strive to minimize the variability of the marginal value of cash flow, thereby allocating scarce funds across different states and periods. This redistribution is aimed at maximizing a firm's financial flexibility by limiting the extent of unused debt capacity and redundant cash. Consistent with the theory developed by Froot et al. (1993), the model suggests that more financially constrained firms, measured as having higher

leverage or lower profit margins, should hedge more and vice versa. The link between this prediction and empirical practices is hard to establish, argue the authors, and highlight the complications of testing intertemporal costs of financing constraints. However, as the model predicts, empirical findings suggest that firms' hedging activities tend to vary over time as financial conditions alter. In addition, the model also shows that hedging contracts may not be accessible for firms that are unable to present sufficient evidence that they are capable of covering the funding requirements in the contract. This result can explain why some empirical papers find that larger and less financially constrained firms hedge more than smaller and more financially constrained firms.

The theoretical framework established by Froot et al. (1993) have prompted numerous researchers to empirically investigate the relationship between financing constraints and risk management. Although the structure and statistical approaches of these papers can vary markedly, several of them, as Rampini et al. (2014) point out, produce results that contradict those predicted by the theory. More concretely, a number of papers find a negative relationship between financing constraints and hedging propensity. One way to gauge the degree of financing constraints is to use firm size as a proxy variable in the statistical procedure. The rationale is that small firms tend to be more financially constrained as their cash flows are more volatile and less predictable (Stulz, 1996). In contrast, larger firms tend to have better access to financial markets, thereby simplifying the process of acquiring external funds. In addition, due to their size and often long history of business, they have more bargaining power when loan contracts are designed. Taken together, these results should imply lower external financing costs and less deadweight loss for larger firms. A paper exploring the relationship between firm size and risk management is that by Nance, Smith, and Smithson (1993). Basing their paper on 169 US firms, the authors conclude that larger firms tend to use various hedging instruments to a greater extent than smaller firms. The results generated by this study is also acknowledged by Froot et al. (1993) and they agree that if firm size is an appropriate proxy for the degree financing constraint, then their theoretical model is not supported by the data. Similarly, Géczy, Minton, and Schrand (1997) find a positive relationship between firm size and hedging activities.

In their paper *Dynamic Risk Management*, Rampini et al. (2014) attempt to address the contradiction between theory and practice by highlighting the unrealistic market settings underpinning the paper by Froot et al. (1993). In the paper by Froot et al. (1993), there is no investment during the period in which the firm hedges, implying that residual cash flow cannot be used for this purpose. Also, the firm in question is not subject to collateral constraints, meaning that entering into derivative

instruments does not require depositing a collateral account that absorbs losses in the event of adverse fluctuations in the underlying asset. In other words, taking a position in a derivative contract does not demand any funds being used for the purpose of ensuring future payments for hedging counterparties. However, as Rampini et al. (2014) point out, this theoretical assumption fails to capture the crucial element of opportunity cost: the trade-off between risk management and financing investments. More concretely, if the assumptions of no collateral constraints and no investments are relaxed, firms are faced with a trade-off between financing investment opportunities and depositing the required collateral to enter into derivative contracts. The decision to prioritize one alternative over the other can be related to the firm's underlying financial condition and ability to raise outside capital. If external financing is expensive, the marginal value of internally generated cash flows is higher and a firm may thus benefit from allocating the limited funds to finance its investments. This result, and the trade-off theory in general, sheds light on why smaller firms often are found to be less inclined to use hedging instruments.

By introducing opportunity costs to the risk management decision, Rampini et al. (2014) argue that the inconsistency between risk management theory and practice is not surprising, but rather an expected result. They support this statement by presenting evidence from airline companies' 10-K filings in which firms highlight the necessity of accounting for collateral constraints before entering into derivative contracts. Several airlines provide detailed and comprehensive elucidations on the interaction between collateral constraints and the level of jet fuel price hedging. These discussions often emphasize the need to maintain acceptable levels of liquidity and how adverse impacts on firms' hedging positions can result in temporary liquidity issues. In the event of adverse fluctuations in the underlying commodity prices, firms may be forced to give up potential investment opportunities as cash is used to pay hedging counterparties. In addition, the paper contains a hand-collected panel data to generate statistical results that strongly support the dynamic trade-off model, i.e. more financially constrained firms hedge less and vice versa. Financing constraints are modelled by using different variables including net worth, based on both market value and book value, and credit ratings. Also, the application of panel data allows for a time-dimensional analysis in the selected time period. Further, the statistical investigation focuses on how financial distress affects the extent to which firms engage in hedging activities. A firm in financial distress is defined as having a rating of CCC+ or worse and only firms that enter this stage during the time-period are included in the analysis. This specification allows the authors to compare firms' hedging ratios at various time periods, both before and after entering financial distress. The results from this comparison indicate that firms in financial distress tend to reduce the extent of risk management, thus supporting the trade-off model in which firms are subject to collateral constraints.

After having discussed the theory of collateral constraints in the airline sector, it is time to introduce a paper that enables a more direct industrial benchmark. Basing his study on 100 oil and gas companies, Haushalter (2000) focuses on mapping the hedging policies of these producers by exploring the importance of widely applied market imperfections that can prompt the application of risk management. Most relevant for our study, he finds a positive relationship between financial leverage and hedging propensity, meaning that as firms become more leveraged they tend to use risk management more extensively in order to reduce financial contracting costs. In addition, Haushalter (2000) asserts that financial flexibility, modeled by current ratio, has an impact on firms' hedging decisions. More concretely, the fraction of output hedged is greater for firm that have less financial flexibility and are more concerned with maintaining a reliable source of internal cash. Taken together, as the author highlights, these results support the theoretical framework put forward by Froot et al. (1993) and therefore contradict the trade-off theory proposed by Rampini et al. (2014). In light of the empirical support against the former theory, this result seems to introduce a notable inconsistency in the research of risk management. Also, as the paper deals with the oil and gas industry, this inference by Haushalter (2000) is especially interesting to keep in mind and consider as we proceed with our study.

2.3 Other influential papers

The conspicuous wedge between theory and risk management in practice is also addressed by Stulz (1996). He portrays a reality in which larger firms use derivatives to a greater extent than smaller firms, even though the latter often are subject to considerably higher volatility in cash flows. In addition, smaller companies have a much harder time to access capital markets and thus have to rely more heavily on internally generated funds to pursue investment opportunities. Traditional hedging theory stipulates that firms, in the presence of market frictions, can increase firm value by reducing the variability of their cash flows. Firms exposed to changes in interest rates, commodity prices, and exchange rates can, as a result, benefit from the implementation of various risk management strategies. However, beyond the desire to reduce cash flow variance, Stulz (1996) identifies another reason why firms engage in hedging activities: selective hedging. Selective hedging implies incorporating a firm's views about future asset prices, including exchange rates, interest rates, and commodity prices, when taking a position in a derivative contract. These views, in turn, affect the appropriate hedging ratios pursued by the firm. In other words, a limited amount of companies employ the traditional practice of full coverage hedging.

According to survey responses, the practice of selective hedging is widespread and its prevalence complicates the process of analyzing the discrepancy between traditional risk management theory

and the empirical results produced by the literature. Stulz (1996) proposes an updated assessment on the purposes and goals of risk management in practice. He asserts that the extent to which a firm should use derivatives to hedge is contingent on a firm's comparative advantage in bearing a certain financial risk. Consequently, different hedging ratios are warranted and firms should strive to estimate their ability to carry financial risks in various states of the world. According to Stulz (1996), the presence of selective hedging and the notion of comparative advantage in risk-carrying (e.g. information advantage of specific firms in an industry) can explain the inconsistency between risk management in theory and practice.

Another influential paper in the field of risk management is that by Tufano (1996). Unlike Rampini et al. (2014), who focus on the airline industry and input hedging, he analyzes the dynamics of risk management based on the hedging activities of North American gold mining firms. The collected data includes detailed hedging positions of these firms and a clear overview of their mean hedging ratios during the three year sample period between 1990 and 1993. The primary objective of the paper is to investigate the underlying drivers of risk management practices in these firms. The selected factors and proxy variables are theory-inspired and devised to incorporate the most important frictions that can warrant the application of risk management including taxes, managerial risk aversion, and financial distress. Based on these variables, the author conducts a statistical approach to gain insight into the hedging practices of the gold mining firms. The first main finding is the limited to non-existent relationship between risk management and firm characteristics, thus contradicting the theories suggested by value maximization. On the other hand, theories pertaining to the concept of risk aversion seem to be supported by the generated results. This relationship is demonstrated by the positive and statistically significant relationship between managerial stock ownership and risk management. In other words, managers that are more heavily invested in the firms they operate are more susceptible to adverse fluctuations and shocks that limit their claim on and remuneration from the company. In light of these risks, managers tend to take advantage of derivative contracts to maintain more stable cash flows and ultimately reduce the probability of being fired because of poor performance.

2.4 Data considerations

In spite of the differences between the papers by Tufano (1996) and Rampini et al. (2014), it is worth pointing out the similarities when it comes to the detail and heterogeneity of the data. Both papers are based on hedging data designed to thoroughly capture variation in hedging ratios. In contrast, as Rampini et al. (2014) stress, more often than not, empirical papers use categorical variables to model heterogeneity in hedging practices including papers by Guay and Kothari (2003)

and De Angelis and Ravid (2016). More concretely, the variable used to evaluate hedging activities is a dummy variable, taking on a value of 1 if a firm hedges and 0 otherwise. Naturally, this representation can limit the versatility of the results and restrict the applicability of the inferences in a real world context. Guay and Kothari (2003) concede that using a categorical variable to model hedging activities can be misleading and that conclusions drawn from the results can be unreliable. Such a crude distinction between firms that hedge and firms that do not can reduce the explanatory power of the statistical results, thus limiting the understanding of risk management practices. Consequently, this limitation prompted our compilation of a detailed dataset in which fractions of output hedged, rather than categorical variables, for American oil and gas companies are computed and used in the statistical models.

2.5 Research rationale

Based on the existing literature and improved data availability in recent years, we believe that our study can expand and further investigate the domain of risk management, specifically for oil and gas companies. Due to more accessible data sources, we are able to take advantage of a larger dataset than Rampini et al. (2014) within an industry in which risk management is widely used. By creating hedging ratios rather than using dummy variables to model hedging activities, we are able to capture and statistically benefit from the cross-sectional variations between the firms in our dataset. Also, the steep fall in oil prices during the later part of 2014 provides a distinct time-dimensional heterogeneity in order to investigate firms' risk management decisions over time and how they are related to financial constraints. Hence, with a comprehensive and detailed dataset, in addition to a well-suited sample period for a difference-in-differences estimation, we are able to expand the empirical hedging research and test the conflicting theories within risk management by employing a largely overlooked statistical approach.

3. Hypotheses

As the literature review underscores, this study is centered around two conflicting theories that both attempt to explain and illuminate how financing constraints affect firms' hedging decisions. On the one hand, Froot et al. (1993) develops a theoretical framework in which costly external financing can warrant firms to engage in risk management in order to secure stable internal cash flows. Thus, in this framework, financially constrained firms are faced with high costs of external financing and are therefore more inclined to use hedging to circumvent these high costs and ensure more stable investment expenses over time. In other words, this theory predicts a positive relationship between financing constraints and hedging.

In contrast, Rampini et al. (2014) identify the importance of collateral constraints in hedging contracts and introduce the notion of opportunity costs between risk management and financing investments. When financing constraints are high, firms must decide between financing investment opportunities and depositing the required collateral to enter derivative contracts. Because the marginal value of internal cash flows is high, financially constrained firms may prioritize allocating their scarce funds to finance investment opportunities at the expense of risk management. More concretely, this theoretical framework predicts a negative correlation between financing constraints and hedging.

Taken together, in combination with non-concordant results produced by previous papers, these frameworks provide the theoretical contradiction that our study attempts to address. As the theories above predict different results about the relationship between financing constraints and hedging, our hypotheses change depending on what theory is considered. Therefore, in order to construct unanimous hypotheses, we need to select one theory over the other. However, the objective of this paper is simply to test the viability of the trade-off theory in a new and different setting by replicating and expanding on the statistical methodology employed by Rampini et al. (2014). As a result, we refrain from presenting concise hypotheses and instead urge the reader to keep both conflicting theories in mind throughout the paper.

4. Methodology

4.1 Data

The raw dataset contains publicly traded American oil and natural gas companies (SIC code 1311) with total assets greater than $1 million and market capitalization greater than zero, rendering an initial sample of 258 companies. The reason why we impose this criterion is that firms should be large enough to have the capacity to hedge. The oil and gas industry is particularly interesting due to the dramatic changes in commodity prices within our sample period, thereby enabling us to take advantage of the difference-in-differences model. Also, according to Haushalter (2000), even though it is difficult to make broad generalizations of risk management practices in the oil and gas industry, firms are largely exposed to similar risks. In particular, changes in oil and gas prices have a great impact on firms' cash flow volatility. Further, risk management strategies are highly dispersed, implying that hedge ratios can range from 0% to above 100% of output hedged, a substantial variation between firms.

The hand-collected data on hedging activities is manually retrieved from each firm's 10-K filings in the EDGAR database provided by the Securities and Exchange Commission (EDGAR, 2017). From this aggregate compilation, we are able to construct hedging ratios, computed as barrels of oil equivalent hedged in the four quarters ahead divided by the annual production (output) one year ahead, for each company. As mentioned in the literature review, this detailed data specification allows for constructing continuous hedging variables instead of having to rely on a categorical variable to model hedging activities. Also, introducing increased heterogeneity in the hedging variable follows the established papers by Tufano (1996) and Rampini et al. (2014). To conduct the statistical tests, we import financial data from Compustat to construct our independent variables and to obtain oil and gas production data. The variable definitions can be found in table 1 and summary statistics in table 2 in the appendix. From the initial dataset, we find that 37 firms present limited or no documentation in the EDGAR database and are therefore excluded from the final dataset. Also, 4 firms that hedge fail to communicate the volumes of their hedging positions, which are key for computing the hedging ratios in our study, and are therefore left out. Another 2 firms are omitted because we are unable to retrieve production data. which is also crucial for creating hedging variables. Lastly, in accordance with Rampini et al. (2014), we want to investigate hedging behaviour over time, and therefore require firms to have at least five quarters of data throughout the sample period. Ultimately, after all adjustments are accounted for, we end up with a dataset comprising 190 firms.

The sample period is based on quarterly observations and covers a period between Q1 2013 and

Q2 2016. The reason for selecting this particular time period can be attributed to the eventful development of oil prices between these quarters. As figure 1 reveals, oil prices plummeted for several months in 2014 and had a significant impact on net worth, before recovering slightly in the beginning of 2015. The factors that prompted this dramatic drop in oil prices, which were essentially cut in half, can be linked to a variety of economic and political courses of events. One crucial cause is the reduced demand for oil by emerging countries, most notably China, after several years of high demand to fuel rapid economic growth. Another reason is related to Saudi Arabia's decision to keep production unchanged, despite dropping oil prices, instead of conceding market share. Since Saudi Arabia has the world's largest oil reserves, it can endure lower oil prices without severely impacting the health of its economy (Arnsdorf, 2014). In any event, the free fall of oil prices provides an interesting basis, and notable heterogeneity, in order to evaluate hedging behaviour for oil and natural gas companies in the time dimension. In other words, the chosen time period, with abnormally low oil prices after the beginning of 2015, introduces suitable preconditions in order to investigate if firms alter their hedging activities when faced with aggravated financial conditions. In addition, the time period naturally provides an updated view on to what extent these firms engage in risk management. The statistical results generated by our study can then, in turn, be compared and contrasted with the results from previous papers on determinants of hedging. Ultimately, the completed dataset allows for an empirical investigation with both cross-sectional and time series elements.

In relation to the dynamic trade-off theory proposed by Rampini et al. (2014), it is important to address potential industrial differences in collateral constraints between airline companies and oil and gas companies. As we mentioned briefly in the literature review, Rampini et al. (2014) present several accounts in which airlines discuss the importance of collateral constraints in risk management decision-making. These companies stress the potential impact of having to deposit cash as a part of entering into derivative contracts on their liquidity in the event of adverse fluctuations in the underlying asset. As a result, the airline industry represents a suitable basis for investigating the trade-off theory between financing investments and engaging in risk management. In light of the importance of collateral constraints in the airline sector, we aim to present comparable evidence from the oil and gas industry in order to support our data selection and thereby enable more consistent comparisons between the results of the two studies. As it turns out, the relevance of collateral constraints in oil and gas companies is similar to that in airlines. Below, we present two accounts from the 2015 annual reports by Anadarko Petroleum Corporation and Devon Energy Corporation to highlight this importance.

"*The Company's [Anadarko Petroleum Corporation's] derivative instruments are subject to individually negotiated credit provisions that may require the Company or the counterparties to provide collateral of cash or letters of credit depending on the derivative portfolio valuation versus negotiated thresholds. These credit thresholds may also require full or partial collateralization or immediate settlement of the Company's obligations if certain credit-risk-related provisions are triggered such as if the Company's credit rating from major credit rating agencies declines to a level that is below investment grade."* (EDGAR, 2017a)

"*Additionally, Devon's derivative contracts generally require cash collateral to be posted if either its or the counterparty's credit rating falls below certain credit rating levels. As of December of 31, 2015 and December 31, 2014 Devon held $75 million and $524 million, respectively, of cash collateral, which represented the estimated fair value of certain derivative positions in excess of Devon's credit guidelines."* (EDGAR, 2017b)

4.2 Statistical models and variables

4.2.1 Calibration with Rampini et al. (2014)

The first part of the statistical investigation in this paper, including variables and models, is inspired by that employed by Rampini et al. (2014). This calibration approach allows for a direct comparison between our results, which are based on updated data from another industry, and their results. Consequently, we are able to investigate the discrepancy between risk management theory and practice by evaluating the validity of the aforementioned trade-off theory in a different setting. Embedded in this dynamic trade-off theory is the prediction that less constrained firms should hedge more whereas more constrained firms should hedge less.

Rampini et al. (2014) incorporate this continuum of financing constraints by presenting correlation diagrams between fractions of fuel hedged and various theory-inspired variables aimed at capturing different levels of financing constraints. From these diagrams, they conclude that firms' net worth, both based on book and market value, have a strong and positive correlation with the fraction hedged by airlines. As a result, consistent with a number of previous studies, Rampini et al. (2014) primarily use firm size to model varying levels of financing constraints. For completeness and statistical continuity, the authors also construct net worth variables scaled by total assets in order to generate normalized and more robust results. Scaling net worth with total assets is expected to produce similar results (same coefficient signs) as using net worth in absolute terms, indicating that the level of net worth is an important determinant of how much firms hedge. If net worth is low,

the presence of collateral constraints implies that firms may be more inclined to use internal resources to finance investments at the expense of hedging. This initial setup generates four independent variables, net worth and net worth to assets in both book and market value, all of which are used separately in the panel data estimations with fraction hedged as dependent variable. In other words, the authors only include one independent variable at a time to measure its effect on how much airlines hedge.

As a final part of the standard panel estimations, Rampini et al. (2014) construct a classification system in which firms are assigned points based on their credit ratings. The allocation of points is set up so that firms with the highest credit ratings receive 4 points whereas firms on the other end of the spectrum receive 1 point, resulting in a series of 4 groups in total. In effect, this division is meant to generate an ordering of firms based on their financial constraints, as more constrained firms are assigned the lowest scores. The four groups are then included in the panel estimations, as an extension to the initial estimations. Also, the three groups with the lowest credit rating scores are then separately compared to the group with highest credit ratings. In our case, a number of firms in the sample lack credit ratings and can therefore not be included in these estimations. However, as previously stressed, our dataset is comprehensive and we ultimately end up with a large enough sample to reliably investigate the relationship between credit ratings and hedging output.

4.2.2 Difference-in-Differences estimations

After calibrating our results with our reference paper, the next focus is to investigate the effect of the fall in commodity prices from Q2 2014 on firms' hedging activities with different ex-ante financial constraints. Arguably, the fall in output prices is an exogenous shock to all firms in our sample and due to the significance of the price change, the ex-ante "constrained" firms should become even more constrained after the fall in output prices. Subsequently, according to Rampini et al. (2014) and their trade-off theory between financing and risk management, one expects the hedging activities of the constrained firms to diminish. Using a difference-in-differences estimation is an effective approach to exploit our sample characteristics with a distinct time-dimensional heterogeneity. Also, by using a different approach we can assess the strength of the trade-off theory, and thereby contribute to and expand upon the existing research.

The difference-in-differences (DID) estimation approach is a model designed to estimate causal effects (Lechner 2011). It is a popular model often used in empirical economics to investigate the effect of exogenous shocks such as policy changes or other exogenous shocks by comparing a "treatment" and a "control" group over time. To illustrate, a common scenario involves comparing

a group affected by a policy change with a group that has not been subjected to a policy change. Also, in order to make a relevant comparison, the two groups need to have similar characteristics ex ante a policy change is implemented. One important assumption in the DID estimation is that the control group and the treatment group should follow a "parallel trend" in the absence of an exogenous shock.

According to Lechner (2011), the standard DID estimation involves comparing four different groups of objects consisting of two groups over time (two states). Therefore, in a standard DID estimation, there is a "pre-treatment control group", "post-treatment control group", "pre-treatment treatment group", and "post-treatment treatment group".

For repeated cross-sections, one obtains the following model (Imbens and Wooldridge, 2009):

$$y = \beta_0 + \beta_1 dB + \delta_0 d2 + \delta_1 d2 \cdot dB + u \qquad (1)$$

where y is the dependent variable of interest, $d2$ is the dummy variable for the second time period, capturing factors that would affect the control and treatment group in absence of a change. dB captures possible differences between the control and treatment group. The coefficient $\hat{\delta}_1$ is what is interesting in the DID estimation as it shows the interaction between $d2$ and dB, i.e. the difference between the control group and treatment group in the second time period. Imbens and Wooldridge (2009) mathematically present $\hat{\delta}_1$, the DID estimate, in the following way:

$$\hat{\delta}_1 = (\bar{y}_{B,2} - \bar{y}_{B,1}) - (\bar{y}_{A,2} - \bar{y}_{A,1}) \qquad (2)$$

This equation can be solved using simple arithmetic by comparing the means between the different states and groups. According to Imbens and Wooldridge (2009), the DID estimation removes biases both between the groups and over time. By subtracting the control group's mean with the treatment group's mean, one removes biases in the second period, which could potentially be a result of permanent differences between the two groups. Also, by taking differences over time, one is able to remove trend features in the data.

In model 1, as seen above, y is our hedging ratio, $d2$ is a dummy variable that takes on a value of 0 in the time period Q1 2013 - Q2 2014 and a value of 1 in the time period Q3 2014 – Q2 2016. dB is also a dummy variable that takes on a value of 0 if a firm is in the control group and a value of 1 if a firm is in the treatment group. Hence, our DID estimate can be specified as follows:

$$\hat{\delta}_1 = \left(\overline{h.\ ratio}_{treated,2} - \overline{h.\ ratio}_{treated,1}\right) - \left(\overline{h.\ ratio}_{control,2} - \overline{h.\ ratio}_{control,1}\right)$$

The assignment of a firm to either the control or the treatment group depends on the different proxies we use for financial constraints (or financial distress), such as size measured by net worth, as defined by Rampini et al. (2014). To illustrate, when we create our control and treatment group, we sort size from highest to lowest in state 1 (i.e. time period Q1 2013 – Q2 2014). As we consider smaller firms to be more financially constrained than larger firms, we assign firms below the median sized firm to the treatment group and firms above the median to the control group. The reason why we assign firms in state 1 is that we want to investigate the effect of the fall in oil prices. Hence, to do this, we have to identify those firms that are more financially constrained prior to the price fall. Subsequently, when conducting our DID estimations according to model 1, we are able to statistically test what effect the fall in output prices had on hedging activities for small and large firms, respectively.

To obtain a more intuitive feeling of the data structure, the difference between the treatment and control groups, and the effect of the fall in oil prices, it is helpful to look at parallel trend figures illustrating the development of the control and treatment groups (see figure 2 - 7 in the appendix). Perhaps the most compelling evidence for such a trend is found by analyzing figure 2. This graph seems to make a strong argument for applying difference-in-differences estimation in which one can see that the control and treatment group converge in state 2. One can also see important differences between figure 2 and 3. When we exclude "non-hedgers" in figure 3 (i.e. firms that do not hedge at all during the sample period), the average hedging ratios of the control group remains fairly stable, whereas it is increases slightly when non-hedgers are included in figure 2. One reason for this could be that as time progresses, a portion of the non-hedgers may leave the sample perhaps due to bankruptcy, which in turn increases the average hedging ratio without an actual hedging increase for those that do hedge. Hence, we address this potential issue by creating a constant sample in which only the firms who survive throughout the whole time period are included. Although this method creates a survivorship bias, we argue that this method is relevant to control for significant changes relating to previous tests.

4.2.2.1 Variables used for sorting the DID estimations

As the primary objective of this paper is to test the theory established by Rampini et al. (2014) we initially sort our sample after net worth (both book value and market value) and net worth to assets (also both book and market value). In terms of these variables, unconstrained firms are located above the median value (control group) and constrained firms are found below the median value

(treatment group). The hypothesis, consistent with the trade-off theory proposed by Rampini et al. (2014), is that constrained firms should hedge less in state 2 as they should be more limited by the imposition of collateral constraints than unconstrained firms.

4.2.2.2 Inclusion and exclusion of non-hedgers

Due to the structure and versatility of our dataset, we conduct the DID estimations in different settings. One important composition to consider is that the dataset includes both firms that hedge, but also firms that do not hedge at all during the sample period. Hence, we estimate our regressions and DID estimations based on both including and excluding "non-hedgers" in order to evaluate potential differences between the model specifications. As for the allocation of firms, approximately 46% of the firms in the sample are "non-hedgers" and therefore have a hedging ratio of 0. In practice, the most important reasons why we distinguish between these two model setups are to improve statistical robustness and assess the sensitivity of our results.

4.2.2.3 Sorting by most unconstrained and constrained firms

After we have conducted the initial DID estimations, we limit our samples to those firms that are the most constrained and unconstrained. For the sample including non-hedgers, we conduct two tests. In the first, we include the 75 most unconstrained firms and the 75 most constrained firms. In the second test we include the 50 most unconstrained firms and 50 most constrained firms. By dividing the sample as explained above, we are able to evaluate the sensitivity of our results, and also see the difference between the most extreme cases in our sample. As for the sample excluding non-hedgers, we apply the same approach but due to the smaller sample size we instead conduct the two tests by including the 40 and 20 most extreme cases respectively.

4.2.2.4 Constant sample

In another statistical robustness test, as discussed above, we only include firms that have observations throughout the whole time period. This specification creates a survivorship bias. However, we conduct this sampling approach as we suspect that average hedge ratios may be substantially impacted by firms, especially non-hedgers, that fall out of sample. Hence, the constant sample setup is used to compare the sensitivity of our results when we allow firms to leave the sample throughout the selected time period.

4.2.2.5 Financial distress

To test how hedging activities are affected by financial distress, we specifically choose firms that have positive operating income in state 1, but that exhibit a specific number of quarters with negative operating income in state 2. We consider a firm to be in distress when it has experienced at least two quarters with negative operating income in state 2. For further robustness, we conduct

additional tests in which we include firms with at least 4 quarters of negative operating income. By conducting these tests, we are able to find those firms that have been the most negatively affected by the price fall and to investigate how financial distress impacts firms' hedging behaviour.

5. Results

5.1 Calibration with Rampini et al. (2014)

In general, we find that our results match those presented by Rampini et al. (2014) although coefficient values differ. More concretely, our initial results show that less financially constrained firms hedge more relative to more financially constrained firms. Consequently, after evaluating the first part of the statistical results, we can conclude that there seems to be some merit to the theory of collateral constraints.

Table 3 and 4 show panel estimates, both including and excluding non-hedgers, and replicate table 4 of Rampini et al. (2014). As for table 3, we obtain similar results to those presented by Rampini et al. (2014), although magnitudes are slightly different. We find statistically significant results for both net worth (book value) and credit ratings. However, our results for net worth (book value) is not economically significant. Still, our credit rating estimates show that if a firm moves down the scale of credit quality, it reduces its hedging during the next year with approximately 9%. This result is also shown in the last column "credit rating dummies" in which firms with the worst credit ratings hedge 15% less relative to firms with credit ratings equal to or higher than BBB-.

When we exclude non-hedgers in table 4, we obtain largely similar results. The greatest difference is that net worth to assets (book value) becomes both economically and statistically significant, meaning that one unit increase in net worth to assets (book value) implies a 10% increase in output hedged in the next year. One can also see that credit ratings are only significant on a 11% significance level. The credit rating dummies are similar to the results produced by the estimates including non-hedgers.

In conclusion, by largely following the methodology used by Rampini et al. (2014), we find similar results, but in another industry and with a completely different dataset. The most apparent results supporting the theory of collateral constraints, when we include non-hedgers, is those of the credit ratings and the credit rating dummies. When a firm is financially constrained (low credit rating), it hedges less in comparison to more unconstrained firms. Also, when we exclude non-hedgers, the results from the credit rating dummies and net worth to assets (book value) show consistent evidence with that of Rampini et al. (2014).

5.2 Difference-in-Differences estimations with variables from Rampini et al. (2014)

As seen above, there seems to be some merit to the theory of collateral constraints shown by simply mimicking the statistical methodology employed by Rampini et al. (2014). However, in order to

improve statistical robustness, we expand our empirical research by using a different methodology largely unutilized in the context of hedging. These estimations involve a wide range of model specifications aimed at assessing how sensitive our results are to these alterations and strengthening our results and overall conclusions.

5.2.1 Including non-hedgers

Looking at the results from the DID estimates in general, we find evidence that both supports and undermines the theory of collateral constraints. Please note that the variable "Time x treated" is the variable of interest (model 2 in the methodology), as it shows how constrained firms alter their hedging behaviour in state 2 relative to the more unconstrained firms. Table 5 in the appendix shows DID estimates for tests that include non-hedgers, sorted for net worth and net worth to assets (book and market value). Looking at net worth, we obtain positive and statistically significant coefficients, a result that conflicts with the collateral theory presented by Rampini et al. (2014). In other words, these results imply that more constrained firms increase their hedging relative to unconstrained firms in state 2. The results when we use the constant sample are shown in table 9. Here, we also obtain positive coefficients but only net worth based on book value is statistically significant. However, as we apply the best/worst settings (the 75 and 50 most unconstrained and constrained firms), the same coefficients become increasingly insignificant (see table 7).

When we sort the groups according to net worth to assets, we obtain negative and significant coefficients. In other words, in contrast to using net worth in absolute terms, these results support the theory of collateral constraints as the more constrained firms hedge less in state 2 and vice versa. The statistical significance for the same coefficients decreases slightly as we consider the 75 and 50 most constrained and unconstrained firms in which net worth to assets book value is insignificant but that of market value remains significant close to a 5% level. More concretely, the net worth to assets coefficients are largely consistent when we limit our sample to the 75 and 50 most unconstrained and constrained firms, and when we keep a constant sample throughout the sample period.

5.2.2 Excluding non-hedgers

As for the DID estimations in which we exclude non-hedgers, a similar story emerges. A notable difference, however, is that the net worth coefficients become statistically insignificant in the standard setup even though their signs remain positive (see table 6). When considering the best/worst (see table 8) and constant sample setups (see table 10), these coefficients remain highly insignificant. In contrast, the net worth to assets coefficients are all statistically significant (and negative) on a 5% significance level regardless of the model specification.

We find similar evidence when we sample firms in financial distress, see table 11 including non-hedgers and table 12 excluding non-hedgers. For firms with 2 and 4 negative quarters, net worth to assets coefficients are negative and significant. When we include non-hedgers, net worth (book value) is consistently positive and significant.

6. Analysis

The first part of the results section is intended to enable a direct comparison with the results presented by Rampini et al. (2014), and thereby evaluate the viability of the collateral theory in a different industry with an updated dataset. In addition, since Rampini et al. (2014) study the airline industry and input hedging, whereas our study investigates output hedging, we are able to extend the practical applicability of the trade-off theory by contributing to a more generalizable theory across industries.

As we concluded above, the obtained results from the calibration section are largely consistent with those found by Rampini et al. (2014). Even though the coefficients and statistical significance of the tests differ in magnitude, the same conclusion can be drawn in the context of collateral constraints, i.e. financially unconstrained firms tend to hedge more than financially constrained firms.

Based on these initial results, our study joins the previous papers that have discovered a negative relationship between financing constraints and hedging activities. Consequently, the theoretical framework established by Froot et al. (1993) is further called into question as it disregards the importance of collateral constraints. Instead, the presence of collateral constraints seems to limit the possibilities of more financially constrained firms with less available cash to use in derivative contracts. These firms also often operate in highly competitive and versatile business environments in which firm managers generally lack the financial cushion, enjoyed by more unconstrained firms, to rely on in the event of economic adversity. As a result, in order to survive in the long run, these firms may prioritize to allocate their cash to finance investments or focus on other expenses instead of resorting to risk management that requires reallocation of limited cash to a deposit account required for hedging contracts.

However, using each variable separately in the statistical tests can be problematic because of endogeneity and omitted variable bias, resulting in unreliable coefficient estimates. Also, the use of firm size and credit ratings as proxy variables is arguably subject to an endogeneity problem. The fact that large firms for instance have more investments, financial sophistication, access debts markets and board-level exposures indicate that there are several factors explaining firms' hedging activities. Therefore, one should interpret these initial results with caution and refrain from making any definitive inferences about firms' hedging behaviour.

Even though the results from the first part of the statistical models provide some insights into oil and natural gas companies' hedging activities, it is the difference-in-differences estimations that

make our study unique and thus warrant the lion's share of our attention. These estimations allows for a more detailed examination of how these firms change their hedging behaviour as oil prices fall and financial constraints intensify across the industry. By using the DID estimations, we isolate the effect of financial constraints on hedging activities by making use of the fall in oil prices. Hence, the DID estimation solves the problem of endogeneity by more clearly highlighting the causal link between financial constraints and hedging.

Identical to the calibration part of the results section, net worth variables, both in absolute terms and scaled with assets, comprise the cornerstone of the DID estimations. However, as our initial results reveal, the DID estimates are influenced by whether net worth or net worth scaled by assets is used. Perhaps the most compelling evidence that can highlight the relative strength between net worth in absolute terms and net worth scaled by assets, can be found by comparing figure 2 and 4. For net worth to assets, the constrained firms hedge less over time whereas unconstrained hedge more, and there is a seemingly strong pattern over time. In comparison, when using net worth, the development over time is less obvious, pointing to the sensitivity of different sample configurations discussed earlier in the results section. The control and treatment group clearly follow a parallel trend, but the effect of the oil price fall is quite significantly less apparent when using net worth compared to net worth scaled by assets. As we conclude in the results section, using net worth to assets produces statistically significant coefficients whereas net worth coefficients become highly insignificant as we change model setup. Considering this difference, and the relative effects of the price fall from eyeballing investigation, the net worth to asset variables produce more explanatory and convincing results.

When considering the estimations in which non-hedgers are included, we find that the signs of the DID estimates (coefficients) are positive when sorting for net worth in absolute terms but negative when sorting for net worth scaled by assets. The positive coefficients indicate that larger firms decrease hedging in state 2 whereas smaller firms increase hedging, implying a convergence in hedging ratios of the two groups over the time period, as seen in figure 4. Interestingly, these results contradict those predicted by the collateral theory, which states that when firms are more financially constrained, they should not afford to increase hedging, especially those firms that are noticeably constrained ex-ante (state 1 in our setup). However, when considering the DID estimates based on net worth scaled by total assets, another story emerges. The coefficients from these estimations, regardless of model setup, imply that firms with higher net worth to assets ratios hedge more in state 2 whereas firms with lower ratios hedge less. This trait can clearly be seen when we plot the two groups against each other in figure 2.

In order to interpret these conflicting results, it is important to dissect the net worth to assets ratio so as to understand what a high or low ratio actually mean in this context. Regardless of whether net worth is based on market value or book value, a high net worth to assets ratio implies that a firm's assets is financed primarily by equity. Conversely, a low net worth to assets ratio means a substantial portion of debt financing. In other words, the net worth to assets ratio can be viewed as something similar to an inverse leverage measure with high ratios indicating low leverage and vice versa. This interpretation is intuitively appealing as firms with low net worth to assets ratios (higher leverage) should have higher interest payments and therefore a reduced ability to deposit cash in a collateral account. However, the net worth to assets measure could initially be questioned as a measure of financial constraints, but due to the mechanical effects of net worth to assets being strongly negatively correlated with leverage (see table 13), and leverage being according to Whited (1992) and Haushalter (2000) a measure of financial constraints, it clearly has its merits. In order to confirm this assertion and improve statistical robustness, we incorporate a similar but more commonly used leverage metric in our DID estimations to compare the results. As it turns out, the DID coefficients from these new estimations point to the same conclusion as more highly leveraged firms (ex-ante the exogenous shock) tend to reduce their outstanding hedging contracts in the second period (see leverage coefficients in table 5 and 6). This result is also confirmed by comparing the parallel trends in figure 3 and 7 in which there are clear similarities. However, due to the ambiguity of the results between using net worth in absolute terms and scaled by assets, we use different sampling methods to compare the results and investigate the sampling sensitivity of our initial results.

When we compare our results in table 5 when we include non-hedgers with table 6 excluding non-hedgers one can see that the coefficients for net worth in absolute terms are still positive but statistically insignificant. The net worth to assets ratios however, are both still negative and significant, suggesting that these results are more insensitive to different sampling configurations. In fact, when we exclude non-hedgers from the sample, we cannot find any significant results for net worth in absolute terms for the majority of our model setups, that is, taking the 40 and 20 most unconstrained and constrained firms and using the constant sample. As the net worth to assets coefficients are significant for all sample specifications, the theory of collateral constraints is supported in the data. Still, one should be aware of the bias that we create when excluding the non-hedgers from the sample as we do not use a full representation of hedging activities in the industry. However, the comparison between the two sample configurations are still highly relevant to test the sensitivity of our results.

Considering this bias, we also conduct the same sample configurations when we include non-hedgers. The results in table 7 reveal that when we test the 75 and 50 most unconstrained and constrained firms, we do not find significant coefficients for net worth in absolute terms but we find significant results for net worth to assets, further supporting the theory of collateral constraints, and that the results involving net worth are more sensitive to the sample structure than those based on net worth to assets. However, when we use a constant sample, we find that net worth (book value) is significant and positive. Consequently, as the results above highlight, there seems to be inferential differences between using net worth in absolute terms (i.e. firm size) and net worth to assets (i.e. approx. inverse leverage) in the DID estimates. When using net worth, smaller and theoretically more financially constrained firms seem to hedge more in state 2 and vice versa for larger firms, in our model specification. In contrast, as we adopt net worth to assets measures, more indebted and thus financially constrained firms hedge less in the second period.

Rampini et al. (2014) show in their paper that hedging is highly affected when a firm is in distress and show a timeline when selected firms' credit quality deteriorates. Instead of using credit ratings, we employ a similar approach as a way to explore similar patterns. We choose firms that have strictly positive operating income in state 1, and select those firms that have a specific number of quarters with negative operating income in state 2. Arguably, as firms exhibit negative operating income, there is more uncertainty with regards to internal cash flows and firms' ability to deposit funds in derivative accounts is more limited. As a result, according to the collateral theory, firms with negative operating income are likely to have issues of liquidity in the near future and may therefore reduce hedging positions. We conduct two tests in which firms with both 2 and 4 negative quarters are included in order to investigate the effect of the price fall on hedging. The results covering distress are consistent with previous results, i.e. net worth coefficients are positive, insignificant, and more sensitive to the sampling setup in comparison to coefficients based on to net worth scaled by assets. On the other hand, net worth to assets coefficients are negative and highly significant, with book values showing the most consistent results. Based on a statistical comparison, using net worth to assets is clearly superior to using net worth

Using size as a proxy for financing constraints has its merits, as it is commonly utilized in several academic papers, but also seems to be a somewhat blunt measure in general. There are a range of factors that are captured by size, and entangling these various forces is not a simple undertaking. Specifically, besides being a proxy for financing frictions, it can also be a proxy for (on average) more investments, more leverage, greater board level exposures and so on. As seen in this paper, size and leverage have different effects on hedging and therefore it is hard to establish exactly what,

in terms of size, determines changes in hedging. The net worth to assets ratio reveals a company's relative portion of debt and equity. Also, it seems reasonable to assume that the connection between leverage and financing constraints is rather direct and clear-cut. In the presence of collateral constraints, more highly leveraged firms should have a harder time to spare precious cash resources in order to enter into derivative contracts since loan repayments have to be made more frequently and in larger amounts. Therefore, even though it is commonly verified that these firms tend to hedge more relative to low leverage firms, we show that these firms will not, or cannot, hedge after a severe exogenous shock. One potential reason for this is the fact that the industry after the price fall faced severe financial conditions in terms of falling profit margins and significantly reduced credit availability, creating severe constraints for those firms highly dependent on debt financing (The Economist Oct 8, 2015). Therefore, for highly leveraged firms, being more financially constrained and distressed, the marginal value of internal cash flows should have increased substantially and the value of hedging should have decreased as collateral constraints impact the relative utility of risk management.

7. Conclusion

Using the paper *Dynamic Risk Management* by Rampini et al. (2014) as a reference point and inspirational source, we initially conduct a set of statistical tests to investigate the theory of collateral constraints in the North American oil and gas industry. In order to ensure a clear-cut and direct comparison, these first tests are replications of those presented in our reference paper. The results from these tests are consistent with those produced by Rampini et al. (2014), indicating that financially constrained firms hedge less than financially unconstrained firms. Consequently, this result provides additional support for the importance of collateral constraints in firms' hedging decisions. At the same time, the influential theoretical framework established by Froot et al. (1993), which emphasizes the significance of costly external financing, is further called into question.

To expand the empirical methodology and gain additional insight into how oil and gas firms change their hedging behaviour in the event of a severe exogenous shock, in the form of plummeting oil prices, we employ a difference-in-differences approach. By using this statistical model, we can evaluate how financially constrained and unconstrained firms, ex-ante the price fall, alter their hedging in the second time period in which financial constraints intensify and financial conditions worsen. As the analysis clearly highlights, the results from these estimations point to a crucial difference between using net worth and net worth to assets in the model specifications. However, based on statistical significance and sampling configurations, using net worth in absolute terms is seemingly inferior to net worth scaled by assets. Therefore, the results from the estimations based on net worth to assets are more reliable when evaluating the theory of collateral constraints. Consistent with the theoretical framework, these results reveal that more financially constrained firms hedge less in state 2 and vice versa, thus supporting the significance of collateral constraints in the North American oil and gas industry. In conclusion, based on the results from the calibration section and the DID estimations, there definitely seems to be some merit to the trade-off theory proposed by Rampini et al. (2014) and we encourage researchers to further explore its relevance in risk management.

8. References

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9. Appendix

Table 1 - Variables	
Variables	Descriptions
	note: Compustat abbreviations in parentheses
Hedge ratio	Barrels of oil equivalent hedged in the four quarters ahead divided by the annual production one year ahead
Net worth (bv)	Shareholder's equity (SEQQ)
Net worth (mv)	Total assets + price per share × number of shares - common equity - deferred taxes - total liabilities (ATQ+PRCC_FQ×CSHOQ-CEQ-TDXBQ-LTQ)
Net worth to assets (bv)	Shareholder's equity divided by total assets (SEQQ/ATQ)
Net worth to assets (mv)	(ATQ+PRCCQ×CSHOQ-CEQQ-TDXBQ-LTQ) divided by market value of common stock + total liabilities + preferred stock - deferred taxes (CSHOQ× PRCCQ+LTQ+PSTKQ-TDXBQ)
Credit rating	CCC+ or worse = 1, B-, B, or B+ = 2, BB-, BB, or BB+ = 3, BBB- or better = 4 (LTRATING)
Leverage	(Short term debt + long term debt) divided by (short term debt + long term debt + market value of equity) (DLCQ+DLTTQ/DLCQ+DLTTQ+PRCCQ× CSHOQ)
Operating income	Operating income before depreciation (OIBDQ)

Table 2 - Summary statistics (including non-hedgers)						
Variables	N	Mean	SD	10th	50th	90th
Hedge ratio	2219	0,2804	0,3208	0	0,1453	0,7729
Net worth (bv), $M	2349	1841	5076	-3	172	4241
Net worth (mv), $M	2349	3000	7931	9	287	7820
Net worth to assets (bv)	2349	0,2414	1,4947	-0,1587	0,4565	0,8194
Net worth to assets (mv)	2349	0,5702	0,2922	0,1541	0,5837	0,9331
Credit rating	1000	2,4590	0,8747	2,000	2,000	4,000
Leverage	2380	0,3183	0,2769	0,000	0,2681	0,7622
Operating income, $M	2380	43	521	-76	1	238

Table 3 - Panel OLS (including non-hedgers)

*note: Coefficients that are statistically different from zero at the 1%, 5% and 10% significance level are denoted: **, *, and +, respectively. All regressions include firm and year fixed effects, and standard errors are clustered at the firm level. For variable definitions, see table 1.*

Dependent variable: Fraction of next year's output hedged

	Net worth to assets (bv)	Net worth to assets (mv)	Net worth (bv)	Net worth (mv)	Credit rating	Credit rating dummies
Coefficients	0,0122	-0,0494	0,0000	0,0000	0,0934	
P-values	(0,3408)	(0,3663)	(0,0116)	(0,3573)	(0,0109)	
Rating = BB-, BB, or BB+						0,0102
						(0,8815)
Rating = B-, B, or B+						-0,0060
						(0,9400)
Rating = CCC+ or worse						-0,1593
						(0,0889)
Observations	2191	2191	2191	2191	941	941
R-squared	0,8401	0,8396	0,8414	0,8394	0,7819	0,7856

Table 4 - Panel OLS (excluding non-hedgers)

*note: Coefficients that are statistically different from zero at the 1%, 5% and 10% significance level are denoted: **, *, and +, respectively. All regressions include firm and year fixed effects, and standard errors are clustered at the firm level. For variable definitions, see table 1.*

Dependent variable: Fraction of next year's output hedged

	Net worth to assets (bv)	Net worth to assets (mv)	Net worth (bv)	Net worth (mv)	Credit rating	Credit rating dummies
Coefficients	0,0969	-0,0931	0,0000	0,0000	0,0852	
P-values	(0,0025)	(0,3657)	(0,0399)	(0,7149)	(0,1021)	
Rating = BB-, BB, or BB+						-0,0446
						(0,4084)
Rating = B-, B, or B+						-0,0732
						(0,3925)
Rating = CCC+ or worse						-0,1773
						(0,0414)
Observations	1432	1432	1432	1432	890	890
R-squared	0,7429	0,7305	0,7325	0,7291	0,7783	0,7788

Table 5 - DID estimations (including non-hedgers)					
*note: Coefficients that are statistically different from zero at the 1%, 5% and 10% significance level are denoted: **, *, and +, respectively. Please note that the variable "Time x treated" is the variable of interest (model 2 in the methodology).*					
Dependent variable: Fraction of next year's output hedged					
Sorted by	Net worth (bv)	Net worth (mv)	Net worth to assets (bv)	Net worth to assets (mv)	Leverage
Time (*coefficient*)	-0,0328+	-0,0427*	0,0386*	0,0453**	0,0371*
P-value	0,0740	0,0147	0,0273	0,0056	0,0124
Treated	-0,3296**	-0,3352**	0,1149**	0,2297**	0,3293**
	0,0000	0,0000	0,0000	0,0000	0,0000
Time x treated	0,0499*	0,0634**	-0,0864**	-0,1056**	-0,1120**
	0,0353	0,0068	0,0020	0,0001	0,0000
Observations	2191	2191	2191	2191	2219
R-squared	0,2213	0,2118	0,0152	0,0749	0,1751

Table 6 - DID estimations (excluding non-hedgers)					
*note: Coefficients that are statistically different from zero at the 1%, 5% and 10% significance level are denoted: **, *, and +, respectively. Please note that the variable "Time x treated" is the variable of interest (model 2 in the methodology).*					
Dependent variable: Fraction of next year's output hedged					
Sorted by	Net worth (bv)	Net worth (mv)	Net worth to assets (bv)	Net worth to assets (mv)	Leverage
Time	-0,0694**	-0,0533**	0,0007	-0,0181	-0,0085
	0,0009	0,0094	0,9725	0,3657	0,6588
Treated	-0,1591**	-0,1314**	0,1267**	0,0610*	0,2171**
	0,0000	0,0000	0,0000	0,0116	0,0000
Time x treated	0,0445	0,0072	-0,1272**	-0,0781*	-0,0972**
	0,1566	0,8204	0,0001	0,0191	0,0022
Observations	1432	1432	1432	1432	1432
R-squared	0,0545	0,0479	0,0233	0,0101	0,0779

Table 7 - DID estimations (best/worst specifications - including non-hedgers)

*note: Coefficients that are statistically different from zero at the 1%, 5% and 10% significance level are denoted: **, *, and +, respectively. Please note that the variable "Time x treated" is the variable of interest (model 2 in the methodology).*

Dependent variable: Fraction of next year's output hedged

Sorted by	Net worth (bv)	Net worth (mv)	Net worth to assets (bv)	Net worth to assets (mv)
75 best/worst				
Time	-0,0400+	-0,0491*	0,0402*	0,0481**
	0,0473	0,0143	0,0195	0,0099
Treated	-0,3722**	-0,3703**	0,2245**	0,2466**
	0,0000	0,0000	0,0000	0,0000
Time x treated	0,0288	0,0367	-0,0647*	-0,0634*
	0,2370	0,1468	0,0205	0,0257
Observations	1813	1787	1784	1799
R-squared	0,3037	0,2862	0,0978	0,1128
50 best/worst				
Time	-0,0287	-0,0159	0,0236	0,0556**
	0,2523	0,5275	0,1650	0,0052
Treated	-0,3705**	-0,4006**	0,1854**	0,2723**
	0,0000	0,0000	0,0000	0,0000
Time x treated	-0,0001	0,0275	-0,0492	-0,0658+
	0,9972	0,3332	0,1172	0,0509
Observations	1179	1155	1149	1190
R-squared	0,3300	0,3550	0,0866	0,1466

Table 8 - DID estimations (best/worst specifications - excluding non-hedgers)

*note: Coefficients that are statistically different from zero at the 1%, 5% and 10% significance level are denoted: **, *, and +, respectively. Please note that the variable "Time x treated" is the variable of interest (model 2 in the methodology).*

Dependent variable: Fraction of next year's output hedged

Sorted by	Net worth (bv)	Net worth (mv)	Net worth to assets (bv)	Net worth to assets (mv)
40 best/worst				
Time	-0,0494	-0,0314	0,0296	0,0216
	0,0581	0,2223	0,2758	0,4156
Treated	-0,1355**	-0,1332**	0,2059**	0,1642**
	0,0000	0,0000	0,0000	0,0000
Time x treated	-0,0182	-0,0249	-0,1287**	-0,0920*
	0,6211	0,5020	0,0004	0,0137
Observations	1020	1008	1012	1023
R-squared	0,0628	0,0607	0,0653	0,0415
20 best/worst				
Time	-0,0261	-0,0294	-0,0001	0,0615
	0,5069	0,4576	0,9971	0,1136
Treated	-0,1307**	-0,1261**	0,2218**	0,1580**
	0,0006	0,0006	0,0000	0,0001
Time x treated	-0,0416	0,0066	-0,1160*	-0,1777**
	0,4463	0,9031	0,0254	0,0012
Observations	507	505	494	507
R-squared	0,0596	0,0377	0,0906	0,0302

Table 9 - DID estimations (constant sample - including non-hedgers)

*note: Coefficients that are statistically different from zero at the 1%, 5% and 10% significance level are denoted: **, *, and +, respectively. Please note that the variable "Time x treated" is the variable of interest (model 2 in the methodology).*

Dependent variable: Fraction of next year's output hedged

Sorted by	Net worth (bv)	Net worth (mv)	Net worth to assets (bv)	Net worth to assets (mv)
Time	-0,0794**	-0,0615**	0,0073	-0,0065
	0,0004	0,0046	0,7268	0,7476
Treated	-0,2885**	-0,2632**	0,2321**	0,2468**
	0,0000	0,0000	0,0000	0,0000
Time x treated	0,0731*	0,0365	-0,1377**	-0,1101**
	0,0139	0,2221	0,0000	0,0006
Observations	1456	1456	1456	1456
R-squared	0,1648	0,1550	0,0741	0,0924

Table 10 - DID estimations (constant sample - excluding non-hedgers)

*note: Coefficients that are statistically different from zero at the 1%, 5% and 10% significance level are denoted: **, *, and +, respectively. Please note that the variable "Time x treated" is the variable of interest (model 2 in the methodology).*

Dependent variable: Fraction of next year's output hedged

Sorted by	Net worth (bv)	Net worth (mv)	Net worth to assets (bv)	Net worth to assets (mv)
Time	-0,0735**	-0,0683**	-0,0117	-0,0243
	0,0028	0,0025	0,6084	0,2544
Treated	-0,1195**	-0,1258**	0,1695**	0,1225**
	0,0000	0,0000	0,0000	0,0000
Time x treated	0,0301	0,0195	-0,1365**	-0,1131**
	0,3791	0,5763	0,0001	0,0022
Observations	1106	1106	1106	1106
R-squared	0,0414	0,0483	0,0452	0,0269

Table 11 - DID estimations (financial distress - including non-hedgers)

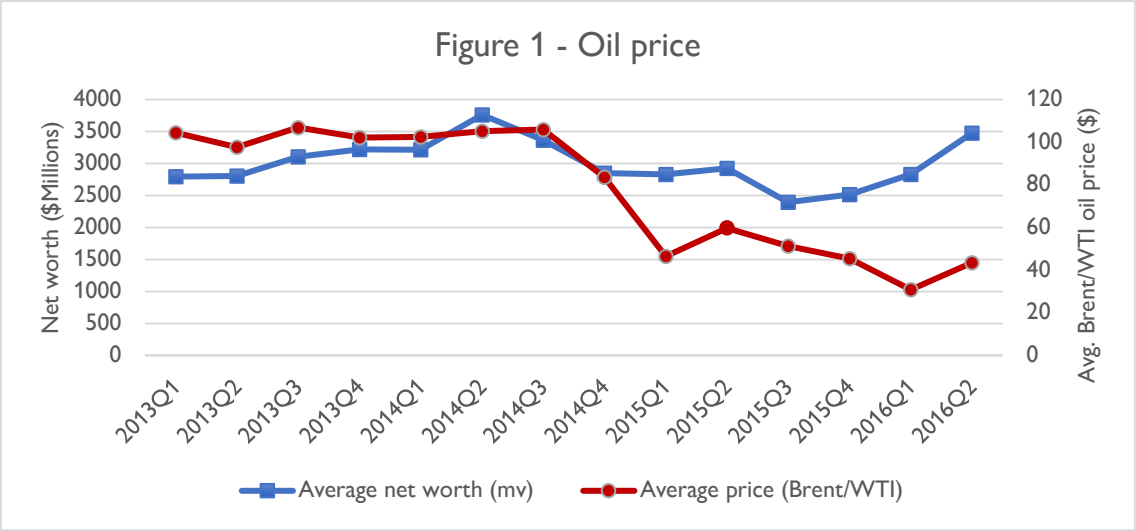
*note: Coefficients that are statistically different from zero at the 1%, 5% and 10% significance level are denoted: **, *, and +, respectively. Please note that the variable "Time x treated" is the variable of interest (model 2 in the methodology).*

Dependent variable: Fraction of next year's output hedged

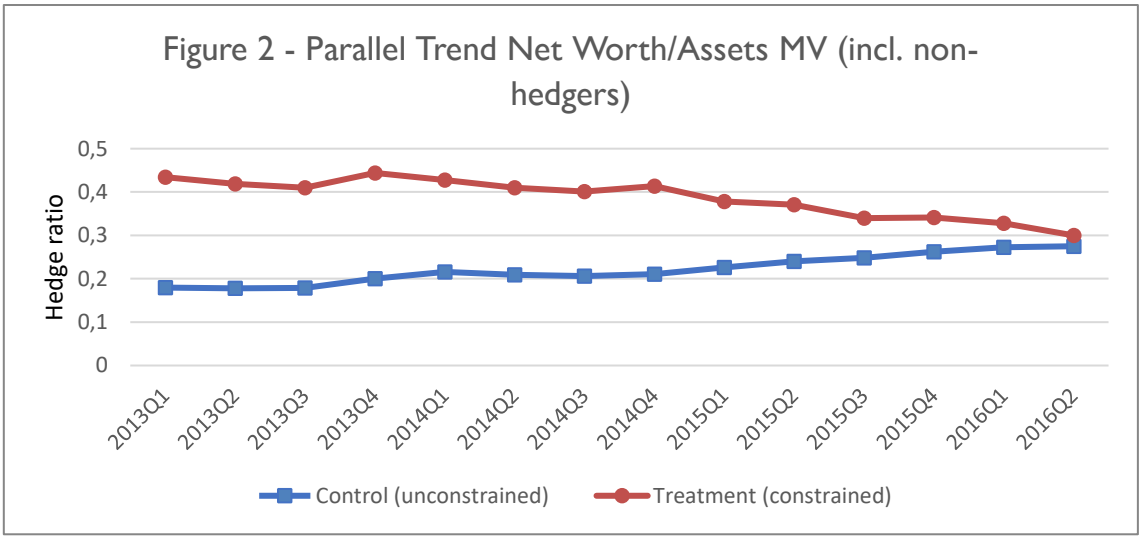
Sorted by	Net worth (bv)	Net worth (mv)	Net worth to assets (bv)	Net worth to assets (mv)
2 quarters				
Time	-0,0613*	-0,0571*	0,0072	0,0030
	0,0106	0,0149	0,7577	0,8995
Treated	-0,1455**	-0,1967**	0,2073**	0,0372
	0,0000	0,0000	0,0000	0,1943
Time x treated	0,0676+	0,0555	-0,1196**	-0,0948*
	0,0726	0,1306	0,0012	0,0145
Observations	949	949	949	949
R-squared	0,0396	0,0844	0,0644	0,0095
4 quarters				
Time	-0,0770**	-0,0654*	-0,0003	-0,0021
	0,0085	0,0204	0,9913	0,9452
Treated	-0,1937**	-0,2400**	0,1288**	0,1250**
	0,0000	0,0000	0,0003	0,0002
Time x treated	0,0913*	0,0687	-0,1112*	-0,1182**
	0,0456	0,1222	0,0210	0,0093
Observations	641	641	641	641
R-squared	0,0678	0,1214	0,0241	0,0216

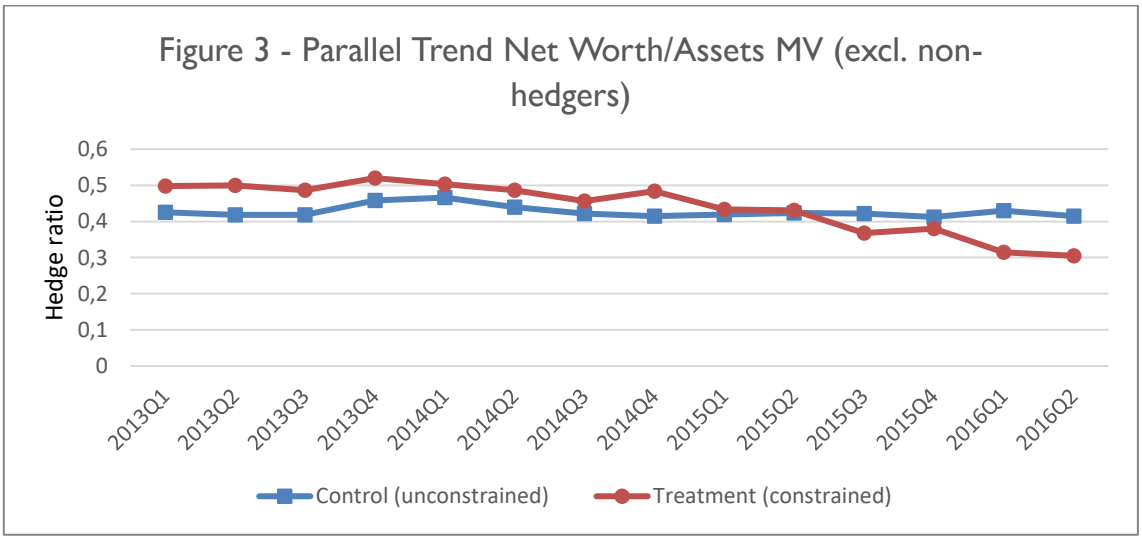
Table 12 - DID estimations (financial distress - excluding non-hedgers)				
*note: Coefficients that are statistically different from zero at the 1%, 5% and 10% significance level are denoted: **, *, and +, respectively. Please note that the variable "Time x treated" is the variable of interest (model 2 in the methodology).*				
Dependent variable: Fraction of next year's output hedged				
Sorted by	Net worth (bv)	Net worth (mv)	Net worth to assets (bv)	Net worth to assets (mv)
2 quarters				
Time	-0,0564*	-0,0497*	-0,0096	-0,0054
	0,0225	0,0381	0,6790	0,8207
Treated	-0,0750**	-0,1560**	0,1510**	0,0129
	0,0061	0,0000	0,0000	0,6536
Time x treated	0,0392	0,0186	-0,0932*	-0,0903*
	0,3019	0,6146	0,0147	0,0205
Observations	902	902	902	902
R-squared	0,0143	0,0694	0,0370	0,0148
4 quarters				
Time	-0,0724*	-0,0581*	0,0014	-0,0157
	0,0176	0,0442	0,9615	0,5991
Treated	-0,1168**	-0,1780**	0,1364**	0,0569+
	0,0005	0,0000	0,0000	0,0945
Time x treated	0,0511	0,0240	-0,1552**	-0,1087*
	0,2657	0,5925	0,0007	0,0192
Observations	594	594	594	594
R-squared	0,0342	0,0910	0,0320	0,0168

Table 13 - Correlation matrix		
	Leverage (mv)	Net worth to assets (mv)
Leverage (mv)	1	-0,7749
Net worth to assets (mv)	-0,7749	1



Source: Compustat and Datastream





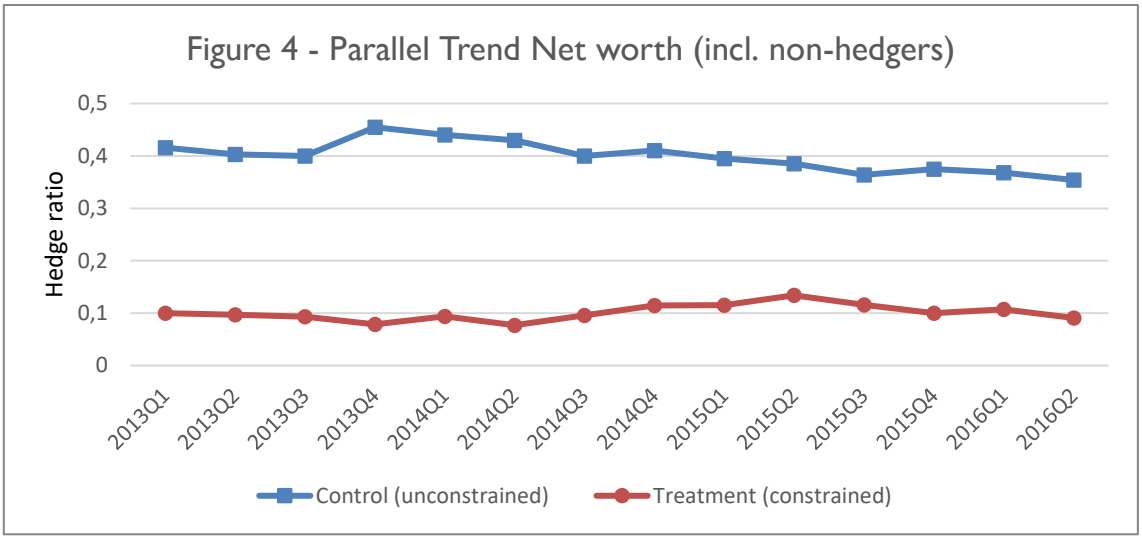


Figure 4 - Parallel Trend Net worth (incl. non-hedgers)
Hedge ratio
0,5
0,4
0,3
0,2
0,1
0
2013Q1
2013Q2
2013Q3
2013Q4
2014Q1
2014Q2
2014Q3
2014Q4
2015Q1
2015Q2
2015Q3
2015Q4
2016Q1
2016Q2
Control (unconstrained)
Treatment (constrained)

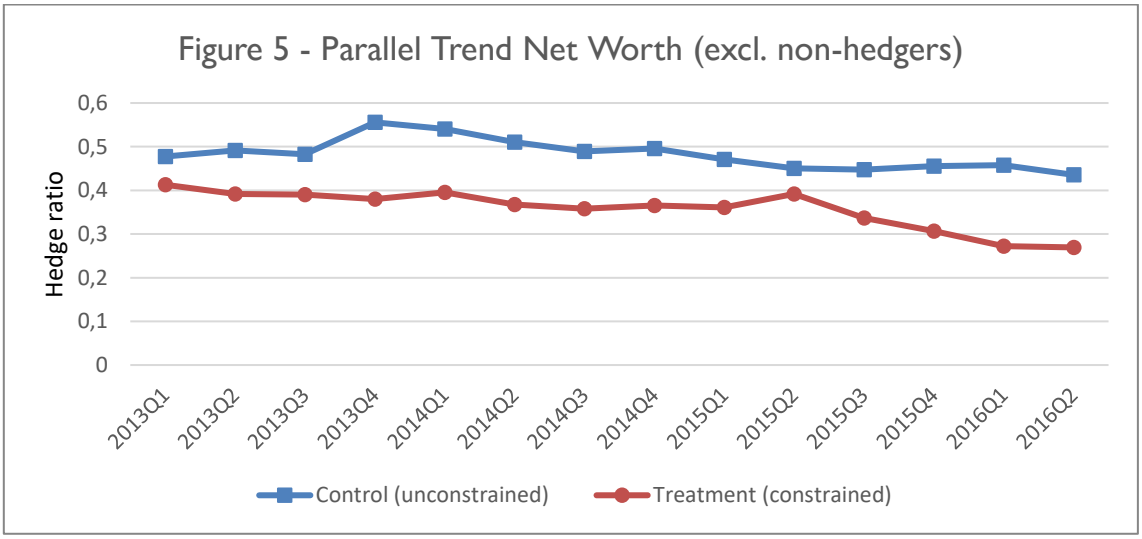


Figure 5 - Parallel Trend Net Worth (excl. non-hedgers)
Hedge ratio
0,6
0,5
0,4
0,3
0,2
0,1
0
2013Q1
2013Q2
2013Q3
2013Q4
2014Q1
2014Q2
2014Q3
2014Q4
2015Q1
2015Q2
2015Q3
2015Q4
2016Q1
2016Q2
Control (unconstrained)
Treatment (constrained)

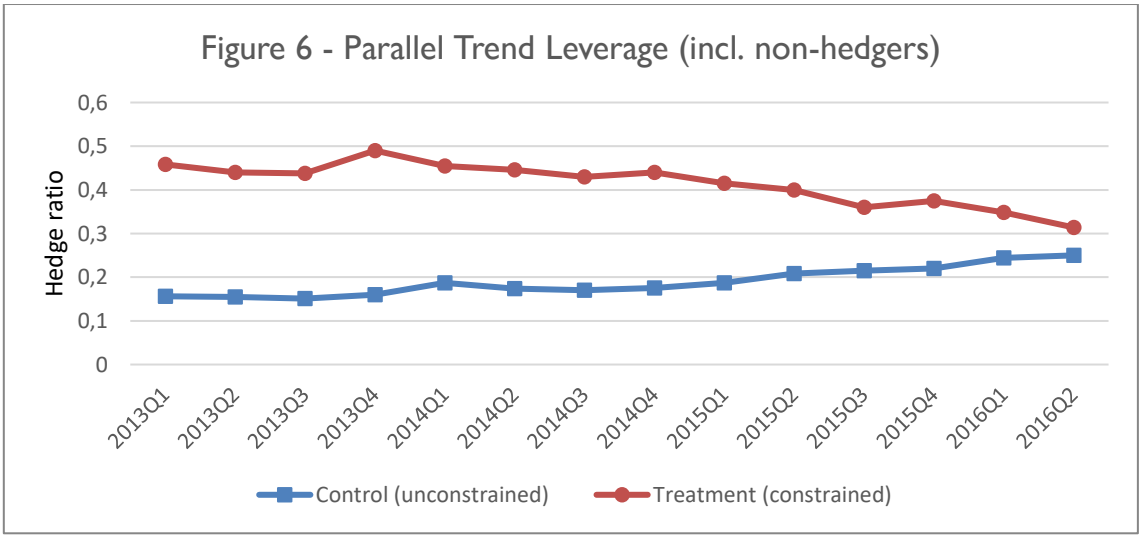


Figure 6 - Parallel Trend Leverage (incl. non-hedgers)
Hedge ratio
0,6
0,5
0,4
0,3
0,2
0,1
0
2013Q1
2013Q2
2013Q3
2013Q4
2014Q1
2014Q2
2014Q3
2014Q4
2015Q1
2015Q2
2015Q3
2015Q4
2016Q1
2016Q2
Control (unconstrained)
Treatment (constrained)

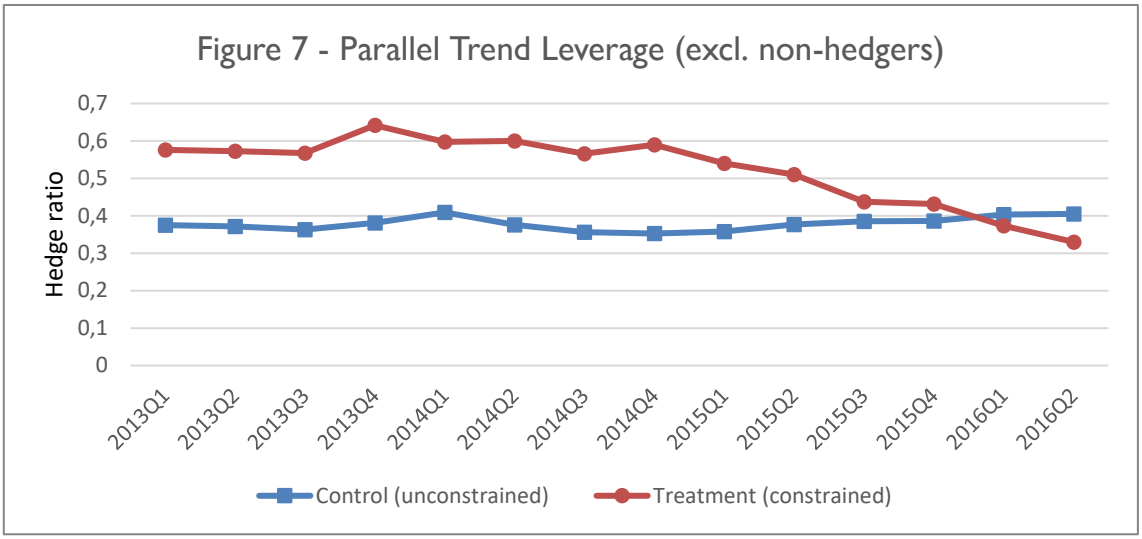


Figure 7 - Parallel Trend Leverage (excl. non-hedgers)
Hedge ratio
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
2013Q1
2013Q2
2013Q3
2013Q4
2014Q1
2014Q2
2014Q3
2014Q4
2015Q1
2015Q2
2015Q3
2015Q4
2016Q1
2016Q2
Control (unconstrained)
Treatment (constrained)