PRICE SHOCKS AND FINANCIAL HEDGING:

EMPIRICAL ANALYSIS

by

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In this dissertation, I study the relationship between financial hedging and financial constraints. The existing literature has defined financial constraints endogenously based on such firm characteristics as size, and the research has shown that unconstrained firms hedge more often than constrained firms. These results contradict those theories of financial hedging proposing that constrained firms should hedge more than unconstrained firms.

In this paper, I treat the sudden drop in the price of oil in the fourth quarter of 2014 as an exogenous shock that constrained oil producers. By studying a sample of 113 U.S. oil and gas producers in the period between 2010 and 2016, I show that these firms increased their hedging activities following drops in the price of oil. Further, constrained firms increased their hedging activities more than unconstrained firms. These results indicate a positive relationship between financial hedging and financial constraints. To the best of my knowledge, this paper provides the first empirical evidence in support of theories of financial hedging.

The empirical results, yielded from a dynamic structural model, shows that the optimum level of financial hedging is negatively related to prices. Since the expected probability of distress is higher when prices are lower, the dynamic model reconfirms the empirical finding of this paper, which is that firms hedge more when they become more constrained. To resolve the high dimensional model, I use the stochastic simulation technique, which provides a novel approach to corporate finance literature.

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CHAPTER 1

INTRODUCTION AND OVERVIEW

Producers never like to hedge on the highs. They always like to hedge on the lows.

Financial Times, July 13, 2015[1]

Theories of financial hedging suggest that financially constrained firms should hedge more than less financially constrained firms (Smith and Stulz 1985, Froot et al. 1993). However, empirical papers showing that large firms hedge more than small firms have challenged this idea (Nance et al. 1993, Tufano 1996, Carter et al. 2006, Rampini et al. 2014). These empirical studies are subject to several limitations including endogeneity and omitted variables. As Stulz (1996) points out, the fact that small companies hedge less may not indicate a negative relationship between hedging and financial constraint; rather, it could result from small firms not having enough resources to afford an active risk management program.

In this paper, I use the sudden drop in the price of oil in the fourth quarter of 2014 as an exogenous event that negatively affected the financial situation of oil and gas producers. I compare changes in the hedging policies of constrained versus unconstrained firms during this drop in the price of oil. Changes in market conditions often have a greater impact on constrained firms than unconstrained ones. Using a diff-in-diff analysis, I show that, following a drop in oil prices, constrained firms increased their hedging activities significantly more than unconstrained firms. This is more evidence for a positive relationship between financial constraint and financial hedging. To the best of my knowledge, this study provides the first empirical evidence in support of theories of financial hedging.

The price of oil dropped from an average of about $97.16 in the third quarter of 2014 to about $48.63 in the first quarter of 2015. Panel A of Figure 1 shows the average monthly oil price along with the average short positions in WTI crude oil futures held by oil and gas producers from 2010 to 2016. Data on short positions are from the U.S. Commodity Futures Trading

[1]http://www.ft.com/intl/cms/s/0/637f8f92-28d2-11e5-8613-e7aedbb7bdb7.html#axzz3xuutmci8

Commission and shows the commitment of producers, which is considered strongly associated with their hedging activities.

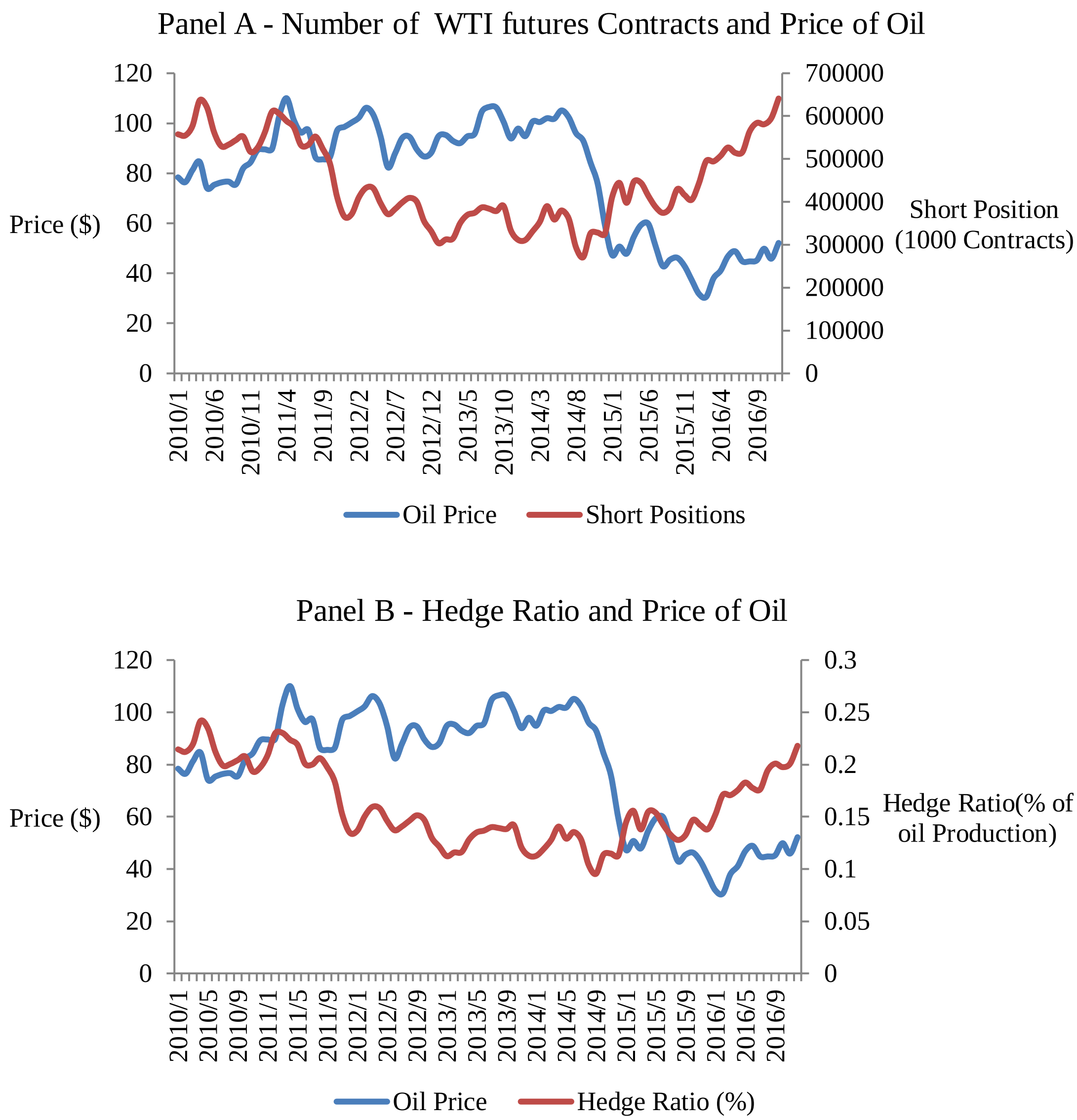


Figure 1. Short position in oil futures contracts and price of oil

Panel A shows the average monthly price of WTI oil and the average monthly number of short positions in WTI oil futures contracts held by oil and gas producers from January 2010 to December 2016. Panel B shows the average monthly price of WTI oil and the average hedge ratio of oil producers from January 2010 to December 2016.

As the figure shows, a sharp drop in oil prices is accompanied by a sharp increase in the hedging activities of oil and gas companies. The average number of futures contracts increased from about 308 million in the third quarter of 2014 to about 418 million in the first quarter of 2015, right after the drop in prices. This constitutes an increase of 35% in just one quarter. The correlation between monthly oil prices and the number of futures contracts is -28% for the whole sample and -62% in 2014 and 2015 (around the drop). Both numbers are significant at 0.1%.

Panel B of Figure 1 shows the same data, but number of futures contracts is replaced by an approximate hedge ratio, defined as the ratio of the number of futures contracts to total U.S. oil production each month. Data on oil production are from the Energy Information Administration website. The same trend can be seen for the hedge ratio. The average hedge ratio increased from about 10% in the third quarter of 2014 to about 15% in the first quarter of 2015, an increase of about 34%. The correlation between the price of oil and hedge ratios is -14% for the whole period and -17% during 2014 and 2015. Here again, both numbers are significant at 0.1%.

The analysis in this paper begins with a dynamic model in which, at each period, management determines the amount of investment, debt financing, cash holding, and hedging required in order to maximize firm value. All of the uncertainty in the model is related to price. The goal of applying the model is to find the relationship between the price at each period and the optimum level of hedging for the next period. Since the probability of distress is higher when prices are lower, the negative relationship between price and hedging shows that firms hedge more when they are more constrained.

In this model, the main benefit of hedging is a decrease in distress costs. Following Hennessey and Whited (2005) and Nikolov and Whited (2014), I define distress costs in relation to fire sale of assets. At each period, the firm is required to repay its debt in full using its internal resources (i.e., operational profits plus cash reserves). In case internal resources are not enough to repay the debt, the firm is in distress and should sell a portion of its capital at a fraction of its fair value to pay the debt. Fire sales of capital assets have been examined in several papers (Asquith, Gertner, and Scharfstein 1994, Pulvino 1998, Duffie and Singleton 1999).

As noted, the model emphasizes investment, debt financing, cash savings, and hedging simultaneously. Several papers have shown that cash can be used as a substitute or complement to financial hedging (Kim et al. 2006, Bolton et al. 2011, Kieschnick et al. 2013, Gamba et al. 2014). In themodel for this research, the benefit of both cash and financial hedging is that itreduces the number of states in which distress can happen. However, while cash transfers funds to both good and bad states, financial hedging transfers funds from good states to bad states. As a result, cash would be the preferred form of risk management in states where the probability of distress is low, while financial hedging is a more effective form of risk management when the probability of distress is high.

Regarding debt, Rampini et al. (2010, 2013, 2014) argue that hedging commitments require collateral and that, therefore, hedging decreases debt capacity. Their argument is based on the limited enforcement theory of Townsend (1979), which proposes that all the debt commitments should be collateralized. On the other hand, Campelo et al. (2011) argue that financial hedging increases debt capacity by reducing the probability of default. In this paper, I follow the argument in Rampini et al. and assume that all debt should be collateralized and that a firm can borrow up to a percentage of capital. Moreover, hedging requires collateral and, as a result, it decreases borrowing capacity; therefore, a reduction in debt capacity is one of the costs of hedging. Finally, a change in prices affects capital and investment opportunities, which, in turn, affects other control variables, including hedging.

To solve the dynamic models of corporate finance, most existing papers use policy or value iteration methods. Strebulaev and Whited (2011) give a comprehensive review of these methods. Two of the most popular methods used in the corporate finance literature are Simulated Method of Moments and Simulated Maximum Likelihood. At each iteration, both methods rely on the value iteration method to solve the model.

The model used for this study has 4 control and 4 state variables. Due to computational limitations, it is practically impossible to solve a model of these dimensions using iteration techniques. To solve the model, therefore, I use the stochastic simulation approach. This technique has been extensively used in Economics literature, but it has not been used in Finance literature so far. In contrast to value iteration methods, which search the whole grid of control variables, the stochastic simulation method concentrates on the part of the grid that is most likely in equilibrium (the Ergodic set). By concentrating on this set, the stochastic simulation approach makes it possible to add more control and state variables.

This approach is not without shortcomings, however. Although I am able to analyze more variables using it, concentrating on only a subspace of control and state variables makes the solution sub-optimal. The outcome may be either a less or more optimal result compared with iteration methods; heuristically, though, it should make the solution less optimal. Stochastic simulation is an alternative approach to iteration methods that enables us to study a more realistic model of the firm.

Stochastic simulation offers an equation showing the relationship between control and state variables. The process begins with guessing a system of equations to explain the control variables as functions of the state variables. Next, in an iterative process, the control variable values obtained from these equations are matched to values obtained from the Investment Euler equation in the dynamic model. The process continues until the simulated values of consecutive iterations converge.

The real challenge with the stochastic simulation approach is achieving this convergence. Following the approach proposed by Judd, Maliar, and Maliar (2011), I was able to get convergence for a wide range of model parameters. The results show a negative relationship between prices and optimum levels of hedging. Also, the coefficient of price hedging is more negative when the volatility of prices is higher, when the probability of a jump is higher, when a firm has higher leverage initially, and for smaller firms. All four of these factors increase the probability, and the costs, of distress. Applying the theoretical model confirms the theories of financial hedging: firms hedge more when they are financially constrained.

I verify these results by studying the hedging policies of a sample of 113 U.S. oil and gas producers around the drop in price of oil in the fourth quarter of 2014. This analysis is based on U.S. oil and gas producers that are active only in oil and gas production (SIC code 1311). Concentrating on this sample has two advantages. First, the most important determinant of the financial situation of the oil and gas companies is the price of oil, for which there is a well-established futures market. As a result, I have an accurate measure of these companies' exposure to the riskiness of the markets.

Second, this sample comprises firms that are active only in the upstream segment and that, therefore, have fewer operational hedging options than firms that are active in both upstream and downstream segments. In other words, financial hedging has a higher weight in the risk management policies of these companies. Therefore, this sample gives me a clean test of the relationship between companies' financial situation and their financial hedging.

In the data I collected from company reports (10Ks and 10Qs) on the quarterly production and hedging activities of companies, hedging often occurs in the form of swaps, futures, options, or collars. The main dependent variable is hedge ratio, which is the ratio of the sum of all open hedging positions at the end of quarter (in barrels of oil equivalent) to total production in that quarter.

I begin with a univariate diff-in-diff analysis whereby the sample is divided into two groups based on company size (book value of assets). In the literature, size has been noted as one of the best indicators of a firm being financially constrained. In the diff-in-diff analysis, I use dummy variables for size group, post-price-drop, and the interaction between these two. Consistent with the literature, the result of this analysis shows that large firms hedge more than small firms. Furthermore, following a drop in the price of oil, oil and gas companies tend to increase their hedging activities. Since a drop in the price of oil exogenously affected the financial situations of these companies, the evidence suggests, firms hedge more as they become more financially constrained, keeping other factors constant.

Third, the diff-in-diff analysis shows that following the drop in prices, small (constrained) firms increased their hedging activities more than large firms. A drop in prices normally has more of an effect on small firms than large ones. I give evidence of this by conducting the same diff-in-diff analysis on three other firm characteristics: investment, cash holding, and debt. My finding is that the fact that constrained firms increased their hedging activities more is evidence of a positive relationship between financial hedging and financial constraint.

Next, I verify these results in a multivariate framework wherein I control for firm and market characteristics. The same results are shown in this multivariate analysis. The results show that large firms hedge more and that firms increased their hedging after a drop in oil prices. Also, the interaction term coefficient is positive, indicating that small firms increase their hedging more than large firms. These results are dependent on how I define financial constraint. To check the robustness of these findings, I use the KZ and SD indexes as alternative measures of constraint, which returns the same results.

This paper contributes to the literature on corporate finance that studies cross sectional differences between the hedging activities of financially constrained versus unconstrained firms. Theories of financial hedging suggest that hedging is a response to financial constraints. The first seminal work in this body of literature is that of Smith and Stulz (1985), who argue that a reduction in distress costs is the main incentive behind financial hedging. The second seminal contribution is that of Froot et al. (1993), who suggest that the main benefit of financial hedging is reduction in underinvestment costs. The conclusion of these theories is that financial hedging is more beneficial to constrained firms and, therefore, that these firms should hedge more than unconstrained firms.

Several empirical papers showing that unconstrained firms hedge more than constrained firms challenge the aforementioned theories. For example, Rampini et al. (2014), in a study of the hedging activities of a sample of U.S. airlines using size as the measure of financial constraintness, show that large airlines have higher hedge ratios than small ones. As an explanation to these results, Rampini et al. (2010, 2013) argue that hedging commitments should be collateralized and, therefore, will decrease the collateral available for debt commitments. As a result, constrained firms prefer to preserve their debt capacity by cutting their hedging activities.

These empirical results have two shortcomings. First, there is no perfect proxy for financial constraint, and none of the proxies used in the literature, such as size or the KZ index, can perfectly distinguish between constrained and unconstrained firms. Second, and more important, the fact that unconstrained firms hedge more does not imply the lower importance of hedging for constrained firms. In fact, as Stulz (1996) mentions, constrained companies may hedge less because they have fewer resources and, thus, cannot afford an active hedging program.

By studying the impact of price shocks on the hedging policies of oil and gas companies, this paper mitigates the above shortcomings. First, the price of oil is the most important factor affecting the financial situation of oil and gas companies. Therefore, changes in the price of oil can be regarded as a good proxy for how constrained these firms are. Specifically, a sharp drop in the prices of oil in the fourth quarter of 2014 exogenously affected the financial situation of oil and gas companies.

Second, in contrast to the existing empirical studies that do cross sectional analyses, in this paper, I study changes in hedging activities through time, and, therefore, to some extent, control for other firm-related factors that affect financial hedging. Third, rather than comparing the amount of hedging for constrained and unconstrained firms, this paper studies changes in the hedging of these companies as their business conditions change and they become more constrained. A significant increase in the hedging activities of all companies, especially constrained firms, following a drop in prices can be interpreted as proving that hedging has a higher marginal value for constrained firms. In summary, this paper offers a clean test of the relationship between financial hedging and financial constraints and, to the best of my knowledge, provides the first empirical results in support of theories of financial hedging.

The rest of the paper is organized as follows. In Chapter 2, I review the related literature. The theory and model that guided this research is explained in Chapter 3. Chapter 4 shows the results of the empirical analysis, and Chapter 5 concludes the paper.

CHAPTER 2

REVIEW OF THE LITERATURE

Here, I review three strands of the literature on financial hedging. First, I review the foundational theoretical papers in the literature on financial hedging and the empirical studies that followed those papers. Next, I review the literature that studies hedging as one component of corporate risk management. This literature examines firms' policies that affect their hedging strategies. Finally, I review papers that propose dynamic models of corporate finance.

2.1. Theories of financial hedging and related empirical works

The first breakthrough in the financial hedging literature is the seminal work of Smith and Stulz (1985), who note three benefits of financial hedging: lower taxes, lower bankruptcy costs, and lower management compensation. Their argument is based on the fact that decreasing volatility increases the expected value of a concave function. Therefore, if (for example) the tax rate is a convex function of company's before-tax profit (and, therefore, after tax value is a concave function of before tax value), hedging can increase firm value by decreasing the volatility of a firm's cash flow.

Among the three aforementioned benefits of financial hedging, the reduction in bankruptcy costs has been appreciated most in the literature. Several papers have explored this aspect of hedging. Smith and Stulz (1985) show that, as a result of bankruptcy costs, the value of a hedged firm will be higher than that of an unhedged firm. They also show that, although shareholders do not benefit directly from a reduction in bankruptcy costs, they benefit from the firm's high reputation in lending relationships, which results in lower debt costs and less binding terms in debt covenants. Campello et al. (2011), who have studied this result empirically, show that corporate hedging reduces the cost of debt financing and that hedgers have fewer investment-constraining terms in their covenants. Therefore, hedging has real effects, and hedgers can utilize their investment opportunities better.

The second seminal contribution made to the financial hedging literature is that of Froot et al. (1993), who show that hedging increases a firm's value by decreasing its underinvestment costs.

In their model, a firm has a neoclassical production function. Since production is concave in capital, hedging increases the expected value of the firm by decreasing the volatility of the firm's cash flow.

One implication of both Smith and Stulz's (1985) and Froot et al.'s (1993) findings is that hedging is more beneficial to firms close to bankruptcy, to distressed firms, and to financially constrained firms; therefore, these firms should hedge more than healthy and unconstrained firms. Nonetheless, the empirical literature on financial hedging has proven the opposite. The literature has suggested the costs of hedging as an explanation for this behavior because the costs of financial hedging are higher than its benefits for distressed or constrained firms. Stulz (1996) argues that the fixed costs of starting a hedging program is the main reason that small or distressed firms prefer not to hedge. In the findings of Bolton et al. (2011), the main cost of hedging is the opportunity cost of margin accounts, and constrained firms generally prefer to use that money in the current period rather than transferring it to future downstates through hedging.

Empirically, Fehle and Tsyplakov (2005) show that gold miners hedge less when they are very close or very far from default and they propose that there is a hump-shaped relationship between their measures of proximity to default and a firm's hedge ratio. Purnanandam (2008) distinguishes default from distress but yields the same results as Fehle and Tsyplakov. Using leverage as a measure of financial distress, Purnanandam finds a hump-shaped relationship between hedging and leverage. In a recent paper, Rampini et al. (2014) argue that since both financing and financial hedging involve promises that need to be collateralized, there is a trade-off between these two; therefore, financially constrained firms hedge less in order to preserve their debt capacity.

Another explanation for the limited hedging of distressed firms is the risk shifting argument, first proposed by Jensen and Meckling (1976). While risk shifting has been considered important to capital structure decisions, there has been very little direct evidence of risk shifting in practice, and several papers have challenged the theory. One of the few studies providing empirical evidence of risk shifting is that of Eisdorfer (2008), who shows that distressed firms increase their investments when volatility is higher, which he proposes is evidence of risk shifting activity.

Almeida et al. (2011), among others, challenge these ideas of risk shifting, show that firms prefer to invest in more liquid projects, to save more cash, and to become more conservative as their financial situation deteriorates. Gilje (2014), studying the effects of leverage shocks on investments among a sample of U.S. oil and gas producers, finds no evidence of risk shifting.

2.2. Financial hedging along with other risk management tools

Next, I review the literature on integrated risk management that studies financial hedging in conjunction with two other risk management tools: operational hedging and liquidity management. This literature is mostly concentrated on the relationship between three methods of risk management and whether and how much each of the three risk management tools should be used. The general take away from this literature is that while operational and financial hedging can be either complements or substitutes, cash and financial hedging are almost always substitutes. Therefore, firms that save more cash, often hedge less. Also, research shows that constrained firms prefer to manage risks by holding cash while unconstrained firms hold less cash and hedge through derivatives more frequently (Almeida et al. 2004, Rampini et al. (2010, 2012, 2014), Nikolov et al. [forthcoming]).

Allayannis, Ihrig, and Weston (2001), in their study of the impact of operational and financial hedging on firms that are exposed to exchange rate risks, define the geographic diversification of firm locations as one means of operational hedging and show that while operational hedging does not decrease a firm's exposure to foreign currency risk, using foreign currency derivatives does. In their paper, operational and financial hedging are complements. The opposite results are reported in Peterson and Thiagarajan (2000) and Aabo and Simkins (2005), who show that the two strategies are substitutes. Chod, Rudi, and Mieghem (2010), proposing an integrated model of operational flexibility and financial hedging, define two types of flexibility — product flexibility and postponement — and show that hedging is a complement to product flexibility and a substitute for postponement.

Acharya et al. (2012), in their study of the relationship between cash holding and financial distress, show that firms hold more cash when they are financially distressed. They argue that the costs of financing are higher for distressed firms; therefore, these firms hold more cash to hedge their liquidity requirements. Their conclusion is that the relationship between cash holding and the probability of financial distress is U-shaped. Their results, combined with the previous papers showing a hump-shaped relationship between financial hedging and distress, suggest that cash hedging and financial hedging are substitutes.

Kieschnick and Rotenberg (2013), in a study of changes in the working capital of 63 Canadian Energy and Mining firms during the 2007-2008 financial crisis, show that cash holding and financial hedging are alternative risk management strategies, and using either of these strategies mitigated the impact of the financial crisis on firm's working capital.

Gamba and Triantis (2014) provide a dynamic model of comprehensive risk management that integrates a firm's liquidity, financial hedging, and operational hedging policies. In contrast to the previous literature, which studies and compares two of the three techniques, their paper provides a study of all three techniques simultaneously to understand the relative importance of different hedging strategies. One implication of their model is that, in general, cash management adds more value to a firm compared to financial hedging. However, the efficiency of the hedge and the correlation betweenthe prices of the hedging contract and the firm's assets plays an important role in the comparative value of financial hedging for companies. Their research shows that financial hedging can be more valuable than cash holding, even for a constrained firm, if this correlation is high.

2.3. Dynamic models of corporate finance

Next, I review the literature on dynamic models of corporate finance. Although it has been long recognized that static models of corporate finance fail to explain even simple stylized facts, the absence of efficient mathematical and computational techniques has impeded researchers from developing and solving dynamic models. However, recent advances in stochastic dynamic optimization and numerical techniques have opened avenues for studying dynamic models.

Dynamic models of corporate finance, as mentioned in Strebulaev and Whited (2011), can be classified into two groups: continuous-time, contingent claim models and discrete-time, dynamic models. Examples of contingent claim models are real option analyses of corporate investments, first proposed by McDonald and Siegel (1985, 1986) and Brennan and Schwartz (1985), and the contingent claim model of Merton (1973, 1974) for valuations of debt and equity. Although, recently, there have been significant advances in contingent claim models, the focus of this literature is mostly on the valuation of investments and optimal capital structures. Few papers study hedging in this framework. Therefore, I concentrate on discrete time models.

Discrete time models are often stochastic, infinite horizon models. At each time, a firm faces state variables based on which it determines corporate policies, such as those regarding the amount of investment, financing, and risk management. These policies, in combination with one or more exogenous shocks, which are often assumed to follow Markov processes, determine the value of the next period state variables. Management's goal is to define policies that maximize firm (or shareholder) value. The problem is often modeled as a recursive Bellman equation or optimal control problem and solved analytically or numerically. An excellent review of analytic methods can be found in Porteus (2002) and Boyd and Vandenberghe (2008), and an excellent review of numerical methods can be found in Judd and Schmedders (2014).

The emphasis on discrete time corporate finance models began in Economics literature with simple partial equilibrium models in which capital is deemed the only factor of production. The early models where simple with only one state variable, capital, one control variable, investment, and one shock. Even in these simple models, a closed form solution can be obtained only by making simplifying assumptions about the shocks. The common assumption is that the logarithm of a shock follows an AR(1) process. Tauchen (1986) and Tauchen and Hussey (1991), among others, explain how to construct a discrete state Markov chain to approximate an AR(1) process.

Gomes (2001) adds capital adjustment costs and external finance to the above model. In his model, external finance is only considered equity injections from current shareholders, and there is no debt. Equity issuance has both fixed and variable costs. Gomes paper estimates that the fixed costs of equity issuance are 0.08 and the variable costs are 0.028 per dollar of equity issued.

Papers that followed Gomes (2001) research tried to introduce more control and state variables into the model. Riddick and Whited (2009) add cash saving as a state variable, but there is no external financing in their model. Hennessey and Whited (2005) and DeAngelo et al. (2011) add risk free debt without cash savings. An important concept in both of these papers is the assumption that all debt should be collateralized. This assumption is based on the limited enforcement concept proposed by Townsend (1979) and Gale and Hellwig (1985). As a result of limited enforcement in a debt contract, a lender may not be able to force borrower to repay debt; therefore, a lender will ask borrower to collateralize all debt so that, in case of a default, the lender can sell the collateral.

Although the assumption of fully collateralized debt may not be realistic, making this assumption has two advantages. First, it significantly simplifies the model, since the risk free rate can be used as the price of debt. Second, a company's available collateral (often, its tangible assets) can be used to endogenously define its financing capacity. Nonetheless, several papers in the literature have relaxed this assumption. Examples include Moyen (2004), Hennessey and Whited (2007), and Titman and Tsyplakov (2007), all of whom propose a dynamic model with capital and debt as state variables while debt is not risk free and its price depends on the probability of default of borrower.

Distress costs are introduced in the research of Hennessey and Whited (2005) in the form of the fire sale of assets. In their model, if a firm does not have enough internal cash to repay a debt, it has to sell its assets at a price lower than their fair value. This is called a fire sell. The existence of fire sell costs in times of distress is documented in Asquith, Gertner, and Scharfstein (1994) and Pulvino (1998).

Gamba and Triantis (2008, 2014) add both cash and debt to develop a model with three state variables: capital, cash, and debt. What is missing in their model is financing constraints. To simplify the model, they assume that a company has a fix amount of debt. They justify this assumption by arguing that debt adjustment is costly and that companies prefer not to pay these costs.

The models mentioned above do not examine either financial hedging or risk management. Probably the first dynamic model of financial hedging is that Froot et al. (1993), which was mentioned earlier. Mello and Parsons (2000) and Fehle and Tsyplakov (2005) study financial hedging in a dynamic framework. Both papers use a continuous contingent claim approach, and the focus of both is on the characteristics of an optimal hedge (type of instrument, maturity, and optimal hedge ratio). What is missing in both papers is consideration of debt and cash management. Similar to Froot et al. (1993), these two papers study the interaction between hedging and investment without modeling debt and cash management.

Rampini et al. (2010, 2012) add one layer of complexity to dynamic risk management models by adding debt to their model. Similar to Hennessey and Whited (2005), the basic idea in their papers is that all debt should be collateralized. Risk management, in their model, is in the form of managing debt capacity and allocating it to bad states. In their model, a company is limited by the amount of money it can borrow. By borrowing less in this period, a company can increase its borrowing capacity in the next period. Also, a company can transfer its borrowing capacity to bad states, using Arrow-Debreu securities. Cash management, however, is missing in their model, and since they define risk management as managing debt capacity, they do not discuss financial hedging.

Using the results of the previous two papers, Rampini et al. (2014) show why small firms hedge less than large firms. They argue that since both financing and financial hedging involve promises that need to be collateralized, there is a trade-off between these two; therefore, financially constrained firms hedge less in order to preserve their debt capacity. Studying a sample of U.S. airlines, the researchers show that these companies significantly decrease their hedging activities as they get close to default. Nikolov et al. (forthcoming) adds another layer of complexity to Rampini et al.'s model with the consideration of cash management in their research. Like Rampini et al., they define risk management as managing debt capacity. They argue that cash is unconditional hedging while debt management is conditional hedging. Using a dynamic model, they show that constrained firms prefer to manage risk through cash management and unconditional hedging while unconstrained firms prefer conditional hedging. They empirically verify results of their model by studying how companies use their credit lines.

CHAPTER 3

MODEL

In this section, I develop a dynamic model for studying the relationship between the price of oil and financial hedging. The expected costs of distress are higher when prices are lower. Therefore, a negative relationship between price and hedging would be evidence in support of existing theories of financial hedging.

3.1 A Simple Model

Before developing the dynamic model, I begin by studying the interaction between state and control variables in a simple, two-period model to provide its intuition. The model has two time points: t and t+1. At time t, the firm has net worth (NW_t). The firm's problem is to choose its control variables from among capital, saving, debt, and hedging for time t+1 in order to maximize the expected value of dividends at times t and t+1. The exogenous variable is the price shown by Z_t and Z_{t+1}. All of the uncertainty in the model is related to Z_{t+1}, which follows a stochastic process. I assume that price follows a mean-reverting process with jumps[2]. The logarithm of price can be written as following stochastic process:

$$dX_t = \kappa(\mu - X_t)dt + \sigma dW_t + J(\mu_J, \sigma_J)d\pi(\lambda_J) \tag{1}$$

Where X_t is the logarithm of price, μ is the long-term mean of log of prices, κ is the speed of mean reversion, σ is the volatility of return, and dW_t is a standard Brownian motion. $J(\mu_J, \sigma_J)$ determines jump size, and it has a normal distribution with a mean of μ_J and a standard deviation σ_J. $\pi(\lambda_J)$ is a Poisson jump process with parameter λ_J.

[2] There is no general agreement between researchers on the best way to model oil prices. Several techniques such as VAR, GBM, Mean-Reverting, Jump-Diffusion, and Stochastic Volatility have been tested in the literature, and it has been shown that each approach may be superior to others in certain conditions. A survey of several of these methods can be found in Baumeister and Kilian (2013). Al-Harthy (2007) compares the performance of GBM and Mean-Reverting, Jump-Diffusion process and shows that jump process is capable of capturing high volatility and sudden changes in price of oil in the long-term. Since price volatility and jump in price of oil are the main sources of risk for oil and gas companies, I use mean-reverting, jump-diffusion process to study the effect of sudden jumps on hedging policies of oil and gas companies. In section 3.8 I will show that price process of equation 1 is a fair representative of oil price process after 2000.

The firm maximization problem is the following:

$$\max_{k_{t=1}, b_{t+1}, s_{t+1}, h_{t+1}} d_t + \frac{1}{1+r(1-\tau)} E_t d_{t+1} \tag{2}$$

The firm chooses among the four control variablesof capital (k_{t+1}), debt (b_{t+1}), saving (s_{t+1}), and hedging (h_{t+1}) in order to maximize the expected value of its dividends (d_t and d_{t+1}). Also, τ is the tax rate and r is the firm's required rate of return.

The funds available to the firm at time t include the firm's net worth (NW_t) plus the next period's debt (b_{t+1}). The firm will use these funds to pay for the next period's capital and costs of hedging, and it will save part of its funds for the next period. Therefore, the dividend at time t will be the following:

$$d_t = NW_t + b_{t+1} - k_{t+1} - S_{t+1} - Ph_{t+1} \tag{3}$$

Here, P is per unit cost of hedging. A positive d_t means dividends paid to shareholders and a negative one means equity financing. For the sake of simplicity, in this section I do not consider the costs of equity financing and taxes on dividends, but I will add them to the dynamic model in the next section.

At time t+1, firm's operations will generate an operating profit. Following previous papers in the corporate finance literature, I assume that firm's operating profit is an increasing and concave function of capital. Also, firm hedges h_{t+1} units of production. Therefore, firm's operating profit at time $t+1$ will be the following:

$$\pi_{t+1} = k_{t+1}^{\alpha} Z_{t+1} + h_{t+1}(Z_t - Z_{t+1}) \tag{4}$$

Here, α is a constant between 0 and 1, and Z_t and Z_{t+1} are prices of oil at times t and t+1, respectively. The first term, on the right-hand side, shows the operating profit before hedging and the second term shows profit/loss from hedging. A firm's net profit is the sum of its operating profit plus interest earned on cash savings minus interest paid on debt.

$$NI_{t+1} = (\pi_{t+1} + rS_{t+1} - rb_{t+1})(1-\tau) \tag{5}$$

I have assumed a single interest rate on cash and debt, which is also equal to the rate of return on firm capital. An alternative formulation is to assume an endogenous interest rate for debt and equity (Moyen (2004); Hennessey and Whited (2007); Titman and Tsyplakov (2007)).

Following Nikolov and Whited (2014), I assume that cash savings is associated with the agency costs of cash. Therefore, a firm's cash-at-hand at time t+1 will be the sum of its net profit plus its cash savings minus the agency costs of cash:

$$C_{t+1} = NI_{t+1} + S_{t+1}(1-\gamma) \tag{6}$$

In this equation, γ shows the agency costs of holding one dollar of cash. In the model of Nikolov and Whited (2014) cash is valuable as a hedging instrument when firm has unanticipated financing needs. However it is also costly because interest is taxed. As a result of misalignment between management and shareholders' interests, management may hold too much cash, which will result in agency costs of cash. Nikolov and Whited (2014) suggest three main reasons for managers to hold extra cash: managerial compensation based on firm size, managerial private benefits from diverting liquid resources, and limited managerial ownership of the firm.

The company uses this cash to repay its debt. The company is in distress if the available internal funds are not enough to repay the debt ($C_{t+1} < b_{t+1}$). To model distress, I follow Hennessey and Whited (2005). In distress, the company has to sell its capital at a percentage of fair value to repay its debt (fire sale). Fire sales capture the costs of financial distress. The existence of fire sales has been documented in Asquith, Gertner, and Scharfstein (1994), who show that asset sales are a common response to distress. They estimate that, in distress, assets are sold at about 80% of their fair value[3]. If each dollar of capital sold at distress is s dollar less than its fair value, the cost of distress will be as follows:

[3] Several factors affect recovery rates for loans and bonds. Some of these factors include type of debt, seniority, debt structure, industry, time of default, and macroeconomic conditions. A discussion of these factors can be found in this docuent from Moody's: https://www.moodys.com/sites/products/DefaultResearch/2006600000428092.pdf. In 2007 the average recovery rate for 1st Lien Bank Loans was 82% while in 2010 it dropped to 72%. For the Senior Secured Bond, the average recovery rate was 55% in 2010 and 56% in 2007. Data on recovery rates as of 2007 can be found in the above document. Data on recovery rates as of 2010 can be found in this document from Moody's:http://efinance.org.cn/cn/FEben/Corporate%20Default%20and%20Recovery%20Rates,1920-2010.pdf.

$$DistressCosts = s(b_{t+1} - C_{t+1})^{+} \tag{7}$$

$$(b_{t+1} - C_{t+1})^{+} = \begin{cases} 0 & if \quad b_{t+1} \leq C_{t+1} \\ b_{t+1} - C_{t+1} & if \quad b_{t+1} \geq C_{t+1} \end{cases} \tag{7.1}$$

Once a firm repays its debt and pays its distress costs, it will distribute the remaining money as dividends to shareholders. Therefore, dividends at time t+1 will be:

$$d_{t+1} = C_{t+1} + k_{t+1}(1-\delta) - b_{t+1} - s(b_{t+1} - C_{t+1})^{+} \tag{8}$$

Where δ is the rate of capital depreciation and $k_{t+1}(1-\delta)$ shows the fair value of capital at time t+1 after depreciation. To model borrowing constraints, I assume that a firm can borrow up to *k* percent of its investment in capital, where *k* depends on factors such as the tangibility of a firm's investments, the company's relationship with the bank, the financial market situation, and so forth. This formulation has been used in several papers, including one by Almeida et al. (2004).

Following Whited (2005), and DeAngelo et al. (2011), I assume that firm is required to collateralize all its debt. This assumption is based on the limited enforcement concept proposed by Townsend (1979). Limited enforcement argues that lender would not be able to force borrower to pay all its debt, at default. Therefore lender would require borrower to collateralize all of its commitments. This assumption is not unrealistic in my sample of U.S. oil and gas producers. The average ratio of Debt to Property, Plant, and Equipment in my sample is about 30% with a median of 25%. The 75 percentile is 42% and the 95 percentile is 73%. Among 2813 firm-quarters in the sample, only 3 firm-quarters have a ratio of above 1.

In addition to debt, following Rampini et al. (2014), I assume that firm is required to collateralize all its hedges, and therefore hedging would decrease firm's borrowing capacity by decreasing the available collateral. Therefore firm's borrowing constraint can be written as following:

$$b_{t+1} \leq k(k_{t+1} - wh_{t+1}) \tag{9}$$

Where ω is the hedge collateral ratio, which is a constant between zero and one equal to the amount of collateral required for one unit of hedging. k is the debt collateral ratio, which shows the amount of collateral required for one unit of debt. Summarizing the above equations, a firm's maximization problem can be expressed as the following optimization problem:

$$\max_{k_{t=1}, b_{t+1}, s_{t+1}, h_{t+1}} d_t + \frac{1}{1+r(1-\tau)} E_t d_{t+1} \qquad \text{s.t.} \tag{10}$$

$$b_{t+1} \leq k(k_{t+1} - wh_{t+1}) \tag{10.1}$$

$$b_{t+1}, S_{t+1}, h_{t+1} \geq 0 \tag{10.2}$$

Where, equations 3 to 8 define dividends at times t and t+1. Conditions 10.1 and 10.2, combined, indicate that capital should be non-negative.

First, I prove that the above equation has a solution. Based on Weierstrauss' Extreme Value Theorem, if an optimization problem is continuous and all variables are defined as a finite set, then the optimization problem will have a maximum value in that set. Since the above maximization problem is continuous and all of its variables are higher than zero, I only need to prove that the variables are restricted from above.

To prove that capital has an upper limit in the constrained optimization (equation 10), I show that the unconstrained problem assumes its maximum value at some finite value of capital. Since any value of capital higher than the global maximum is not economically efficient, the existence of a global maximum with respect to capital indicates that capital is bounded from above. To find the upper limit for capital, I calculate the derivative of equation 10 without constraints with respect to k_{t+1}. Applying Leibniz's rule to the expectation at time t+1, I yield (proof in appendix A):

$$1 + r(1-\tau) - (1-\delta) = \alpha k_{t+1}^{\alpha-1} Z_t (1-\tau) + E_t(s(\alpha k_{t+1}^{\alpha-1} Z_{t+1}(1-\tau))^+) \tag{11}$$

Equation 11 shows the value of capital at which the Lagrangian derivative for the unconstrained problem with respect to capital is zero. Assuming that a firm has a neoclassical production function — i.e., its α (production return to scale) is less than 1 — equation 11 shows the value of capital for the global maximum of the unconstrained problem. Capital values higher than this point are not economically efficient. Therefore, capital has a finite efficient value, which is its upper limit. Further, the higher the probability of distress, the higher the optimum value of capital.

The existence of an upper limit for capital combined with the inequality constraints 10.1 and 10.2 guarantees that debt and hedging will have an upper limit, as well. Regarding cash, holding a large amount of cash makes the probability of distress close to zero. At zero probability of distress, the present value of each dollar of cash is $-\gamma$, which is the agency cost of cash. Therefore, holding cash above a certain limit is not economically efficient. Consequently, all of the model parameters are bounded from above and equation 10 satisfies all the conditions of Extreme Value Theorem, and therefore has a solution.

Differentiating the Lagrangian with respect to cash and applying the Leibnitz rule to the expectation, I yield (proof in appendix A):

$$\gamma = s \times (r(1+\tau)+1-\gamma) \times \int_A f(z_{t+1}) dz_{t+1} + \lambda \qquad (12)$$

The integral shows the probability of distress at the optimum point while A is the set of states (prices) at which distress happens (C_{t+1} lower than b_{t+1}). The left-hand side of 12 shows the agency cost of one additional unit of cash. The first term on the right hand side shows the reduction in distress costs expected to result from holding one additional unit of cash. The second term on the right hand side, λ, is the Lagrange multiplier for non-negativity of cash, and shows the shadow cost of one less dollar of saving when saving is zero. Therefore, equation 12 shows the level of cash at which the marginal benefit of cash equals the marginal cost of cash.

Equation 12 also shows the optimum probability of distress (i.e., the probability of distress at an optimum point) as a function of the model's parameters. The optimum probability of distress is not zero. This implies that, for example, it is not optimal to hedge extensively. Moreover, the optimum probability of distress goes up with the agency costs of cash and goes down with distress costs, tax rates, and required rates of return. The optimum probability of default given the base model parameters (shown in Appendix B) is about 0.5%.

Differentiating the Lagrangian with respect to hedging, I have (proof in appendix A):

$$P(1+r(1-\tau)) + \lambda_1 K\omega + \lambda_2 = s\int_A (Z_t - Z_{t+1}) f(Z_{t+1}) dZ_{t+1} \qquad (13)$$

Here, λ_1 and λ_2 are Lagrange multipliers for financing constraints and the non-negativity of hedging, respectively. The first term on the left hand side of equation 13 shows the future value of the cost of one additional unit of hedging. The second term shows the shadow cost of one more unit of hedging when constraint 10.1 is binding. The third term shows the shadow costs of hedging one less unit when hedging is zero. Hedging may be negative if the company is the buyer of financial derivatives. Since Oil and Gas produers are net sellers of derivatives, in this article I have assumed that hedging can not be negative. Therefore, for the non-negative values of hedging, the left hand side shows the marginal cost of one additional unit of hedging.

The right hand side of 13 shows the marginal benefit of one more unit of hedging in the form of a decrease in distress costs. Therefore, equation 13 shows the level of hedging at which the marginal benefit of one more unit of hedging equals its marginal cost. Here, hedging decreases distress costs by decreasing the number of states at which distress happens (shown by A, the integral domain). Distress normally happens in states where Z_{t+1} is sufficiently lower than Z_t. By locking the price at Z_t for a portion of production, hedging increases profits in low states and, thus, decreases the costs of distress.

Comparing equations 12 and 13 shows the differences between cash and hedging as two risk management tools. While both tools decrease the number of distress states by improving a firm's cash flow at bad states, cash does so independently of realized price, while hedging's benefits depend on the realized price.

3.2 Dynamic Model

Next, I study the model in a dynamic framework. In the dynamic model, time is discrete and horizon is infinite. The dynamic model at each time point is similar to the two-period model described above. At each time, there is one exogenous state variable, price (Z_t), and three endogenous state variables: company cash reserves (C_t), debt (b_t), and capital (k_t).

At each time and state, management determines four control variables that, together with price, determine the state of the company in the next period. Similar to the two-period model, in the dynamic framework, the control variables are investment in capital (k_{t+1}), cash saving

(S_{t+1}), next period's debt (b_{t+1}), and hedging (h_{t+1}). I assume hedging in the form of future contracts.

The rest of the equations for the dynamic framework model are the same as those of the two-period model presented in the previous section. At each time, the company pays the difference between sources as dividends if there is a cash surplus and raises equity if there is a cash shortfall. Also, the company should pay taxes on dividends, and floatation costs on equity financing (cost of equity financing). For each dollar of external equity paid into the firm, there is a floatation cost of $\lambda > 0$. Gomes (2001) estimates that the floatation costs of a firm are approximately 2.8% of its equity issuance amount.

Equation 8 shows the amounts of dividends paid or equity financing raised at each time frame without considering taxes and floatation costs. Equations 3 and 8 can be combined to write the following budget constraint for the dynamic model:

$$e_t = C_t + k_t(1-\delta) - b_t - s(b_t - C_t)^+ - k_{t+1} + b_{t+1} - S_{t+1} - Ph_{t+1} \tag{14}$$

$$d_t = (1 - \phi_d \tau + \varphi_e \lambda) e_t$$

$$\phi_d = \begin{cases} 0 & if \quad e_{t+1} \le 0 \\ 1 & if \quad e_{t+1} > 0 \end{cases} \qquad \phi_e = \begin{cases} 1 & if \quad e_{t+1} \le 0 \\ 0 & if \quad e_{t+1} > 0 \end{cases}$$

In this equation, e_t is the amount of cash surplus (or shortfall) that will be paid as dividends (or will be financed by issuing equity) and ϕ_d and ϕ_e are indicator functions.

Management maximizes shareholders' value, which can be formulated as the following Bellman equation:

$$V(k_t, C_t, b_t, z_t) = \max_{b_{t+1}, S_{t+1}, k_{t+1}, h_{t+1}} \{d_t + \frac{1}{1+r(1-\tau)} E_t(V(k_{t+1}, C_{t+1}, b_{t+1}, z_{t+1}))\} \tag{15}$$

This equation is subject to equation 9, financing constraint, equation 14, budget constraint, and the non-negativity of debt, capital, and hedging.

Instead of defining S as cash, I define it as net working capital. Several papers have shown that firms use working capital management as a hedging tool. By defining S as net working capital, I am able to study the combined effect of cash and other components of working capital as hedging instruments. This is a new insight that has not been studied in previous models of corporate risk management. Also, since net working capital can have negative values, there is no need to put a constraint on values of S.

3.3 Quantitative Analysis

Equation 15 does not admit a closed form solution and, so, should be solved numerically. However, given the large number of state and control variables, value and policy iteration methods cannot be implemented. These methods require finding, for each state, the subspace of control variables that are feasible in that state as well as finding the combination of feasible control variables that maximize the sum of distribution and continuation value. Moreover, since cash reserves in the model (C_t) area function of other variables, this step entails using methods such as Spline approximation to locate the proper value of cash reserves in the grid for each combination of control and state variables.

This procedure should be done at each iteration for the space of the state variables. This space equals a matrix of size $nk \times nb \times nC \times nz$, where nk, nb, nC, and nZ are the number of grid points for capital, debt, cash reserves, and price, respectively. Therefore, this problem is plagued by a curse of dimensionality, and the amount of computer CPU time required increases exponentially with the number of state and control variables being added to the equation.

Two of the most popular methods used in corporate finance literature to solve dynamic models are Simulated Method of Moments (SSM) and Simulated Maximum Likelihood (SML)[4]. Both of these methods rely on value and policy iteration techniques to solve the problem, and therefore are limited in the number of state and control variables that can be added to the model.

To solve the problem with dimensionality, I use the method of Stochastic Simulation. This numerical technique has been used extensively in Economics literature, but it has not been used in the corporate finance literature so far. In contrast to iteration methods that search the whole space of control and state variables, stochastic simulation approach studies a subspace of variables which is mostly seen in equilibrium (Ergodic set). By concentrating on the subspace, stochastic simulation enables modeler to add more state and control variables. However focusing

[4]A survey of many of these methods can be found in Strebulaev and Whited (2011)

on a subspace is not costless and this approach is only able to find a suboptimal solution of the dynamic model.

The stochastic simulation approach can be summarized as follows. First, I find the investment Euler equation for the firm optimization problem. The Euler equation gives the relationship between the state and control variables at the optimum level. Then I posit a functional form between the state and control variables (such as, for example, a linear equation). The goal of this approach is to find the parameters of this functional form.

Using this initial guess, the value of control variables and future states can be simulated. Then, at each point, the Euler equation is used to calculate the optimal value of control variables in that state and a regression model is run to find the updated functional form between the state and control variables. This recursive process continues until the simulated values converge and the mean percentage difference between points in subsequent simulations is lower than a predefined threshold.

The main challenge with stochastic simulation is convergence. As mentioned, the process continues until the simulated values converge. However, there is no guarantee that convergence will occur. Unfortunately, there areno universal guidelines on how to address the convergence problem in different models, and a customized solution based on the structure of the model is needed. I will address this issue in section 3.6.

3.4 Method in More Details

In this section, I explain the recursive process of stochastic simulation approach in more detail. First,I find the investment Euler equation for the dynamic problem to be solved. The Euler equation gives the relationship between state variables at time t and the expected value of a function of control and state variables at time t+1. Therefore, the Euler equation is the following:

$$f(X_t) = E_t(\beta \times g(X_t, X_{t+1}, C_{t+1})) \tag{16}$$

Here, X_t is the vector of the state variables at time t, $f(X_t)$ is a function of the state variables at time t, E_t is an expectation operator, β is a discount factor from time t+1 to t, X_{t+1} is a vector of state variables at time t+1, C_{t+1} is a vector of control variables at time t+1, and $g(X_t, X_{t+1}, C_{t+1})$ is a function of state and control variables.

It is possible to multiply both sides of this equation by any t-measurable[5] variable. For example, since, in our model, the control variables (like capital) for time t+1 are defined at time t (and are t-measurable), I can multiply both sides of 16 by any of the control variables and will yield:

$$C_{i,t+1} = \frac{E_t(\beta \times g(X_t, X_{t+1}, C_{t+1}) \times C_{i,t+1}}{f(X_t)} \tag{17}$$

Where $C_{i,t+1}$ shows the ith control variable. Therefore, I have the optimal value of each of the control variables as a function of the state and other control variables.

Next, I assume a functional form for each control variable. For example, I may assume the following form for hedging:

$$h_{t+1} = \alpha_0^h + \alpha_1^h \times z_t + \alpha_2^h \times k_t + \alpha_3^h \times C_t + \alpha_4^h \times b_t \tag{18}$$

Equations 17 and 18 are written for each of the control variables. Using equation 18, I simulate the values of the control variables. The correct, ideal functional form gives control variable values that match those obtained by Euler equation 17. This (hypothetical) functional form can be achieved if it contains all of the factors that affect the optimal decision. The goal of the stochastic simulation technique is to solve the fix point problem by finding a stable functional form that is as close to the optimal solution as possible. To do so, the stochastic simulation goes through a recursive process and calculates the values of parameters in equation 18 until the subsequent simulated values converge. The recursive process is as follows:

Initialization:

- Guess a function for each of the control variablesand propose an initial guess for parameters α_0^i (i represents capital, net working capital, debt, or hedging).
- Choose an initial state (k_0, b_0, C_0, z_0) for simulations.
- Choose a simulation length T and draw a sequence of shocks to simulate prices based on equation 1. For that, I would need two sets of standard normal shocks for the diffusion

[5] In measure theory, a t-measurable variable is a variable whose value is known at time t.

term and the size of the jump and one set of poison shocks for the occurrence of the jump.

Step 1. At iteration n, I use α_n^i to simulate the model *T* periods forward. To do this, I simulate a price based on equation 1 and use parameters α_n^i to simulate the values of the state and control variables at each time.

Step 2. Check for convergence and end the process if

$$\frac{1}{4}\sum_{i=1}^{4}\left(\frac{1}{T}\sum_{t=0}^{T}\left|\frac{Sim_{n,t}^{i}-Sim_{n-1,t}^{i}}{Sim_{n-1,t}^{i}}\right|\right)<\varpi \qquad (19)$$

Here, $Sim_{n,t}^{i}$ shows the simulated value of control i at iteration n, and $Sim_{n-1,t}^{i}$ shows the simulated value of control i at iteration n-1. ϖ is a user defined constant (convergence threshold).

Step 3. For t = 0, … , T-1 define k_{t+1}, b_{t+1}, h_{t+1}, and S_{t+1} to be an approximation of the conditional expectation of each of four control variables at time t+1 using Euler equation 17 and J integration nodes (J draws from the price stochastic process of equation 1 based on price at time t):

$$k_{t+1}=\frac{E_t(\beta\times g(X_t,X_{t+1},C_{t+1})\times k_{t+1}}{f(X_t)} \qquad (20a)$$

$$b_{t+1}=\frac{E_t(\beta\times g(X_t,X_{t+1},C_{t+1})\times b_{t+1}}{f(X_t)} \qquad (20b)$$

$$h_{t+1}=\frac{E_t(\beta\times g(X_t,X_{t+1},C_{t+1})\times h_{t+1}}{f(X_t)} \qquad (20c)$$

$$S_{t+1}=\frac{E_t(\beta\times g(X_t,X_{t+1},C_{t+1})\times S_{t+1}}{f(X_t)} \qquad (20d)$$

Step 4. Use the values obtained from step 3 to find the updated parameter estimates for the next iteration, α_{n+1}^i with the following regression equations for four control variables:

$$k_{t+1}=\psi_k(k_t,C_t,b_t,z_t;\alpha_k^{n+1})+\varepsilon_{k_{t+1}} \qquad (21a)$$

$$b_{t+1}=\psi_b(k_t,C_t,b_t,z_t;\alpha_b^{n+1})+\varepsilon_{b_{t+1}} \qquad (21b)$$

$$S_{t+1} = \psi_s(k_t, C_t, b_t, z_t; \alpha_s^{n+1}) + \varepsilon_{s_{t+1}} \quad (21c)$$

$$h_{t+1} = \psi_h(k_t, C_t, b_t, z_t; \alpha_h^{n+1}) + \varepsilon_{h_{t+1}} \quad (21d)$$

Step 5. Compute α_{n+1}^i for control *i* at iteration *n+1* using fixed point iteration.

$$\alpha_{n+1}^i \approx (1-\xi)\alpha_n^i + \xi\alpha_{n+1}^i \quad (22)$$

Here, $\xi \in [0,1]$ is a damping parameter. Go to step 1.

3.5 Calculating the Euler Equation

As mentioned, the first step is to find the investment Euler equation as a function of the state and control variables. The firm maximization problem can be written as the following recursive optimization problem:

$$V(k_t, C_t, b_t, z_t) = \max_{b_{t+1}, S_{t+1}, k_{t+1}, h_{t+1}} \{d_t + \frac{1}{1+r(1-\tau)} E_t(V(k_{t+1}, C_{t+1}, b_{t+1}, z_{t+1}))\} \quad (23)$$

s.t.

$d_t = (1-\phi_d\tau + \phi_e\lambda)e_t$ and

$$e_t = C_t + k_t(1-\delta) - b_t - s(b_t - C_t)^+ - k_{t+1} + b_{t+1} - S_{t+1} - Ph_{t+1} \quad (23a)$$

$$b_{t+1} \le k(k_{t+1} - wh_{t+1}) \quad (23b)$$

$$b_{t+1} \ge 0 \quad (23c)$$

$$h_{t+1} \ge 0 \quad (23d)$$

Combined, constraints 23b, 23c, and 23d imply that $k_{t+1} \ge 0$. As noted earlier, I assume that S represents net working capital and, therefore, can get negative values.

Differentiating the Lagrangian with respect to S_{t+1} gives the following investment Euler equation:

$$(1-\varphi_{dt}\tau + \varphi_{et}\lambda) = \frac{1}{1+r(1-\tau)} E_t\left\{(1-\varphi_{dt+1}\tau + \varphi_{et+1}\lambda)\left[r(1-\tau) + (1-\gamma) + s(r(1-\tau) + (1-\gamma))^+\right]\right\}$$

φ_{dt} and φ_{et} show the value of the indicator functions at time t, and φ_{dt+1} and φ_{et+1} show the value of the indicator functions at time t+1. Also, the term $(r(1-\tau)+(1-\gamma))^{+}$ equals zero if the firm is not in distress. Since control variables are t-measurable, I can use the investment Euler equation to find a formula for each of the control variables. For example, for hedging Ihave

$$h_{t+1} = \frac{1}{1+r(1-\tau)} E_t \left\{ h_{t+1} \frac{(1-\varphi_{dt+1}\tau+\varphi_{et+1}\lambda)}{(1-\varphi_{dt}\tau+\varphi_{et}\lambda)} \left[r(1-\tau)+(1-\gamma)+s(r(1-\tau)+(1-\gamma))^{+} \right] \right\} \tag{24}$$

The above formula will be used in the stochastic simulation process to find the value of control variables based on the Euler equation.

3.6 Convergence, Consistency, and Constraints

In this section, I explain how I address two main issues with the model: convergence and the existence of inequality of constraints.

The major challenge with all stochastic simulation techniques, as mentioned, is convergence. In our model, convergence is checked by calculating the mean absolute percentage change between the simulated values of control variables in two consecutive iterations. This measure may never become less than the convergence threshold or it might be unstable and non-monotonic. In the latter case, the process may converge at apoint and then diverge again.

To solve the convergence problem, several authors have suggested approaches that help to stabilize the process. However, as mentioned earlier, there is no general rule that applies to all problems, and customized solutions should be applied based on the structure of the model being used. I start by following the guidelines suggestedin Judd, Maliar, and Maliar (2011) (henceforth JMM), who propose a numerically stable algorithm to solve stochastic dynamic problems in Economics. Their approach partially solves the stability problem. Next, I add an additional step that results in a stable solution for a wide range of model parameters.

The stochastic simulation approach is based on solving linear models at each iteration. JMM identify two factors that make the model unstable: differences between variable scales and collinearity between variables.

Differences in scales are not a problem in theory; however, in practice, they make optimization models unstable. When one variable has a higher volatility and scale than another variable, the optimization problem puts more weight on the variable with the higher standard deviation and can be easily trapped in a local solution. As a result, at consequent iterations, different solutions will appear and the model does not converge. JMM solves this problem by normalizing the variables at each iteration. Specifically, in our dynamic model the values of prices are significantly lower than the values of the other state variables of capital, cash, and debt. Normalization helps to yields table price coefficients.

The solution to collinearity is more involved. Collinearity is inherent in all stochastic simulation models. The process of using a single shock drawn from a well-specified distribution for all variables, make the variables highly correlated. As a result the coefficients of the least square model will be unstable and significantly change from one iteration to another. To solve this problem JMM propose two solutions. Both of these solutions are modified versions of least square (LS) to deal with collinearity.

The first approach, called LS with SVD, uses a singular value decomposition of independent variables. This approach is similar to principal component analysis. At each iteration, the independent variables are replaced by their singular values, which, by definition, are (almost) orthogonal to each other. Then, these singular values are used to solvethe LS model instead of the original independent variables.

The second method to solve for collinearity and stabilize the model is by using another modified version of OLS, called the RLS-Tikhonov approach. In this approach, a penalty will be assigned to the coefficients so that they cannot jump from one iteration to another. In this way, the optimization problem will minimize the sum of the squared error subject to a penalty for coefficients with large absolute values. The minimization problem to be solved, therefore, is the following:

$$\min_b [(y - Xb)^2 + \eta b^2] = \min_b [(y - Xb)^T (y - Xb) + \eta b^T b] \tag{25}$$

Here, η is a positive number. In this paper, I use the second approach, RLS-Tikhonov, to find the model's parameters.

Finally, to achieve convergence it is necessary to regularize equation 24, which defines the new values of the control variables to be used in the next iteration:

$$h_{t+1} = \frac{1}{1+r(1-\tau)} E_t \left\{ h_{t+1} \frac{(1-\varphi_{dt+1}\tau + \varphi_{et+1}\lambda)}{(1-\varphi_{dt}\tau + \varphi_{et}\lambda)} \left[r(1-\tau) + (1-\gamma) + s(r(1-\tau) + (1-\gamma))^{+} \right] \right\} \qquad (24)$$

In equation 24, both sides are multiplied by the control variables, which, as mentioned, are t-measurable. The large scale of the control variables results in sudden jumps and large volatility in the results of equation 24. Therefore, the speed of convergence will be very low, and achieving convergence below a 0.01 threshold is practically impossible. To regularize equation 24 and control fluctuations, I use the standardized values of the control variables.

Even after doing all of these regularizations, getting convergence is not possible for all the values of the model's parameters. For example, large values for fire-sells (values higher than about 0.6) would result in an ascending series of control variables given equation 24, and the process would never converge.

In summary, for a large set of model parameters, the three steps that I used (the normalization of variables, RLS-Tikhonov regularization, and the normalization of equation 24), controls fluctuations in the numerical simulations, which is an important step in getting convergence in numerical techniques. Using these three steps, I was able to get convergence thresholds of 0.0001.

The regularization mentioned above also helps with the model's constraints (the non-negativity of capital, debt, hedging, and the financing constraints). This point is worth explaining, as it shows how simulated values at each iteration look alike.

The process involves trying to find coefficients for linear equation 21. These equations should satisfy the model's constraints. Therefore, the least square formulation should minimize the error but, at the same time, penalize coefficients that result in a violation of constraints. In fact, I am looking for a solution to the following system of constrained linear equations:

$$\hat{k}_{t+1} = \beta_{k0} + \beta_{kk} k_t + \beta_{kb} b_t + \beta_{kc} C_t + \beta_{kP} P_t \qquad (26a)$$

$$\hat{b}_{t+1} = \beta_{b0} + \beta_{bk} k_t + \beta_{bb} b_t + \beta_{bc} C_t + \beta_{bP} P_t \qquad (26b)$$

$$\hat{h}_{t+1} = \beta_{h0} + \beta_{hk}k_t + \beta_{hb}b_t + \beta_{hc}C_t + \beta_{hP}P_t \tag{26c}$$

$$\hat{S}_{t+1} = \beta_{S0} + \beta_{Sk}k_t + \beta_{Sb}b_t + \beta_{Sc}C_t + \beta_{SP}P_t \tag{26d}$$

$S.t.\ \hat{k}_{t+1}, \hat{b}_{t+1}, \hat{h}_{t+1} \geq 0\ and\ K(\hat{k}_{t+1} - \omega \hat{h}_{t+1}) \geq \hat{b}_{t+1}$ for all values of t.

One solution for the above system of equations is to assume that all of the coefficients except for the intercept are zero. In this case, the optimal policy will be constant, irrespective of the state. Obviously, this solution is not interesting. In the stochastic simulation, the effect of regularization and RLS-Tikhonov is that the coefficients of the regression equation will be small. So, the optimal policy for each control variable moves around and gets close to the sample mean of each control variable. This is essential to get convergence. Stochastic simulation does not give the global optimal policy, however. Rather, it shows the linear relationship between control and space variables under a sub-optimal solution. With regularization, the system of regression equations explains a small percentage of the variation in the dependent variable (optimal policy). Also regarding constraints, as long as the sample means for capital, debt, and hedging satisfy the constraints, all of the constraints will be satisfied in the final solution.

3.7 Model Results

To define the model parameters, I use Hennessey and Whited (2005), Gamba and Triantis (2008), Nikolov et al. (2014), and Judd et al. (2011). Appendix B shows the base parameters. I solve the model for the base parameters first and then do sensitivity analyses of some of the model parameters. The parameters for oil price process, equation 1, are obtained by calibrating the model based on monthly oil prices from January 2000 to December 2016. The calibration process is explained in appendix A.

Following Asquith, Gertner, and Scharfstein (1994) and Hennessey and Whited (2005), fire sell costs are assumed to be 20% of the fair value of the asset. The agency costs of cash are assumed to be 0.1% of cash savings, as suggested by Nikolov et al. (2014). The hedge-collateral ratio is 25%, which is based on the opinion of industry experts. Following Gamba and Triantis (2008), the debt-collateral ratio is assumed to be 80%. Finally, equity floatation cost is assumed to be 0.028, following Gomes (2001) and Hennessey and Whited (2005). Other values — including risk-free rate, tax rate, and depreciation rate — are based on the overall opinion in the literature.

For the parameters in the stochastic simulation model, I follow Judd et al. (2011). The damping parameter (ξ), which is equivalent to alearning rate in machine learning, is 0.1. This parameter is an important factor in achieving convergence. The process will not converge with high values of ξ while small ξ values make the convergence rate slow. 0.1 is a reasonable value that balances convergence and speed.

The length of the simulation path is 200 at each point. Based on equation 24, I draw 10 integration nodes to find new values of the control variables. Finally, the convergence threshold is assumed to be 0.0001. This is a fair threshold. Considering the number of state variables (4), JMM would suggest a convergence threshold of 10^{-9}; however, due to the complex structure of our model, achieving a convergence rate of that order is practically impossible.

I assume that the control variables are the first order polynomials of state variables. Since all of the variables are normalized, the equations will not have an intercept. Therefore, the equations for Capital, Debt, Net Working Capital, and Hedging, as a function of the previous period's Price, Capital, Debt, and Cash, will be the following:

$$k_{t+1} = \beta_{kk} k_t + \beta_{kC} C_t + \beta_{kb} b_t + \beta_{kZ} Z_t + \varepsilon_{k_{t+1}} \tag{27a}$$

$$b_{t+1} = \beta_{bk} k_t + \beta_{bC} C_t + \beta_{bb} b_t + \beta_{bZ} Z_t + \varepsilon_{b_{t+1}} \tag{27b}$$

$$S_{t+1} = \beta_{Sk} k_t + \beta_{SC} C_t + \beta_{Sb} b_t + \beta_{SZ} Z_t + \varepsilon_{S_{t+1}} \tag{27c}$$

$$h_{t+1} = \beta_{hk} k_t + \beta_{hC} C_t + \beta_{hb} b_t + \beta_{hZ} Z_t + \varepsilon_{h_{t+1}} \tag{27d}$$

As explained, JMM starts the algorithm by assigning initial values for βs. Starting with an initial β may result in sequence of control variables that do not satisfy the model constraints, however. Therefore, instead of starting with an initial guess for the coefficients, I start the algorithm by assigning initial values for the control variables. In this way, I control the values so that they satisfy the constraints.

I define initial state using the median of capital, cash, debt, and price in our sample of U.S. oil and gas producers, explained in chapter 4. The initial value of capital is the median of Property, Plant, and Equipment, which is 1500 million dollars. The initial values for debt and cash are 750 and 25 million dollars, respectively. The initial value of price is assumed to be the average of the monthly price of oil from 2000 to 2016, which is $62.

These initial values are used to simulate the initial path of the state and control values. I assume that the control variables follow a log-normal distribution with a distribution mean equal to initial values (the sample median for that variable). Since the number of periods in the model is 200, so I draw 200 random values for each control variable. The initial value for production return to scale is assumed to be the value that makes net cash and debt equal to each other at the median point of control variables and that is equal to 0.815.

Using initial values as control variables, I calculate the initial values for Cash at each point. Next, the initial values for βs are calculated using regression equation 27 and the process continues until convergence is achieved. I run the model 10 times and calculate the average of model parameters for 10 runs of the model.

Table 1 shows the results of the model with base parameters (shown in Appendix B). The rows show the control variables at time t+1 and the columns show the state variables at time t. The values in the table show the coefficient for each control-state variable in the system of equation 27.

Table 1. Model results for base parameters

	Capital_t	Cash_t	Debt_t	Price_t
Capital_{t+1}	-5.32e-04	3.33e-04	-6.82e-04	-5.41e-04
Debt_{t+1}	-1.48e-04	8.42e-06	-1.12e-04	-7.61e-05
Hedging_{t+1}	-1.51e-04	1.32e-04	-1.71e-04	**-1.87e-04**
Saving_{t+1}	1.06e-06	-1.42e-07	2.44e-07	-2.13e-06

This table shows results of the model using base parameters of Appendix B. Rows represent control variables and columns represent state variables. Values in the table show coefficient of each state-control variable pair in the system of equations 27. I run the model 10 times. Numbers reported in the table are the average coefficients of 10 runs of the model.

As Table 1 shows, the coefficient of price-hedging is negative, which indicates a negative relationship between price and hedging. In other words, the model suggests that the optimal level of hedging is higher when the prices are lower. Since the probability of distress, on average, is higher when prices are lower, these results are consistent with theories of financial hedging indicating that companies should hedge more when they are more financially constrained.

The relationship between hedging and other state variables is also interesting. First, the model shows a negative relationship between capital and hedging. Since capital is a proxy for firm size, the model suggests that smaller firms hedge more than large firms. Size has been used as one of the most popular determinants of financial constraintin the literature. Several empirical papers have shown a positive relationship between size and hedging and have found this to be evidence of contradiction in theories of financial hedging. However, size is an endogenous determinant of distress, and other factors may affect the relationship between size and hedging. The results of the present model show that hedging is negatively related to size, while other firm and market characteristics are constant.

The relationship between debt and hedging is negative. This is consistent with Rampini et al. (2010, 2012, 2014), who suggest that hedging requires collateral and that firms that need to maintain their financing capacity for debt financing prefer to hedge less. In the same way, the positive relationship between cash and hedging can be explained. In my model, a firm pays back its debt using internal cash flow. Therefore, a higher cash flow would enable firms to pay back a higher portion of debt, which preserves debt capacity and creates room for hedging.

Table 1 also shows the relationship between state variables and other control variables. First row shows the results for capital. Coefficient of capital (capital in the previous period) is negative. Note that all variables are standardized and can get negative values. Negative value for coefficient of lag of capital indicates that capital is a mean reverting process.

The coefficient of cash is positive which shows that firms invest in more capital when their cash flow is higher. The coefficient of debt is negative. The reason is that firm has less borrowing capacity and resources to invest in capital when the level of debt is high. This is related to the argument in Nikolov et al. (2014) who suggest that firms manage their debt capacity as a hedging instrument to be able to exploit investment opportunities in the future.

The second row of Table 1 shows the coefficients for debt. The coefficient of capital is negative, indicating that large firms have lower debt to asset ratio compared to small firms. Also, the coefficient of cash is positive, indicating that firms with higher internal cash flow have higher debt capacity. Finally the coefficient of price is negative; meaning that firms have less debt when prices are higher. The reason might be that when prices are higher, operational profit and internal cash flow are higher; therefore firms depend less on debt financing for investment.

The last row of Table 1 shows the coefficients for saving. The coefficient of capital is positive, showing that large firms save more. The coefficient of price is negative, consistent with the idea that firms use saving as a hedging instrument. Similar to the argument for hedging, on average firms are more financially constrained when prices are lower. The negative relationship between saving and price is another evidence for that firms hedge more when they are more financially constrained.

The coefficient of cash is negative. This result can be related to Almeida et al. (2004) who study the liquidity demand of firms and show that constrained firms have a positive cash flow sensitivity of cash while there is no systematic relationship between cash saving and cash flow for unconstrained firms. Since lower cash flow on average means higher financial constraint, negative coefficient of cash flow may show that firms with lower cash flow save more to hedge their liquidity demands. For the same reason, the coefficient of debt is positive showing that firms hedge more when the level of debt is high, again to hedge their liquidity demands and to decrease distress costs. In general, the results for cash is more evidence for that firms hedge more when they are more financially constrained.

In summary, the results of the model show how four important state variables affect hedging policies. The literature on financial hedging commonly misses one or two of these factors and gets mixed results with regard to the relationship between hedging and firm characteristics. This research is an attempt to study the simultaneous effect of some of the most important firm and market characteristics on the complex process of financial hedging.

3.8 Sensitivity Analysis

As mentioned, the literature on financial hedging is full of contradictory results. Regarding the relationship between price and hedging, several papers have suggested the idea of selective hedging, which suggests that firms attempt to time their market prices to benefit from hedging. For example, Brown et al. (2006), in a study of a sample of gold companies, show that gold companies hedge more when prices are high to benefit from probable drops in prices. Adam et al. (2017) use the same sample of gold miners but, applying a different econometric approach, show a negative relationship between the price of gold and financial hedging. Another example is Doshi et al. (2017), whose study of a sample of oil and gas producers in the period between 1990 and 2013 shows that hedging is positively related to prices.

To address these contradictory results, in this section I offer a sensitivity analysis of model parameters to see how they affect the model results. My goal is to check if changes in market conditions would change firms' behaviors (for example, making them either more conservative or more opportunistic). Specifically, I study how the parameters of price processes — such as the speed of mean reversion, the long-term mean, the volatility of price, the mean and volatility of jump intensity, and the mean of jump processes — affect the price-hedging relationship. I also do a sensitivity analysis on the initial values of capital, debt, and price.

Due to the random generation of price and initial variables at each iteration of the model, the results slightly change in different runs of the model. Therefore, for each set of parameters, I run the model 20 times and calculate the average of these runs'coefficients.

Table 2 compares the price characteristics for the prices in my sample (the monthly oil price from January 2000 to December 2016) and the prices in Doshi et al.'s (2017) sample (monthly oil prices from January 1990 to December 2013). As mentioned, Doshi et al. (2017) have shown a positive relationship between price of oil and hedging. I use equation 1 to calibrate the parameters of the price process. This calibration is explained in appendix A.

Before doing the sensitivity analysis and to check whether equation 1 is a fair model of oil prices, I simulate the oil prices, using the estimated parameters in Table 2, and perform the Chi-

Squared Goodness of Fit Test on the actual and the simulated prices, using 10 bins[6]. This test identifies whether two samples are from the same distribution. Since the price will be simulated several times in the model, I run 10 simulations, and compare the distribution of oil prices with the distribution of 10 simulated paths combined.

Table 2. Comparison between price parameters in my sample vs. Doshi et al. (2017) sample

	My Sample (Oil prices from Jan 2000 to Dec 2016)	Doshi et al. Sample (Oil prices from Jan 1990 to Dec 2013)
Long Term mean of return	1.0835	0.1075
Volatility of return	0.3052	0.2402
Coefficient of Mean Reversion	0.2612	1.2032e-05
Mean of Jump Intensity	0.34	-0.0483
Volatility of Jump Intensity	0.2717	0.1559
Mean of Jump Process	0.3673	1.2000e-05

This table shows the calibrated price parameters based on my sample vs. Doshi et al.'s (2017) sample. Parameters are calibrated based on equation 1, as explained in appendix A. The first column shows the results for our sample, which arecomposed of the monthly prices of oil from 2000 to 2016. The second column shows the results for Doshi et al.'s (2017) sample, which is composed of monthly price of oil from 1990 to 2013.

For the period of January 2000 to December 2016, the value of Chi-Squared test statistic with 10 degrees of freedom (number of bins) is 19.04. This value rejects the null hypothesis of equality of distributions at 5% but fails to reject it at 2.5%. Considering the relatively small size of sample (204 observations) I conclude that equation 1 is a fair representative of oil prices for the period of 2000 to 2016.

For the period of January 1990 to December 2013, the value of Chi-Squared test statistic with 10 degrees of freedom is 47.34. This value rejects the null hypothesis of equality of distributions at 0.1%. I conclude that equation 1 is not a fair representative of oil prices in the period of 1990 to 2013. One reason is that oil price behavior changed significantly after 2000 compared with

[6] For a thorough discussion of how to use Chi Square Goodness of Fit test for two samples with unequal number of observations please see: http://www.itl.nist.gov/div898/software/dataplot/refman1/auxillar/chi2samp.htm

before 2000. Therefore, fitting a model that accurately captures the behavior of oil price in this period is very difficult.

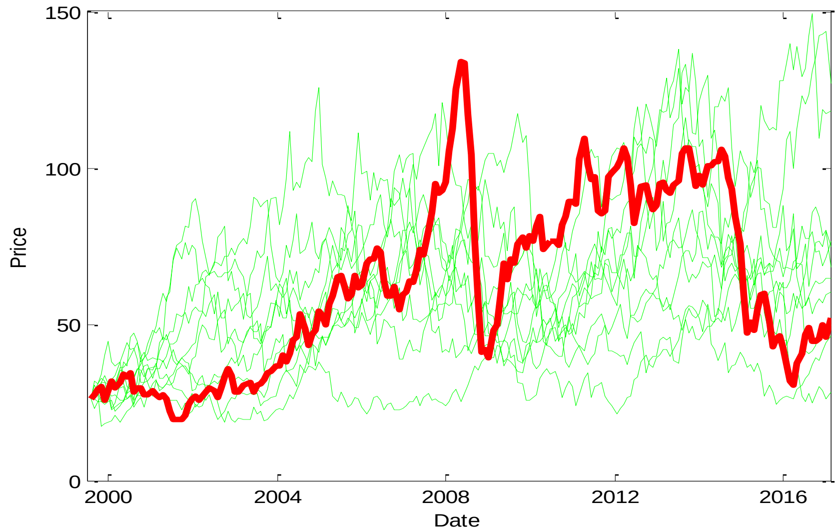
Figure 2 illustrates actual versus simulated prices for 10 simulated paths. The thick, red lines in both panels show the actual prices. The green lines show 10 simulated paths. Panel A shows the results of simulation for the period of 2000 to 2016, and Panel B shows the results for the period of 1990 to 2013. Simulations are based on the price process of equation 1 with estimated parameters of Table 2.

Figure 2 confirms the results of Chi-Squared test. Simulated prices in Panel A fairly represent the actual prices in that period (2000 to 2016), while in Panel B, there are large deviations from the actual prices in some simulated paths. In Panel B, note the change in the behavior of oil prices before and after 2000, which as mentioned complicates the modeling of prices in this period.

Going back to the sensitivity analysis, Table 2 shows that there is a large difference in the price process between the two samples. Mean return is much higher in my sample, which is the result of increases in oil prices after 2000, followed by sharp jumps around 2004 and 2008. Also, the volatility of prices (price uncertainty) is higher after 2000. The period after 2000 also has a much higher speed of mean reversion compared to the period before 2000. Finally, there are different patterns in both size and probability of jumps between the two periods. The period after 2000 is characterized by several medium-size positive jumps followed by large negative jumps. The mean of the jump sizes is much higher after 2000 compared with before 2000. Also, the probability of jumps is much higher in the period after 2000. Both the volatility of prices and the probability of jumps shows higher risk and uncertainty in my sample compared to that of Doshi et al. (2017). This might be a reason for firms to be more conservative with respect to changes in market conditions.

Next, I do sensitivity analyses on the six parameters of price processes in Table 2 to show how the relationship between price and hedging will change as a result of changes in these parameters. For each parameter, I keep the other parameters constant at their base values and, as mentioned, I run the model 20 times for each set of parameters and calculate the average of the price coefficients for hedging among the 20 runs.

Panel A – Actual versus Simulated Prices in the period of 2000 to 2016



Panel B - Actual versus Simulated Prices in the period of 1990 to 2013

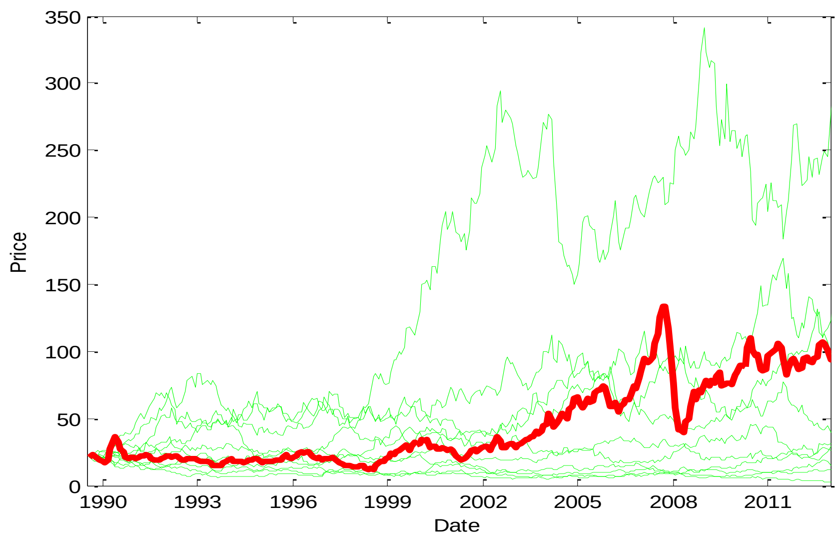


Figure 2. Actual versus Simulated Oil Prices

This Figure shows simulated versus actual prices of oil. The thick, red lines in both panels show the actual prices. Green lines show the simulated prices, based on the mean-reverting, jump-diffusion process of equation 1. Each Panel shows 10 simulated paths. Panel A shows the results for the period of 2000 to 2016. Panel B shows the results for the period of 1990 to 2013 which is the period of analysis in Dushi et al. (2017). Estimated parameters of both Panels are shown in the Table 2.

Figure 3 shows the results of the sensitivity analysis. Panel A shows the results for the long term mean of return (μ), whenthe mean return is changed from 0.1 to 1.5 at 0.1 increments. Although an overall negative slope can be seen, the graph does not show a monotonic relationship between the mean return and the price-hedging relationship. I can conclude that the long term mean of return is not a factor affecting firms' decisions.

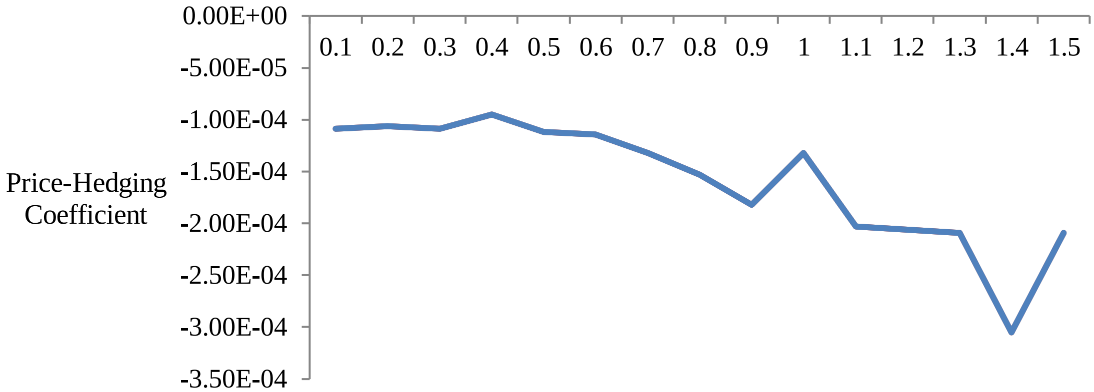
Panel B shows the sensitivity analysis with respect to the standard deviation of the price return (volatility of price). The results show a negative relationship between price uncertainty and the price-hedging coefficient. Several papers have shown that firms manage their risk more aggressively when uncertainty is higher. In other words, risk management becomes more important as uncertainty goes up. This is consistent with the results in panel B, which shows a higher sensitivity between hedging and company's financial situation when market risk is higher. Comparing these results with the results in Table 2, one explanation for the difference in the results between this paper and Doshi et al.'s might be that market risk is lower in the period analyzed by Doshi et al. In those circumstances, firms can be less cautious and more opportunistic, tying to do selective hedging.

Panel C shows sensitivity analysis with respect to the coefficient of mean reversion, when the values change from 0.05 to 0.4 at 0.05 increments. No relationship can be seen between the coefficient of mean reversion and price-hedging sensitivity, and the speed of the mean reversion does not appear to bean important factor affecting firms' decisions.

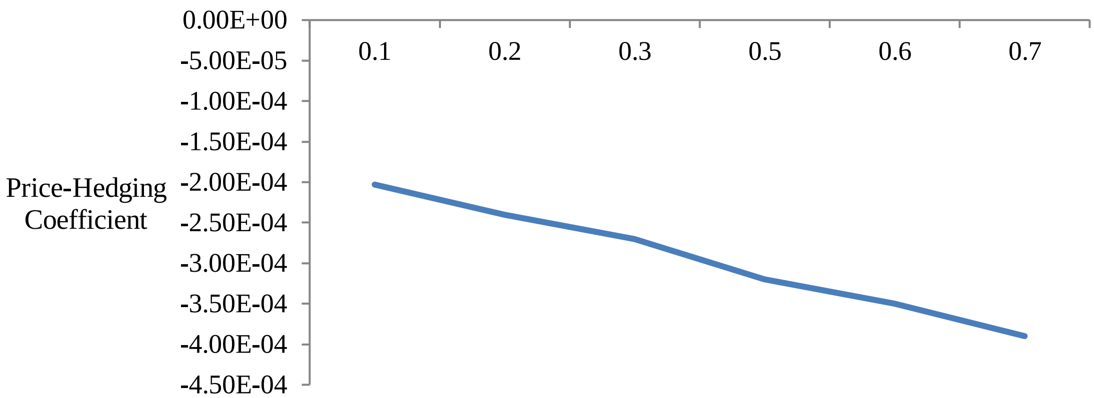
Panel D shows the results for mean of jump intensity which is the average size of jumps. This parameter is positively related to price-hedging sensitivity. This result is in contradiction to results in this paper when compared with results in Doshi et al. (2017). Mean of jump intensity is lower in the period analyzed in Doshi et al. compared to our period. Therefore based on Panel D I expect that price-hedging coefficient be higher in my study.

One way to explain this contradiction is by noticing that the period after 2000 is characterized by several medium-size, positive jumps followed by large negative jumps. It is like that jump size in this period is negatively skewed. A risk-averse agent would put more weight on negative jumps than positive ones and would be more cautious when prices and operating profit is low because negative jumps can result in large distress costs at these periods. A more complete approach in analyzing jumps would be to distinguish between negative and positive jumps and study their effects separately.

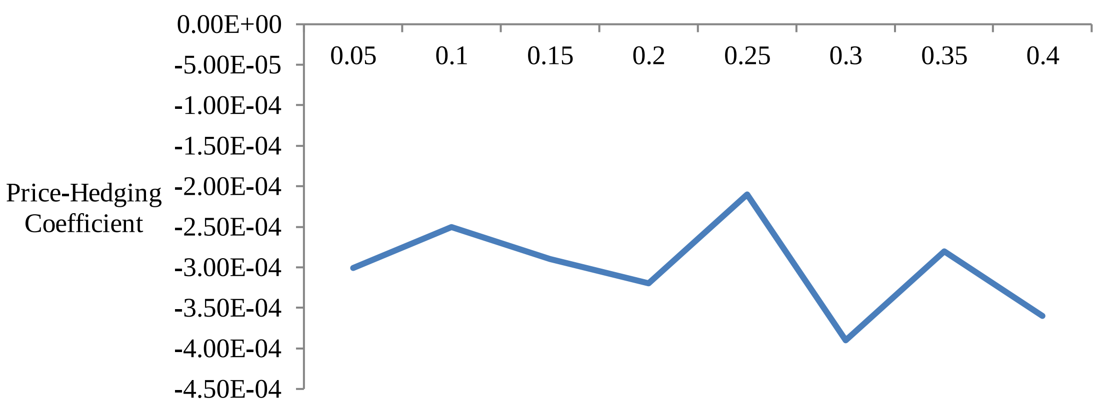
Panel A - Long Term Mean of Return



Panel B -STD of Return



Panel C - Coefficient of Mean Reversion



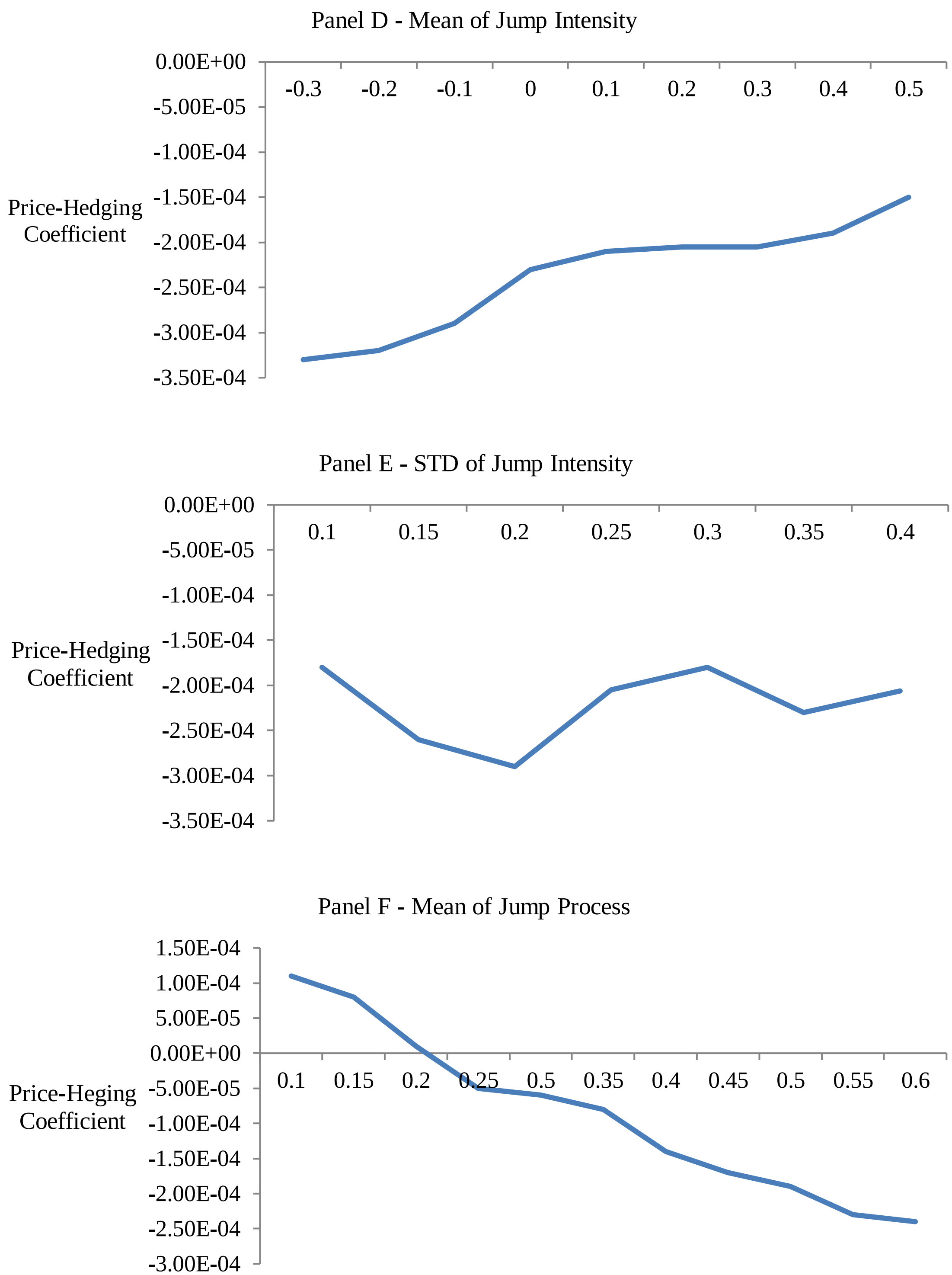


Figure 3. Sensitivity of Price-Hedging relationship with respect to price process parameters

Panel E shows that there is no relationship between the standard deviation in jump intensity and the price-hedging coefficient, which suggests that jump volatility does not affect the firm's hedging decisions.

Probably the most significant result of this section is Panel F, which shows a negative relationship between the probability of jump and the price-hedging coefficient. The price-hedging coefficient becomes more negative as the probability of a jump goes up. In fact, the only time that I find a positive coefficient for price is for small jump probabilities. A higher jump probability means higher market volatility and uncertainty, which makes risk management more valuable. When prices are low and the probability of a jump is high, expected distress costs are high. Therefore, firms hedge more to decrease distress costs.

The results in Panel F suggest an explanation for the difference between my results and the results in Doshi et al. (2017). As Table 2 shows, the jump probability in Doshi et al.'s sample is close to zero while, in my sample, the mean of the jump process is about 0.36. Therefore, importance of risk management, especially at low prices, is higher in my sample.

Next, I examine how the initial state affects the price-hedging relationship by performing sensitivity analysis oninitial values of price, debt, and capital. The initial price value in my sample is $62, which is the average of monthly price of oil in the period between 2000 and 2016. The price of oil was much lower before 2000. The initial price value has a significant effect on the simulated values of prices at each iteration. Therefore, it would be interesting to see if initial values can affect the price-hedging relationship. Figure 4, panel A shows how initial price values affect the price-hedging relationship. Prices are changed from 10 to 100 in increments of 10. Panel A suggests that the initial price does not have a clear impact on the price-hedging relationship.

Next, I study how initial debt values affect the price-hedging relationship. By changing the initial values of debt, I change firm leverage, which affects distress costs. In my base model, the initial value of debt is $725 million. I change the debt values from $200 to $1200 million, keeping the other values constant. Panel B in Figure 4 shows the results. Consistent with expectations, as the initial value of debt (and, therefore, firm leverage) goes up, firm hedging policies become more sensitive to prices and market conditions. These results, again, confirm that risk management becomes more valuable when the expected costs of distress are higher.

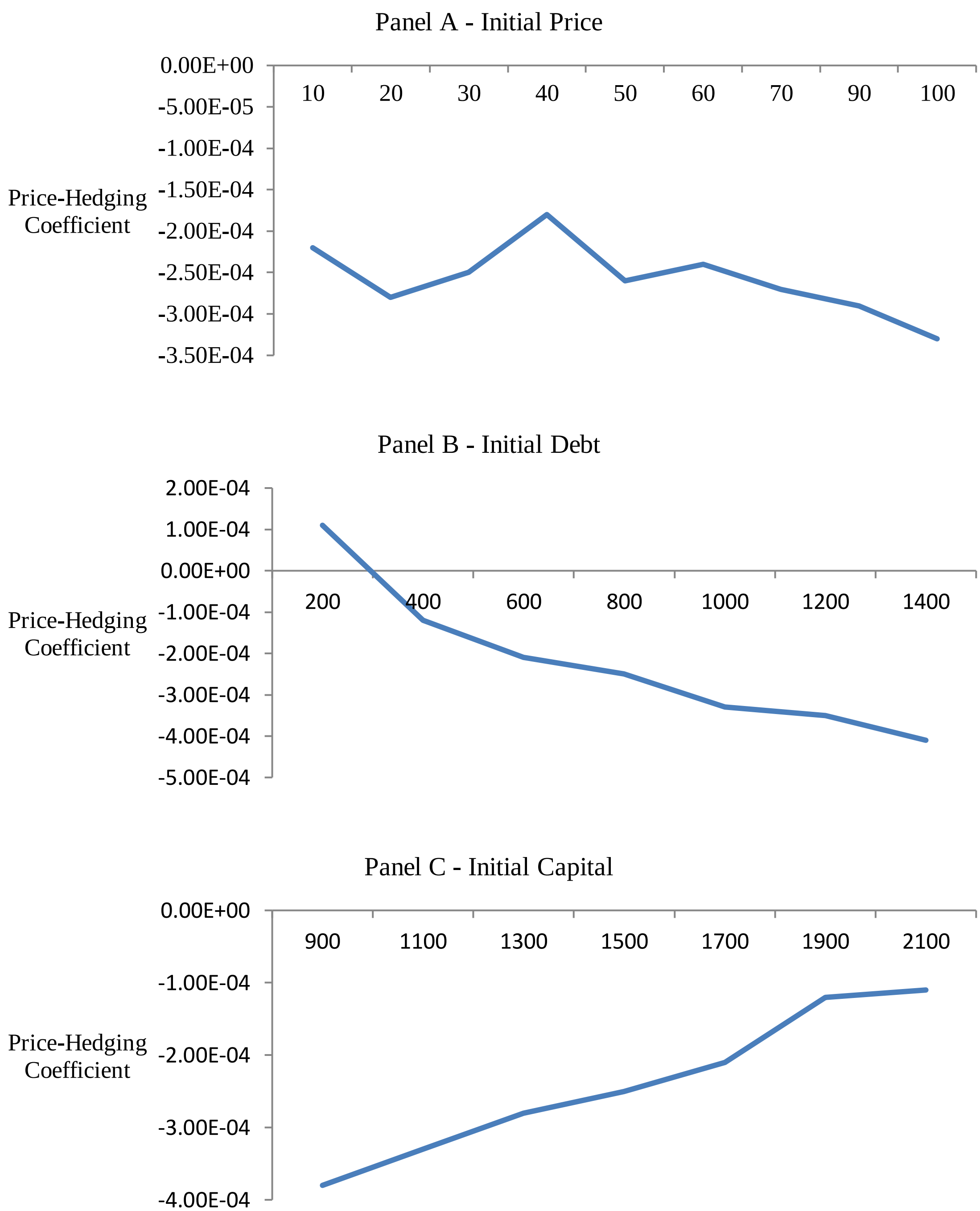


Figure 4. Sensitivity of Price-Hedging relationship with respect to initial values of price, debt, and capital

Panel C of Figure 4 shows how initial values of capital, affect price-hedging relationship. Capital is the proxy for size, which has been mentioned as the most important indicator of financial constraint in the literature. In my model, larger size means higher operational profit and higher financing capacity; both factors affecting level of financial constraint. Panel C shows that price-hedging relationship is positively related to size. In other words, price-hedging coefficient is more negative for small firms compared to large ones; meaning that hedging policies of small firms are more sensitive to the changes in prices. This result is directly related to my empirical analysis in Chapter 4 where I show that small firms increased their hedging activities significantly more than large firms, following drop in price of oil in the fourth quarter of 2014, and is another evidence for higher value of hedging for constrained firms compared to unconstrained ones.

CHAPTER 4

EMPIRICAL ANALYSIS

4.1 Data

My sample comprises U.S. oil and gas producers as categorized under SIC code 1311. I include companies that are active and have a record in the merged CRSP-Compustat database for four quarters before and after the oil price drop in the fourth quarter of 2014. Therefore, the company should have a record for all the eight quarters of 2014 and 2015. In addition, the company's major currency should be U.S. Dollars (i.e., curcdq = "USD"). After these filters are applied, the final dataset is composed of 113 U.S. based oil and gas companies and 2,814 firm quarters.

Companies with SIC code of 1311 are active in oil and gas production only. Therefore, companies like Exxon Mobil, which is active in other segments like refining, are not included in the sample. The reason for excluding these firms is that they are often active in segments that may affect their exposure to prices. For example, an oil company that both produces oil and operates a refinery is simultaneously a producer and consumer of oil. This operational flexibility decreases firm's exposure to oil price changes, and hedging activities in these companies are less likely to be related to the price of oil. Some of the largest firms in our sample include Conoco Philips, Apache Corp., Anadarko Petroleum Corp., and Occidental Petroleum Corp.

The main dependent variable is hedge ratio which is defined as the ratio of total hedge to total production. I use volume of hedge and production instead of fair value. Fair value of derivatives measures the amount that the contract holder would pay, or receive, to liquidate the contract. Therefore fair value does not convey the amount of production hedged by the company.

The first empirical paper that used notional value of derivatives, rather than fair value, is Graham and Rogers (2002). Before that, empirical papers often defined hedging as a binary variable (hedgers versus non-hedgers) and used fair value of hedges. Since Graham and Rogers (2002) almost all the empirical papers define hedging as a continuous variable, using notional value of hedges.

Companies report the production and hedging of oil, natural gas, and liquefied natural gas (LNG) separately. Oil production is reported in Barrels of Oil (bbl), natural gas is reported in

British Thermal Units (Btu), and LNG is reported in Gallons. For a unique measure of hedging and production, I convert the volume of natural gas and LNG to equivalent of barrels of oil using unit conversion factors on the Society of Petroleum Engineers website.[7] To convert one million Btu of natural gas to equivalent barrels of oil, the former is multiplied by 0.17245496. For LNG, each gallon of LNG is multiplied by 0.0238095 to yield its equivalent barrels of oil.

My period of analysis ranges from the first quarter of 2010 to the fourth quarter of 2016. This period contains enough data to study firms' behaviors before and after drop in prices of oil in the fourth quarter of 2014. Hedging and production data are manually extracted from company'squarterly and annual reports (10Ks and 10Qs). The SEC website has recently added a feature to show the content of 10Ks and 10Qs in an interactive view, which makes information gathering much easier. From the interactive view, hedging activities are usually reported in the section "Notes to Financial Statements" of company notes. For some companies, this section does not exist. After reading the HTML version of company reports for some of these companies, I realized that if this section does not exist, it means that the company does not have hedging activity in that period.

Hedging activities are reported in a tabular format. Since there are several tables that show different information (such as gain / loss from derivative positions), I then search the tables for the words "volume," "bbl," "btu," and "gallon" and download the tables containing at least one of those phrases.

From interactive view I download the mentioned table plus one paragraph above the table, which shows the hedging period. Next, I manually extract data on hedging volume. There is some heterogeneity in the ways that companies report their hedging activities. For example, some companies report quarter-end and some report their daily volume of hedges. Two examples illustrate the data gathering process and calculation of hedge ratios. The first, following example is from form 10Q for Chesapeake Energy Corporation as of September 30, 2016 (only part of table has been shown):

[7]http://www.spe.org/industry/unit-conversion-factors.php

Table 3. Sample 10Q form - Chesapeake Energy Corporation

	September 30, 2016 Volume	December 31, 2015 Volume
Oil (mmbbl):		
Fixed-price swaps	21.8	13.5
Call options	8.7	19.2
Total oil	30.5	32.7
Natural gas (tbtu):		
Fixed-price swaps	640	500
Collars	38	—
Call options	160	295
Basis protection swaps	44	57
Total natural gas	882	852
NGL (mmgal):		
Fixed-price swaps	36	—

The table shows open hedging positions at the end of the third quarter of 2016. I use this data to calculate hedging activities for the fourth quarter. By converting the volumes of natural gas and liquefied natural gas to barrels of oil equivalent, the volume of open hedges as of September 30, 2016 will be 31.5 mmbbl. These hedges will have different maturities. Companies except for few cases do not report the detail information on the maturity of hedges. However almost all the hedges have maturities of up to one year. To find the quarterly hedging I divide the volume of hedging at the end of each quarter by 4. Therefore volume of hedging for Chesapeake for the fourth quarter of 2016 will be 7.875 mmbbl.

Next example is from Stone Energy Corp. which I show its 10K report for year 2014 (only part of table has been shown). This company reports its daily volume of open contracts. I multiply the daily volume by the number of days in the next quarter, which is 90. After converting the volume of natural gas to barrels of oil equivalent, the total hedging for the first quarter of 2015 for this company will be 1,008,646 bbl.

Table 4. Sample 10K form - Stone Energy Corporation

Fixed-Price Swaps NYMEX (except where noted)			
Natural Gas Daily Volume (MMBtus/d)	**Swap Price ($)**	**Oil Daily Volume (Bbls/d)**	**Swap Price ($)**
10,000	4.000	10,000	90.06
10,000	4.040	10,000	92.25
10,000	4.105	10,000	93.55
10,000	4.190	10,000	94.00
10,000	4.250	10,000	98.00
10,000	4.250	10,000	98.30
10,000	4.350	20,000	98.85
		10,000	99.65
		10,000	103.30

Next, I calculate the company's volume of production. I use the production in the currect quarter as prediction of production in the next quarter. Therefore, for example, production in the third quarter of 2012 is used as a prediction of production for the fourth quarter of 2012, which will be used in calculating the hedge ratio.

The problem with measuring production is that firms rarely report their volumes of production, or production is only briefly mentioned, for example, in asection containing management discussions of financial statements, which is usually difficult to find in financial reports and often incomplete (for example, they might mention the volume of a portion of the company's production, such as only oil production, or only production in specific geographic locations). To find the volume of production, I download the dollar value of production in a quarter and divide it by the average monthly price of oil in that quarter. Data on value of production can be found in the interactive view under the "Consolidated Statement of Income" or the "Consolidated Statement of Operations" table headings. For example, table 5 shows consolidated statement of operations for Chesapeake as of September 30, 2016 (only part of table has been shown).

Total revenue from production is 1,177 million dollars. Dividing that by 44.85, which is the average price of oil in the third quarter of 2016, production volume is 26.24 mmbbl. Therefore, with 7.875 mmbbl of oil hedged (calculated previously), the hedge ratio for Chesapeake for the fourth quarter of 2016 is 30%.

Table 5. Consolidated statement of operations – Chesapeake Energy Corporation

CONDENSED CONSOLIDATED STATEMENTS OF OPERATIONS – USD ($) shares in Millions, $ in Millions	**3 Months Ended**		**9 Months Ended**	
	Sep. 30, 2016	**Sep. 30, 2015**	**Sep. 30, 2016**	**Sep. 30, 2015**
REVENUES:				
Oil, natural gas and NGL	$ 1,177	$ 1,363	$ 2,610	$ 4,122
Marketing, gathering and	1,099	2,013	3,241	5,993
Total Revenues	2,276	3,376	5,851	10,115

Next, I explain the control variables. Oil prices are taken from the website of the Energy Information Association. The expected price of oil in each quarter is defined as the average of daily contract 3 WTI futures in that quarter, which is a forward-looking measure of oil prices. This is the futures contract that has the closest to three-months time to maturity.

To measure the volatility of oil prices, I use daily data on the Crude Oil ETF Volatility Index (OVX) from the website of the Chicago Board of Exchange (CBOE). OVX shows market expectations for the 30-day volatility of crude oil prices. I use the quarterly averages of this index as a measure of expected volatility. For other control variables, I follow Doshi et al. (2017). All other data are from the CRSP-Compustat merged database.

Table 6 shows summary statistics of the variables. As the table shows, there is a lot of heterogeneity among firms in terms of size, total debt, cash holding, production, and hedging activities. Large mean and median differences show that the distributions of all five variables are highly skewed to the right. In terms of hedging, while more than 25% of firm-quarters have zero hedging, more than 25% of firm-quarters have hedging for more than 50% of oil production. An explanation of all variables can be found in Appendix D.

Table 6. Summary Statistics

Variable	Mean	Median	StdDev	P25	P75	N
Total Assets	8382.28	1891.64	18054	367.46	6751.63	2814
Size	7.309	7.545	2.163	5.907	8.818	2814
Leverage	0.309	0.288	0.257	0.133	0.428	2813
Tobin's Q	1.760	1.450	3.394	1.076	2.040	2744
Cash flow	-0.120	0.026	4.378	-0.008	0.047	2748
Cash	0.077	0.025	0.127	0.005	0.090	2809
Sales	0.099	0.078	0.092	0.049	0.116	2770
Dividend dummy	0.350	0.000	0.477	0.000	1.000	2814
Capex	0.078	0.056	0.137	0.029	0.090	2750
Profit	-0.084	0.005	0.756	-0.055	0.046	2807
Debt	0.340	0.308	0.313	0.166	0.441	2749
Total Debt	2336.09	725.80	4319.30	74.42	2470.00	2749
Cash Holding	433.45	25.60	1442.07	4.10	173.76	2809
Futures Price of Oil	41.932	28.92	29.134	19.7	60.02	1758
OVX	34.263	33.22	11.173	26.68	41.39	1762
Production (1000 barrels)	2119.93	353.45	8249.52	60.9	2548.57	2794
Hedging (1000 barrels)	658.42	56.38	1712.88	0	744.83	2794
Hedge Ratio	0.33	0.21	0.37	0	0.55	2794

This table shows the summary statistics of variables defined in Appendix D from the first quarter of 2010 to the fourth quarter of 2016. For each variable mean, median, standard deviation, 25th percentile, 75th percentile, and number of variables in the sample has been reported.

4.2 Univariate Analysis

In this section, I introduce a univariate analysis to study the effect of a drop in oil prices on the hedging policies of companies. The price drop of 2014 represents a sudden exogenous shock that affected the financial situation of companies in our sample, while other factors, such as macroeconomic factors, were almost stable during this period. Therefore, this event offers an excellent opportunity to study how companies change their hedging policies in response to an exogenous shock to their financial situations, other factors being unchanged.

To check the results of the dynamic model, I also examine changes in the policies of companies regarding other control variables in our models — i.e., investment, cash holding, and debt financing — around the shock. This analysis also sheds more light on how shock affects small versus large firms.

To gain a more complete view of how changes in financial situations affect firms' policies, I run a diff-in-diff model to show differences in the responses of financially constrained versus unconstrained firms. In the literature, size has been underscored as one of the best indicators of financial constraint. Therefore, at each quarter, the sample is divided into two size groups based on the book value of their assets. Book value of assets is defined as sum of book values of equity and interest-bearing debt (i.e., Compustat 'seqq'+'dltt'+'dlc')

The diff-in-diff model for hedging follows. The same model is used for capital investments (defined as the ratio of quarterly capex to net PPE), cash (defined as the ratio of cash and cash equivalents to total assets), and debt (defined as the ratio of total debt to total assets).

$$HedgeRatio_{it} = \alpha_i + \beta_1 \times Size_{it} + \beta_2 \times PostShock_t + \beta_3 \times Size_{it} \times PostShock_t + \varepsilon_{it} \qquad (28)$$

Where Hedge Ratio is the quarterly hedge ratio of company *i* at quarter *t*, and size is a dummy variable of 1 if the company belongs to small group in a quarter or of 0 if the company belongs to large group. PostShock is a dummy variable that equals 1 for the period after the shock, which is from the first quarter of 2015 to the last quarter of 2016, and equals 0 otherwise.

Table 7 shows the results of this analysis. The first row shows the results for hedging. The size coefficient is negative and significant, supporting the results in the literature showing that small firms hedge less than large firms. Several empirical papers have found this result to be evidence against theories of financial hedging that suggest that financially constrained firms should hedge more than unconstrained firms. However, as noted earlier, these results can be a function of other factors and do not necessarily indicate a negative relationship between hedging and financial constraint. For example, as found in Stulz (2006), small firms may have fewer resources and may not be able to manage an active risk management program. Or, as mentioned in Rampini et al. (2010), small firms may have less debt capacity and prefer to preserve their debt capacity by cutting their hedging activities.

Therefore, the negative coefficient of size, by itself, does not imply a negative relationship between financial constraint and hedging. This is proven by the positive, significant coefficient on the PostShock variable. The positive sign shows that companies increased their hedging activities after the drop in oil prices. Since companies in the sample are the same before and after the drop, this is a clean test showing that the companies increased their hedging activities as they became more financially constrained, keeping other factors constant. To the best of my knowledge, this is the cleanest empirical study to date regarding differences in the hedging policies of constrained versus unconstrained firms.

Table 7. Difference in Difference Analysis

	Size	PostShock	Size× PostShock
Hedge Ratio	-0.31*** (-38.13)	0.059*** (3.94)	0.061*** (3.16)
Cash	0.069*** (10.55)	-0.031*** (-3.73)	-0.026** (-2.74)
Debt	-0.087*** (-5.58)	0.16*** (9.54)	0.082*** (3.48)
Capex	0.040*** (5.86)	-0.046*** (-6.24)	-0.032** (-2.87)

This table shows the Difference in Difference analysis for Hedging, Cash Saving, Debt, and Capital Expenditure Based on Size dummy and Price Level. The period of analysis is from the first quarter of 2010 to the fourth quarter of 2016. The size is a dummy variable that equals 1 for companies in the smaller half of the sample at each quarter and 0 for firms in the larger half. The PostShock is a dummy that equals 1 for the periods after the drop in prices and 0 for the period before the drop in prices. Column 4 shows the interaction between columns 2 and 3. Hedging is defined as the ratio of the total amount of hedging to production in a period. Cash is the ratio of cash and cash equivalents to total assets. Debt is the ratio of total debt to total assets. Capex is the ratio of capital expenditures to net property, plants, and equipment.

The coefficient of interaction term shows differences in the responses of large versus small firms to price shocks. The positive coefficient shows that small firms increased their hedging activities more than large firms. Assuming that a drop in prices, on average, affects small firms more than large firms, this evidence shows that hedging and risk management has a higher value for financially constrained firms than unconstrained ones.

To summarize, the price drop of 2014 deteriorated the financial situations of all oil producers; however, it was the smaller companies that significantly increased their hedging activities. I interpret these results as evidence that the marginal value of financial hedging is higher for more constrained firms. Although, for several reasons (such as having fewer resources), these firms hedge less than large firms, these empirical results show that the smaller firms assign more value to financial hedging and risk management.

Table 7 also shows the changes in the cash holdings, debt financing, and investment policies of companies around the price drop. All three variables are scaled by total assets. The second row of the table shows the results for cash. The table shows that small firms, on average, hold more cash (as a percentage of their total assets) than large firms. This is consistent with the ideas that cash holdings can be substitute for financial hedging and, as suggested by several papers, that small firms prefer cash management to financial hedging since cash management requires fewer resources (Almaida et al. 2004, Rampini et al. (2010, 2012, 2014), Schmid et al. 2014).

Further, the cash reserves of companies decreased following the price drop. This is expected since the price drop affected the cash flow of these firms negatively. Finally, the cash reserves of small firms decreased more compared than the cash reserves of large firms. This confirms that small firms are affected more by price shocks. Small firms used more financial hedging as their cash reserves depleted.

The third row of Table 7 shows the results for debt. Small firms have lower debt to asset ratios. Also the amount of debt financing for all firms significantly increased after the price drop, which shows that firms rely on debt financing more following a decrease in their internal funds. More need for debt financing is another reason for firms to increase their hedging activities. As the following quote from *The Financial Times* suggests, after the drop in prices, many banks required energy companies to hedge a larger portion of their reserves in order to be approved for loans.

"I think we could see some 'forced hedging' by producers to ensure that lenders extend credit" says Virendra Chauhan, oil analyst at Energy Aspects[8]

Indeed, in contrast to the argument in Rampini et al. (2010, 2013, and 2014), not only did hedging not decrease financing capacity, but, consistent with Campello et al. (2011), it increased the financing capacity of oil companies by decreasing their distress costs.

Finally, the coefficient of interaction term is positive, which shows that small companies increased their debt more than large firms. This might be due to the fact that price and profitability shocks affect the financial situation of these companies more, and they tend to need more external resources.

The last row of Table 7 shows the results for capital expenditure. CAPEX, relative to total assets, is higher for small firms than large firms. This maybe due to the smaller denominator (asset size). Following a drop, firms decreased their capital expenditures, which is a result of the lower NPV of projects and fewer financial resources. In addition, small firms cut their investments more than large firms; another proof that small firms suffer more from shocks to liquidity than large firms.

In summary, diff-in-diff analysis shows that price shocks had more effect on small firms compared to large companies. The fact that small firms increased their hedging activities more than large firms shows that companies hedge more when they are more constrained, other factors be constant.

4.3 Multivariate Analysis

In this section, I test the results of the univariate analysis in a multivariate setting. To do this, I add controls to the diff-in-diff analysis of equation 28 and run the following regression:

$$HedgeRatio_{it} = \alpha_i + \beta_1 \times Size_{it} + \beta_2 \times PostShock_t + \beta_3 \times Size_{it} \times PostShock_{it} + Controls + \varepsilon_{it} \quad (29)$$

Table 8 shows the results of the multivariate analysis. Similar to univariate analysis, PostShock indicates the period after drop in price of oil which is from the first quarter of 2015 to

[8] https://www.ft.com/content/637f8f92-28d2-11e5-8613-e7aedbb7bdb7?mhq5j=e7

the last quarter of 2016. The coefficient of the PostShock is positive and significant, indicating that firms increased their hedging activities in response to a drop in prices. Furthermore, the sign of the interaction term is positive and significant, confirming the results of the univariate analysis, which showed that small firms increased their hedging activities more than large firms in respond to the drop in prices.

The results of the multivariate analysis confirm results of the univariate analysis. Oil and gas companies increased their hedging activities in response to a sudden drop in price of oil in the fourth quarter of 2014. The drop in prices represents an exogenous shock to the liquidity and profitability of these companies. The results in this paper confirm theories of financial hedging suggesting that financially constrained firms should hedge more. Regardless of whether the incentive for hedging is to decrease distress costs or to increase financing capacity, this analysis shows that hedging becomes more valuable as a company becomes more constrained.

Table 8. Multivariable regression of hedge ratio

	Dependent Variable: Hedge Ratio
Size Dummy	-0.29*** (-21.04)
PostShock	0.041*** (7.18)
Size Dummy×PostShock	0.055*** (9.04)
Future Prices / 1000	-0.09 (-0.83)
Volatility Index / 100	0.16*** (7.09)
Future minus Spot Price	0.05 (1.03)
Leverage	0.21*** (6.11)
Tobin's Q	-0.06** (-2.14)
Dividends	-0.02 (-0.09)

Cash	-0.36**
	(-2.32)
Cash Flow	0.083*
	(1.90)
Operational Profit	0.15**
	(2.06)
Sales	-0.24***
	(-5.13)
Constant	-0.84
	(-1.64)
Observations	2744
R^2	0.31
Fiscal Quarter Dummies	Yes
Firm Fixed Effects	Yes

This table shows the multivariate, diff-in-diff analysis for hedge ratio. The period of analysis is from the first quarter of 2010 to the fourth quarter of 2016. The Size Dummy is a dummy variable that equals 1 for companies in the smaller half of the sample at each quarter and 0 for firms in the larger half. The PostShock is a dummy variable that equals 1 for the periods after the drop in prices and 0 for the periods before the drop in prices. All other variables are explained in Appendix D. The analysis is based on 113 U.S. oil and gas producers. The dependent variable is the hedge ratio defined as the quantity of derivatives sold for the next quarter divided by total production in the current quarter. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance of 10%, 5%, and 1%, respectively.

4.4 Robustness Tests

There is no general agreement on the determinants of financial constraint, and different measures for it have been suggested in the literature. For a base regression analysis, I use size as the determinant of financial constraint. As a robustness check, I repeat the multivariate tests with two alternative measures of financial constraint: KZ index proposed by Kaplan and Zingales (1997), and SA index proposed by Hadlock and Pierce (2010). These two indexes are defined as follows:

$$SAIndex = (-0.737 \times Size) + (0.043 \times Size^2) - (0.04 \times age) \tag{30}$$

$$KZIndex = -1.002 \times CashFlow + 0.238 \times Q + 3.130 \times Leverage - 39.36 \times Dividends - 1.315 \times CashHoldings \tag{31}$$

Table 9 shows the results of the robustness test. Column 1 shows the results for the SA Index and column 2 shows the results for the KZ Index. In this table, the size dummy has been replaced by a dummy variable called the constraint dummy. Constraint dummy is 1 for the lower half of the sample based on the SA Index and higher half of the sample based on KZ Index (with a value of 1 meaning that the company is more constrained).

Table 9 confirms the results of the base model. The Coefficient of the Constraint Dummy is negative and significant, showing that, on average, constrained firms hedge less than unconstrained firms. The coefficient of the PostShock is positive, indicating that firms increased their hedging activities in response to a drop in prices. Finally, the coefficient of the interaction term is positive, confirming that constrained firms increased their hedging activities more than unconstrained firms, following the drop in prices. Therefore, the results are confirmed by alternative measures of financial constraint.

Table 9. Robustness test

	SA Index	KZ Index
Constraint Dummy	-0.34*** (-28.33)	-0.27*** (-18.44)
PostShock	0.040*** (7.11)	0.039*** (7.02)
Constraint Dummy × PostShock	0.047*** (7.12)	0.051*** (9.31)
Future Prices / 1000	-0.08 (-0.88)	-0.09 (-0.84)
Volatility Index / 100	0.15*** (6.81)	0.15*** (7.11)
Future minus Spot Price	0.09* (1.71)	0.06 (1.14)
Leverage	0.25*** (8.31)	0.23*** (6.42)
Tobin’s Q	-0.04* (-1.83)	-0.04* (-1.91)
Dividends	-0.03 (-0.15)	-0.12 (-0.88)

Cash	-0.41***	-0.34**
	(-3.12)	(-2.10)
Cash Flow	0.084*	0.086*
	(1.82)	(1.92)
Operational Profit	0.12	0.15*
	(1.11)	(1.92)
Sales	-0.33***	-0.42***
	(-6.55)	(-7.41)
Constant	-1.04*	-0.98*
	(-1.87)	(-1.72)
Observations	2744	2744
R^2	0.30	0.31
Fiscal Quarter Dummies	Yes	Yes
Firm Fixed Effects	Yes	Yes

This table shows the multivariate, diff-in-diff analysis for the hedge ratio. The period of analysis is from the first quarter of 2010 to the fourth quarter of 2016. In the first column, constraint is defined based on the SA index and, in the second column, constraint is defined based on the KZ Index. Constraint is a dummy variable that equals 1 for companies in the lower half of the sample at each quarter based on the SA Index and higher half of the sample based on the KZ Index. The PostShock is a dummy variable that equals 1 for the periods after the drop in prices and is 0 for the periods before the drop in prices. All other variables are explained in Appendix D. This analysis is based on 113 U.S. oil and gas producers. The dependent variable is the hedge ratio, defined as the quantity of derivatives sold for the next quarter divided by total production in the current quarter. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

CHAPTER 5

SUMMARY AND CONCLUSION

The main benefit of financial hedging is that it decreases distress costs. By transferring funds from good to bad states, financial hedging decreases the number of states in which distress happens and, therefore, also decreases the expected costs of distress. Based on this argument, theories of financial hedging suggest that financially constrained firms are the main beneficiaries of hedging, and there should, therefore, be a positive relationship between financial hedging and financial constraint.

Testing the above theory presents two challenges. First, there is no exact proxy for financial constraint. Many of the proxies for financial constraint, such as size or KZ index, may also measure financial distress (Kim and Park 2017). Second, risk management is a complex process that is affected by several firm and market conditions. Empirical tests that define constraint based on firm characteristics are all subject to endogeneity. For example, several papers use size as a measure of financial constraint and show that large firms hedge more than small firms. These tests do not take into consideration several other factors that affect hedging decisions. For example, as Stulz (1996) mentions, small firms may hedge less because they have fewer resources, and the fact that small firms hedge less than large firms does not indicate a negative relationship between hedging and financial constraint.

The analysis in this paper begins with a dynamic model showing the relationship between oil prices and optimum level of hedging. Keeping other factors constant, the probability of distress is higher when prices are lower. Therefore, a negative relationship between price levels and optimum levels of financial hedging indicates a positive relationship between hedging and financial constraint.

Application of the theory model shows that hedging is negatively related to prices. I also show that the price-hedging relationship is more negative for smaller firms, and when price volatility, the probability of a jump in prices, or a firm's leverage is higher. All four factors increase the probability of distress. Therefore, these results show that firms' hedging policies become more sensitive to market conditions when the probability of distress is higher, providing additional evidence for the role of financial distress in determining hedging policies.

On the computational side, I use the stochastic simulation approach, which has not been used in corporate finance literature, to solve the dynamic model. By regularizing the coefficients and simulated values, I was able to achieve convergence for a large set of model parameters. In this regard, this paper has introduced new quantitative techniques to solve high dimensional dynamic corporate finance models.

On the empirical side, I use an approach to exogenously test the relationship between financial hedging and financial constraint. The sudden drop in oil prices in the fourth quarter of 2014 was an exogenous event that made oil and gas producers more constrained. By studying the behavior of oil producers before and after the drop, I showed that these firms significantly increased their hedging activities after the drop. This test shows that, keeping other factors constant, firms tend to hedge more when they become more constrained.

Moreover, I compare the changes in hedging policies of small versus large firms following drop in prices. A negative change in market conditions often has a greater effect on the financial situation of smaller than larger firms. The reason for this is that small firms have fewer resources. For example, they have less debt capacity and may not be able to respond to cash flow shocks through debt financing as much as large firms can. As a result, comparing how the financial hedging policies of large versus small firms change in response to price drop is another way to study the relationship between financial hedging and financial constraints.

Through diff-in-diff analysis, I show that small firms increased their hedging activities significantly more than large firms. This is more evidence showing the positive relationship between financial hedging and financial constraint. To the best of my knowledge, this paper provides the first empirical evidence in support of theories of financial hedging that suggest a positive relationship between financial hedging and financial constraint.

APPENDIX A

DERIVATIONS

Derivation of equation 11

To show that capital in equation 10 has a finite optimum value, I show that the unconstrained problem has a finite solution, therefore constrained problem will have a finite solution as well. The Lagrangian for equation 10 without constraints is follows:

$$L = \underset{k_{t+1},b_{t+1},s_{t+1},h_{t+1}}{Max} d_t + \frac{1}{1+r(1-\tau)} E_t d_{t+1} \qquad \text{A-1}$$

Derivative of the Lagrangian should be equal to zero, therefore we will have:

$$\frac{\partial L}{\partial k_{t+1}} = 0 \Rightarrow -1 + \frac{1}{1+r(1-\tau)} E_t \left[(1-\delta) + \alpha k_{t+1}^{\alpha-1} Z_{t+1}(1-\tau) + s(\alpha k_{t+1}^{\alpha-1} Z_{t+1}(1-\tau))^+ \right] = 0 \qquad \text{A-2}$$

Therefore:

$$1 + r(1-\tau) - (1-\delta) = \alpha k_{t+1}^{\alpha-1} Z_t (1-\tau) + E_t (s(\alpha k_{t+1}^{\alpha-1} Z_{t+1}(1-\tau))^+) \qquad \text{A-3}$$

Where $(\alpha k_{t+1}^{\alpha-1} Z_{t+1}(1-\tau))^+$ is non-zero only when firm is in distress.

To show that this point is a maximum, I calculate the second derivative with respect to k_{t+1}.

$$\frac{\partial^2 L}{\partial k_{t+1}^2} = \alpha(\alpha-1) k_{t+1}^{\alpha-2} Z_{t+1}(1-\tau) + E_t (s(\alpha(\alpha-1) k_{t+1}^{\alpha-2} Z_{t+1}(1-\tau))^+) \qquad \text{A-4}$$

Equation A-4 is negative for values of alpha (production return to scale) less than 1. This is the case for a neoclassical production function in which production is a concave function of capital. In this paper I follow the majority of literature in corporate finance and assume an alpha less than 1. Moreover in section 3.7 I show that based on the sample of oil and gas companies in this paper, the value of alpha will be about 0.815.

Negativity of equation A-4 which is the second derivative of Lagrangian with respect to capital, guarantees that A-3 shows the value of capital that maximizes the unconstrained problem.

Derivation of equation 12

Writing the Lagrangian for equation 10 with saving constraints I will have:

$$L = d_t + \frac{1}{1+r(1-\tau)} E_t d_{t+1} + \lambda S_{t+1} \qquad \text{(A-5)}$$

Differentiating equation A-5 with respect to $k_{t+1}$and put it equal to zero would result in:

$$\frac{\partial L}{\partial S_{t+1}} = 0 \Rightarrow -1 + \frac{1}{1+r(1-\tau)} E_t[r(1-\tau\_+(1-\gamma)+s(r(1-\tau)+(1-\gamma))^+] + \lambda = 0 \qquad \text{(A-6)}$$

Simplifying equation A-6 I will have:

$$\gamma = s \times (r(1+\tau)+1-\gamma) \times \int_A f(z_{t+1}) dz_{t+1} + \lambda \qquad \text{(A-7)}$$

Derivation of equation 13

Writing the Lagrangian with hedging constraints I will have:

$$L = \underset{k_{t+1}, b_{t+1}, s_{t+1}, h_{t+1}}{Max} d_t + \frac{1}{1+r(1-\tau)} E_t d_{t+1} + \lambda_1 (K(k_{t+1} - \omega h_{t+1}) - b_{t+1}) + \lambda_2 h_{t+1} \qquad \text{(A-8)}$$

$$\frac{\partial L}{\partial k_{t+1}} = 0 \Rightarrow -P + \frac{1}{1+r(1-\tau)} E_t\left[(Z_t - Z_{t+1})(1-\tau) + s((Z_t - Z_{t+1})(1-\tau))^+\right] - \lambda_1 K\omega - \lambda_2 = 0 \qquad \text{(A-9)}$$

Therefore:

$$P(1+r(1-\tau)) + \lambda_1 K\omega + \lambda_2 = s\int_A (Z_t - Z_{t+1}) f(Z_{t+1}) dZ_{t+1} \qquad \text{(A-10)}$$

Calibration of price process

Price process has the following from:

$$dX_t = \kappa(\mu - X_t)dt + \sigma dW_t + J(\mu_J, \sigma_J) d\pi(\lambda_J)$$

To calibrate the model I write it in discrete form. In a time period of Δt the probability of jump happening is $\lambda_J \Delta t$. Therefore price at time t conditional on price at time t-1 will be:

$$X_t = \kappa\mu\Delta t + (1-\kappa\Delta t)X_{t-1} + \sigma dW_t$$

With probability $1-\lambda_J \Delta t$

And $X_t = \kappa\mu\Delta t + (1-\kappa\Delta t)X_{t-1} + \sigma dW_t + J(\mu_J, \sigma_J) d\pi(\lambda_J)$

With probability $\lambda_J \Delta t$

Therefore density function for X_t conditional on X_{t-1} will be:

$f(X_t \mid X_{t-1}) = (\lambda\Delta t) N_1(X_t \mid X_{t-1}) + (1-\lambda\Delta t) N_2(X_t \mid X_{t-1})$ where

$$N_1(X_t \mid X_{t-1}) = (2\pi(\sigma^2 + \sigma_J^2))^{-\frac{1}{2}} \exp\left(\frac{-(X_t - \kappa\mu\Delta t - (1-\kappa\Delta t)X_{t-1} - \mu_J)^2}{2(\sigma^2 + \sigma_J^2)}\right)$$

$$N_2(X_t \mid X_{t-1}) = (2\pi\sigma^2)^{-\frac{1}{2}} \exp\left(\frac{-(X_t - \kappa\mu\Delta t - (1-\kappa\Delta t)X_{t-1})^2}{2\sigma^2}\right)$$

I use $f(X_t \mid X_{t-1})$ in formulating maximum likelihood to calibrate the model based on monthly price of oil.

APPENDIX B

BASE CASE PARAMETER VALUES

Parameter	Definition	Value
μ	Long-term mean of return	1.0835
σ	Volatility of return	0.3052
κ	Coefficient of Mean Reversion	0.2612
μ_J	Mean of Jump Intensity	-0.34
σ_J	Volatility of Jump Intensity	0.2717
λ_J	Mean of Jump Process	0.02
α	Production return to scale parameter	0.815
r	Risk free rate	1.00%
τ	Average tax rate	20%
γ	Agency costs of cash per dollar of saving	0.001
s	Fire sell value per dollar of capital sold	0.8
δ	Depreciation rate	0.1
ω	Hedge collateral ratio	0.25
k	Debt Collateral Ratio	0.8
λ	Equity floatation cost per dollar of equity	0.028
P	Hedging Cost	0
J	Number of integration nodes	10
T	Number of periods	200
ϖ	Convergence threshold	0.0001
ξ	Damping parameter	0.1
k_0	Initial value of capital (MM $)	1500
S_0	Initial value of saving (MM $)	25
b_0	Initial value of debt (MM $)	750
Z_0	Initial price ($)	62

This table shows base values of model parameters. Price process parameters are calculated by calibrating the model using monthly price of oil from 2000 to 2016. Calibration process is explained in appendix A. Source of all other parameters is explained in the text.

APPENDIX C

PYTHON CODE TO SOLVE THE DYNAMIC MODEL

```
# Jump process parameters, based on Jan 2000 to December 2016
# Xt = log(Pt)
# dXt = (alpha-kappa*Xt)dt+sigma*dWt+J(miu_j,sigma_j)*dP(lamda)
def jump_basic():
    global alpha, kappa, mu_j, sigma, sigma_j, landa, dt
    alpha = 1.0835
    kappa = 0.2612
    mu_j = -0.34  ###
    sigma = 0.3052
    sigma_j = 0.2717
    landa = 0.02  ###

    dt = 1/12


# dynamic model parameters

import math
def model_basic():
    global risk_free, tax_rate, agency_cost, fire_sell, depreciation_rate, hedge_collateral \
    ,debt_collateral, equity_floataion, hedging_cost, capital_0, debt_0, saving_0, hedge_0,
price_0, production_return \

    risk_free = 0.01
    tax_rate = 0.2
    agency_cost = 0.001
    fire_sell = 0.2
    depreciation_rate = 0.1
    hedge_collateral = 0.25
    debt_collateral = 0.8
    equity_floataion = 0.028
    hedging_cost = 0

    # production_return is calculated based on zero excess profit at median of values
    capital_0 = 1500000000
    debt_0 = 725000000
    saving_0 = 25000000
    hedge_0 = 0
    price_0 = 62
```

```
    production_return = math.log(((debt_0 - saving_0*(1-agency_cost))/(1-tax_rate)+
    debt_0*risk_free-saving_0*risk_free)/price_0)/math.log(capital_0)

    print(production_return)


# simulation model parameters
def simulation_basic():
    global number_of_nodes, number_of_periods, convergence_threshold, damping_parameter \
    ,capital_cons, debt_cons, hedge_cons, all_cons, RLS
    number_of_nodes = 10
    number_of_periods = 200
    convergence_threshold = 0.0001
    damping_parameter = 0.1

    capital_cons = 10
    capital_cons_2 = 10
    debt_cons = 10
    hedge_cons = 10
    all_cons = 10
    RLS = 10000


# initial grid, maximum values based on 75th percentile of empirical values

import numpy

def initial_grid():
    global initial_capital, initial_hedge, initial_debt, initial_saving
    initial_capital = capital_0*(numpy.random.lognormal(0,1,number_of_periods+1))
    initial_hedge = numpy.zeros(number_of_periods)
    initial_debt = numpy.zeros(number_of_periods+1)
    initial_saving = saving_0*(numpy.random.lognormal(0,1,number_of_periods)-0.2)*1.25

    initial_capital[0] = capital_0
    initial_debt[0] = debt_0


    for i in range (0, number_of_periods):
        initial_hedge[i] = initial_capital[i+1]*min(numpy.random.lognormal(0, 0.2, 1),0.5)
        initial_debt[i+1] = debt_collateral*(initial_capital[i+1]-initial_hedge[i])
```

```
# price simulation

def price_simulation(period_number, price0):
    initial_price_log = numpy.zeros(period_number+1)
    initial_price_log[0] = math.log(price0)

    n1 = numpy.random.normal(0,1,period_number)
    n2 = numpy.random.normal(0,1,period_number)
    jump = numpy.random.binomial(1,landa,period_number)

    for i in range (1, period_number+1):
        initial_price_log[i] = alpha * dt + (1-kappa*dt)*initial_price_log[i-1] +
sigma*math.sqrt(dt)*n1[i-1] + \
        jump[i-1]*(mu_j+sigma_j*n2[i-1])


    initial_price = numpy.exp(initial_price_log)
    return initial_price



# initial cash
def initial_cash_generate():
    global initial_cash, initial_price
    initial_price = price_simulation(number_of_periods , price_0)

    initial_cash = numpy.zeros(number_of_periods+1)
    initial_cash[0] = (numpy.power(capital_0,production_return)*price_0+risk_free*saving_0-
risk_free*debt_0) \
    *(1-tax_rate)+saving_0*(1-agency_cost)

    initial_cash[1:number_of_periods+1] =
numpy.multiply(numpy.power(initial_capital[1:number_of_periods+1],production_return), \
                                              initial_price[1:number_of_periods+1])
    initial_cash[1:number_of_periods+1] = initial_cash[1:number_of_periods+1] \
    + numpy.multiply(initial_hedge,(initial_price[0:number_of_periods]-
initial_price[1:number_of_periods+1]))

    initial_cash[1:number_of_periods+1] = initial_cash[1:number_of_periods+1] \
    + risk_free * initial_saving - risk_free * initial_debt[1:number_of_periods+1]

    initial_cash[1:number_of_periods+1] = initial_cash[1:number_of_periods+1]*(1-tax_rate) \
    +initial_saving*(1-agency_cost)
```

```
    distress = numpy.maximum((initial_debt[1:number_of_periods+1]-
initial_cash[1:number_of_periods+1]),0)

    initial_cash[1:number_of_periods+1] = initial_cash[1:number_of_periods+1] - fire_sell *
distress



# optimization

from scipy import optimize

# standardize matrices and make X vector
def standard_local(X):
    return (X - numpy.mean(X))/numpy.std(X)



def prepare_for_opt_first():
    global K_standard, C_standard, P_standard, H_standard, B_standard, S_standard, X, K, H, B,
S

    K_standard = standard_local(initial_capital)
    C_standard = standard_local(initial_cash)
    P_standard = standard_local(initial_price)
    H_standard = standard_local(initial_hedge)
    B_standard = standard_local(initial_debt)
    S_standard = standard_local(initial_saving)

    temp_X =
numpy.vstack([K_standard[0:number_of_periods],C_standard[0:number_of_periods] \
            ,B_standard[0:number_of_periods],P_standard[0:number_of_periods]])

    X = numpy.transpose(temp_X)
    ##########################################

    # coefficients
    # first four are for capital
    # second four are for debt
    # third four are for hedging
    # fourth four are for saving
    # at each one the sequence is as following: capital, cash, debt, price
    # therefore beta[11] is the coefficient of interest
```

```
    # define Y vectors
    K = K_standard[1:number_of_periods+1]
    H = H_standard
    B = B_standard[1:number_of_periods+1]
    S = S_standard

    # means and stds
    global K_mean, K_std, H_mean, H_std, B_mean, B_std, S_mean, S_std, C_mean, C_std,
P_mean, P_std, all_divisor

    K_mean = numpy.mean(initial_capital)
    K_std = numpy.std(initial_capital)

    H_mean = numpy.mean(initial_hedge)
    H_std = numpy.std(initial_hedge)

    B_mean = numpy.mean(initial_debt)
    B_std = numpy.std(initial_debt)

    S_mean = numpy.mean(initial_saving)
    S_std = numpy.std(initial_saving)

    C_mean = numpy.mean(initial_cash)
    C_std = numpy.std(initial_cash)

    P_mean = numpy.mean(initial_price)
    P_std = numpy.std(initial_price)
    ########################################

    all_divisor = (max(K_std,H_std,B_std,S_std))**2



def local_optimize(beta):

    K_diff = K_std*(K - numpy.dot(X,beta[0:4]))
    B_diff = B_std*(B - numpy.dot(X,beta[4:8]))
    H_diff = H_std*(H - numpy.dot(X,beta[8:12]))
    S_diff = S_std*(S - numpy.dot(X,beta[12:16]))

    K_deStand = K_std*numpy.dot(X,beta[0:4])+K_mean
    B_deStand = B_std*numpy.dot(X,beta[4:8])+B_mean
    H_deStand = H_std*numpy.dot(X,beta[8:12])+H_mean
```

```
    K_cons = numpy.minimum(K_deStand,0)
#    K_cons_2 = numpy.maximum(K_deStand-max_capital,0)
    B_cons = numpy.minimum(B_deStand,0)
    H_cons = numpy.minimum(H_deStand,0)
    Fin_cons = numpy.minimum(debt_collateral*K_deStand -
debt_collateral*hedge_collateral*H_deStand \
                  -B_deStand,0)

    optim_result = numpy.dot(numpy.transpose(K_diff),K_diff)/all_divisor + \
    numpy.dot(numpy.transpose(B_diff),B_diff)/all_divisor + \
    numpy.dot(numpy.transpose(H_diff),H_diff)/all_divisor + \
    numpy.dot(numpy.transpose(S_diff),S_diff)/all_divisor + \
    RLS*numpy.dot(numpy.transpose(beta),beta) + \
    capital_cons*numpy.dot(numpy.transpose(K_cons),K_cons)/all_divisor + \
    debt_cons*numpy.dot(numpy.transpose(B_cons),B_cons)/all_divisor + \
    hedge_cons*numpy.dot(numpy.transpose(H_cons),H_cons)/all_divisor + \
    all_cons*numpy.dot(numpy.transpose(Fin_cons),Fin_cons)/all_divisor
 #    capital_cons_2*numpy.dot(numpy.transpose(K_cons_2),K_cons_2)/all_divisor + \
    return optim_result



def local_gradient(beta):

    K_diff = K_std*(K - numpy.dot(X,beta[0:4]))
    B_diff = B_std*(B - numpy.dot(X,beta[4:8]))
    H_diff = H_std*(H - numpy.dot(X,beta[8:12]))
    S_diff = S_std*(S - numpy.dot(X,beta[12:16]))

    K_deStand = K_std*numpy.dot(X,beta[0:4])+K_mean
    B_deStand = B_std*numpy.dot(X,beta[4:8])+B_mean
    H_deStand = H_std*numpy.dot(X,beta[8:12])+H_mean

    K_cons = numpy.minimum(K_deStand,0)
    # K_cons_2 = numpy.maximum(K_deStand-max_capital,0)
    B_cons = numpy.minimum(B_deStand,0)
    H_cons = numpy.minimum(H_deStand,0)
    Fin_cons = numpy.minimum(debt_collateral*K_deStand -
debt_collateral*hedge_collateral*H_deStand \
                  -B_deStand,0)

    gradient = numpy.ones(16)
```

```
    gradient[0] = -2*K_std*numpy.sum(numpy.multiply(X[:,0],K_diff))/all_divisor + \
2*RLS*beta[0]+capital_cons*2*K_std*numpy.sum(numpy.multiply(X[:,0],K_cons))/all_divisor
+ \
    all_cons*2*K_std*debt_collateral*numpy.sum(numpy.multiply(X[:,0],Fin_cons))/all_divisor
    #    capital_cons_2*2*K_std*numpy.sum(numpy.multiply(X[:,0],K_cons_2))/all_divisor + \

    gradient[1] = -2*K_std*numpy.sum(numpy.multiply(X[:,1],K_diff))/all_divisor + \

2*RLS*beta[1]+capital_cons*2*K_std*numpy.sum(numpy.multiply(X[:,1],K_cons))/all_divisor
+ \
    all_cons*2*K_std*debt_collateral*numpy.sum(numpy.multiply(X[:,1],Fin_cons))/all_divisor
    #    capital_cons_2*2*K_std*numpy.sum(numpy.multiply(X[:,1],K_cons_2))/all_divisor + \

    gradient[2] = -2*K_std*numpy.sum(numpy.multiply(X[:,2],K_diff))/all_divisor + \

2*RLS*beta[2]+capital_cons*2*K_std*numpy.sum(numpy.multiply(X[:,2],K_cons))/all_divisor
+ \
    all_cons*2*K_std*debt_collateral*numpy.sum(numpy.multiply(X[:,2],Fin_cons))/all_divisor
    #    capital_cons_2*2*K_std*numpy.sum(numpy.multiply(X[:,2],K_cons_2))/all_divisor + \

    gradient[3] = -2*K_std*numpy.sum(numpy.multiply(X[:,3],K_diff))/all_divisor + \

2*RLS*beta[3]+capital_cons*2*K_std*numpy.sum(numpy.multiply(X[:,3],K_cons))/all_divisor
+ \
    all_cons*2*K_std*debt_collateral*numpy.sum(numpy.multiply(X[:,3],Fin_cons))/all_divisor
    #    capital_cons_2*2*K_std*numpy.sum(numpy.multiply(X[:,3],K_cons_2))/all_divisor + \

    gradient[4] = -2*B_std*numpy.sum(numpy.multiply(X[:,0],B_diff))/all_divisor + \
    2*RLS*beta[4]+debt_cons*2*B_std*numpy.sum(numpy.multiply(X[:,0],B_cons))/all_divisor
\
    -all_cons*2*B_std*numpy.sum(numpy.multiply(X[:,0],Fin_cons))/all_divisor

    gradient[5] = -2*B_std*numpy.sum(numpy.multiply(X[:,1],B_diff))/all_divisor + \
    2*RLS*beta[5]+debt_cons*2*B_std*numpy.sum(numpy.multiply(X[:,1],B_cons))/all_divisor
\
    -all_cons*2*B_std*numpy.sum(numpy.multiply(X[:,1],Fin_cons))/all_divisor

    gradient[6] = -2*B_std*numpy.sum(numpy.multiply(X[:,2],B_diff))/all_divisor + \
    2*RLS*beta[6]+debt_cons*2*B_std*numpy.sum(numpy.multiply(X[:,2],B_cons))/all_divisor
\
    -all_cons*2*B_std*numpy.sum(numpy.multiply(X[:,2],Fin_cons))/all_divisor

    gradient[7] = -2*B_std*numpy.sum(numpy.multiply(X[:,3],B_diff))/all_divisor + \
```

```
    2*RLS*beta[7]+debt_cons*2*B_std*numpy.sum(numpy.multiply(X[:,3],B_cons))/all_divisor
\
    -all_cons*2*B_std*numpy.sum(numpy.multiply(X[:,3],Fin_cons))/all_divisor

    gradient[8] = -2*H_std*numpy.sum(numpy.multiply(X[:,0],H_diff))/all_divisor + \

2*RLS*beta[8]+hedge_cons*2*H_std*numpy.sum(numpy.multiply(X[:,0],H_cons))/all_divisor
\
    -
all_cons*2*debt_collateral*hedge_collateral*H_std*numpy.sum(numpy.multiply(X[:,0],Fin_con
s))/all_divisor

    gradient[9] = -2*H_std*numpy.sum(numpy.multiply(X[:,1],H_diff))/all_divisor + \

2*RLS*beta[9]+hedge_cons*2*H_std*numpy.sum(numpy.multiply(X[:,1],H_cons))/all_divisor
\
    -
all_cons*2*debt_collateral*hedge_collateral*H_std*numpy.sum(numpy.multiply(X[:,1],Fin_con
s))/all_divisor

    gradient[10] = -2*H_std*numpy.sum(numpy.multiply(X[:,2],H_diff))/all_divisor + \

2*RLS*beta[10]+2*RLS*beta[10]+hedge_cons*2*H_std*numpy.sum(numpy.multiply(X[:,2],H
_cons))/all_divisor  \
    -
all_cons*2*debt_collateral*hedge_collateral*H_std*numpy.sum(numpy.multiply(X[:,2],Fin_con
s))/all_divisor

    gradient[11] = -2*H_std*numpy.sum(numpy.multiply(X[:,3],H_diff))/all_divisor + \

2*RLS*beta[11]+hedge_cons*2*H_std*numpy.sum(numpy.multiply(X[:,3],H_cons))/all_diviso
r  \
    -
all_cons*2*debt_collateral*hedge_collateral*H_std*numpy.sum(numpy.multiply(X[:,3],Fin_con
s))/all_divisor

    gradient[12] = -
2*S_std*numpy.sum(numpy.multiply(X[:,0],S_diff))/all_divisor+2*RLS*beta[12]
    gradient[13] = -
2*S_std*numpy.sum(numpy.multiply(X[:,1],S_diff))/all_divisor+2*RLS*beta[13]
    gradient[14] = -
2*S_std*numpy.sum(numpy.multiply(X[:,2],S_diff))/all_divisor+2*RLS*beta[14]
    gradient[15] = -
2*S_std*numpy.sum(numpy.multiply(X[:,3],S_diff))/all_divisor+2*RLS*beta[15]
```

```
    return gradient


# generate path using beta

def simulate_path():
    global price, capital, debt, cash, hedge, saving
    price = price_simulation(number_of_periods , price_0)

    capital = numpy.zeros(number_of_periods+1)
    capital[0] = initial_capital[0]

    debt = numpy.zeros(number_of_periods+1)
    debt[0] = initial_debt[0]

    cash = numpy.zeros(number_of_periods+1)
    cash[0] = initial_cash[0]

    hedge = numpy.zeros(number_of_periods)

    saving = numpy.zeros(number_of_periods)

    for i in range (1, number_of_periods+1):
        capital[i] = (res.x[0]*(capital[i-1]-K_mean)/K_std + \
        res.x[1]*(cash[i-1]-C_mean)/C_std + \
        res.x[2]*(debt[i-1]-B_mean)/B_std + \
        res.x[3]*(price[i-1]-P_mean)/P_std) * K_std + K_mean

        debt[i] = (res.x[4]*(capital[i-1]-K_mean)/K_std + \
        res.x[5]*(cash[i-1]-C_mean)/C_std + \
        res.x[6]*(debt[i-1]-B_mean)/B_std + \
        res.x[7]*(price[i-1]-P_mean)/P_std) * B_std + B_mean

        hedge[i-1] = (res.x[8]*(capital[i-1]-K_mean)/K_std + \
        res.x[9]*(cash[i-1]-C_mean)/C_std + \
        res.x[10]*(debt[i-1]-B_mean)/B_std + \
        res.x[11]*(price[i-1]-P_mean)/P_std) * H_std + H_mean

        saving[i-1] = (res.x[12]*(capital[i-1]-K_mean)/K_std + \
        res.x[13]*(cash[i-1]-C_mean)/C_std + \
        res.x[14]*(debt[i-1]-B_mean)/B_std + \
        res.x[15]*(price[i-1]-P_mean)/P_std) * S_std + S_mean

        temp = numpy.sign(capital[i])*numpy.abs(capital[i])**production_return
```

```
        cash[i] = (temp*price[i]+ hedge[i-1]*(price[i-1]-price[i]) \
                + risk_free*saving[i-1]-risk_free*debt[i])*(1-tax_rate)+saving[i-1]*(1-agency_cost)
        distress = max(debt[i]-cash[i],0)
        cash[i] = cash[i]-distress




# values at each point
def local_indicator(surplus):
    if surplus > 0:
        indicator = 1 - tax_rate
    else:
        indicator = 1 + equity_floataion
    return indicator

def distress_indicator(distresscost):
    if distresscost > 0:
        indicator = 1 + fire_sell
    else:
        indicator = 1
    return indicator

def value_at_each():
    global newcapital, newdebt, newhedge, newsaving, newcash

    newcapital = numpy.zeros(number_of_periods+1)
    newdebt = numpy.zeros(number_of_periods+1)
    newhedge = numpy.zeros(number_of_periods)
    newsaving = numpy.zeros(number_of_periods)
    newcash = numpy.zeros(number_of_periods+1)

    newcapital[:] = capital[:]
    newdebt[:] = debt[:]
    newhedge[:] = hedge[:]
    newsaving[:] = saving[:]
    newcash[:] = cash[:]

    newcapital[0] = capital[0]
    newdebt[0] = debt[0]
    newhedge[0] = hedge[0]
    newsaving[0] = saving[0]
    newcash[0] = cash[0]
```

```
for i in range (0, number_of_periods):
    e_t = cash[i] + capital[i]*(1-depreciation_rate) - debt[i] - capital[i+1] \
    + debt[i+1] - saving[i] - hedging_cost * hedge[i]
    d_t = local_indicator(e_t)
    d_t = d_t * (1+risk_free*(1-tax_rate))
    k_col = numpy.zeros(number_of_nodes)
    b_col = numpy.zeros(number_of_nodes)
    h_col = numpy.zeros(number_of_nodes)
    s_col = numpy.zeros(number_of_nodes)

    for j in range (0, number_of_nodes):
        price_j = price_simulation(1 , price[i])
        this_price = price_j[1]
        temp = numpy.sign(capital[i+1])*numpy.abs(capital[i+1])**production_return
        thiscash = (temp*this_price+ hedge[i]*(price[i]-this_price) \
              + risk_free*saving[i]-risk_free*debt[i+1])*(1-tax_rate)+saving[i]*(1-agency_cost)
        distress = max(debt[i+1]-thiscash,0)
        thiscash = thiscash-distress
        distress_coef = distress_indicator(distress)

        thiscapital = (res.x[0]*(capital[i+1]-K_mean)/K_std + \
        res.x[1]*(thiscash-C_mean)/C_std + \
        res.x[2]*(debt[i+1]-B_mean)/B_std + \
        res.x[3]*(price[i+1]-P_mean)/P_std) * K_std + K_mean

        thisdebt = (res.x[4]*(capital[i+1]-K_mean)/K_std + \
        res.x[5]*(thiscash-C_mean)/C_std + \
        res.x[6]*(debt[i+1]-B_mean)/B_std + \
        res.x[7]*(price[i+1]-P_mean)/P_std) * B_std + B_mean

        thishedge = (res.x[8]*(capital[i+1]-K_mean)/K_std + \
        res.x[9]*(thiscash-C_mean)/C_std + \
        res.x[10]*(debt[i+1]-B_mean)/B_std + \
        res.x[11]*(price[i+1]-P_mean)/P_std) * H_std + H_mean

        thissaving = (res.x[12]*(capital[i+1]-K_mean)/K_std + \
        res.x[13]*(thiscash-C_mean)/C_std + \
        res.x[14]*(debt[i+1]-B_mean)/B_std + \
        res.x[15]*(price[i+1]-P_mean)/P_std) * S_std + S_mean

        e_t1 = thiscash + capital[i+1] - debt[i+1] - thiscapital \
           + thisdebt - thissaving - hedging_cost * thishedge
        d_t1 = local_indicator(e_t1)
```

```
        k_abalfazl1 = (capital[i+1] - numpy.mean(capital))/numpy.std(capital)
        k_abalfazl2 = (d_t1*k_abalfazl1*distress_coef*(risk_free*(1-tax_rate)+(1-
agency_cost))/d_t)
        k_col[j] = k_abalfazl2 * numpy.std(capital) + numpy.mean(capital)

        b_abalfazl1 = (debt[i+1] - numpy.mean(debt))/numpy.std(debt)
        b_abalfazl2 = (d_t1*b_abalfazl1*distress_coef*(risk_free*(1-tax_rate)+(1-
agency_cost))/d_t)
        b_col[j] = b_abalfazl2 * numpy.std(debt) + numpy.mean(debt)

        h_abalfazl1 = (hedge[i] - numpy.mean(hedge))/numpy.std(hedge)
        h_abalfazl2 = (d_t1*h_abalfazl1*distress_coef*(risk_free*(1-tax_rate)+(1-
agency_cost))/d_t)
        h_col[j] = h_abalfazl2 * numpy.std(hedge) + numpy.mean(hedge)

        s_abalfazl1 = (saving[i] - numpy.mean(saving))/numpy.std(saving)
        s_abalfazl2 = (d_t1*s_abalfazl1*distress_coef*(risk_free*(1-tax_rate)+(1-
agency_cost))/d_t)
        s_col[j] = s_abalfazl2 * numpy.std(saving) + numpy.mean(saving)

        #k_col[j] = (d_t1*capital[i+1]*distress_coef*(risk_free*(1-tax_rate)+(1-
agency_cost))/d_t)
        #b_col[j] = (d_t1*debt[i+1]*distress_coef*(risk_free*(1-tax_rate)+(1-agency_cost))/d_t)
        #h_col[j] = (d_t1*hedge[i]*distress_coef*(risk_free*(1-tax_rate)+(1-agency_cost))/d_t)
        #s_col[j] = (d_t1*saving[i]*distress_coef*(risk_free*(1-tax_rate)+(1-agency_cost))/d_t)
      newcapital[i+1] = numpy.mean(k_col)
      newdebt[i+1] = numpy.mean(b_col)
      newhedge[i] = numpy.mean(h_col)
      newsaving[i] = numpy.mean(s_col)
      temp = numpy.sign(newcapital[i+1])*numpy.abs(newcapital[i+1])**production_return
      newcash[i+1] = (temp*price[i+1]+ newhedge[i]*(price[i]-price[i+1]) \
          + risk_free*newsaving[i]-risk_free*newdebt[i+1])*(1-tax_rate)+newsaving[i]*(1-
agency_cost)
      distress = max(newdebt[i+1]-newcash[i+1],0)
      newcash[i+1] = newcash[i+1]-distress




# optimization

def prepare_for_opt():
   global K_standard, C_standard, P_standard, H_standard, B_standard, S_standard
```

```
    K_standard = standard_local(newcapital)
    C_standard = standard_local(newcash)
    P_standard = standard_local(price)
    H_standard = standard_local(newhedge)
    B_standard = standard_local(newdebt)
    S_standard = standard_local(newsaving)

    temp_X =
numpy.vstack([K_standard[0:number_of_periods],C_standard[0:number_of_periods] \
                ,B_standard[0:number_of_periods],P_standard[0:number_of_periods]])

    global X, K, H, B, S
    X = numpy.transpose(temp_X)
    ########################################

    # coefficients
    # first four are for capital
    # second four are for debt
    # third four are for hedging
    # fourth four are for saving
    # at each one the sequence is as following: capital, cash, debt, price
    # therefore beta[11] is the coefficient of interest


    # define Y vectors
    K = K_standard[1:number_of_periods+1]
    H = H_standard
    B = B_standard[1:number_of_periods+1]
    S = S_standard

    # means and stds
    global K_mean, K_std, H_mean, H_std, B_mean, B_std, S_mean, S_std, C_mean, C_std,
P_mean, P_std

    K_mean = numpy.mean(newcapital)
    K_std = numpy.std(newcapital)

    H_mean = numpy.mean(newhedge)
    H_std = numpy.std(newhedge)

    B_mean = numpy.mean(newdebt)
    B_std = numpy.std(newdebt)

    S_mean = numpy.mean(newsaving)
```

```
    S_std = numpy.std(newsaving)

    C_mean = numpy.mean(newcash)
    C_std = numpy.std(newcash)

    P_mean = numpy.mean(price)
    P_std = numpy.std(price)
    ########################################

    global all_divisor
    all_divisor = (max(K_std,H_std,B_std,S_std))**2



def check_convergence(old_k, old_b, old_h, old_s, new_k, new_b, new_h, new_s):
    kk = numpy.mean(numpy.divide(old_k-new_k,old_k))
    bb = numpy.mean(numpy.divide(old_b-new_b,old_b))
    hh = numpy.mean(numpy.divide(old_h-new_h,old_h))
    ss = numpy.mean(numpy.divide(old_s-new_s,old_s))

    hkj = (kk+bb+hh+ss)/4
    return abs(hkj)# > convergence_threshold




def frange(start, stop, step):
    i = start
    while i < stop:
        yield i
        i += step





# iterative process

#alpha
alpha_values = numpy.zeros(18)
alpha_general = numpy.zeros(17)
for i in frange (0.5, 1.5, 0.1):
    temp_values_general = numpy.zeros(17)
    counter_general = 0
```

```
    for j in range(10):
        jump_basic()
        alpha = i

        model_basic()
        simulation_basic()

 #      capital_cons = 10
#       debt_cons = 10
#       hedge_cons = 10
#       all_cons = 10
#       RLS = 10

        initial_grid()
        initial_cash_generate()
        prepare_for_opt_first()

        res = optimize.minimize(local_optimize, beta, jac=local_gradient,method='SLSQP')
        simulate_path()
        value_at_each()
        old_k = numpy.ones(number_of_periods+1)
        old_b = numpy.ones(number_of_periods+1)
        old_h = numpy.ones(number_of_periods)
        old_s = numpy.ones(number_of_periods)

        counter = 0
        temp_values = numpy.zeros(18)
        while (check_convergence(old_k, old_b, old_h, old_s, capital, debt, hedge, saving)\
> convergence_threshold) and counter<100:

            #value_at_each()
            prepare_for_opt()

            #optimize.check_grad(local_optimize, local_gradient, beta)
            old_res = res.x
            res = optimize.minimize(local_optimize, beta, jac=local_gradient,method='SLSQP')

            old_k = capital
            old_b = cash
            old_h = hedge
            old_s = saving

            res.x = (1-damping_parameter)*old_res + damping_parameter*res.x
            simulate_path()
```

```
            value_at_each()
            counter = counter + 1
        temp_values[0] = alpha
        temp_values[1] = counter
        temp_values[2] = res.x[0]
        temp_values[3] = res.x[1]
        temp_values[4] = res.x[2]
        temp_values[5] = res.x[3]
        temp_values[6] = res.x[4]
        temp_values[7] = res.x[5]
        temp_values[8] = res.x[6]
        temp_values[9] = res.x[7]
        temp_values[10] = res.x[8]
        temp_values[11] = res.x[9]
        temp_values[12] = res.x[10]
        temp_values[13] = res.x[11]
        temp_values[14] = res.x[12]
        temp_values[15] = res.x[13]
        temp_values[16] = res.x[15]
        temp_values[17] = res.x[15]
        alpha_values = numpy.vstack([alpha_values,temp_values])
        if counter < 100:
            counter_general = counter_general+1
            temp_values_general[1:18] = temp_values_general[1:18] + temp_values[2:19]

        print(i)
    temp_values_general[0] = i
    if counter_general > 0:
        temp_values_general[1:18] = temp_values_general[1:18]/counter_general
    alpha_general = numpy.vstack([alpha_general,temp_values_general])
numpy.savetxt('alpha.txt', alpha_values, delimiter=',')
numpy.savetxt('alpha_general.txt', alpha_general, delimiter=',')


# iterative process

#all_cons
all_cons_values = numpy.zeros(18)
all_cons_general = numpy.zeros(17)
for i in frange (0, 20000, 2000):
    temp_values_general = numpy.zeros(17)
    counter_general = 0
    for j in range(10):
        jump_basic()
```

```
    all_cons = i

    model_basic()
    simulation_basic()
    initial_grid()
    initial_cash_generate()
    prepare_for_opt_first()

    res = optimize.minimize(local_optimize, beta, jac=local_gradient,method='SLSQP')
    simulate_path()
    value_at_each()
    old_k = numpy.ones(number_of_periods+1)
    old_b = numpy.ones(number_of_periods+1)
    old_h = numpy.ones(number_of_periods)
    old_s = numpy.ones(number_of_periods)

    counter = 0
    temp_values = numpy.zeros(18)
    while (check_convergence(old_k, old_b, old_h, old_s, capital, debt, hedge, saving)\
> convergence_threshold) and counter<100:

        #value_at_each()
        prepare_for_opt()

        #optimize.check_grad(local_optimize, local_gradient, beta)
        old_res = res.x
        res = optimize.minimize(local_optimize, beta, jac=local_gradient,method='SLSQP')

        old_k = capital
        old_b = cash
        old_h = hedge
        old_s = saving

        res.x = (1-damping_parameter)*old_res + damping_parameter*res.x
        simulate_path()
        value_at_each()
        counter = counter + 1
    temp_values[0] = alpha
    temp_values[1] = counter
    temp_values[2] = res.x[0]
    temp_values[3] = res.x[1]
    temp_values[4] = res.x[2]
    temp_values[5] = res.x[3]
    temp_values[6] = res.x[4]
```

```
        temp_values[7] = res.x[5]
        temp_values[8] = res.x[6]
        temp_values[9] = res.x[7]
        temp_values[10] = res.x[8]
        temp_values[11] = res.x[9]
        temp_values[12] = res.x[10]
        temp_values[13] = res.x[11]
        temp_values[14] = res.x[12]
        temp_values[15] = res.x[13]
        temp_values[16] = res.x[15]
        temp_values[17] = res.x[15]
        all_cons_values = numpy.vstack([all_cons_values,temp_values])
        if counter < 100:
            counter_general = counter_general+1
            temp_values_general[1:18] = temp_values_general[1:18] + temp_values[2:19]

        print(i)
    temp_values_general[0] = i
    if counter_general > 0:
        temp_values_general[1:18] = temp_values_general[1:18]/counter_general
    all_cons_general = numpy.vstack([all_cons_general,temp_values_general])
numpy.savetxt('all_cons.txt', all_cons_values, delimiter=',')
numpy.savetxt('all_cons_general.txt', all_cons_general, delimiter=',')


# iterative process

#landa
landa_values = numpy.zeros(18)
landa_general = numpy.zeros(17)
for i in frange (0.01, 0.1, 0.01):
    temp_values_general = numpy.zeros(17)
    counter_general = 0
    for j in range(10):
        jump_basic()
        landa = i

        model_basic()
        simulation_basic()
        initial_grid()
        initial_cash_generate()
        prepare_for_opt_first()

        res = optimize.minimize(local_optimize, beta, jac=local_gradient,method='SLSQP')
```

```
    simulate_path()
    value_at_each()
    old_k = numpy.ones(number_of_periods+1)
    old_b = numpy.ones(number_of_periods+1)
    old_h = numpy.ones(number_of_periods)
    old_s = numpy.ones(number_of_periods)

    counter = 0
    temp_values = numpy.zeros(18)
    while (check_convergence(old_k, old_b, old_h, old_s, capital, debt, hedge, saving)\
> convergence_threshold) and counter<100:

        #value_at_each()
        prepare_for_opt()

        #optimize.check_grad(local_optimize, local_gradient, beta)
        old_res = res.x
        res = optimize.minimize(local_optimize, beta, jac=local_gradient,method='SLSQP')

        old_k = capital
        old_b = cash
        old_h = hedge
        old_s = saving

        res.x = (1-damping_parameter)*old_res + damping_parameter*res.x
        simulate_path()
        value_at_each()
        counter = counter + 1
    temp_values[0] = alpha
    temp_values[1] = counter
    temp_values[2] = res.x[0]
    temp_values[3] = res.x[1]
    temp_values[4] = res.x[2]
    temp_values[5] = res.x[3]
    temp_values[6] = res.x[4]
    temp_values[7] = res.x[5]
    temp_values[8] = res.x[6]
    temp_values[9] = res.x[7]
    temp_values[10] = res.x[8]
    temp_values[11] = res.x[9]
    temp_values[12] = res.x[10]
    temp_values[13] = res.x[11]
    temp_values[14] = res.x[12]
    temp_values[15] = res.x[13]
```

```
        temp_values[16] = res.x[15]
        temp_values[17] = res.x[15]
        landa_values = numpy.vstack([landa_values,temp_values])
        if counter < 100:
            counter_general = counter_general+1
            temp_values_general[1:18] = temp_values_general[1:18] + temp_values[2:19]

        print(i)
    temp_values_general[0] = i
    if counter_general > 0:
        temp_values_general[1:18] = temp_values_general[1:18]/counter_general
    landa_general = numpy.vstack([landa_general,temp_values_general])
numpy.savetxt('landa.txt', landa_values, delimiter=',')
numpy.savetxt('landa_general.txt', landa_general, delimiter=',')



# iterative process

#sigma_j
sigma_j_values = numpy.zeros(18)
sigma_j_general = numpy.zeros(17)
for i in frange (0.1, 1, 0.1):
    temp_values_general = numpy.zeros(17)
    counter_general = 0
    for j in range(10):
        jump_basic()
        sigma_j = i

        model_basic()
        simulation_basic()
        initial_grid()
        initial_cash_generate()
        prepare_for_opt_first()

        res = optimize.minimize(local_optimize, beta, jac=local_gradient,method='SLSQP')
        simulate_path()
        value_at_each()
        old_k = numpy.ones(number_of_periods+1)
        old_b = numpy.ones(number_of_periods+1)
        old_h = numpy.ones(number_of_periods)
        old_s = numpy.ones(number_of_periods)

        counter = 0
```

```
    temp_values = numpy.zeros(18)
    while (check_convergence(old_k, old_b, old_h, old_s, capital, debt, hedge, saving)\
> convergence_threshold) and counter<100:

        #value_at_each()
        prepare_for_opt()

        #optimize.check_grad(local_optimize, local_gradient, beta)
        old_res = res.x
        res = optimize.minimize(local_optimize, beta, jac=local_gradient,method='SLSQP')

        old_k = capital
        old_b = cash
        old_h = hedge
        old_s = saving

        res.x = (1-damping_parameter)*old_res + damping_parameter*res.x
        simulate_path()
        value_at_each()
        counter = counter + 1
    temp_values[0] = alpha
    temp_values[1] = counter
    temp_values[2] = res.x[0]
    temp_values[3] = res.x[1]
    temp_values[4] = res.x[2]
    temp_values[5] = res.x[3]
    temp_values[6] = res.x[4]
    temp_values[7] = res.x[5]
    temp_values[8] = res.x[6]
    temp_values[9] = res.x[7]
    temp_values[10] = res.x[8]
    temp_values[11] = res.x[9]
    temp_values[12] = res.x[10]
    temp_values[13] = res.x[11]
    temp_values[14] = res.x[12]
    temp_values[15] = res.x[13]
    temp_values[16] = res.x[15]
    temp_values[17] = res.x[15]
    sigma_j_values = numpy.vstack([sigma_j_values,temp_values])
    if counter < 100:
        counter_general = counter_general+1
        temp_values_general[1:18] = temp_values_general[1:18] + temp_values[2:19]

    print(i)
```

```
    temp_values_general[0] = i
    if counter_general > 0:
        temp_values_general[1:18] = temp_values_general[1:18]/counter_general
    sigma_j_general = numpy.vstack([sigma_j_general,temp_values_general])
numpy.savetxt('sigma_j.txt', sigma_j_values, delimiter=',')
numpy.savetxt('sigma_j_general.txt', sigma_j_general, delimiter=',')


# iterative process

#mu_j
mu_j_values = numpy.zeros(18)
mu_j_general = numpy.zeros(17)
for i in frange (-0.5, 0.5, 0.1):
    temp_values_general = numpy.zeros(17)
    counter_general = 0
    for j in range(10):
        jump_basic()
        mu_j = i

        model_basic()
        simulation_basic()
        initial_grid()
        initial_cash_generate()
        prepare_for_opt_first()

        res = optimize.minimize(local_optimize, beta, jac=local_gradient,method='SLSQP')
        simulate_path()
        value_at_each()
        old_k = numpy.ones(number_of_periods+1)
        old_b = numpy.ones(number_of_periods+1)
        old_h = numpy.ones(number_of_periods)
        old_s = numpy.ones(number_of_periods)

        counter = 0
        temp_values = numpy.zeros(18)
        while (check_convergence(old_k, old_b, old_h, old_s, capital, debt, hedge, saving)\
> convergence_threshold) and counter<100:

            #value_at_each()
            prepare_for_opt()

            #optimize.check_grad(local_optimize, local_gradient, beta)
            old_res = res.x
```

```
            res = optimize.minimize(local_optimize, beta, jac=local_gradient,method='SLSQP')

            old_k = capital
            old_b = cash
            old_h = hedge
            old_s = saving

            res.x = (1-damping_parameter)*old_res + damping_parameter*res.x
            simulate_path()
            value_at_each()
            counter = counter + 1
        temp_values[0] = alpha
        temp_values[1] = counter
        temp_values[2] = res.x[0]
        temp_values[3] = res.x[1]
        temp_values[4] = res.x[2]
        temp_values[5] = res.x[3]
        temp_values[6] = res.x[4]
        temp_values[7] = res.x[5]
        temp_values[8] = res.x[6]
        temp_values[9] = res.x[7]
        temp_values[10] = res.x[8]
        temp_values[11] = res.x[9]
        temp_values[12] = res.x[10]
        temp_values[13] = res.x[11]
        temp_values[14] = res.x[12]
        temp_values[15] = res.x[13]
        temp_values[16] = res.x[15]
        temp_values[17] = res.x[15]
        mu_j_values = numpy.vstack([mu_j_values,temp_values])
        if counter < 100:
            counter_general = counter_general+1
            temp_values_general[1:18] = temp_values_general[1:18] + temp_values[2:19]

        print(i)
    temp_values_general[0] = i
    if counter_general > 0:
        temp_values_general[1:18] = temp_values_general[1:18]/counter_general
    mu_j_general = numpy.vstack([mu_j_general,temp_values_general])
numpy.savetxt('mu_j.txt', mu_j_values, delimiter=',')
numpy.savetxt('mu_j_general.txt', mu_j_general, delimiter=',')


# iterative process
```

```
#kappa
kappa_values = numpy.zeros(18)
kappa_general = numpy.zeros(17)
for i in frange (0.1, 0.7, 0.1):
    temp_values_general = numpy.zeros(17)
    counter_general = 0
    for j in range(10):
        jump_basic()
        kappa = i

        model_basic()
        simulation_basic()
        initial_grid()
        initial_cash_generate()
        prepare_for_opt_first()

        res = optimize.minimize(local_optimize, beta, jac=local_gradient,method='SLSQP')
        simulate_path()
        value_at_each()
        old_k = numpy.ones(number_of_periods+1)
        old_b = numpy.ones(number_of_periods+1)
        old_h = numpy.ones(number_of_periods)
        old_s = numpy.ones(number_of_periods)

        counter = 0
        temp_values = numpy.zeros(18)
        while (check_convergence(old_k, old_b, old_h, old_s, capital, debt, hedge, saving)\
> convergence_threshold) and counter<100:

            #value_at_each()
            prepare_for_opt()

            #optimize.check_grad(local_optimize, local_gradient, beta)
            old_res = res.x
            res = optimize.minimize(local_optimize, beta, jac=local_gradient,method='SLSQP')

            old_k = capital
            old_b = cash
            old_h = hedge
            old_s = saving

            res.x = (1-damping_parameter)*old_res + damping_parameter*res.x
            simulate_path()
            value_at_each()
```

```
            counter = counter + 1
        temp_values[0] = alpha
        temp_values[1] = counter
        temp_values[2] = res.x[0]
        temp_values[3] = res.x[1]
        temp_values[4] = res.x[2]
        temp_values[5] = res.x[3]
        temp_values[6] = res.x[4]
        temp_values[7] = res.x[5]
        temp_values[8] = res.x[6]
        temp_values[9] = res.x[7]
        temp_values[10] = res.x[8]
        temp_values[11] = res.x[9]
        temp_values[12] = res.x[10]
        temp_values[13] = res.x[11]
        temp_values[14] = res.x[12]
        temp_values[15] = res.x[13]
        temp_values[16] = res.x[15]
        temp_values[17] = res.x[15]
        kappa_values = numpy.vstack([kappa_values,temp_values])
        if counter < 100:
            counter_general = counter_general+1
            temp_values_general[1:18] = temp_values_general[1:18] + temp_values[2:19]

        print(i)
    temp_values_general[0] = i
    if counter_general > 0:
        temp_values_general[1:18] = temp_values_general[1:18]/counter_general
    kappa_general = numpy.vstack([kappa_general,temp_values_general])
numpy.savetxt('kappa.txt', kappa_values, delimiter=',')
numpy.savetxt('kappa_general.txt', kappa_general, delimiter=',')



# iterative process

#sigma
sigma_values = numpy.zeros(18)
sigma_general = numpy.zeros(17)
for i in frange (0.1, 1, 0.1):
    temp_values_general = numpy.zeros(17)
    counter_general = 0
    for j in range(10):
        jump_basic()
```

```
    sigma = i

    model_basic()
    simulation_basic()
    initial_grid()
    initial_cash_generate()
    prepare_for_opt_first()

    res = optimize.minimize(local_optimize, beta, jac=local_gradient,method='SLSQP')
    simulate_path()
    value_at_each()
    old_k = numpy.ones(number_of_periods+1)
    old_b = numpy.ones(number_of_periods+1)
    old_h = numpy.ones(number_of_periods)
    old_s = numpy.ones(number_of_periods)

    counter = 0
    temp_values = numpy.zeros(18)
    while (check_convergence(old_k, old_b, old_h, old_s, capital, debt, hedge, saving)\
> convergence_threshold) and counter<100:

        #value_at_each()
        prepare_for_opt()

        #optimize.check_grad(local_optimize, local_gradient, beta)
        old_res = res.x
        res = optimize.minimize(local_optimize, beta, jac=local_gradient,method='SLSQP')

        old_k = capital
        old_b = cash
        old_h = hedge
        old_s = saving

        res.x = (1-damping_parameter)*old_res + damping_parameter*res.x
        simulate_path()
        value_at_each()
        counter = counter + 1
    temp_values[0] = alpha
    temp_values[1] = counter
    temp_values[2] = res.x[0]
    temp_values[3] = res.x[1]
    temp_values[4] = res.x[2]
    temp_values[5] = res.x[3]
    temp_values[6] = res.x[4]
```

```
        temp_values[7] = res.x[5]
        temp_values[8] = res.x[6]
        temp_values[9] = res.x[7]
        temp_values[10] = res.x[8]
        temp_values[11] = res.x[9]
        temp_values[12] = res.x[10]
        temp_values[13] = res.x[11]
        temp_values[14] = res.x[12]
        temp_values[15] = res.x[13]
        temp_values[16] = res.x[15]
        temp_values[17] = res.x[15]
        sigma_values = numpy.vstack([sigma_values,temp_values])
        if counter < 100:
            counter_general = counter_general+1
            temp_values_general[1:18] = temp_values_general[1:18] + temp_values[2:19]

        print(i)
    temp_values_general[0] = i
    if counter_general > 0:
        temp_values_general[1:18] = temp_values_general[1:18]/counter_general
    sigma_general = numpy.vstack([sigma_general,temp_values_general])
numpy.savetxt('sigma.txt', sigma_values, delimiter=',')
numpy.savetxt('sigma_general.txt', sigma_general, delimiter=',')
```

APPENDIX D

VARIABLE DEFINITIONS

Variable	Definition
Tobin's Q	Ratio of the sum of the market value of equity ('prccq'×'cshoq') and the book value of interest-bearing debt (i.e., 'dltt'+'dlc') to the sum of book values of equity and interest-bearing debt (i.e., 'seqq'+'dltt'+'dlc')
Cash Flow	Ratio of the sum of net income before extraordinary items ('ibq') and depreciation & amortization ('dpq') to the net property, plant & equipment ('ppentq')
Leverage	Ratio of long-term debt ('dltt') to total assets ('atq')
Size	Natural logarithm of total assets ('atq')
Cash	Ratio of cash and equivalents ('cheq') to total assets ('atq')
Sales	Ratio of net sales ('saleq') to the net property, plant & equipment ('ppentq')
Dividends	A dummy variable that indicates whether the firm paid any dividends to its common shareholders
CAPEX	Capital expenditure during the current fiscal quarter scaled by net property, plant & equipment (i.e., 'ppentq'). Since COMPUSTAT reports year-to-date values for CAPEX, values for fiscal quarters 2, 3, and, 4 are these values minus lag of these values in the last quarter
Hedge Ratio	Ratio of the number of barrels of oil equivalent hedged to the number of barrels of total oil produced in that period
Profit	Ratio of earnings before taxes ('piy') to total assets ('atq')
Debt	Ratio of total debt (dltt'+'dlc') to total assets ('atq')
Futures Price	Price of the contract 3 of the WTI crude oil futures which is the contract closest to 3-months to maturity
VIX	An indicator that shows volatility of the S&P500 Index, 30 days forward

This table defines the variables used in the empirical analysis of Chapter 4.

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Amir Zemoodeh was born in Iran. He received a Bachelor's degree in Industrial Engineering in 2003, and an MBA in 2006, both from The Sharif University of Technology. Upon graduation from MBA, he worked as a credit rating analyst at a credit rating agency in Iran. He entered the PhD program at The University of Texas at Dallas in the Fall of 2012. His research interests are quantitative and numerical methods in finance, risk management, and derivative pricing. He is interested in the application of Machine Learning techniques in Finance and Risk Management. Since September 2016 he has been working as Credit Scoring Modeler at Citibank, Irving, U.S.

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