Essays on Oil Price Shocks and Financial Markets

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Declaration

This is to declare that the work presented in the thesis is my own. This thesis does not incorporate any material previously submitted for a degree or professional qualification in any universities.

Jiayue Wang, August 2011

Abstract

This thesis is composed of three chapters, which can be read independently.

The first chapter investigates how oil price volatility affects the investment decisions for a panel of Japanese firms. The model is estimated using a system generalized method of moments technique for panel data. The results are presented to show that there is a U-shaped relationship between oil price volatility and Japanese firm investment. The results from subsamples of these data indicate that this U-shaped relationship is more significant for oil-intensive firms and small firms.

The second chapter aims to examine the underlying causes of changes in real oil price and their transmission mechanisms in the Japanese stock market. I decompose real oil price changes into three components; namely, oil supply shock, aggregate demand shock and oil-specific demand shock, and then estimate the dynamic effects of each component on stock returns using a structural vector autoregressive (SVAR) model. I find that the responses of aggregate Japanese real stock returns differ substantially with different underlying causes of oil price changes. In the long run, oil shocks account for 43% of the variation in the Japanese real stock returns. The response of Japanese real stock returns to oil price shocks can be attributed in its entirety to the cash flow variations.

The third chapter tests the robustness of SVAR and investigates the impact of oil price shocks on the different U.S. stock indices. I find that the responses of real stock returns of alternate stock indices differ substantially depending on the underlying causes of the oil price increase. However, the magnitude and length of the effect depends on the firm size. The response of U.S. stock returns to oil price shocks can be attributed to the variations of expected discount rates and expected cash flows.

Contents

Introduction **12**

1 The Effect of Oil Price Volatility on Firm-Level Investment: Evidence from Japan **15**

1.1 Introduction . . . 15

1.2 Literature Review . . . 17

1.2.1 Uncertainty and Investment: Economic Theory . . . 18

1.2.2 Uncertainty and Investment: Empirical Evidence . . . 21

1.2.3 Oil Price Uncertainty and Investment Spending . . . 24

1.2.4 Theoretical Basis and Hypothesis . . . 27

1.3 The Model and Data . . . 29

1.3.1 Tobin's q Theory . . . 29

1.3.2 Empirical Model Specification . . . 34

1.3.3 Econometric Methods of Estimation . . . 36

1.3.4 Data . . . 38

1.4 Empirical Results . . . 42

1.4.1 Results of Pooled Firm Estimation . . . 42

1.4.2 Results of Robustness Check . . . 46

1.4.3 Oil-Intensive Firms and Less Oil-Intensive Firms . . . 47

1.4.4 Large and Small Firms . . . 48

1.4.5 Oil Price Volatility and Market Volatility . . . 50

1.5 Conclusion . . . 52

2 Oil Price Shocks and the Stock Market: Evidence from Japan 71

2.1 Introduction 71

2.2 Literature Review 75

2.3 Data and Methodology 79

2.3.1 Data 79

2.3.2 Methodology 80

2.4 Empirical Analysis 83

2.4.1 Unit Root Tests 83

2.4.2 Factors Affecting the Real price of Oil in Japan 84

2.4.3 Effects on Japanese Real Stock Returns 86

2.4.4 Effects on Japanese Real Dividend Growth Rates 88

2.4.5 Transmission Channels of Oil Price Shocks on Japan Stock Market 89

2.4.6 Robustness Checks 92

2.4.7 Relating Results for the U.S. and Japan 93

2.5 Conclusion 95

Appendix 2A. Data and Sources Descriptions for Data Used to Obtain Main Results 97

Appendix 2A. Data and Sources Descriptions for Data Used to Perform Robustness Check 98

3 Oil Price Shocks and Stock Markets: How Robust Are Results Based on Structural VARs? 109

3.1 Introduction 109

3.2 Background and Prior Research 111

3.2.1 Oil Shocks and Stock Returns 111

3.2.2 Previous Studies on Oil Price Shocks and Stock Markets 112

3.2.3 Structural VARs 115

3.2.4 Oil shocks and the Macroeconomy 116

3.2.5 Changing relationship between Oil Shocks and Economy 117

3.2.6 Hypothesis 119

3.3 Econometric Methodology 119
3.3.1 Regression-Based Methods 119
3.3.2 Structural VAR 120
3.3.3 Identifying Assumptions 121
3.3.4 Tests of VAR 125
3.3.5 Data Set Description 127
3.4 Empirical Results and Discussion 131
3.4.1 Results of Unit Root Tests 131
3.4.2 The Short-Run Response of Oil Prices to Oil Shocks 133
3.4.3 The Long-Run Response of Oil Prices to Oil Shocks 134
3.4.4 The Response of Stock Returns to Oil Shocks 135
3.4.5 The Response of Dividend Growth Rates to Oil Shocks 136
3.4.6 Does the Effect of Oil Shocks on Stock Returns Come from Expected Discount Rates or Expected Cash Flows 137
3.5 Conclusion 140
Appendix 3A. Summary of Literature on analysing relationships between oil prices and stock markets 143

Conclusion **187**

References **190**

Introduction

Crude oil price is one of the important costs faced by firms and households. It attracts considerable attention from economists, policymakers and the media. The fluctuation of oil price can affect the economy from many aspects (Hamilton, 2003; Kilian, 2009). Hamilton (2009b) finds that 10 out of the 11 post-war U.S. recessions have been preceded by a sharp increase in the price of crude oil. This thesis studies the interaction between oil price shocks and financial markets. It consists of three self-contained chapters, which can be read individually.

The topic of the first chapter is related to theoretical and empirical tests of the relationship between oil price uncertainty and firm-level investment. The impact of oil price volatility on firms' investment is considered one of the main channels through which oil price shocks are transmitted to the economy (Hamilton, 2008). The volatility of oil price introduces uncertainty about future energy prices, which make firms postpone their irreversible investment (Pindyck, 1991). The purpose of this chapter is to investigate how oil price volatility affects investment for a panel of Japanese firms. The literature on real options and compound options suggests that there are two options interacting with each other in the face of oil price uncertainty. One is the option to wait for the uncertainty to resolve, and the other is the option to grow the business. My results show that there is a U-shaped relationship between oil price volatility and Japanese firm-level investment. This result is robust with alternate measures of volatility. The model is estimated using a large sample of Japanese data and a system generalized method of moments technique for panel data. Further, my results from subsamples of these data indicate that this U-shaped relationship is more significant for oil-intensive firms and small firms. Finally I find that the significant role of market volatility in explaining investment suggests that market volatility is not fully captured by the Q ratio, as previously documented.

While the first chapter focuses on the effect of oil price uncertainty on firm-level investment, the other two focus on the effect of oil price shocks on the aggregate stock markets. Oil price shocks affect stock price through their effect on the expected cash flows and discount rate, which are the two determinants of stock price based on the present value model.

In the second chapter, I study, using a structural vector autoregressive (SVAR) method, the dynamic relationship between oil price shocks and the Japanese stock market. There is surprisingly little research on Japan given that it is the third-largest economy in the world and has almost no domestic oil resources. I find that unexpected increases in global demand for all industrial commodities cause a persistent increase in the real price of Japanese Crude Cocktail while the effect of unexpected oil production disruption and unexpected increases in the precautionary demand for oil are relatively minor. Next, I find that, in contrast to the conventional perception, demand shocks rather than supply shocks explain most of the changes in the real price of the Japanese Crude Cocktail. Third, in contrast to research on the U.S. stock market, I find only marginal evidence that oil price shocks contribute to the variation in Japanese real stock returns. Finally, again in contrast to results for the U.S. market, I find that the variation of Japanese stock market returns caused by oil price shocks can be explained by changes of expected real cash flows rather than changes of expected returns. These results remain qualitatively similar to a number of robustness checks using alternate model specifications and data.

The purpose of third chapter is to test the robustness of SVAR and to investigate the impact of oil price shocks on the different U.S. stock indices using alternate data. Kilian and Park (2009) show that the response of U.S. value-weighted stock in0dex to oil shocks depends greatly on the different underlying causes of increased prices. I use five different stock indices and two economic indices to carry out robustness check on these results. I find that the responses of real stock returns of alternate stock indices differ substantially depending on the underlying causes of the oil price increase. For instance, the effect of oil supply shock on U.S. stock returns is statistically insignificant, but an unexpected increase in the global demand for industrial commodities driven by increased global real economic activity will cause a sustained increase in U.S. stock returns. However the magnitude and length of the effect depends on the firm size. The results for an increase in the precautionary demand for oil are a bit mixed. For large firms, it causes persistently negative stock returns. For small firms, it does not have any significant effect. Overall, oil supply and demand shocks combined account for 42% of the long-run variation in U.S. real stock returns at best. The response of U.S. stock returns to shocks in oil markets can be attributed to revisions of expected discount rates and revisions of expected cash flows.

Chapter 1

The Effect of Oil Price Volatility on Firm-Level Investment: Evidence from Japan

1.1 Introduction

The price of energy is one of the many input costs faced by firms. Although there is considerable literature focusing on the effect of oil price shocks at the aggregate level (Bernanke, Gertler and Watson, 1997; Barsky and Kilian, 2002; Blanchard and Jordi, 2007; Kilian and Park, 2009; Hamilton, 2009b), there is little research on the effects of energy price on firm-level investment. Hamilton (2008) points out that one of the main channels through which energy price affects the economy is through its effect on firm investment expenditure. Edelstein and Kilian (2007) point out that there are two channels by which energy price can affect firm investments. First, an increase in energy price drives up the marginal cost of production, as energy is an important input cost in the whole production cycle; even though some firms may not directly consume energy, such as crude oil, as part of the production process, they do nevertheless use energy for indirect costs, such as heating and transportation. Second, rising oil prices reduce consumer expenditures, which in turn reduces demand for the firm's product.

Fluctuations in the price of energy introduce uncertainty about future energy prices, which results in firms postponing irreversible investments (Pindyck, 1991). Edelstein and Kilian (2007) also show that firms respond to energy uncertainty from both the supply and demand sides. As a result, when energy prices go up, firms reduce investment because of declining sales and considerations over future cost expenditure. This negative effect is magnified by uncertainty, which reduces the incentive to invest. However, when energy prices fall, higher investment spending triggered by increasing demand and falling costs is dampened by the increased uncertainty caused by the price fluctuation itself, reducing the incentive to invest.

The purpose of this paper is to investigate how oil price volatility affects investment for a panel of Japanese firms. Japan is the third largest economy in the world and has little crude oil reserve to support its growing economy and large population. So understanding oil price shocks and volatility is very important to Japan's economy. However, as to my best knowledge, there is no paper studying the relationship between oil price volatility and Japanese firm-level investments. Mohn and Misund (2009) and Henriques and Sadorsky (2011) are the two recent papers which focus on how oil price volatility affects U.S firm-level investment. Mohn and Misund (2009) find that oil price volatility has a positive effect on investment of international oil and gas firms. Henrique and Sadorsky (2011) expand to a large sample of U.S. firms and use both real options and compound option theory to investigate how oil price volatility affects strategic investments. They find that there is a U-shaped rather than linear relationship between oil price uncertainty and investment. Since Japan fully depends on imports mainly from Middle East for its oil consumption, I would expect to see a more significant negative effect of oil price volatility on Japanese firm investments. In addition, Ratti, Seol and Yoon (2011) find that firm size matters when determining the effect of energy price shocks on investment. Since large firms have more resources and greater capability to protect from high energy prices, I would expect that small firms suffer more from energy price fluctuations and hence oil price volatility has a stronger effect on the investment decisions of small firms than large firms.

The literature on real options suggest that two options interact with each other in the face of oil price uncertainty. One is the option to wait for the resolution of price uncertainty and the other is the option to grow the business. My results show that there is a U-shaped relationship between oil price volatility and Japanese firm-level investment. I estimate the model using a large sample of Japanese data and system-generalized method of moments (GMM) techniques for panel data. Further, my results from subsamples of these data indicate that this U-shaped relationship is more significant for oil-intensive firms and small firms. Finally, I find that the significant role of market volatility in explaining investment suggests that market volatility is not fully captured by Q-ratio, as previously documented (Abel and Eberly, 1999).

The rest of the paper is organized as follows. Section 2 reviews the literature on uncertainty and investment from both the theoretical and empirical perspectives. Further, the relationship between oil price volatility and investment is examined in detail. Section 3 derives the Tobin's q model used in this study and discusses econometrics issues. It also introduces the data used in this paper. Section 4 presents the empirical results and discusses their implications. Section 5 summarizes and sets forth conclusions.

1.2 Literature Review

In this section, I review the theory and empirical evidence about the relationship between uncertainty and investment in general. I focus on the more recent literature and the link between energy price uncertainty and investment.

1.2.1 Uncertainty and Investment: Economic Theory

There has been considerable work done on the relationship between uncertainty and investment. However, the results are mixed. Leahy and Whited (1996) point out that these mixed results are attributable to different theories emphasizing different channels. Economic theory does not provide a clear conclusion and the empirical evidence is not strong enough to assert a specific relationship between uncertainty and investment.

Leahy and Whited point out that it is important to differentiate the firm in isolation from firms viewed in relation to other firms. In the former, we need to consider the variance of several aspects of the firm's environment, for example, the variance in daily stock returns. In the latter case, we emphasize the relationship with other firms and focus on the covariance of returns with other projects. In the former case, the uncertainty is directly linked to the investment. In the latter, uncertainty can affect the investment only through its effect on the covariance between different projects. Based on these two cases, there are three popular models from different perspectives to address the relationship between uncertainty and investment (Leahy and Whited, 1996).

The first model is based on the role of covariance. The capital asset pricing model (CAPM) describes the relationship between an asset's required rate of return and its risk. Risk is measured by the covariance of its return and market portfolio return. Thus, higher covariance means higher risk of investment, which in turn drives up the required rate of return and reduces the level of capital stock. As a result, the CAPM predicts that there is a negative relationship between investment and uncertainty.

The remaining two models emphasize the variance of shocks faced by individual firms. They predict different effects from uncertainty on investments depending on the shape of the marginal revenue product of capital. The first model supports a convex marginal revenue product of capital function.

Hartman (1972), for example, uses the relative flexibility of labour-to-capital to produce the convex return. His model is based on two assumptions. First, firms can choose only the capital input prior to knowing the labour cost and output price. Second, firms can choose the labour after observing wage and output prices. So, under a linearly homogeneous production function, the marginal product of both capital and labour is a function of the labour–capital ratio. If the labour–capital ratio can be changed to adjust to fluctuation of output price, the change in marginal revenue product of capital will be more than the changes in output price. Thus, increased output price uncertainty increases the incentive to invest. Abel (1983) finds that no matter what curvature the marginal product of capital has, higher uncertainty leads to higher investment given current product price. However, this curvature is important in explaining the relationship between the expected growth rate of investment and the expected growth rate of the marginal product of capital. When the function of the marginal product of capital is convex, the expected growth rate of investment is less than the expected growth rate of marginal product of capital, multiplied by the elasticity of investment uncertainty, and vice versa.

The main class of models focuses on the role of irreversibility of firm investment decisions and predicts a concave marginal revenue product of capital. Most investments, however, are at least partly irreversible. They always involve a sunk cost that cannot be recovered if the market turns out to be worse than expected. However, firms are in control of the timing of their investments. They can always postpone the investment decision and wait until new information arrives. Thus, if a project is irreversible and can be delayed, they become very sensitive to uncertainty over future payoffs.

Irreversibility can arise from many aspects of business. Factories cannot disinvest their projects or refund purchased machinery, because used machinery and used equipment is very difficult to value. Government and regulations can also affect irreversibility. For example, capital controls may make it impossible to exchange foreign currency after selling assets (Dixit and Pindyck, 1994).

It is useful to think of an irreversible investment opportunity as a financial call option. A call option is an agreement between two parties where the buyer of the option has the right to buy an asset at a specific price within a specific time period. The value of the real option depends on the spot price of the underlying asset and the volatility of the change in its future value. After exercising the option, the buyer cannot retrieve the cost, although the buyer could sell the asset to someone else. A firm with investment opportunities can excise the option, that is, spend the money now on projects, or do so in the future to pursue another opportunity. This action is also irreversible. Similarly, this investment opportunity can be an asset or a project that can be transferred to another firm. If a firm invests today, it loses the opportunity to invest the resource elsewhere while waiting for the new information. Changes in market conditions that can affect the fluctuation of future cash flows can have a significant impact on firm investment.

Bernanke (1983) uses irreversibility to explain the business cycle and investment fluctuation. He argues that because of the irreversibility of investment and the opportunity cost of not investing in future, a firm's optimal decision may well be to postpone investment until new information emerges. Pindyck (1988) argues that irreversibility makes the net present value rule invalid. That is, the value of a unit capital must equal the sum of the cost of a unit and the opportunity cost of investing now rather than in future. Caballero (1991) shows that uncertainty can affect irreversible investment in two ways: first through its effect on a firm's expected path of marginal revenue of capital, and second through its effect on its competitors' expected path of marginal revenue of capital.

The recent literature on real options focuses on the compound option theory. Basically, compound option theory suggests that there are two options when firms make their investments: the option to wait and the option to grow. The first option tends to discourage investment while waiting for new information to make a better decision. The other option encourages early investment to take advantage in terms of market share and opportunities for growth. Kulatilaka and Perotti (1998) investigate decision making with respect to irreversible investment under imperfect competition and uncertainty. They point out that there are two assumptions in the literature: first, firms are assumed to have monopoly over investment opportunities. That is, the investment opportunity is secured and there is only a small impact on the market. Second, the product market is assumed to be perfectly competitive. However, these two assumptions do not always hold in the real world. For example, while firms wait for new information, other firms may take this opportunity to gain market share or grow their business. Thus, when facing uncertainty in an imperfect market, firms are affected by two options: the option to wait for new information and the option to grow the business. Rising uncertainty increases the value of the option to wait to invest, which results in delayed investments. However, this effect does not hold permanently. After a certain point, uncertainty eventually leads to an increase in investments, due to the increased option value of taking market share or business expansion. They also point out that as uncertainty rises, the value of the growth option increases more than the value of the option to wait to invest.

1.2.2 Uncertainty and Investment: Empirical Evidence

The existing studies on the relationship between investment and uncertainty are not conclusive in response to the theories discussed above. In order to test the role of covariance in uncertainty, Brainard, Shoven and Weiss (1980) use the risk measured by CAPM to test its effect on Tobin's q, and the ratio of market-to-book value of the capital stock; they find that although non-diversifiable risk is important in explaining market value, the sign of the coefficient is mixed. It can be positive or negative, and only some of them are significant. However, Leahy and Whited (1996) find that changes in covariance have very little effect on investment. They study the relationship between investment and uncertainty using a panel of firms from COMPUSTAT. They use the yearly volatility of firms' daily stock return as the measure for uncertainty, and find a negative relationship in favour of the concave model. Thus, irreversibility is the only explanation for this negative relationship.

At the industry level, Caballero and Pindyck (1996) study the effect of uncertainty on the total investment of firms across different industries. They note that it is important to distinguish between industry-level risk and firm-level risk when studying the relationship between investment and uncertainty across industries, because the distribution of future marginal revenue of capital differs for different risks. They find that industry-level risk raises the required rate of capital and affect future distribution of cash flows while firm-level risk has less impact on firm willingness to invest.

At the country level, Pindyck and Solimano (1993) explore the role of irreversibility on the relationship between uncertainty and aggregate investment behaviour for both developed and developing countries. They argue that firms only invest in projects when the required return reaches 'hurdle rates', which are typically three or four times the cost of capital. Moreover, uncertainty could raise this threshold. They use the variance of marginal revenue product of capital as the measure of uncertainty and analyse the real option value from the perspective of market structure. They find that, although the increase in this volatility increases the required return for investment, which in turn reduces investment spending, there is only a small negative effect of uncertainty on the level of investment. However, this does not mean that volatility is not important in explaining the spending level, given the large scale of investment and changing risk. Further, they find that for developing countries, this relationship is more negative than that for developed countries.

In more recent work, Bloom, Bond and Van Reenen (2007) use different types of adjustment costs, uncertainty effects, and functional form of revenue functions, and conclude, because of the cautionary effect and convexity effect caused by the high level of uncertainty, that investment responds less to a given demand shock, for a large panel of U.K. manufacturing firms. Ogawa and Suzuki (2000) study the relationship between uncertainty and fixed investment for Japanese industries in the backdrop of stagnating fixed investment in Japan after the bubble burst in the early 1990s. They use different statistical methods to construct the uncertainty proxy and decompose these measures into three components: economy-wide, industry-wide, and firm-wide. They find a significantly negative relationship between uncertainty and fixed investment for Japanese manufacturing firms. Similar to Ogawa and Suzuki (2000), Bulan (2005) focuses on U.S. manufacturing firms and decomposes all uncertainty into market-level, industry-level, and firm-level components. Bulan's results show that both industry-level and firm-level uncertainty have a negative effect on firm investment after controlling Tobin's q, cash flow, profitability, and leverage. Bloom (2009) builds a model that structurally analyses the macroeconomic uncertainty shocks on hiring and investment and evaluates the joint adjustment of labour and capital costs. He finds that uncertainty raises the value of options to wait, which in turn causes a temporary pause in investment and hiring.

The rest of the work focuses on the use of different measures of uncertainty. Federer (1993) examines the relationship between uncertainty and aggregate investment spending using the risk premium embedded in the term structure of interest rates to measure uncertainty. The justification for using risk premium is that it is related to the market's uncertainty about future movements in interest rates and other macroeconomic variables. He finds a significant and negative relationship between the lagged risk premium and investment spending after controlling the cost of capital and average q. Guiso and Parigi (1999) contribute to the literature by introducing an alternative uncertainty measure: a survey-based measure for probability distribution of future demand for products of firms. They find that firms facing greater uncertainty respond less to future expected demand and have an incentive to invest less, for their sample of Italian manufacturing firms. Bond and Cummins (2004) study the empirical relationship between uncertainty and firm investment for publicly traded U.S. firms between 1982 and 1999. They use three different measures of uncertainty: the volatility of firm stock returns, disagreement among future forecasts of firm profit, and the variance of forecast error of future profit. They find that these three measures are correlated with each other and overall, they have a significant negative long-run effect on capital accumulation.

In supporting the compound option theory, Sarkar (2000) studies the effect of uncertainty on the probability that investment will take place. He finds a U-shaped relationship between volatility and investment. That is, at low levels of uncertainty, the probability of investment firstly increases with uncertainty, but after volatility surpasses 0.39, it becomes a decreasing function of uncertainty. Folta and O'Brien (2004) investigate the relationship between industry uncertainty and the decision of established firms to enter a new industry, using COMPUSTAT industry and business sector data between 1980 and 1999. They find that this relationship is not monotonic. Overall, 93% of the range of uncertainty has a negative effect on entry, which suggests that the option to wait is dominant most of the time. However, at high levels of uncertainty, the uncertainty has a positive effect on entry, which suggests that the option to grow outweighs the option to wait as uncertainty reaches very high levels.

1.2.3 Oil Price Uncertainty and Investment Spending

Since oil price shocks have a significant impact on the economy, they also affect firm investment decisions. Pindyck (1991) points out that energy price shocks introduce uncertainty and affect the marginal product of several types of capital. This may be the reason for declining investment spending during the recessions of 1975 and 1980. Bernanke (1983) develops a model of decision making between adding energy-efficient capital and energy-inefficient capital. He argues that when the value of option to wait for new information is high, firms prefer to invest later in order to receive more information.

In an early study, Uri (1980) introduces a model of investment behaviour that considers the effect of changing energy prices. He finds that the impact of energy price on investment differs for energy-intensive industries and less energy-intensive ones. For energy-intensive industries, energy price has a very dominant effect on the investment for the next three years. For less energy-intensive industry sectors, the results are mixed. Glass and Cahn (1987) develop a theoretical model to relate investment with the price of energy under different economic conditions. They find that energy price spikes do reduce aggregate real investment. These effects are greatest during economic booms and lowest during recessions. Moreover, these effects are diminishing as energy prices keep climbing. Hurn and Wright (1994) test the effect of oil price and oil price variance on irreversible investment using data from the oil field in the North Sea. They argue that resource extraction firms place a positive value on waiting when facing uncertainty, since time brings more information about the future payoff of the project. As long as the investment opportunity is still available, a late decision is always a better decision. The overall value of a late decision is equal to the value of waiting for new information, minus the potential profit of the losing investment opportunity. Their results show that oil price influences the lag between the discovery of a new field and the decision to develop it. However, the variance of oil price is not significant with respect to this lag.

Mohn and Misund (2009) are the first researchers to relate oil price volatility to firm-level investment. They investigate the effect of oil price uncertainty on investment for international oil and gas firms over the period 1992-2005. Their measures of uncertainty include volatility of overall stock market returns and oil price volatility. They find that stock market uncertainty has a negative effect on investment, while oil price uncertainty increases investment. Elder and Serletis (2010) also examine the effect of oil price uncertainty on investment and economic growth for U.S. firms based on a structural vector regressive model that incorporates GARCH-in-mean error. They use the conditional variance of oil price as the measure of uncertainty. Their main results show a negative effect of oil price uncertainty on GDP, consumption, investment and industrial production, which are robust to different measures of oil price, sample periods, and measures of output. Elder and Serletis (2009) test the robustness of these results for Canadian firms and find similar results to those reported for the U.S.

In a very recent paper, Henriques and Sadorsky (2011) investigate how oil price volatility affects strategic investment using real options and compound option theory. They study a sample of U.S. firms over the period 1990-2007. They use both oil price volatility and squared oil price volatility as measures of uncertainty. They conclude that there is a U-shaped rather than linear relationship between oil price uncertainty and investment. Yoon and Ratti (2011) use an error correction model of capital stock adjustment to study the effect of energy price uncertainty for 2600 U.S. manufacturing firms over the period 1971-2006. They find that energy uncertainty reduces investment via a negative effect on sales growth. However, this effect is a response effect rather than a direct effect, compared with Mohn and Misund (2009). Ratti, Seoul and Yoon (2011) study the effect of energy price on firm-level investment across 15 European countries and across different industries. They argue that their research benefits from using the relative price of energy over time and across countries and overcomes the drawback of using low-frequency energy prices that yield a small impact on investment. They find a negative relationship between energy price shock and firm-level investment both within individual countries and across the whole panel. They also show that this negative effect is more significant for manufacturing firms than for other non-financial firms.

1.2.4 Theoretical Basis and Hypothesis

The model used in this paper assumes a concave marginal revenue product of capital and focuses on the role of irreversibility of firm investment. Bernanke (1983) argues that because of the irreversibility of investment and the opportunity cost of not investing in future, the optimal decision of a firm is always to postpone investment until new information emerges when facing uncertainty. This model predicts a negative effect of uncertainty on the firm investments.

Furthermore, I also incorporate compound option theory into this model. Compound option theory suggests that there are two options when firms make their investments: the option to wait and the option to grow. The option to wait encourages firms to wait for new information and make a better and late investment decision, while the option to grow encourages to take early advantage in terms of market shares and opportunities. Kulatilaka and Perotti (1998) point out that the relationship between uncertainty and investment is not monotonic. At first uncertainty increases the value of the option to wait, which delays investment. After a certain point, uncertainty eventually increases the size of the investment because the value of the growth option increases more than the value of the option to wait to invest.

On the empirical level, Henrique and Sadosky (2011) use a sample of U.S. firms and find that there is a U-shaped relationship between oil price uncertainty and investment based on both real options and compound option theory. Thus, since Japan fully depends on imports mainly from the Middle East for its oil consumption, I would expect to see a more significant negative effect of oil price volatility on Japanese firm investments. Moreover, because two options interact with each other based on compound option theory, my second hypothesis is that there is a U-shaped rather than linear relationship between oil price volatility and Japanese firm-level investments.

The most recent work by Ratti, Seoul and Yoon (2011) uses a dynamic model of investment with data on non-financial firms in 15 European countries and relative energy price across different countries. They consider the effect of oil price changes on firm investments both over time and between countries. They estimate a dynamic model of investment based on the Euler equation approach, which assumes that capital and energy are the only inputs in production, that it is costly to adjust capital, and that there is debt financing. The first difference of this chapter from the above paper is that I focus on a single country and use the absolute oil price imported by Japan. Secondly, the dynamic model used in this chapter is based on neoclassical assumptions and inputs include fixed capital inputs, gross investment, labour inputs and current inputs. This model assumes that the firm's only quasi-fixed input is homogeneous capital goods and the function of marginal adjustment cost is defined.

Ratti, Seoul and Yoon (2011) also introduce the firm size into the baseline model to test if firm size affects the relationship between oil price shocks and investments. They find that large firms have less persistence in investment than smaller firms. The negative effect of increased energy prices on firm investment is less for large firms. These results suggest that large firms are flexible when facing energy price increases and have better resources to protect from the high energy prices than small firms. Thus, my hypothesis regarding to the role of firm size in this study is that there is a U-shaped relationship between oil price volatility and firm investment for both large and small firms. However, I would expect this relationship is stronger for small firms.

1.3 The Model and Data

1.3.1 Tobin's q Theory

Tobin's q is introduced by Tobin (1969), who provides the starting point relating investment to q. Tobin's q is defined as the ratio between the market value and replacement value of an asset or a firm. It assumes that the maximised value of the firm can be measured by its stock market valuation under the conditions of perfectly competitive markets and constant returns to scale technology. Thus, the stock market valuation would capture all relevant information about future profitability. Additional information, such as cash flows, could not contribute to current expectations.

If the market value simply reflects the book value of the firm, Tobin's q is equal to 1. When the market value is more than the book value of the firm's assets and Tobin's q is greater than 1, it implies that the firm stock is over-valued and this is a good time to invest more, because the real cost of capital is less than what the firm can get by issuing shares. When Tobin's q is less than 1, it suggests that the market undervalues the firm and that the market value of the firm is less than its book value. As a result, the firm will not replace the capital. Tobin's q suggests that firm value is the driving force behind investment spending in this model.

Tobin's q model has been the most popular model among all models that capture the dynamics of investment. Following Bond and Van Reenen (2007), the Tobin's q model can be derived as follows.

Assumptions are made to simplify many aspects. First, the objective of the firm is assumed to be the maximization of the value of the equity owned by all shareholders, who are assumed to be risk-neutral. So in this research, I do not consider the effect of risk on the firm's required rate of return. Second, this firm pays no taxes and issues no debt, so financial policy is also outside my consideration. Third, the market is perfectly competitive and investors can access all information about prices and products at zero cost.

There are three types of factors to be considered for production. Capital assets include both tangible and intangible assets, which are durable. Labour inputs are the people hired by the firm each year. The last factor is current inputs, which are purchased by the firm but will not be fully consumed in a particular period.

Based on the neoclassical assumptions above, the dynamic optimisation problem for the firm can be characterized as

$$\begin{aligned} V_t &= [\max \Pi_t(K_t, I_t, L_t, M_t) + \beta_{t+1} E_t(V_{t+1})] \\ &= \max[\sum_{i=0}^{\infty} \beta_{t+i} \Pi_t(K_{t+i}, I_{t+i}, L_{t+i}, M_{t+i})] \end{aligned} \quad (1)$$

where V_t is the firm value with output price p_t, $\Pi(\cdot)$ is the firm's net revenue function, K_t is the fixed capital inputs, I_t is the gross investment with price p_t^K, L_t is the labour inputs with wage ω_t, M_t is the different types of current inputs with price p_t^M. β_{t+i} is the firm's discount rate equal to $(1+\rho_{t+i})^{-1}$, where ρ_{t+i} is the risk-free rate between period $t+i-1$ and period $t+i$ and $\rho_t = 0$. $E(\cdot)$ denotes the expected value conditioned on information available in period t.

Due to capital accumulation, capital inputs can be expressed as

$$K_t = (1-\delta)K_{t-1} + I_t \qquad (2)$$

where δ is the rate of depreciation for capital.

Based on this equation, the net revenue function is given by

$$\Pi_t(K_t, I_t, L_t, M_t) = p_t F(K_t, L_t, M_t) - p_t^K I_t - \omega_t L_t - p_t^M M_t \quad (3)$$

where p_t is the price of product and $F(K_t, L_t, M_t)$ is the neoclassical production function.

To solve the Eq.1, the first-order conditions are

$$\frac{\partial \Pi_t}{\partial I_t} = -\lambda_t \quad (4)$$

$$\frac{\partial \Pi_t}{\partial K_t} = \lambda_t - (1-\delta)\beta_{t+1}E_t(\lambda_{t+1}) \quad (5)$$

$$\frac{\partial \Pi_t}{\partial L_t} = 0 \quad (6)$$

$$\frac{\partial \Pi_t}{\partial M_t} = 0 \quad (7)$$

where $\lambda_t = \frac{1}{1-\delta}(\frac{\partial V_t}{\partial K_{t-1}})$ is shadow value related to capital accumulation. Eq.4 sets the additional cost of capital equal to the shadow value. Eq.5 describes the evolution path of shadow values and capital stock. Eq.6 and Eq.7 are standard first-order conditions for non-durable goods.

The linear homogeneity of the revenue function yields

$$\Pi_t(K_t, I_t, L_t, M_t) = K_t \frac{\partial \Pi_t}{\partial K_t} + I_t \frac{\partial \Pi_t}{\partial I_t} \quad (8)$$

Put Eq.4 and Eq.5 into Eq.8

$$\Pi_t(K_t, I_t, L_t, M_t) = K_t(\lambda_t - (1-\delta)\beta_{t+1}E_t(\lambda_{t+1})) + I_t(-\lambda_t) \quad (9)$$

Combine Eq.9 and Eq.2

$$\Pi_t(K_t, I_t, L_t, M_t) = -K_t(1-\delta)\beta_{t+1}E_t(\lambda_{t+1}) + \lambda_t(1-\delta)K_{t-1} \quad (10)$$

Re-arrange Eq.10

$$\lambda_t(1-\delta)K_{t-1} = \Pi_t(K_t, I_t, L_t, M_t) + K_t(1-\delta)\beta_{t+1}E_t(\lambda_{t+1}) \quad (11)$$

Solving forward by repeated substitution gives

$$\lambda_t(1-\delta)K_{t-1} = E_t(\sum_{s=0}^{\infty}\beta_{t+s}\Pi_s(K_{t+s}, I_{t+s}, L_{t+s}, M_{t+s}) = V_t \qquad (12)$$

Because λ_t is a forward-looking measure of current and future marginal revenue product of capital, Tobin's q, which measures ratio of the maximized value of firm to the replacement cost, can be expressed as

$$q_t = \frac{\lambda_t}{p_t^K} = \frac{V_t}{(1-\delta)K_{t-1}p_t^K} \qquad (13)$$

Tobin's q model assumes the firm's only quasi-fixed input is homogeneous capital goods. To obtain an empirical investment model, the function of marginal adjustment cost must be defined. Followed by Summers (1981) and consistent with mainstream research in q theory, the function can be specified in asymmetric and quadratic form as follows:

$$G(I_t, K_t) = \frac{b}{2}[\frac{I_t}{K_t} - a]^2 K_t \qquad (14)$$

The basic q model requires function $G(I_t, K_t)$ to be homogeneous of degree one in (I_t, K_t), which is constant return to scale. Then Eq.3 can be rewritten as

$$\Pi_t(K_t, I_t, L_t, M_t) = p_t[F(K_t, L_t, M_t) - G(I_t, K_t)] - p_t^K I_t - \omega_t L_t - p_t^M M_t \quad (15)$$

Assuming the market is perfectly competitive,

$$\frac{\partial \Pi_t}{\partial I_t} = -p_t\frac{\partial G_t}{\partial I_t} - p_t^K \qquad (16)$$

Combined with Eq.4

$$\frac{\partial G_t}{\partial I_t} = (\frac{\lambda_t}{p_t^K} - 1)\frac{p_t^K}{p_t} \qquad (17)$$

Meanwhile, the first-order condition of Eq.14 is

$$\frac{\partial G_t}{\partial I_t} = b(\frac{I_t}{K_t} - a) \tag{18}$$

Finally, combining Eq.17, Eq.18, and Eq.13

$$\begin{aligned}
\frac{I_t}{K_t} &= a + \frac{1}{b}[(\frac{\lambda_t}{p_t^K} - 1)\frac{p_t^K}{p_t}] \\
&= a + \frac{1}{b}[(\frac{V_t}{(1-\delta)K_{t-1}p_t^K} - 1)\frac{p_t^K}{p_t}] \\
&= a + \frac{1}{b}[(q_t - 1)\frac{p_t^K}{p_t}] \\
&= a + \frac{1}{b}Q_t
\end{aligned} \tag{19}$$

where $Q_t = q_t - 1$.

The advantage of q model is that the current investment decision is explicitly modelled, and the parameter in the model is from the adjustment cost function, which should be invariant to structural changes. On the other hand, q model may be seriously mis-specified because the adjustment cost function may not be symmetric and quadratic as specified above. This relationship can be asymmetric or even non-linear. Perfect competition and constant returns to scale may not be realistic for any firm.

Many authors have critiqued q theory because there is discrepancy between its theoretical assumptions and the real conditions under which the empirical work is done. For example, Blanchard, Rhee and Summers (1993) find that fundamentals are more useful in predicting investment of U.S. firms than Tobin's q from 1920s to 1990s. However, much literature challenges this interpretation. Gomes (2001) develops a dynamic general equilibrium model with financial frictions and tests it with simulated data. He finds that Tobin's q has good explanatory power for the variability in Investment, and that cash flow does not provide any additional power. Cooper and Ejarque (2003) point out that with a reasonable amount of curvature in proper function, q theory is still very useful for modelling investment. Bond et al. (2004) argue that because q theory relates the firm's maximized value with its stock market valuation, if the stock market experiences bubbles or other factors besides cash flows and future profitability, Tobin's q could not capture all the information about the expected future profit of current investment decisions.

The attractiveness of q model has at least two advantages. First, it is simple and has an intuitive relationship between investment and book to market ratio. Second, q represents a sufficient statistic for investment based on neoclassical economic theory and is tested extensively in the empirical applications. The focus of this study is the role of uncertainty in the investment behaviour of Japanese firms, thus the q model is a good starting point for my theoretical model.

1.3.2 Empirical Model Specification

The q model in Eq.19 is a deterministic relationship between the investment rate and the q variable. In order to introduce stochastic variation into the q model we add an error term. Thus Eq.19 can be written as

$$\frac{I_t}{K_t} = a + \frac{1}{b} Q_t + e_t \tag{20}$$

where e_t is the additive shock to the investment. Eq.20 implies that Q_t should be an endogenous variable in this model.

In addition, Eq.20 is usually augmented with other explanatory variables of interest. Following Fazzari, Hubbard and Petersen (1988), many empirical studies have added cash flow into the model, which relates the investment to Tobin's q. They argue that when firms face financial constraints, investment may be sensitive to the availability of internal funds. Furthermore, since the purpose of this study is to test the effect of oil price uncertainty on investment, oil price uncertainty can be from both the supply side and the demand side, such as oil supply disruptions caused by cartel action or unrest in the Middle East, world economic expansion, or precautionary demand from speculators (Kilian 2009). Oil prices are a direct measure of uncertainty in the crude oil market. Thus, following Henriques and Sadorsky (2011), I include cash flows cf_t, oil price volatility o_t, and squared oil price volatility o_t^2 into Eq.20.

$$\frac{I_t}{K_t} = a + \frac{1}{b}Q_t + \gamma_1 cf_t + \gamma_2 o_t + \gamma_3 o_t^2 + e_t \tag{21}$$

Moreover, since firms may not have similar investment rates due to technology shocks, and there may be common trends affecting all firms in the same way (e.g., business cycles), Eq.21 is further augmented with fixed effects for individual firms η_i and time period effect υ_t, where i is for individual firms and t is for different time periods

$$\frac{I_{it}}{K_{it}} = a + \frac{1}{b}Q_{it} + \gamma_1 cf_{it} + \gamma_2 o_t + \gamma_3 o_t^2 + \eta_i + \upsilon_t + e_{it} \tag{22}$$

There is no compelling reason to believe e_t is serially uncorrelated, following Mohn and Misund (2009), I assume that e_t follows an AR(1) process

$$e_{it} = \rho e_{it-1} + \zeta_{it} \tag{23}$$

Substituting Eq.22 into Eq.23 yields

$$\begin{aligned}\frac{I_{it}}{K_{it}} &= a(1-\rho) + \rho\frac{I_{it-1}}{K_{it-1}} + \frac{1}{b}Q_{it} - \frac{\rho}{b}Q_{it-1} + \gamma_1 cf_t - \rho\gamma_1 cf_{t-1} \\ &\quad + \gamma_2 o_t - \rho\gamma_2 o_{t-1} + \gamma_3 o_t^2 - \rho\gamma_3 o_{t-1}^2 + (1-\rho)\eta_i + \upsilon_t - \rho\upsilon_{t-1} + \zeta_{it}\end{aligned} \tag{24}$$

For econometrics purposes, Eq.23 can be rewritten as

$$
\begin{aligned}
\frac{I_{it}}{K_{it}} &= b_0 + b_1\frac{I_{it-1}}{K_{it-1}} + b_2 Q_{it} + b_3 Q_{it-1} + b_4 cf_t + b_5 cf_{t-1} \\
&\quad + b_6 o_t + b_7 o_{t-1} + b_8 o_t^2 + b_9 o_{t-1}^2 + (1-\rho)\eta_i + \upsilon_t - \rho\upsilon_{t-1} + \zeta_{it} \qquad (25)
\end{aligned}
$$

where ζ_{it} is the white noise and serially uncorrelated. b_6 and b_7 measure the instantaneous effect of oil price volatility and lag of oil price volatility on investment. b_8 and b_9 measure the instantaneous effect of squared oil price volatility and lag of squared oil price volatility on investment.

1.3.3 Econometric Methods of Estimation

Eq.25 can be estimated as a dynamic panel model which contains an unobserved panel effect η_i. Since $\frac{I_{it}}{K_{it}}$ is correlated with η_i and there are endogenous variables and lags associated with them on the right-hand side, ordinary least squares (OLS) could give a biased estimation of parameters. The standard solution of endogeneity in dynamic panel models is to use exogenous variables that are uncorrelated with error terms to instrument the endogenous dependent variables. However, these exogenous variables are very difficult to find for the panel firm data.

The first-difference GMM estimator introduced by Arellano and Bond (1991), provides consistent estimates of parameters as long as the number of firms is large. Heterogeneity is eliminated using a first-difference transformation; it is specially designed for samples in which N is large and T is small[1], since company panels are usually composed of a large number of firms with a relatively small number of time periods. However, when the instrumental variables are only weakly correlated with the lagged value of variables, this

[1] The Arellano-Bond estimator is designed for large number of cross-sectional units and a small number of time-serious units. If T is relatively large, the use of all possible instruments may lead to low power estimate (Arellano and Bond, 1998). Alvarez and Arellano (2003) derive the asymptotic properties of first difference GMM. It suggests that if there are no endogenous regressors present, this estimator is biased towards within the group, which is not a serious concern because it is still consistent. In this study the number of time periods is 24 and there are endogenous regressors in the model. Thus, readers are advised to look at the findings using first difference GMM with caution.

GMM estimator could have a large bias for an infinite sample. Arellano and Bover (1995) provide an alternative, using the lagged values of the first differenced independent variable as the additional instrumental variables. This significantly improves the effectiveness of the first-differenced estimator in both the asymptotic and small samples. Blundell and Bond (1998) expand the system-GMM estimator by introducing more instrumental variables, such as suitably lagged value of levels of dependent variables and independent variables. The system-GMM estimator combines equations in levels with equations in first difference and significantly improves asymptotic efficiency and small sample properties.

While one-step GMM estimator uses a weighting matrix that is independent of estimated parameters, the two-step estimation uses the error from the first step to construct the variance-covariance matrix, and re-estimates the model in the second step. Arellano and Bond (1991) suggest using a first-step estimator for coefficient estimation and a two-step estimator for the over-identification test. Bond (2002) points out that two-step weight matrix can improve efficiency in large samples. However, in small samples, the two-step GMM estimator has severe downward bias. Windmeijer (2005) proposes a solution for the biased two-step estimator in small samples and takes the fact into consideration that the usual asymptotic standard errors do not consider the extra variation generated by the estimated parameters in constructing the efficient weighting matrix. He finds that using a bias-correction could gain a more accurate approximation in a finite sample even though the correction effects are decreasing with sample size. Thus, in this paper, all the estimations are performed with two-step, bias-corrected, and robust estimators for the covariance matrix.

Furthermore, Hansen J test is used to test the validity of the over-identification assumption for the instrument matrix, following Roodman (2006). Compared with Hansen J, the Sargan test, which also tests over–identification, is not robust and is sensitive to heteroscedasticity and autocorrelation, and tends to over-reject the hypothesis. Thus, Hansen J is used in this paper for the over-identification test. In addition, Arellano and Bond (1991) tests for autocorrelation in differences are provided up to order 4. The null hypothesis is that there is no autocorrelation. First-order autocorrelation is acceptable while a higher order of autocorrelation could be troublesome. This is because the idiosyncratic errors are independently and identically distributed, and the first-differenced errors should be serially correlated at first order. If the model is correctly specified, there should be no higher-order correlation.

In this paper, I use different econometric approaches including OLS, GMM and system-GMM with different lags. All models are estimated using Stata 11. Oil volatility, squared oil volatility, time effects and their lags are treated as exogenous, while Q, cash flow, their lags, and lagged investment are treated as endogenous. The reason for using both oil volatility and squared oil volatility in the model is that compound option theory suggests that the option to wait and the option to grow interact with each other when firms face investment decisions. Both volatilities are used to test the non-linear relationship between investment and oil price uncertainty in this study.

1.3.4 Data

Firm-level Data

The firm-level data are obtained from DataStream[2]. The data set consists of an unbalanced panel of publicly traded firms drawn from TOPIX1000, excluding both financial and utility firms. The reason to use TOPIX 1000 is simply because they are the largest data sample I could get from DataStream. The data sample spans 24 years from 1987–2010 only because DataStream did not report Japanese firm data in earlier years. The data sample

[2] Please refer to Table 1 for detailed description and variable codes.

is mainly after the big Japanese recession, during which the performance of the Japanese economy has been less impressive compared with other developed countries. As shown in Figure 1, after 'miracle' economic expansion in 1980s, Japanese overall real economic growth slowed significantly in the late 1990s, due to over investment and failed monetary policy. The economy's stagnation finally ended in recent years, when the GDP growth rate surpassed that of the U.S. and European Union.

TOPIX1000 are selected based on free-float adjusted market capitalization. The TOPIX1000 consists of TOPIX core30, TOPIX large70, TOPIX mid400, and 500 highly market-capitalized stocks from the TOPIX. Leahy and Whited (1996) note that the advantage of using panel data to study uncertainty is that it provides a firm-level environment. All firm data are obtained from DataStream.

Consistent with previous literature, the Tobin's q is calculated following Chuang and Pruitt (1994)

$$Tobin's\ q = \frac{(CE + PS + LD + CL - CA)_t}{TA_{t-1}} \tag{26}$$

where CE is the market value of equity, PS is the preferred stock, LD is the long-term debt, CL is the current liability, CA is the current asset and TA is the total asset.

Firm investment is measured by capital expenditure on property, plant, and equipment. Capital stock is represented by the total asset. So the investment over the total asset is as follows

$$\frac{I_t}{K_t} = \frac{PPE_t}{TA_t} \tag{27}$$

where PPE is the expenditure on property, plant and equipment and TA is the total asset.

The control variable, cash flow, is measured as

$$cf_t = \frac{(NI + DDA)_t}{TA_t} \qquad (28)$$

where NI is the net income before extra items and preferred dividends, DDA is the depreciation, depletion and amortization, TA is the total asset.

Whited (2006) points out that it is important to remove the outliers when working with firm panel data. So for $Tobin'sq, \frac{I_t}{K_t}$, cf_t, any observations lying outside the 99% confidence intervals are removed as outliers. In addition, compared with other developed countries, mergers and acquisitions are less frequent in Japan, so I lose no other data in my samples.

Oil Price Volatility

I compute the oil price volatility as a historical estimate of the variance over the sample period. I use the daily oil price obtained from the U.S. Energy Information Agency, and choose the daily closing oil price of the nearest contract to maturity of West Texas Intermediate. Annual oil price volatility is measured following Sadorsky (2008):

$$o_t = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(r_t^o - E(r_t^o))^2} \cdot \sqrt{N} \qquad (29)$$

where r_t^o is the daily oil price return, which is calculated as $r_t^o = 100Ln(p_t/p_{t-1})$. N is the number of trading days each year, 252. For the calculation of market volatility, the oil price return is replaced by the TOPIX1000 stock index return.

For a robustness check, I also use alternate volatility estimated from a exponential-GARCH(1,1). The GARCH-type models allow the conditional variance to be dependent upon previous own lag. The EGARCH proposed by Nelson (1991) releases the non-negative constraints in the pure GARCH model. Moreover, EGARCH captures the asymmetric effects that are apparent in many financial time series. EGARCH has demonstrated superior in-sample estimation and forecasting than other conditional variance models in many studies (e.g., Alexander, 2008). In this study, EGARCH well captures the asymmetric effect of oil price shocks, which indicates that negative shocks have a greater impact on conditional volatility than positive shocks of the same magnitude.

Subsamples

Oil-intensive Industries and Less Oil-intensive Industries I apply the industry classification used in Fukunaga, Hirakata and Sudo (2010) to construct two subsamples. They use the cost share of oil in each industry as the criterion to decide whether a particular industry is oil-intensive. Results show that in Japan, oil intensity is high in Oil and Coal Products, Glass and Ceramic Products, Non-ferrous Metals, Iron and Steel, and Chemicals. On the other hand, Pulp and Paper, Metal Products, Rubber Products, Machinery, Precision Instruments, Transportation Equipment and Electric Appliances are classified as 'less oil-intensive industries'. All data are obtained from DataStream.

Large Firms and Small Firms The large firms group is composed of TOPIX Large Cap and Mid Cap. The Topix100 Index calculates the index value based on market capitalization and includes the 100 most liquid and largest stocks. The TOPIX Mid400 excludes Topix100 stocks and includes the remaining stocks in the Topix500. The small firms group is composed of TOPIX Small Cap stocks, 1169 small firms; it excludes the stocks in the TOPIX500 and includes the remaining firms in the TOPIX. All data are obtained from DataStream.

Statistical Summary

Table 2 provides summary statistics of the variables used in the model. Investment rate I/K, Cash flow rate CF/K and Tobin's q is measured in

Eq.26, Eq.27 and Eq.28, where $Q = q - 1$. $Oilvol$ is the annual oil price volatility in percentage. $Oilvolsq$ is the squared value of $Oilvol$. $MOilvol$ is the oil price volatility in percentage calculated from EGARCH(1,1) in Eq.31 for the robustness check. $MOilvolsq$ is the squared value of $MOilvol$. $Marvol$ is the market volatility of TOPIX1000. The average investment rate (I/K) for Japanese firms from 1987-2010 is 30.4% while the average cash flow rate (CF/K) is only 5.6%. Q has a range of -0.957 to -0.065 for all the firms in this time period, which suggests that all the firms are undervalued and their market values are less than the book values.

Table 3 shows the correlations among investment rate (I/K), cash flow rate (CF/K), q and volatilities. As expected, investment (I/K) is positively correlated with Q and Cash flow (CF/K). Investment (I/K) is negatively related to oil price volatility ($Oilvol$) and the square of oil price volatility ($Oilvolsq$), but positively correlated to market volatility ($Marvol$).

1.4 Empirical Results

As pointed out by Bond (2002), when series are highly persistent, weak instruments could lead to finite sample bias when using first-differenced GMM estimators. First-difference GMM estimator, introduced by Arellano and Bond (1991), requires the autoregressive parameters to be significantly less than 1. Thus, before we estimate the dynamic q model, we have to decide whether the dynamic properties of these variables are suitable to be used in GMM. A simple AR(1) regression with and without fixed effects is presented in Table 4. All the coefficients of lagged value are below 1, suggesting that the first-difference of all the variables are suitable as instruments for the dynamic model.

1.4.1 Results of Pooled Firm Estimation

Table 5 reports the empirical results of the impact of oil price volatility on firm-level investment. There are eight regression methods to be used for the estimation: OLS, OLS with fixed effect, first-difference GMM, and five System-GMM models.[3] The OLS ignores the unobserved panel-level effect and provides a biased estimation. The fixed effect estimator is chosen based on the Hausman test which evaluates the significance of fixed effect estimator versus a random effect estimator. Test results show that the χ^2 statistic is equal to 2366 and p-value is equal to 0, which means we reject the hypothesis that the individual effect is uncorrelated with the other regressors in the model. Thus a random effect model produces a biased estimator while a fixed effect model is preferred. The fixed effect model uses a transformation to remove the unobserved effect prior to estimation. The GMM and system-GMM consider the unobserved panel effect and control for the endogeneity. Investment ($\frac{I}{K}$), cash flow (CFK), Tobin's q (Q) are treated as endogenous. Each equation includes the fixed effect for individual firm effects and time period effects. The time period effects are represented as year dummies. The GMM estimators differ in the choice of instrument variables. The purpose of using different GMM estimators is to see how sensitive the results are to different estimation techniques. Table 6 provides details of model specification for first-difference GMM and system-GMM.

The estimated coefficient on the lagged investment ($L.\frac{I}{K}$) is positive and statistically significant at the 0.001 level. The coefficient value is from 0.5426 (GMM) to 0.9576 (OLS); all the estimated values from system-GMM are within this range. This is consistent with econometric theory, which states that the estimations from OLS and GMM give the highest and lowest benchmarks separately. Q ratio ($L.Q$) contributes significantly to the explanation of investment rates (I/K), especially current value. The literature generally rejects the empirical performance of Tobin's q in explaining investment and shows that cash flow and other measures of profitability have strong explanatory power for investment (see Chirinko, 1993, for a review). However,

[3] Please find in Table 6 the specification for each system-GMM model.

Hayashi (1990) shows that q has significant explanatory power for Japanese manufacturing firms. This effect is even more significant than cash flow. In addition, the lagged value of Q ($L.Q$) in my data sample has no statistically significant impact on firm-level investment. Results for the cash flows (CF/K) show a significant effect on firm investments. This indicates that the cash flow variable contains additional information about future profitability not captured by Q. There are explanations in the literature of the significance of cash flow in explaining investment spending. Myers and Majluf (1984) identify the adverse selection that firm insiders have better information than the capital markets about the value of their firms. Fazzari, Hubbard and Petersen (1988) show that excessive cost of external financing from financial markets causes some firms to be liquidity-constrained, so such firms rely heavily on cash flow to finance investment. Moreover, Jensen (1986) argues from the perspective of agency theory that managers may invest the free cash flow of firms into unprofitable projects rather than paying it out to shareholders. This could also link cash flow with investment spending. The immediate response of investment to cash flow is negative, but this negative effect disappears for the lagged cash flow. This suggests that Japanese firms treat cash flow with caution. They do not spend cash flow in the same year but with a delay. Hovakimian (2009) finds an explanation of the negative relationship between cash flow and investment based on the corporate life-cycle hypothesis. Cash flow and investment may follow different directions in the different stages of growth opportunities. Firms can raise considerable funds from external resources, such as stock and debt, as long as the market perceives that the investment could lead to large future profits. Moreover, it takes time for firms to accumulate enough cash flows to use as a source of financing.

The estimated coefficient of oil price volatility ($Oilvol$) is negative and significant for all models except system-GMM 5. All estimations for both current volatility ($Oilvol$) and lagged volatility ($L.Oilvol$) are negative, suggesting that oil price volatility reduces the investment rates of Japanese firms. The estimated coefficient of the squared oil price volatility ($Oilvolsq$) is positive and significant. The results of oil price volatility and squared oil price volatility suggest a U-shaped relationship between oil price volatility and Japanese firm-level investment. This is consistent with the theoretical prediction from the strategic growth options literature. It is also consistent with the empirical results of Henriques and Sadorsky (2011), which suggest that there is a U-shaped relationship between oil price volatility and U.S. firm investment. This U-shaped relationship also holds for lagged value of oil price volatility ($L.Oilvolsq$), suggesting that this relationship is robust and persistent.

The Wald χ^2 is reported to test the joint significance of all model parameters. They are all insignificant, which shows that the null hypothesis that all the coefficients are not equal to 0 at the same time holds for my data sample. The $AR(1)$ to $AR(4)$ are used to test the higher-order autocorrelation. Arellano and Bond (1991) introduce a test for zero autocorrelation in the first-differenced errors of GMM. If the model is correctly specified, the first-differenced errors are serially correlated at first order, and at higher order the autocorrelation should be statistically insignificantly different from zero. The p-value for these high order test for all my GMM models are greater than 0.10, indicating that there is no higher-order correlation at the 10% level of significance.

Hansen J statistic is used to test over-identifying restrictions when there are more moment conditions than parameters to be estimated. It follows a χ^2 distribution with degrees of freedom equal to the number of over-identifying restrictions. The null hypothesis is that there is no over-identifying problem. The limitation of the Hansen J statistic is that when the null hypothesis is rejected, it does not give any guidance as to the sources of failure of the model. The results of the Hansen J statistic show that there is no over-identification for GMM_SYS2 and GMM_SYS4. The null hypothesis cannot be rejected with a p-value larger than 0.05, indicating that the instruments are appropriately uncorrelated with the disturbance process. All the other models show a mis-specification in the instrument list from Hansen J, which suggests unreliable estimates from these models. However, the purpose of displaying all the models here is to show a consistent U-shaped relationship between oil price volatility and investment under different model specifications.

There are eight regression methods used for the estimation: OLS, OLS with fixed effect, first-difference GMM and five system GMMs. OLS ignores the unobserved panel-level effect and provides a biased estimation. The fixed effect estimator uses a transformation to remove the unobserved effect prior to estimation but ignores the endogeneity of dependent variables. First-difference GMM is designed for short T and large N, where T=24 in this study. Thus the preferred method of estimation is the system GMM. Among all 5 system GMMs, the best model is chosen based on the autocorrelation test and the over-identifying test.

1.4.2 Results of Robustness Check

I now briefly report the alternate results of redoing the analysis when the volatility is measured in a different way. The EGARCH (1,1) is used to re-estimate the oil price volatility ($Oilvol$)from 1987-2010 as follows,

$$z_t = a_0 + a_1 z_{t-1} + e_t,\ where\ e_t \mid I_{t-1} \sim N(0, \sigma_t^2) \qquad (30)$$

$$In(\sigma_t^2) = \varpi + \beta In(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \qquad (31)$$

where z_t is the log difference in oil price, e_t is the error term and σ_t^2 is the conditional variance of the error from the EGARCH model.

Eq.25 is re-estimated with this volatility and the results are reported in Table 7. The coefficient of lagged value of investment is positive and significant at the 1% level. The Q-ratio also has a positive effect on the current investment. The effect of cash flow on the investment is still non-monotonic, with a negative effect from the current cash flow and a positive effect from the lagged cash flow on the firm's investment. The negative coefficient of oil price volatility and the positive coefficient of squared oil price volatility suggest that there is a U-shaped relationship between oil price volatility and firm investment. In summary, the estimation with EGARCH volatility changes just slightly in terms of magnitude and significance. The main results still hold and remain robust.

1.4.3 Oil-Intensive Firms and Less Oil-Intensive Firms

I now consider the effect of energy intensity of industries on the relationship between oil price volatility and firm-level investment. There are two groups of firms constructed, as in 1.3.4: oil-intensive firms and less oil-intensive firms. Table 8 provides a summary statistics of these two groups. The means of investment (I/K), cash flow (CF/K), and Tobin's q (Q) are all larger in oil-intensive firms than in less oil-intensive ones.

Results in Tables 9 and 10 show the estimation of these two groups separately. Overall, the coefficients of I/K, Q, CF/K and their lagged values are similar to those from the full sample. The consistent negative coefficient of lagged oil price volatility ($L.Oilvol$) in oil-intensive firms indicates that firm-level investment responds negatively to oil price volatility with a delay. Also, the lagged value of squared oil price volatility ($L.Oilvolsq$) increase investment spending with a delay. In summary, there is a U-shaped relationship between the investments of oil-intensive firms and lagged oil price volatility. For the less oil-intensive subsample, the results are quite different. The hypothesis that oil price volatility has an effect on investment is strongly rejected in all five of my system-GMM models. This suggests that a rise in uncertainty about oil prices has no statistically significant effect on investment by less oil-intensive firms. This is consistent with the intuition that less oil-intensive firms use lower proportion of oil in production and that oil intensity is a key characteristic of the transmission channel of oil price to firms on the supply side (Fukunage, Hirakata and Sudo, 2010). The reason for different results for oil-intensive firms and less oil intensive ones is because of the role of crude oil played in the whole production process. For example, the chemical industry uses crude oil as one of its important raw inputs. The price fluctuations of crude oil directly affect the production and cost, and thus investment decisions are strongly affected by oil price volatility. On the other hand, electric appliances industry may only use oil for heating and transportation. Oil prices thus form only a small part of cost faced by firms in this industry. Hence, any changes in the oil price would have very limited impact on production, and the investment decision is not affected significantly by oil price volatility.

1.4.4 Large and Small Firms

These two subsamples are used here to test the role of firm size in the relationship between investment and oil price volatility. Using subsamples rather than dummy variables to assess the size effect brings with it the difficulty of how to classify whether a firm is large or not, given changing market values each year. Suppose firm A is classified as a large firm in year 1, it might become a small firm in year 2. Although we could classify all 757 firms spanning 24 years by market value each year, it will give us two very unbalanced panels merged with missing years for some of the firms. Using TOPIX Mid400 and TOPIX Small Cap as two subsamples is better as it includes more firms in the data sample and each firm is assigned as small or large consistently over the time period.

Sadorsky (2008) summarizes three streams of research about the relationship between oil price movement and stock price. The first stream finds that large firms have more resources and greater capability to shift away from high energy prices. Small firms lack economies of scale and have difficultly changing their input mix (Caves and Barton, 1990). The second stream shows that small firms may be innovative and efficient dealing with energy price increases, because of less complex management structure and quick decision making (Aigniger and Tichy, 1991). In the third stream, Nguyen and Lee (2002) find that both small and large firms are equally efficient in their U.S. manufacturing-firm samples. This implies that when facing energy price movement, firm size is not a decisive factor in measuring the efficiency of adjustment of the input.

Table 11 compares the summary statistics of large and small firms. Large firms have higher Q-ratio (Q) and investment (I/K) and less cash flow (CF/K) as a percentage of total assets than small firms. In Tables 12 and 13, Eq.25 is re-estimated for large and small firms separately. Similar to the results for the full sample, all the variables except lagged Q ratio (Q) are significant for both subsamples. It is worth noting that in small firms the coefficient of cash flow is (CF/K) positive. This result is consistent with Bond et al. (2004) that higher coefficients on cash flow are reported for smaller firms because of bubbles in their share prices. Moreover, Vogt (1994) argues that firms with low Q-ratio should rely heavily on internal cash flows to finance investment, based on the free cash flow hypothesis.

Oil price volatility ($Oilvol$) and its lagged value ($L.Oilvol$) have a significant and negative effect on investment rate for both groups. In addition, squared oil price volatility ($Oilvolsq$) and its lagged value ($L.Oilvolsq$) have a significant and positive effect on investment. The U-shaped relationship between oil price volatility and investment based on compound option theory is present in both large and small firms. However, the negative effect on investment is stronger and more significant for small firms. These results are consistent with Ratti, Seol and Yoon (2011), who use total assets as a measure of firm size and find that the negative effect of increased energy price on investment is less for larger firms.

1.4.5 Oil Price Volatility and Market Volatility

Table 14 provides the estimation results of the impact of both oil price uncertainty and market turbulence on total investment expenditure. The relationship between investment and uncertainty is tested with a variety of control variables. Model 1 shows the standard econometric procedure of using Q via market-to-book ratio as the control variable. The results indicate that the basic Tobin's q model is mis-specified for Japanese firms. The Hansen J test of over-identification restriction rejects the hypothesis that the model meets the over-identification restrictions, regardless of which instrument set is used. This is either because the model is mis-specified or there is new information in addition to stock market valuation about the fundamental value of the firm. Thus, in model 2, cash flow (CF/K) is augmented in the model 1. The p-value of Hansen J statistics shows that including cash flow (CF/K) and its lagged value $(L.CF/K)$ in the model helps to pass the battery of specification tests. Q-ratio contributes significantly to the explanation of investment rates. Cash flow and its lagged value have strong explanatory power for investment. The results show that the role of oil price volatility $(Oilvol)$ and market volatility $(Marvol)$ is robust with augmented cash flows. Lagged oil price volatility $(L.Oilvol)$ has a significant and negative effect on firm-level investment, while lagged market volatility $(L.Marvol)$ has a significant and positive effect. In model 3, I further augment the previous model and include both squared oil price volatility $(Oilvolsq)$ and squared market volatility $(Marvolsq)$. The immediate investment response to an increase in the oil price volatility $(Oilvol)$ is negative. However, this negative effect is not persistent, because of the positive coefficient of lagged oil price volatility $(L.Oilvol)$. This may be caused by the fact that high oil price volatility is usually transitory. The irreversibility dominates if the volatility is temporary, whereas the compound options prevail if the volatility is permanent (Mohn and Misund, 2009). On the other hand, both market volatility $(Marvol)$ and its lagged value ($L.Marvol$) have a positive effect on firm investment. The squared volatility ($Marvolsq, Oilvolsq$) has exactly opposite results on firm investment compared with that of volatility itself.

Omitted variable bias occurs when a model leaves out one or more important independent variables. In Table 14 from Model 1 to Model 3, each time we allows additional factors to enter the analysis, the Wald Chi^2 is statistically significant based on p-value, which suggests all variables are jointly significant. For example, from Model 1 to Model 2, we include extra independent variables cash flow (CF/K) and its lagged value ($L.CF/K$). The Wald Chi^2 shows joint significance of all variables including the newly added ones. This is also consistent with the correlation results from Table 3, where cash flow rates (CF/K) do have a correlation with Q. That means in Model 1 the cash flow rates become part of the noise term. Thus, the conclusion drawn here is that the coefficients of Q, oil price volatility and market volatility are different in these 3 models.

Table 15 shows a summary of estimated investment and uncertainty results. In the third row of Table 15, we observe that the cumulative effect of positive oil price shocks can be calculated to -0.05733, with a p-value equal to 0.[4] The dependent variable is the investment (I/K) as a share of total assets, which is a ratio and can be interpreted as a percentage. The volatility variables ($Oilvol$) are also calculated from the standard deviation of daily percentage price change. So the cumulative coefficient means that a 1 percentage point increase in oil price volatility ($Oilvol$) will reduce the investment rate (I/K) by 5.733 percentage points. While the instantaneous effect on investment (I/K) from uncertainty is directly given by the coefficients of estimations, the last row of Table 15 calculates the long-term effect of oil price volatility ($Oilvol$) and its lagged value ($L.Oilvol$), when taking account of the autoregressive coefficient on $L.I/K$. According to Eq.25, the persistent effect is equal to $(b_6 + b_7)/(1 - b_1)$. Thus, the persistent effect of oil

[4]The p-value is calculated through the non-linear test procedure in Stata.

price volatility ($Oilvol$) is -0.5676 (p=0.000). This implies that a permanent increase in oil price volatility of 1 percentage point reduces the average investment by 56.76 percentage points. Compared to the Mohn and Misund (2009) results, the investment rate of Japanese firms responds more strongly to oil price volatility than U.S. firms. This can be partly attributed to the fact that Japan has meagre oil reserves and depends entirely on imported oil. Japanese firms are more sensitive to oil price volatility than firms in other oil importing countries.

As illustrated in the second column of Table 15, results are quite different for market volatility. Both contemporaneous ($Marvol$)and lagged effects ($L.Marvol$)take a positive sign, and the latter is higher in magnitude than the former. The cumulative effect of market volatility ($Marvol$)of 1 percentage point increases the investment (I/K)rate by 5.937 percentage points. When taking the coefficient of lagged investment rate ($L.I/K$)into consideration in the long run, a 1 percentage point increase in market volatility ($Marvol$)will increase the investment by 58.78 percentage points. My results show a strong relationship between market volatility and firm-level investment. Abel and Eberly (1999) argue that long-run capital stock already incorporates uncertainty by increasing the hurdle rate at which projects would be profitable. In other words, macroeconomic volatility is embedded in the q ratio. This is contrary to my results, which show the market valuation of firm value does not fully capture the effect of aggregate uncertainty.

1.5 Conclusion

The investment decision is the most important decision firms face because it helps to grow the business and achieve competitive advantage. Crude oil as an important input of production has been very volatile, especially in recent years. This makes decision making more difficult for managers, policy makers, and others. In this paper, I use real option theory and relate oil price volatility to firm strategic investments for a panel of Japanese firms. I find that there is not simply a linear relationship between oil price volatility and strategic investment. Instead, there is a U-shaped relationship between them after controlling Tobin's q-ratio and cash flow. This is consistent with compound option theory, which suggests that two options, the option to wait to invest and the option to grow the business, interact with each other. The U-shaped relationship is robust to a number of different econometric estimations and different measures of volatility. The results for two subsamples, oil-intensive firms and less oil-intensive firms, show that oil volatility has a strong and significant effect on investment by oil-intensive firms, whereas oil volatility has no statistically significant effect on less oil-intensive firms. Firm size matters when considering the relationship between oil price volatility and investment. The negative effect of oil price volatility on investment is stronger and more significant for small firms. The cumulative effect of oil price volatility shows that a one percentage point increase in oil price volatility will reduce the investment rate by 5.733 percentage points. Compared to Mohn and Misund (2009), the investment rates of Japanese firms respond more strongly to oil price volatility than U.S. firms. Furthermore, the model is augmented with stock market volatility. Both market volatility and oil price volatility have significant effects on firm investment, which suggests that the market valuation of firm value through Tobin's q does not fully capture the effect of aggregate uncertainty.

This is the first paper to address the relationship between oil price volatility and Japanese firm investments. It is clear that for Japanese firms, especially the oil intensive firms and small firms, oil price volatility plays a very important role in firm-level investment decisions. The fact that Japan is fully dependent on crude oil imports sharpens the role of oil as an input into production and an influence on investment demand. Beyond this there is a strong indication that over the period of dramatic oil price fluctuations, oil price uncertainty first depresses the firm's investment by increasing the value of the option to wait, then encourages the investment when the value of the option to grow exceeds the value of the option to wait. Thus for the policy maker, a stable oil price could benefit firm-level investment, especially for oil-intensive firms and small firms. For future study, it would be interesting to separate the different causes of oil price fluctuation, and test whether the response of investment to oil price volatility comes from the supply side or the demand side.

Table 1. Construction of firm variables

Variable	Symbol	Definition	Source and Code
Investment	PPE,I	Property, Plant and Equipment-Net	DataStream: WC02501
Total asset	TA,K	Total Asset-Total	DataStream: WC02999
Net income	NI	Net Income Before Extra items and Preferred Dividends	DataStream: WC01551
Depreciation	DDA	Depreciation, Depletion and Amortization	DataStream: WC01151
Common equity	CE	Common Equity	DataStream: WC03501
Current asset	CA	Current Asset-Total	DataStream: WC02201
Current liability	CL	Current Liability-Total	DataStream: WC03101
Long term debt	LD	Long Term Debt	DataStream: WC03251
Preferred stock	PS	Preferred Stock	DataStream: WC03451
Tobin's q	q	(CE+PS+LD+CL-CA)/K	
Q	Q	q-1	
Cash flow	CF	NI+DDA	
Oil price volatility	Oilvol	Historical Volatility of NYMEX Futures Contract	U.S. Energy Information Agency
Squared oil price volatility	Oilvolsq	Oilvolˆ2	
Alternate oil price volatility	MOilvol	Volatility of Oil Price Calculated from EGARCH(1,1)	
Squared alternate oil price volatility	MOilvolsq	Moilvolˆ2	
Market volatility	Marvol	Historical Volatility of TOPIX1000	DataStream

Note: Firm data are obtained from DataStream Country Index and oil prices are from E.I.A. All the financial firms and utility firms are removed from the sample. Following Whited (2006), any observations of $I/K, CF/K, Q$ outside their respective 99% confidence intervals are deleted. So totally there are 757 firms in the sample. The data sample spans 24 years from 1987-2010, which make the overall observation equal to 18168.

Table 2. Statistical summary

Variable	Obs	Mean	Std. Dev.	Min	Max
I/K	15932	0.304	0.146	0.012	0.825
CF/K	14274	0.056	0.039	-0.124	0.185
Q	14999	-0.594	0.161	-0.957	-0.065
Oilvol	18168	37.096	11.747	19.879	62.084
Oilvolsq	18168	1514.119	975.592	395.158	3854.474
MOilvol	18168	3.682	2.284	1.314	10.464
MOilvolsq	18168	18.768	25.840	1.726	109.487
Marvol	18168	20.070	6.584	8.808	41.985

Note: Investment rate I/K is calculated as Property, Plant and Equipment / total assets. Cash flow rate CF/K is measured as (Net Income+Depreciation) / Total Asset. Tobin's q is measured as (Market Value of Equity+Preferred Stock+Long Term Debt+Current Debt-Current Asset)$_t$ / Total Asset$_{t-1}$, and $Q = q - 1$. *Oilvol* is the annual oil price volatility in percentage by calculating the square root of the sum of squared daily returns for each calendar year. *Oilvolsq* is the squared value of *Oilvol*. $MOilvol$ is the oil price volatility in percentage calculated from EGARCH(1,1) in Eq.31 for the robustness check. $MOilvolsq$ is the squared value of $MOilvol$. $Marvol$ is the market volatility of TOPIX1000 in percentage using the same calculation method for *Oilvol*.

Table 3. Correlation

	I/K	**CF/K**	**Q**	**OilvolB**	**Oilvolsq**	**ROilvol**	**ROilvosq**	**Marvol**
I/K	1							
CF/K	0.121	1						
Q	0.730	0.190	1					
Oilvol	-0.008	0.049	-0.033	1				
Oilvolsq	-0.016	0.043	-0.039	0.989	1			
MOilvol	-0.012	0.055	-0.022	0.839	0.887	1		
MOilvolsq	-0.014	0.056	-0.025	0.811	0.872	0.981	1	
Marvol	0.016	0.053	-0.001	0.568	0.639	0.721	0.771	1

Note: Table 3 shows the correlation between all the variables in the regression. As expected, investment I/K is positively related to Q, cash flow CF/K, and market volatility $Marvol$, and negatively related to oil price volatility $Oilvol$.

Table 4. AR(1) estimation for model variables

Estimator	I/K	CF/K	Q	Oilvol	MOilvol	Marvol
OLS	0.977***	0.727***	0.918***	0.189***	0.357***	0.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)
FE	0.815***	0.481***	0.650***			
	(0.000)	(0.000)	(0.000)			

Notes: Table 4 reports estimated coefficients and their p-values on the lagged dependent variable for a AR(1) process: $y_t = \rho y_{t-1} + u_t$ using OLS and fixed effect (FE) estimator with Stata. The results show all the autoregressive parameters are all below 1, implying the first difference of variables contains information beyond that of a random walk.
* p<0.1, ** p<0.05, *** p<0.01.

Table 5. The impact of oil price volatility on firm-level investment

	OLS	OLS_FE	GMM	GMM_SYS1	GMM_SYS2	GMM_SYS3	GMM_SYS4	GMM_SYS5
L.I/K	9.576e-01***	7.711e-01***	5.426e-01***	8.736e-01***	8.999e-01***	9.551e-01***	8.875e-01***	9.297e-01***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q	6.282e-02***	8.007e-02***	9.921e-02***	8.853e-02***	6.611e-02**	6.386e-02	5.148e-02**	-1.808e-02
	(0.000)	(0.000)	(0.005)	(0.000)	(0.014)	(0.104)	(0.017)	(0.630)
L.Q	-2.917e-02***	-2.177e-02***	5.531e-02**	1.041e-02	7.185e-03	-1.423e-02	6.716e-04	6.992e-02*
	(0.001)	(0.006)	(0.018)	(0.462)	(0.671)	(0.687)	(0.973)	(0.051)
CF/K	-1.381e-01***	-8.541e-02***	-1.754e-01***	-1.444e-01***	-1.497e-01***	-2.437e-01***	-1.441e-01***	-1.711e-01***
	(0.000)	(0.000)	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.008)
L.CF/K	7.226e-02***	3.970e-02***	1.606e-01***	7.250e-02***	1.267e-01***	2.477e-01***	8.610e-02**	9.945e-02
	(0.000)	(0.004)	(0.001)	(0.009)	(0.001)	(0.000)	(0.019)	(0.141)
Oilvol	-8.531e-04***	-2.365e-03***	-2.072e-03***	-3.493e-02*	-4.526e-02**	-5.257e-02**	-3.276e-02*	-3.571e-02
	(0.000)	(0.000)	(0.000)	(0.080)	(0.035)	(0.032)	(0.092)	(0.122)
L.Oilvol	-1.367e-03***	-3.137e-03***	-3.756e-03***	-3.603e-02**	-4.559e-02**	-5.126e-02**	-3.454e-02**	-3.561e-02*
	(0.000)	(0.000)	(0.000)	(0.044)	(0.020)	(0.020)	(0.048)	(0.085)
Oilvolsq	1.311e-05***	3.159e-05***	2.853e-05***	3.927e-04*	5.068e-04**	5.874e-04**	3.683e-04*	4.000e-04
	(0.000)	(0.000)	(0.000)	(0.075)	(0.033)	(0.031)	(0.087)	(0.117)
L.Oilvolsq	1.828e-05***	4.036e-05***	4.746e-05***	4.184e-04**	5.289e-04**	5.939e-04**	4.004e-04**	4.138e-04*
	(0.000)	(0.000)	(0.000)	(0.044)	(0.019)	(0.020)	(0.048)	(0.084)
Wald Chi^2	234673.48	420.29	1523.36	10720.00	24170.00	11470.00	10150.00	9180.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AR(1)			-14.59	-14.95	-14.60	-13.55	-14.40	-13.93
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AR(2)			-0.72	0.03	0.17	0.80	0.16	-0.82
			(0.47)	(0.98)	(0.86)	(0.42)	(0.87)	(0.41)
AR(3)			1.30	1.27	1.23	1.20	1.20	1.05
			(0.19)	(0.21)	(0.22)	(0.23)	(0.23)	(0.30)
AR(4)			-1.44	-1.33	-1.33	-1.50	-1.29	-1.08
			(0.15)	(0.18)	(0.18)	(0.14)	(0.20)	(0.28)
Hansen J			468.45	537.82	711.55	336.93	626.28	286.39
			(0.00)	(0.00)	(0.67)	(0.00)	(0.24)	(0.00)
N	12455	12455	11524	12455	12455	12455	12455	12455

Notes: Table 5 reports the results of dynamic investment model with two-step estimated coefficients and their p-values based on robust standard errors. The sample is based on an unbalanced panel of 772 Japanese firms over the period 1987-2010. The estimated coefficients of time dummy variables are not reported. All estimates are obtained from the system-GMM estimator of Blundell and Bond (1998), as implemented in Stata by Roodman (2006). I/K, CF/K, Q are treated as endogenous. AR(1)-AR(4) are Arellano and Bond (1991) tests for autocorrelation in differences. Hansen J is used for over-identification restrictions. The specification of GMM models is shown in Table 6.

Table 6. Number of lags for each GMM specification

	OLS	OLS_FE	GMM	GMM_SYS1	GMM_SYS2	GMM_SYS3
I/K			2,...	2,...	3,...	3,4,5
Q			2,3,4	2,3,4	3,...	3,4,5
CF/K			2,3,4	2,3,4	3,...	3,4,5

Notes: Table 6 provides the number of lags for each specification of GMM models reported in Table 5. It is used to specify the lag limits of instrument variables in GMM and system-GMM. (a b) means for the differenced equation, lagged levels dated t-a to t-b are used as instrument. For the level equation, the first difference dated t-a+1 is normally used. For example, the column of GMM means for first difference equation, two lagged value and further of I/K, two, three and four lagged value of Q and CF/K are used as instrument. For the levels equation, lagged valued of first differenced I/K, Q, CF/K are used as instrument.

Table 7. Robustness check for an alternate volatility measure

	OLS	OLS_FE	GMM	GMM_SYS1	GMM_SYS2	GMM_SYS3	GMM_SYS4	GMM_SYS5
L.I/K	9.571e-01***	7.711e-01***	5.426e-01***	8.736e-01***	8.999e-01***	9.551e-01***	8.875e-01***	9.297e-01***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q	6.493e-02***	8.007e-02***	9.921e-02***	8.853e-02***	6.611e-02***	6.386e-02	5.148e-02**	-1.808e-02
	(0.000)	(0.000)	(0.005)	(0.000)	(0.004)	(0.104)	(0.017)	(0.630)
L.Q	-3.205e-02***	-2.177e-02***	5.531e-02**	1.041e-02	7.184e-03	-1.423e-02	6.716e-04	6.992e-02*
	(0.000)	(0.006)	(0.018)	(0.462)	(0.697)	(0.687)	(0.973)	(0.051)
CF/K	-1.436e-01***	-8.541e-02***	-1.754e-01***	-1.444e-01***	-1.497e-01***	-2.437e-01***	-1.441e-01***	-1.711e-01***
	(0.000)	(0.000)	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.008)
L.CF/K	7.153e-02***	3.970e-02***	1.606e-01***	7.250e-02***	1.267e-01***	2.477e-01***	8.610e-02**	9.945e-02
	(0.000)	(0.004)	(0.001)	(0.009)	(0.000)	(0.000)	(0.019)	(0.141)
MOilvol	-5.778e-03***	-9.582e-03***	-1.322e-02***	-2.642e-01***	-2.983e-01***	-2.852e-01***	-2.780e-01***	-2.193e-01***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.MOilvol	-4.123e-04	5.264e-04	-1.509e-03	-9.526e-02***	-1.062e-01***	-9.967e-02***	-1.010e-01***	-7.769e-02***
	(0.503)	(0.714)	(0.403)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MOilvolsq	5.765e-04***	9.058e-04***	1.161e-03***	2.024e-02***	2.283e-02***	2.183e-02***	2.128e-02***	1.680e-02***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.MOilvolsq	1.392e-04***	2.071e-04*	4.043e-04**	9.786e-03***	1.093e-02***	1.027e-02***	1.034e-02***	8.021e-03***
	(0.008)	(0.065)	(0.012)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wald Chi ^2	238920.92	420.29	1523.36	10720.00	15740.00	11470.00	10150.00	9180.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AR(1)			-14.59	-14.95	-14.54	-13.55	-14.40	-13.93
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AR(2)			-0.72	0.03	0.17	0.80	0.16	-0.82
			(0.47)	(0.98)	(0.86)	(0.42)	(0.87)	(0.41)
AR(3)			1.30	1.27	1.23	1.20	1.20	1.05
			(0.19)	(0.20)	(0.22)	(0.23)	(0.23)	(0.30)
AR(4)			-1.44	-1.33	-1.34	-1.50	-1.29	-1.08
			(0.15)	(0.18)	(0.18)	(0.13)	(0.20)	(0.28)
Hansen J			468.45	537.80	711.30	336.90	626.30	286.40
			(0.00)	(0.00)	(0.67)	(0.00)	(0.24)	(0.00)
N	12455	12455	11524	12455	12455	12455	12455	12455

Table 7 reports the results of dynamic investment model using oil price volatility calculated from EGARCH(1,1). p-value is reported in bracket. The sample is based on an unbalanced panel of 772 Japanese firms over the period 1987-2010. The estimated coefficients of time dummy variables are not reported. All estimates are obtained from the system-GMM estimator of Blundell and Bond (1998), as implemented in Stata by Roodman (2006). I/K, CF/K, Q are treated as endogenous. AR(1)-AR(4) are Arellano and Bond (1991) tests for autocorrelation in differences. Hansen J is used for over-identification restrictions. The specification of GMM models is shown in Table 6.

Table 8. Statistic summary of oil-intensive industries and less oil-intensive industries

Panel A: Oil-Intensive Industries					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
I/K	4566	0.343	0.099	0.056	0.650
CF/K	3995	0.056	0.036	-0.081	0.203
Q	4349	-0.581	0.106	-0.896	-0.227
Panel B: Less Oil-Intensive Industries					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
I/K	8602	0.280	0.116	0.021	0.632
CF/K	7720	0.054	0.045	-0.147	0.190
Q	8190	-0.650	0.129	-0.963	-0.252

Note: These two subsamples are constructed based on Fukunaga, Hirakata and Sudo (2010). Investment rate I/K is calculated as Property, Plant and Equipment / total assets. Cash flow rate CF/Q is measured as (Net Income+Depreciation) / Total Asset. Tobin's q is measured as (Market Value of Equity+Preferred Stock+Long Term Debt+Current Debt-Current Asset)$_t$ / Total Asset$_{t-1}$, and $Q = q - 1$.

Table 9. The impact of oil price volatility on investment of oil-intensive firms

	GMM_SYS1	GMM_SYS2	GMM_SYS3	GMM_SYS4	GMM_SYS5
L.I/K	7.978e-01***	8.045e-01***	8.197e-01***	8.139e-01***	8.295e-01***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q	1.279e-01***	9.572e-02**	9.486e-02*	8.575e-02**	9.391e-02
	(0.002)	(0.014)	(0.094)	(0.030)	(0.146)
L.Q	1.569e-02	1.585e-02	1.044e-02	5.340e-02*	2.898e-02
	(0.529)	(0.641)	(0.823)	(0.096)	(0.638)
CF/K	-3.144e-01***	-3.087e-01***	-3.563e-01***	-2.671e-01***	-3.608e-01***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.CF/K	8.292e-02*	1.430e-01**	1.580e-01**	1.620e-01**	1.373e-01
	(0.093)	(0.019)	(0.031)	(0.034)	(0.283)
Oilvol	-6.036e-02	-6.838e-02*	-6.384e-02*	-6.971e-02	-8.166e-02
	(0.111)	(0.087)	(0.100)	(0.106)	(0.109)
L.Oilvol	-6.051e-02*	-6.774e-02*	-6.347e-02*	-6.859e-02*	-7.998e-02*
	(0.077)	(0.060)	(0.067)	(0.077)	(0.078)
Oilvolsq	6.766e-04	7.649e-04*	7.144e-04*	7.794e-04	9.118e-04
	(0.106)	(0.084)	(0.096)	(0.103)	(0.105)
L.Oilvolsq	7.033e-04*	7.872e-04*	7.373e-04*	7.981e-04*	9.284e-04*
	(0.076)	(0.059)	(0.067)	(0.075)	(0.078)
AR(1)	-9.50	-9.37	-8.69	-9.32	-8.18
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AR(2)	-0.23	-0.19	-0.03	-0.54	-0.20
	(0.82)	(0.85)	(0.97)	(0.59)	(0.84)
AR(3)	0.78	0.68	0.62	0.63	0.62
	(0.44)	(0.49)	(0.54)	(0.53)	(0.54)
AR(4)	0.00	0.18	0.18	0.39	0.21
	(1.00)	(0.86)	(0.86)	(0.69)	(0.83)
Hansen J	197.00	195.90	193.40	201.50	194.90
	(1.00)	(1.00)	(0.98)	(1.00)	(0.55)
N	3531	3531	3531	3531	3531

Note: Table 9 reports the results of dynamic investment model for oil-intensive Japanese firms. Two-step estimated coefficients and their *p*-values based on robust standard errors are reported. The estimated coefficients of time dummy variables are not reported. All estimates are obtained from the system-GMM estimator of Blundell and Bond (1998), as implemented in Stata by Roodman (2006). I/K, CF/K, Q are treated as endogenous. AR(1)-AR(4) are Arellano and Bond (1991) tests for autocorrelation in differences. Hansen J is used for over-identification restrictions. The specification of GMM models is shown in Table 6.

* p<0.1, ** p<0.05, *** p<0.01

Table 10. The impact of oil price volatility on investment of less oil-intensive firms

	GMM_SYS1	GMM_SYS2	GMM_SYS3	GMM_SYS4	GMM_SYS5
L.I/K	8.825e-01	8.997e-01***	9.574e-01***	8.437e-01***	9.037e-01***
	(0.109)	(0.000)	(0.000)	(0.000)	(0.000)
Q	2.096e-02	7.690e-02***	9.401e-02**	7.681e-02**	-6.042e-03
	(0.983)	(0.004)	(0.011)	(0.013)	(0.898)
L.Q	4.591e-02	-2.218e-02	-5.351e-02	-1.515e-02	5.179e-02
	(0.928)	(0.347)	(0.141)	(0.559)	(0.226)
CF/K	-1.095e-01	-1.556e-01***	-1.586e-01**	-1.771e-01***	-1.289e-01**
	(0.821)	(0.000)	(0.011)	(0.000)	(0.034)
L.CF/K	1.096e-01	1.324e-01***	1.602e-01***	1.019e-01***	1.256e-01*
	(0.819)	(0.000)	(0.002)	(0.005)	(0.056)
Oilvol	2.072e-02	1.196e-02	1.057e-02	1.520e-02	2.503e-02
	(0.968)	(0.640)	(0.727)	(0.569)	(0.439)
L.Oilvol	1.140e-02	3.004e-03	1.352e-03	6.012e-03	1.607e-02
	(0.981)	(0.896)	(0.960)	(0.801)	(0.578)
Oilvolsq	-2.239e-04	-1.265e-04	-1.106e-04	-1.623e-04	-2.718e-04
	(0.969)	(0.655)	(0.741)	(0.582)	(0.447)
L.Oilvolsq	-1.331e-04	-3.684e-05	-1.835e-05	-7.156e-05	-1.871e-04
	(0.981)	(0.890)	(0.953)	(0.796)	(0.576)
AR(1)	-2.11	-11.45	-11.19	-11.45	-11.02
	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)
AR(2)	0.06	1.50	1.83	1.40	0.38
	(0.96)	(0.13)	(0.07)	(0.16)	(0.70)
AR(3)	0.62	0.83	0.77	0.81	0.91
	(0.53)	(0.41)	(0.44)	(0.42)	(0.36)
AR(4)	-0.51	-1.21	-1.25	-1.22	-1.05
	(0.61)	(0.23)	(0.21)	(0.22)	(0.30)
Hansen J	464.80	394.60	274.80	398.60	240.40
	(0.15)	(1.00)	(0.03)	(1.00)	(0.02)
N	6797	6797	6797	6797	6797

Note: Table 10 reports the results of dynamic investment model for less oil-intensive Japanese firms. Two-step estimated coefficients and their p-values based on robust standard errors are reported. The estimated coefficients of time dummy variables are not reported. All estimates are obtained from the system-GMM estimator of Blundell and Bond (1998), as implemented in Stata by Roodman (2006). I/K, CF/K, Q are treated as endogenous. AR(1)-AR(4) are Arellano and Bond (1991) tests for autocorrelation in differences. Hansen J is used for over-identification restrictions. The specification of GMM models is shown in Table 6.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 11. Statistic summary of large firms and small firms

Panel A: Large Firms					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
I/K	10173	0.299	0.193	0.003	0.927
CF/K	8565	0.060	0.040	-0.091	0.213
Q	8510	-0.562	0.173	-0.920	-0.016
Panel B: Small Firms					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
I/K	21128	0.277	0.170	0.003	0.792
CF/K	16320	0.081	0.172	-0.384	2.391
Q	18551	-0.616	0.180	-0.991	-0.018

Note: The large firm group is composed of TOPIX large cap and mid cap. The small firm group is composed of TOPIX small cap. Investment rate I/K is calculated as Property, Plant and Equipment / total assets. Cash flow rate CF/Q is measured as (Net Income+Depreciation) / Total Asset. Tobin's q is measured as (Market Value of Equity+Preferred Stock+Long Term Debt+Current Debt-Current Asset)$_t$ / Total Asset$_{t-1}$, and $Q = q - 1$.

Table 12. The impact of oil price volatility on investment of large firms

	GMM_SYS1	GMM_SYS2	GMM_SYS3	GMM_SYS4	GMM_SYS5
L.I/K	8.977e-01***	8.932e-01***	9.227e-01***	9.121e-01***	9.238e-01***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q	8.082e-02***	8.947e-02***	8.491e-02**	7.119e-02*	7.842e-02**
	(0.000)	(0.001)	(0.017)	(0.089)	(0.022)
L.Q	6.018e-03	-9.608e-03	-9.419e-03	-1.881e-02	-3.251e-02
	(0.644)	(0.678)	(0.782)	(0.581)	(0.348)
CF/K	-1.540e-01***	-1.107e-01*	-1.066e-01	-1.913e-01**	-2.241e-01***
	(0.002)	(0.054)	(0.218)	(0.042)	(0.003)
L.CF/K	9.137e-02**	1.323e-01***	1.907e-01***	8.108e-02	1.376e-01*
	(0.013)	(0.004)	(0.004)	(0.331)	(0.068)
Oilvol	-4.511e-02*	-4.865e-02*	-5.424e-02**	-4.327e-02	-6.416e-02**
	(0.086)	(0.071)	(0.049)	(0.298)	(0.036)
L.Oilvol	-4.618e-02*	-4.925e-02**	-5.338e-02**	-4.483e-02	-6.259e-02**
	(0.051)	(0.042)	(0.032)	(0.230)	(0.022)
Oilvolsq	5.057e-04*	5.448e-04*	6.065e-04**	4.855e-04	7.165e-04**
	(0.082)	(0.067)	(0.047)	(0.292)	(0.034)
L.Oilvolsq	5.358e-04*	5.717e-04**	6.196e-04**	5.193e-04	7.249e-04**
	(0.050)	(0.041)	(0.032)	(0.230)	(0.022)
AR(1)	-10.91	-10.71	-10.25	-9.50	-10.09
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AR(2)	1.10	1.26	1.22	1.24	1.54
	(0.27)	(0.21)	(0.22)	(0.22)	(0.12)
AR(3)	0.75	0.71	0.70	0.66	0.59
	(0.45)	(0.48)	(0.48)	(0.51)	(0.55)
AR(4)	-0.56	-0.53	-0.57	-0.56	-0.60
	(0.58)	(0.60)	(0.57)	(0.58)	(0.55)
Hansen J	403.80	405.20	291.00	405.70	226.50
	(0.85)	(1.00)	(0.01)	(1.00)	(0.08)
N	7064	7064	7064	7064	7064

Note: Table 12 reports the results of dynamic investment model for large Japanese firms. Two-step estimated coefficients and their *p*-values based on robust standard errors are reported. The estimated coefficients of time dummy variables are not reported. All estimates are obtained from the system-GMM estimator of Blundell and Bond (1998), as implemented in Stata by Roodman (2006). I/K, CF/K, Q are treated as endogenous. AR(1)-AR(4) are Arellano and Bond (1991) tests for autocorrelation in differences. Hansen J is used for over-identification restrictions. The specification of GMM models is shown in Table 6.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 13. The impact of oil price volatility on investment of small firms

	GMM_SYS1	GMM_SYS2	GMM_SYS3	GMM_SYS4	GMM_SYS5
L.I/K	8.828e-01***	8.721e-01***	9.230e-01***	8.416e-01***	9.351e-01***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q	8.200e-02***	1.104e-01***	1.431e-01***	1.212e-01***	6.993e-02*
	(0.001)	(0.000)	(0.000)	(0.000)	(0.084)
L.Q	1.397e-03	-2.398e-02	-8.963e-02***	-9.130e-03	-6.807e-03
	(0.923)	(0.305)	(0.002)	(0.711)	(0.861)
CF/K	1.272e-02	1.925e-02**	3.318e-02**	1.026e-02	1.361e-02
	(0.300)	(0.038)	(0.045)	(0.318)	(0.330)
L.CF/K	-2.278e-02**	-4.184e-02***	-3.958e-02**	-2.727e-02**	-3.772e-02**
	(0.025)	(0.000)	(0.013)	(0.020)	(0.015)
Oilvol	-3.683e-02**	-4.656e-02***	-3.135e-02	-4.570e-02**	-3.353e-02
	(0.047)	(0.010)	(0.103)	(0.012)	(0.105)
L.Oilvol	-3.790e-02**	-4.695e-02***	-3.328e-02*	-4.596e-02***	-3.525e-02*
	(0.024)	(0.004)	(0.055)	(0.005)	(0.059)
Oilvolsq	4.129e-04**	5.211e-04***	3.531e-04*	5.115e-04**	3.766e-04*
	(0.044)	(0.009)	(0.097)	(0.011)	(0.100)
L.Oilvolsq	4.410e-04**	5.455e-04***	3.865e-04*	5.345e-04***	4.095e-04*
	(0.023)	(0.004)	(0.054)	(0.005)	(0.058)
AR(1)	-14.90	-14.73	-14.42	-14.60	-14.29
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AR(2)	0.54	0.86	1.74	0.76	0.48
	(0.59)	(0.39)	(0.08)	(0.45)	(0.63)
AR(3)	1.04	1.12	1.08	1.09	1.07
	(0.30)	(0.26)	(0.28)	(0.28)	(0.29)
AR(4)	-1.48	-1.57	-1.68	-1.58	-1.49
	(0.14)	(0.12)	(0.09)	(0.11)	(0.14)
Hansen J	559.70	820.40	353.30	680.90	280.80
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
N	13253	13253	13253	13253	13253

Note: Table 13 reports the results of dynamic investment model for small Japanese firms. Two-step estimated coefficients and their p-values based on robust standard errors are reported. The estimated coefficients of time dummy variables are not reported. All estimates are obtained from the system GMM estimator of Blundell and Bond (1998), as implemented in Stata by Roodman (2006). I/K, CF/K, Q are treated as endogenous. AR(1)-AR(4) are Arellano and Bond (1991) tests for autocorrelation in differences. Hansen J is used for over-identification restrictions. The specification of GMM models is shown in Table 6.

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 14. The relationship between firm-level investment and uncertainty: oil price volatility and market volatility

	Model 1	Model 2	Model 3
L.I/K	9.383e-01***	8.999e-01***	8.999e-01***
	(0.000)	(0.000)	(0.000)
Q	3.783e-02	6.611e-02***	6.612e-02***
	(0.135)	(0.004)	(0.003)
L.Q	-1.844e-02	7.184e-03	7.184e-03
	(0.453)	(0.697)	(0.704)
CF/K		-1.497e-01***	-1.497e-01***
		(0.000)	(0.000)
L.CF/K		1.267e-01***	1.267e-01***
		(0.000)	(0.000)
Oilvol	6.124e-04*	-5.514e-07	-1.323e-01***
	(0.071)	(0.999)	(0.000)
L.Oilvol	-4.760e-04***	-4.322e-04***	7.497e-02***
	(0.000)	(0.000)	(0.000)
Marvol	-3.177e-04	5.747e-04	2.341e-02***
	(0.492)	(0.225)	(0.000)
L.Marvol	1.027e-03***	1.342e-03***	3.596e-02***
	(0.002)	(0.000)	(0.000)
Oilvolsq			1.649e-03***
			(0.000)
L.Oilvolsq			-1.039e-03***
			(0.000)
Marvolsq			-8.809e-04***
			(0.000)
L.Marvolsq			-2.176e-04***
			(0.000)
Wald Chi^2	14390.00	15740.00	15160.00
	(0.00)	(0.00)	(0.00)
AR(1)	-14.56	-14.54	-14.51
	(0.00)	(0.00)	(0.00)
AR(2)	0.49	0.17	0.17
	(0.63)	(0.86)	(0.86)
AR(3)	0.91	1.23	1.23
	(0.36)	(0.22)	(0.22)
AR(4)	-1.08	-1.34	-1.34
	(0.28)	(0.18)	(0.18)
Hansen J	560.40	711.30	711.30
	(0.01)	(0.67)	(0.67)
N	14059	12455	12455

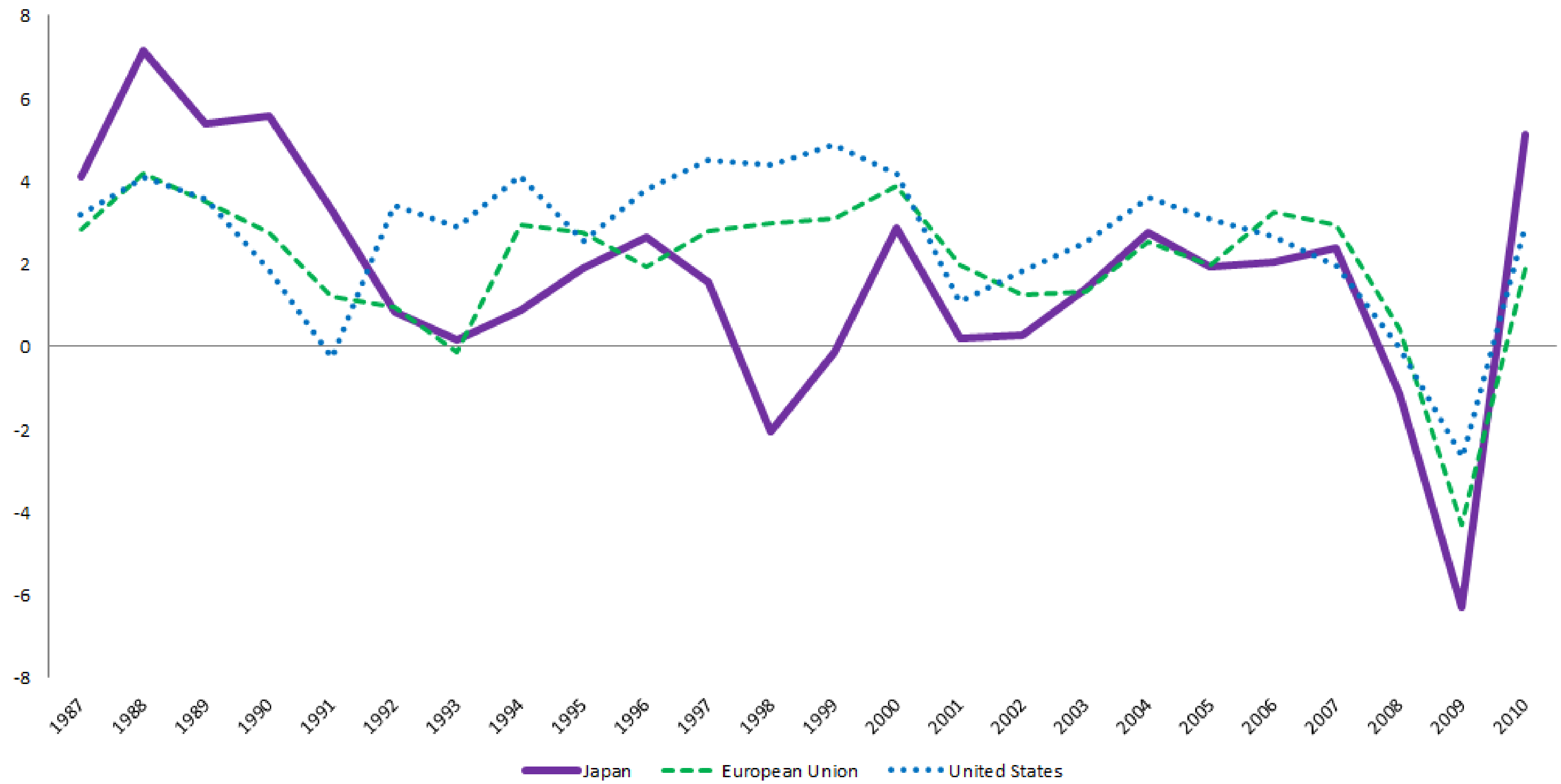
Note: Table 14 reports the results of dynamic investment model with both oil price volatility and market volatility. Model 1 is constructed to test the basic Q model. Model 2 is augmented by cash flow. Model 3 is further augmented by squared volatility. Two-step estimated coefficients and their p-values based on robust standard errors are reported. The estimated coefficients of time dummy variables are not reported. All estimates are obtained from the system-GMM estimator of Blundell and Bond (1998). I/K, CF/K, Q are treated as endogenous. AR(1)-AR(4) are Arellano and Bond (1991) tests for autocorrelation in differences. Hansen J is used for over-identification restrictions.

Table 15. Estimated investment and uncertainty effect

	Oilvol	**Marvol**	**Oilvolsq**	**Marvolsq**
Contemporaneous effect	-1.323E-01	2.341E-02	1.649E-03	-8.809E-04
	(0.000)	(0.000)	(0.000)	(0.000)
lagged effect	7.497E-02	3.596E-02	-1.039E-03	-2.176E-04
	(0.000)	(0.000)	(0.000)	(0.000)
Cumulative effect	-5.733E-02	5.937E-02	6.100E-04	-1.099E-03
	(0.000)	(0.000)	(0.000)	(0.000)
long-term effect	-5.676E-01	5.878E-01	6.040E-03	-1.088E-02
	(0.000)	(0.000)	(0.000)	(0.000)

Note: Table 15 summarizes the contemporaneous and lagged effects of oil price volatility and market volatility on investment, and calculates the cumulative effect and long-term effect of uncertainty on investment. Estimated coefficients are based on model 3 in table 14. The cumulative effect is calculated as the sum of contemporaneous effect and lagged effect. The long-term effect is calculated as $(b_6 + b_7)/(1 - b_0)$ in Eq.25. That is (contemporaneous effect + lagged effect) / (1 - coefficient of lagged investment). The *p*-value is obtained through non-linear test procedure in Stata.
* p<0.1, ** p<0.05, *** p<0.01

Figure 1 GDP growth rate of Japan, U.S. and European Union 1987-2010



Note: Figure 1 shows the percentage GDP growth rates of Japan, U.S. and European Union for the period over 1987-2010. The x-axis is the year and the y-axis is the percentage growth rate of GDP.

Chapter 2

Oil Price Shocks and the Stock Market: Evidence from Japan

2.1 Introduction

A central question for economists and financial analysts is how the economy responds to an exogenous change in the price of oil. The answer to this question is critical for many decisions, such as the formulation of macroeconomic policy, asset pricing, risk management and portfolio management. Yet, despite a large body of empirical studies that analyze how oil price shocks affect output, consumption, employment, inflation and stock returns, there is generally a lack of consensus as to the nature and significance of the effects (see for example, Lee, Ni and Ratti, 1995; Hamilton, 1996; Jones, Leiby and Paik, 2004; Huntington, 2007; Gronwald, 2008). This lack of consensus may be due to two assumptions that are common in many existing studies. The first is that the price of oil is often treated as exogenous ignoring any reverse causality from the global economy. The second is that studies that ignore different shocks i.e., whether a higher oil price is driven by oil production shortfalls, by a booming world economy or by an increase in the precautionary demand for crude oil with increased concerns about future supply shortfalls, also assumes the same effect on the economy of an exogenous increase in the price of oil. Kilian (2009) who disentangles these effects finds, in contrast to previous studies, that the U.S. economy responds very differently with respect to these underlying oil price shocks.

However, much remains unknown about the response to oil price shocks of economies other than the U.S.. It is particularly surprising that Japan, the world's third-largest oil consumer and a country without any reserves of its own, has not been the subject of more research. Japan lacks significant domestic sources of fossil energy and has to import substantial amounts of crude oil to meet its rapid economic and industrial growth. After two oil crises in the 1970s, Japan made efforts to diversify its energy resource to increase energy security including nuclear power, LNG development etc. Moreover, Japan has a large amount of strategic oil reserves that equal more than 150 days of consumption both by state and private stockpiles. Most of the crude oil in Japan is imported from Middle Eastern countries, followed by Southeast Asian countries and European countries. Although Japan is fully dependent on foreign crude oil reserves, the major portion of petroleum product supply in Japan is covered by domestic production making it different from the U.S. and other oil-importing countries. The domestic petroleum refining system has been able to provide a stable and efficient supply of quality products. As a result, the Japanese economy is rather resilient to the oil shocks despite its large dependence on oil (Mork, 1994). Furthermore, from the second half of 1980s, the Japanese economy overheated with rising stock and real estate prices, later known as the Japanese asset price bubble. Over the next 30 years, the performance of Japanese economy has been less impressive compared with other developed countries, such as the U.S. and European Union. Since the second half of the 1990s till present, the interest rate in Japan has only been slightly above 0%. As in other oil-importing countries like the U.S., oil price shocks ought to affect Japan's economy through different channels. For example, oil is one of the key production components for most goods and services, so higher energy costs lower usage of oil and lead to lower real output. Furthermore, higher oil prices reduce the purchasing power of domestic households as consumers have lower discretionary income for other goods because of the increased cost of energy (Kilian, 2010b). In addition, Hamilton (2003) observes that oil price shocks raise uncertainty about future oil-market conditions and slow down the economy with reduced or postponed investments and purchases of energy-dependent durable goods. There are several empirical studies (see for example Jimenez-Rodriguez and Sanchez, 2005; Blanchard and Gali 2007) that focus on investigating the relationship between oil price shocks and real economic activity in Japan. Blanchard and Gali (2007) compare the effect of oil price shocks on CPI, GDP and employment for United States, France, Germany, United Kingdom, Italy and Japan. Japan behaves differently from other countries since oil price shocks only have a weak effect on wage and no significant effect on other economic indicators. Jimenez-Rodriguez and Sanchez (2005) also fail to identify any real effect of oil prices on Japanese GDP growth whereas for U.S., U.K., Germany, France and Italy, they find that an increase in oil prices has a significant negative impact on the GDP growth. Finally, only a few papers study the implications of oil price shocks on the Japanese stock markets (see for example, Jones and Kaul, 1996; Apergis and Miller, 2009). Apergis and Miller (2009) investigate how structural oil price shocks affect stock market returns in a sample of eight countries including Japan. They find that oil market shocks have a significant but small magnitude effect on international stock market returns. Previous studies on Japan are in the context of international comparisons between countries, of which Japan is one. My chapter is, to the best of my knowledge, the first to study the impact of oil shocks specially on the Japanese stock markets using the approach in Kilian (2009). In addition, different from previous studies, I fill the gap by testing whether the variations in Japan real stock returns to specific supply and demand shocks in the crude oil market are driven by fluctuations in cash flows or by discount rates variations.

The main contribution in this paper is that I use a structural vector autoregressive (SVAR) approach to study the dynamic relationship between oil price shocks and the Japanese stock market. The effects of oil price shocks on stock returns and dividend growth rates are examined. Using a structural VAR controls the reverse causality between oil price and stock returns. It also identifies three different shocks to the crude oil market: shock to the global supply of crude oil, shock to the global demand for all industry commodities, and oil-market specific demand shock. Moreover, I explicitly test which demand and supply channels affect the movement of future cash flows and discount rates, which eventually determine the asset price. The main results are as follows. First, I find that unexpected increases in global demand for all industrial commodities cause a persistent increase in the real price of Japanese Crude Cocktail while the effect of unexpected oil production disruption and unexpected increases in the precautionary demand for oil are relatively minor. Next, I find that in contrast to the conventional perception, demand shocks rather than supply shocks explain most of the changes in the real price of the Japanese Crude Cocktail. Third, in contrast to research on the U.S. stock market, I find only marginal evidence that oil price shocks contribute to the variation in Japanese real stock returns and real dividend growth. Finally, again in contrast to results for the U.S. market, I find that the variation of Japanese stock market returns caused by oil price shocks can be explained by changes of expected real cash flows rather than changes of expected returns. These results remain qualitatively similar even after using a number of robustness checks using alternate model specifications and data. The reason that these results are different from what Kilian and Park (2009) have for U.S. is mainly because of the special Japanese economic circumstances and its heavy dependence on imported oil, as well as an efficient energy security policy.

The rest of the paper is organized as follows. Section 2 reviews the existing literature. Section 3 describes the data and empirical methodology, and discusses the structural shocks to the global oil market and the Japanese stock market. Section 4 presents empirical results for the global oil market and stock market blocks, and reports the robustness check for my main results. Section 5 compares and contrasts the oil transmission mechanisms in the U.S. and Japan markets. Section 6 details the main conclusions. Appendices A and B provide details of the data I use.

2.2 Literature Review

Oil price shocks tend to influence stock prices and returns through their effects on current and future changes in real cash flows and/or changes in expected returns. For example, oil price increases can affect current and future company earnings negatively by making production more expensive and reducing demand. Bernanke, Gertler and Watson (1997), for example, suggest that monetary policy makers tend to increase interest rates in response to the inflationary pressures triggered by the oil price shocks; a higher interest rate then implies a higher required rate of return and lower future cash flows and consequently a fall in stock prices.

Empirical studies that analyze the effects of oil price shocks on stock prices or returns fall into two broad categories depending on the level of aggregation: market-level and industry-level. At the market-level, the empirical evidence is mixed. For example, Jones and Kaul (1996) find a negative relationship between oil price shocks and aggregate stock returns based on Campbell's (1991) cash-flow dividend valuation model. Huang, Masulis and Stoll (1996) fail to find any relationship between returns on oil future contracts and U.S. stock returns using both a regression model and a vector autoregressive (VAR) model. Sadorsky (1999) uses a VAR model and finds that oil prices and oil price volatility both play important roles in affecting U.S. real stock returns. Ciner (2001) identifies a nonlinear relationship between oil price shocks and the U.S. stock returns. More recently, Park and Ratti (2008) find a positive response of real stock returns to an oil price increase for Norway, but negative responses for 12 other European countries.

Apergis and Miller (2009) modify Kilian's (2009) structural VAR to first decompose oil price changes into three supply and demand shocks using a structural vector error correction (VEC) or VAR model. Next, they use a VAR to determine the effects of these structural shocks on the stock market returns. However, they did not find international stock market returns respond in a large way to oil market shocks. Finally, Kilian and Park (2009) use a structural VAR model to examine the impact of oil price shocks on the U.S. stock market, and find the responses of aggregate U.S. real stock returns differ greatly depending on the causal factors.

In contrast to studies using an aggregate stock market index, the general conclusion, using industry-level data, is that oil price shocks affect industries differently depending on their nature (see Lee and Ni, 2002; Sadorsky, 2001; Boyer and Filion, 2007). For example, for oil-intensive industries such as petroleum refinery and industrial chemicals, the predominant effects of oil shocks are on the supply side and their returns tend to move together with the price of oil. However, for other industries such as automobiles, leisure and travel the effects of oil shocks are on the demand side, where higher oil prices lower demand on their products and services and consequently there is a fall in stock prices. A recent study by Fukunaga, Hirakata and Sudo (2010) using Japanese data finds that the response of stock returns of industry portfolios depends not only on the nature of the industry but also the specific underlying causes of the oil price shocks.

On the country level, there are a few empirical studies that focus on the implication of oil price shocks on the Japanese stock market and all of them are international comparison studies. Jone and Kaul (1996) conduct a detailed investigation of the effects of changes in oil prices on stock prices for U.S., Canada, U.K. and Japan. They also test whether the reaction of the international stock market to oil shocks can be justified by current and future changes in cash flows and expected stock returns. They find that international stock prices do react to oil price shocks, and that stock price changes caused by oil price shocks are substantially greater than that can be justified by the effects of these shocks on future cash flows. Apergis and Miller (2009) investigate how oil shocks affect stock market returns for Australia, Canada, France, Germany, Italy, Japan, U.K. and U.S.. They find a significant but small effect of oil market shocks on the international stock market returns.

In the studies referred to above, the relationship between oil price and stock returns is examined via three main approaches. The first is to use regression analysis. However, a major drawback of this approach is that oil prices are treated as exogenous with respect to the global economy. Second, many studies use standard VAR models to control the reverse causality to the global macroeconomic aggregates but these models assume the same effect of an exogenous increase in the price of oil regardless of the underlying causes. Finally, most recent studies following Kilian and Park (2009) use a structural VAR model that avoids these problems and studies the effects of demand and supply shocks in the global crude oil market on the stock market. Kilian and Park (2009) propose a structural vector autoregression (VAR) model for the global crude oil market and test its interaction with the U.S. stock market. Using a structural VAR controls the reverse causality between oil price and stock returns. Further, it also identifies three different shocks to the crude oil market: shock to the global supply of crude oil, shock to the global demand for all industry commodities, and oil-market specific demand shock. Their results suggest that the real price of oil as well as the stock market respond differently to the different causes of the oil price increase. In this paper, I follow Kilian's (2009) approach to examine the implications of oil price shocks on the Japanese stock market. To my knowledge, this is the first paper to specifically study the dynamic relationship between oil price shocks and the Japanese stock market as opposed to previous studies that focused on international comparison. In addition, I also test whether the reaction of Japanese stock market to oil price shocks can be justified by current and future changes in real cash flow and changes in expected discounted rate.

Kilian and Park (2009) show that the real price of oil as well as the stock market respond differently to the different causes of the oil price increases. Specifically, the supply shock does not have a significant effect on U.S. stock returns but a negative effect on stock dividend growth. In contrast, the aggregate demand shock causes a sustained increase in both U.S. stock returns and dividend growth. Finally, an increase in the precautionary demand shock causes a persistent negative effect on both U.S. stock returns and dividend growth. In addition, they demonstrate that the response of estimated stock returns to the changes in the oil market can be explained by both changes in the expected cash flows and changes in the expected discount rates. Similar to the U.S., Japan is an oil importing country but with a higher dependence on the imports. Thus, I would expect similar results for the Japanese market but with different magnitude and persistence. First, the Japanese economy is more export-driven compared to U.S., so I expect to see more persistent effects of aggregate demand shock on both stock return and dividend growth rate. Second, Japan has an efficient energy security policy and plenty of strategic oil reserves. The hypothesis for the effect of oil market specific shocks is that it would have less effect on Japanese stock returns and dividend growth rate compared to U.S.. Third, the interest rate in Japan has remained close to zero since 1990. This may weaken the role of expected discount rates in explaining the response of stock returns to oil price shocks. I would expect to see that the response of aggregate Japanese real stock returns to oil supply and demand shocks in the crude oil market is driven by the changes in expected cash flows only.

2.3 Data and Methodology

2.3.1 Data

I now provide a brief description on the data used in the empirical analysis. Further details of the data including sources and transformations used in the main analysis and in the robustness checks are provided in Appendices 2A and 2B respectively. All data used in this paper are monthly and the sample period starts from January 1988 and ends in December 2009. Table 1 provides the statistical summary of the variables used in the model.

First, I use the DataStream country equity indices for Japan (denominated in U.S. dollars) to obtain data on real stock returns and real dividend growth rates. The index rather than individual stock price is used because this purpose of this study is to examine the effect of oil price shocks on the aggregate stock market. The individual stock price has undiversifiable risk associated with the individual entity and industry it belongs to. Different industries have different degrees of oil dependence. Some use crude oil as a raw input while others may only use it for transportation and heating. Thus, the individual stock price may show a biased response when facing oil price fluctuations. The real stock return is calculated by substracting the CPI inflation rate from the log returns of Japanese stock price index (TOTMJP$)[1]. The nominal dividend is constructed from the product of Japanese stock price index and Japanese stock market dividend yield (TOT-MJP$(DY)). By deflating these dividends by the prevailing level of the CPI, we obtain corresponding real monthly dividend payments. Second, my measure of the real price of oil imported by Japan is based on 'Japan Crude Cocktail' (JCC). The JCC is the average price of customs-cleared crude oil imported into Japan, and monthly prices are reported by the Trade Statistics of Japan since January 1988. Figure 1 depicts the time series plot of JCC. It is worth noting that it is influenced by exogenous events such as political

[1] DataStream Code in the bracket.

instabilities, wars, and global macroeconomic conditions. For example, I observe a significant increase in the price of oil during the Persian Gulf War in 1990; a sharp drop in the real price of oil seems followed the Asian crisis from 1997 to 1998; and a significant increase between 2003 and 2008 coincidently consistent with the stylized facts about oil prices during this period (i.e., booming global economies increase the demand of oil dramatically). Third, I use global oil production to reflect the OPEC cartel activities and political instabilities for both OPEC and non-OPEC countries. The data is obtained from the Energy Information Administration (EIA). Finally, I use a proxy of global real economic activity based on the single-voyage bulk dry cargo ocean shipping freight rates. This index is proposed by Kilian (2009), and reflects global economic activity in that the supply and demand for shipping services is a good proxy for global trade and therefore for global trends in real activity.[2] A key advantage of this index is its ability to capture the total world demands, especially demands from emerging countries, such as China and India. The Baltic Dry Index (BDI) is an alternative proxy measure of the world economy activity. It tracks worldwide international shipping prices of various dry cargoes and is seen as one of the purest leading indicator of economic activity. I also report the results on using the BDI in my robustness checks.

2.3.2 Methodology

I use, following Kilian (2009), a block-recursive structural VAR model to decompose the real price of oil in Japan into three components: supply shocks, aggregate demand shocks and oil-specific demand shocks.[3] Structural VAR is widely used to capture the dynamic relationships among economic variables of interest. Each variable in the Structural VAR is a linear function of

[2] The data is available at Kilian's homepage http://www.personal.umich.edu/~lkilian/reaupdate.txt.

[3] Recursive ordering implies that the first variable in the system will not react contemporaneously to any shocks from the remaining variables, but all other variables can react to shocks in the first variable, and so on. This restriction is concerned with the contemporaneous relations only.

its own lagged value and the lagged value of some other variables. The recursive short-run restriction suggested by Kilian and Park (2009) is used as identifying assumptions, where the variables are ordered from most exogenous to most endogenous. Next, I estimate the dynamic effects of these three components of oil price shocks on the Japanese stock market variables using both impulse response functions and variance decomposition. The impulse responses trace the response of the real stock return or dividend growth rate to a one-time shock from the three components while the variance decomposition gives the contributions of each source of shock to the variance of the h-period ahead forecast error for the real stock return or dividend growth rate.

My structural VAR model comprises a global oil market block and a Japanese stock market block. It is estimated using monthly data, for the time series vector , that includes the percentage change in global crude oil production ($\Delta prod_t$), the Kilian index of global real economic activity index (rea_t), the real price of JCC (rpo_t), and two Japanese stock market variables i.e., the real stock return (rs_t) and dividend growth rate (rd_t). I include three variables in the global oil market block (i.e., $\Delta prod_t$, rea_t and rpo_t). For the Japanese stock market block, I estimate the response of the Japanese stock market variables (i.e., rs_t and rd_t) to these supply and demand shocks in the global oil market. More formally, this model can be written as:

$$A_0 z_t = \alpha + \sum_{i=1}^{24} A_i z_{t-i} + \varepsilon_t \qquad (1)$$

where A_0 are the contemporaneous terms of z_t, α is the intercept vector, A_i is the i-th matrix of autoregressive coefficients for $i = 1$ to lag 24, and ε_t denotes the vector of serially and mutually uncorrelated structural innovations.[4]

In the global oil market block, three separate causes of oil price shocks are modelled: the oil supply shock (ε_{1t}) caused by unexpected disruptions in

[4] I also perform robustness checks for the results at different lags i.e., 6, 12 and 18 respectively – see section 4.6 for details.

global crude oil production; the aggregate demand shock (ε_{2t}) arising from global real economic activity; oil-specific demand shock (ε_{3t}) caused by the precautionary demand for crude oil. In the Japanese stock market block, there is only one structural shock: other shocks to stock returns or dividend growth rate (ε_{4t}) not driven by global crude oil demand and supply shocks.

Note that, Eq.1 contains contemporaneous terms on the left hand side and this would yield inconsistent parameter estimations when using ordinary least square estimation. In order to overcome this I rewrite the structural VAR model in its reduced form as follows:

$$z_t = \beta + \sum_{i=1}^{24} B_i z_{t-i} + e_t \qquad (2)$$

where $\beta = A_0^{-1}\alpha$, $B_i = A_0^{-1}A_i$ and $e_t = A_0^{-1}\varepsilon_t$. Here, the reduced form residuals e_t are correlated between each equation and cannot be interpreted as structural shocks. In order to orthogonalize the shocks, I impose a block-recursive structure on the contemporaneous terms (i.e., matrix A_0 in Eq.1) between the reduced form innovations and the structural shocks as follows:[5]

$$e_t = \begin{pmatrix} e_{1t}^{\Delta global\ oil\ production} \\ e_{2t}^{global\ economy} \\ e_{3t}^{oil\ price} \\ e_{4t}^{stock\ returns} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}^{oil\ \sup ply\ shock} \\ \varepsilon_{2t}^{aggregate\ demand\ shock} \\ \varepsilon_{3t}^{oil-specific\ demand\ shock} \\ \varepsilon_{4t}^{other\ shocks\ to\ stock\ returns} \end{pmatrix} \qquad (3)$$

In the global oil market block, following Kilian (2009) again, I impose three exclusion restrictions that are based on the following assumptions and

[5] For a nonsingular triangular matrix (both upper and lower), the inverse is still triangular.

economic reasoning. First, I assume that global oil production will not respond immediately to changes in demand driven by the world economy or oil market specific demand because the costs of adjusting production are expensive in the short run as well as due to uncertainty about future crude oil prices. Second, I assume that real economic activity will be affected by oil supply shocks and aggregate demand shocks contemporaneously, but will respond with a delay of at least a month to the real price of oil driven by shocks that are specific to the oil market. Finally, I assume that the real price of oil is affected by oil supply shocks, aggregate demand shocks and oil-specific demand shocks contemporaneously. I note that the innovations to the real price of oil that cannot be explained by supply shocks and aggregate demand shocks must be demand shocks that are specific to the oil market.

In the Japanese stock market block, there is only one equation. Here I follow Lee and Ni (2002) and assume that global crude oil production, global real activity and the real price of oil are predetermined with respect to Japanese stock returns. Specifically, in common with the literature, I assume that stock market shocks only affect global crude oil production, global real activity and the real price of oil with a delay of at least one month.

2.4 Empirical Analysis

2.4.1 Unit Root Tests

I begin the analysis with tests for unit roots in all variables i.e., $\Delta prod_t$, rea_t, rpo_t, rs_t and rd_t used in the structural VAR model. I apply Augmented Dickey-Fuller (ADF), Phillips- Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests and report results both with and without a trend. Further, I determine the optimal lag length using the Schwarz-Bayes Information Criterion (SBIC). The null hypotheses for ADF and PP is the existence of a unit root I(1), so if the series is stationary I(0), the ADF and PP tests should reject the null hypothesis. In contrast, the null hypothesis of the KPSS statistic is that the series is stationary I(0).

Table 2 reports the results of these ADF, PP and KPSS tests for each series. I find that I can reject the null hypothesis that $\Delta prod_t$, rea_t, rs_t and rd_t contain a unit root at the 1% significant level, and rpo_t at 5% under the ADF test without trend option. Although the PP and KPSS tests suggest that the real price of JCC contains a unit root, this can be accepted because economic theory suggests there is a link between the cyclical fluctuation of global real activity and the real price of oil (Kilian and Murphy, 2010). Further, taking a first difference of the JCC will result in removal of the slow-moving component and it will be difficult to find the persistent effect of aggregate demand shocks. Second, even if the JCC can be approximately predicted by a random walk, it is not clear whether this is a unit root or not. Third, the estimated impulse response is robust even if the stationary assumption is violated (Pesavento and Rossi, 2007). The cost of not taking the first difference is a loss of asymptotic efficiency, which leads to a wider error band (see for example, Kilian, 2010a; Kilian and Murphy, 2010). Hence, non-stationarity of the real price of oil is not a major concern if impulse responses are reasonably estimated. This assumption is in common with the previous literature cited earlier.

2.4.2 Factors Affecting the Real price of Oil in Japan

I next study the response of the real price of JCC to the three structural shocks – an oil supply shock, an aggregate demand shock and an oil-specific demand shock. I note that in order to ensure all shocks have a positive impact on the real price of oil (i.e., a higher price), the oil supply shocks are normalized to represent a negative one percent shock, while the aggregate demand shocks and oil-market specific demand shocks are normalized to represent one percent positive shock. All statistical inference is based on a recursive-design wild bootstrap method with 2,000 replications (see for example Goncalves and Kilian, 2004).

Figure 2 reports the impulse responses of the real price of JCC to the three types of shocks that drive the global crude oil market. One-standard error and two-standard error bands are indicated by dashed and dotted lines in the Figures. The first column of Figure 2 shows that oil supply shocks caused by unexpected oil production disruption lead to a minor increase in the real price of oil, but these effects are statistically insignificant for my sample period based on one-standard error bands. On the other hand, the two demand shocks have larger and more persistent effects. First, aggregate demand shocks from unexpected increases in global demand for all industrial commodities cause a persistent increase in the real price of oil. The response reaches its peak at 8% after five months, followed by a declining trend and stabilizes after approximately ten months. This is highly statistically significant based on both one and two-standard error bands. Second, oil-specific demand shocks arising from unexpected increases in the precautionary demand for oil, increase oil prices immediately and this reaches its maximum of 8.5% but the effect declines sharply after two months. It is however, statistically significant for the first nine months based on one-standard error bands as shown in the third column of Figure 2.

I next report the historical decomposition in the real price of the JCC over time in Figure 3. I find that the real price of oil for the period 1988 to 2009 is mainly driven by aggregate demand shocks and oil-market specific demand shocks with relatively smaller contributions from oil supply shocks. For example, the JCC decline during the 1997 Asian Crisis and recent financial crisis in late 2008 is largely driven by decreases in global demand and precautionary demand rather than the oil supply disruptions; the recent surge in oil price from 2002 to 2008 further underlines the role and importance of these demand shocks.

To summarize, the impulse response results indicate that the real price of the JCC responds differently to supply and demand shocks in both timing and magnitude. Supply shocks include production changes driven by political events as well as other oil producers' response to this shortfall. Demand shocks capture both shock to the aggregate demand for industrial commodities in global commodity market which are driven by changes in global real economic activity, and shock to changes in precautionary demand for crude oil that reflect concerns about the availability of future oil supplies. In contrast to the conventional perception, I find that supply shocks play a relatively minor role while demand shocks explain most of the changes in the real price of the JCC.

2.4.3 Effects on Japanese Real Stock Returns

I now turn to the response of real stock returns to oil price shocks. Figure 4 shows the cumulative impulse responses of real stock returns to each of the three supply and demand shocks in the global crude oil market. I find that the response of real stock returns differs greatly depending on the underlying cause of the oil price increases. For example, oil supply shocks from unanticipated disruptions of crude oil production do not affect stock returns in Japan greatly. In contrast, higher oil prices caused by aggregate demand shocks from unexpected increases in global demand for all industrial commodities cause a significant positive impact on Japanese real stock returns. The initial response is fairly small (i.e., less than 1%), but the response builds for about six months to 2.5% and then followed by a slight declining trend. This is mainly because positive innovations to the global business cycle tend to initially stimulate Japan's economy, but they also drive up the oil price while adversely affects the Japanese economy in the long-run. In section 2.4.2, I find out that the recent oil price surge has been mainly driven by the aggregate demand shock, and this explains why the Japanese stock market has not been adversely affected in recent years. Finally, the conventional view that higher oil prices lead to lower stock returns only applies when oil price shocks are driven by oil-specific demand factors, such as unexpected increases of precautionary demand for crude oil caused by concerns about future oil supply shortfalls.

Next, I study the relative importance of each demand and supply shocks on real stock returns using the variance decomposition. Table 3 reports the contribution of each demand and supply shock to the total variation in real stock returns in percentage terms. In the short-run, the effects of these three shocks on real stock returns are very low, and 99% of the fluctuations are explained by the other shocks. As the horizon increases, the explanatory power of demand and supply shocks in the global crude oil market increases significantly. In the long-run, about 43% of the variations in real stock returns are driven by the global crude oil market, where the aggregated demand shocks alone account for 24% of the variability of returns, and oil supply shocks account for 12% and 6% from the oil-specific demand shocks.[6] Therefore, I conclude that shocks to the global crude oil market play an important role affecting the Japanese stock market.

My results differ from Apergis and Miller (2009) who find marginal evidence that oil price shocks contribute to the variation in Japanese real stock returns, with only 3% of the changes in the Japanese real stock returns are accounted for by oil supply shocks, aggregate demand shocks account for 2% and 3% from the oil-specific demand shocks. The first reason for these differences is that they use a modified procedure of Kilian (2009). They first employ a vector error-correction or a vector autoregressive model to decompose oil price changes into three parts. Then these shocks are recovered from the first step analysis, which are used to determine the effects of oil price shocks on the stock market using a vector autoregressive model. Second, it is likely that the main reason for this difference in results is due to their use of first-order differenced real prices of oil to remove non-stationarity. This differencing, as I point out earlier, removes the slow-moving component and reduces the chance of detecting persistent effects of global shocks on the

[6] The rounded components do not add up to the sum due to rounding.

demand for all industrial commodities (see for example by Kilian and Murphy, 2010, for a similar argument). In addition, Apergis and Miller (2009) include seven lags in their VAR model, while Hamilton and Herrera (2004) and Kilian (2009) suggest that the dynamics effects are more persistent with a longer lag length (e.g., 12, 18 or 24).

2.4.4 Effects on Japanese Real Dividend Growth Rates

Next, I investigate the response of real dividend growth rates to demand and supply shocks in the crude oil market. I do this by replacing real stock returns in the last element of z_t with real dividend growth rates, and then re-estimating Eq.1. The cumulative impulse responses of real dividend growth rates to each of the three demand and supply shocks in the crude oil market are shown in Figure 5.

My findings are similar to those reported in Kilian and Park (2009). They also find that expected dividend growth does not remain constant in response to oil supply and demand shocks using U.S. stock market data. I find that unanticipated oil supply disruptions lead to a higher real dividend, the response is significantly positive for the first three months. Next, I find that aggregate demand shocks lead to an immediate fall in dividend growth followed by an increase after three months. Further I find that oil-specific demand shocks have only marginal effects on the real dividend growth.

Table 4 reports the results for the variance decomposition for real dividend growth rates. I find, that in the short-run, the effect of these shocks is minor with only about 2% of the variations of real dividend growth rates are associated with shocks from the global crude oil market. In the long run, 42% of the variability of real dividend growth rates is driven by these three shocks from the global crude oil market, where the aggregate demand shocks alone account for 24% of the total variability.

2.4.5 Transmission Channels of Oil Price Shocks on Japan Stock Market

The contemporaneous approach to explain the movement of stock returns tends to ignore the channels through which demand and supply shocks affect asset prices. In this study, I aim to fill this gap by testing whether the variations in Japan real stock returns to specific supply and demand shocks in the crude oil market are driven by fluctuations in cash flows or by discount rates variations.

I do this using Campbell's (1991) stock return decomposition and write the unexpected changes in asset returns from the previous period $(t-1)$ to the current period (t) as follows:

$$rs_t - E_{t-1}(rs_t) = \left[E_t\left(\sum_{i=0}^{\infty}\rho^i rd_{t+i}\right) - E_{t-1}\left(\sum_{i=0}^{\infty}\rho^i rd_{t+i}\right)\right] - \left[E_t\left(\sum_{i=0}^{\infty}\rho^i rs_{t+i}\right) - E_{t-1}\left(\sum_{i=0}^{\infty}\rho^i rs_{t+i}\right)\right] \quad (4)$$

where rs_t is the real stock returns, rd_t is the real dividend growth rates, E_t is the expectation at time t, ρ is the discount coefficient that is slightly less than one, and it is computed as follows: $\rho \equiv 1/(1+\exp(\overline{d-p})$, where $\overline{d-p}$ is the average log dividend-price ratio.

Revisions of expected future cash flows are written as $\left[E_t\left(\sum_{i=0}^{\infty}\rho^i rd_{t+i}\right) - E_{t-1}\left(\sum_{i=0}^{\infty}\rho^i rd_{t+i}\right)\right]$, and changes of future discount rates are written as $\left[E_t\left(\sum_{i=0}^{\infty}\rho^i rs_{t+i}\right) - E_{t-1}\left(\sum_{i=0}^{\infty}\rho^i rs_{t+i}\right)\right]$. Eq.4 states that stock returns vary through time due to revised expectations about future cash flows and variations in future discount rates. I can write Eq.4 more compactly as:

$$rs_t - E_{t-1}(rs_t) = N_{CF,t+1} - N_{DR,t+1} \quad (5)$$

where $N_{CF,t+1}$ and $N_{DR,t+1}$ denote the news about future cash flows, and news about discount rates respectively.

In order to incorporate the changes in real stock returns arising from a given supply or demand shock in the crude oil market, I follow Kilian and Park (2009), and reconstruct Eq.5 in terms of the responses to unanticipated disturbances in the crude oil market. First, I normalize all expectations of period $t-1$ in Eq.5 to zero. Then, I write the changes in real cash flows and changes in expected returns relative to the baseline in response to an unexpected disturbance in the crude oil market as follows:

$$rs_t - E_{t-1}(rs_t) = E_t(rs_t) - E_{t-1}(rs_t) = \Psi_{0,j} - 0 = \Psi_{0,j} \tag{6}$$

$$N_{CF,t+1} = E_t\left(\sum_{i=0}^{\infty} \rho^i \delta_{ij}\right) - E_{t-1}\left(\sum_{i=0}^{\infty} \rho^i \delta_{ij}\right) = \sum_{i=0}^{\infty} \rho^i \delta_{ij} - 0 = \sum_{i=0}^{\infty} \rho^i \delta_{ij} \tag{7}$$

$$N_{DR,t+1} = E_t\left(\sum_{i=0}^{\infty} \rho^i \varphi_{ij}\right) - E_{t-1}\left(\sum_{i=0}^{\infty} \rho^i \varphi_{ij}\right) = \sum_{i=0}^{\infty} \rho^i \varphi_{ij} - 0 = \sum_{i=0}^{\infty} \rho^i \varphi_{ij} \tag{8}$$

where $\Psi_{0,j}$ is measured by the first element of the impulse response coefficients of real stock returns to a shock j in the crude oil market in month t; δ_{ij} (φ_{ij}, respectively) is the impulse response of real dividend growth (real stock returns, respectively) in period i to a given structural shock j in the crude oil market; j = oil supply shock, aggregate demand shock, and oil-specific demand shock. I note that all these coefficients are estimated by running the two structural VAR models in sections 2.4.3 and 2.4.4.

Finally, I can test whether the impact on real stock returns arising from different supply and demand shocks in the global crude oil market can be fully accounted for by revisions of real cash flows or revisions of expected real returns. In this case, the null and alternative hypotheses can be stated as follows:

$$H_0\colon \Psi_{0,j} = \sum_{i=0}^{\infty} \rho^i \delta_{ij} \approx \sum_{i=0}^{36} \rho^i \delta_{ij} \tag{9}$$

$$H_0\colon \Psi_{0,j} = -\sum_{i=0}^{\infty} \rho^i \varphi_{ij} \approx \sum_{i=0}^{36} \rho^i \varphi_{ij} \tag{10}$$

$$H_1\colon \Psi_{0,j} = \sum_{i=0}^{36} \rho^i \delta_{ij} - \sum_{i=0}^{36} \rho^i \varphi_{ij} \tag{11}$$

Following the practice in the literature I truncate the infinite sum in the above expressions for the purposes of estimation at 36 lags.

I report, in Panels A and B of Table 5, the Wald-test statistics and p-values for null hypotheses in Eq.9 and Eq.10. I cannot reject the null hypothesis that the change in real stock returns arising from a given shock in the crude oil market can be attributed in its entirety to revisions of expected real dividend growth rate based on results in Panel A. On the other hand, Panel B shows that I can reject the null hypothesis on that expected real dividend growth do not affect the variation of Japanese real stock returns caused by three oil price shocks (at 10% significance level). Taking together my empirical results imply that Japanese real stock returns are affected by supply and demand shocks in the global crude oil market from changes of expected real cash flows rather than changes of expected returns. One possible explanation as to why expected returns do not seem to matter is Japan's zero-rate monetary policy (Bernanke, 2000). Economic theory suggests that oil price shocks hurt the stock returns indirectly through the future discount rate channel. To be more specific, monetary policy makers tend to increase interest rates in response to the actual or potential inflationary pressures triggered by the oil price shocks. A higher interest rate therefore implies a higher required rate of return and lowers firms' future cash flows and leads to a lower stock price. However, the interest rates in Japan have been less than 1% from 1996, and the Bank of Japan imposed a zero-rate policy to further stimulate the economy and fight for deflation since 2001. Therefore, my failure to find changes in discount rates to have any effect on Japanese stock returns may be due to the persistent low interest rates seen in Japan since the early 1990s.

2.4.6 Robustness Checks

I test the robustness of the estimation results using different specifications of the model. First, I study whether my main results are affected by using different lag lengths in estimating the structural VAR model. The optimal lag number based on Akaike information criterion is 4. However, 4 months are not enough to capture the dynamic effect of oil price shocks on the stock market. Firms need time to adjust production and strategy when facing oil price fluctuations. Hamilton and Herrera (2004) offer evidence in favour of a longer lag length and conclude that for monthly data 12 lags is preferred for studies about the relationship between oil price shocks and economy. Kilian and Park (2009) use 24 lags in their study for the U.S. market and find that impulse responses are still significant after 15 months. Thus in this paper I use 24 lags for my main model. However, I find that impulse responses of real stock returns to the three oil price shocks are not affected by using alternative lag length (i.e., 6, 12 and 18). With respect to the variance decomposition, my findings are consistent with Hamilton and Herrera (2004) and Kilian (2009) who find that including more lags in the VAR model increases the importance of the global crude oil market in explaining the fluctuations of real stock returns. Second, I replace the real economic index proposed by Kilian (2009) with the BDI. The directions of the responses to the three structural shocks do not change much, but the negative effects of the oil-specific demand shocks on stock returns are weaker when using the BDI. Third, I replace JCC with the West Texas Intermediate (WTI) and my empirical results remain unchanged. Finally, I use the FTSE Japan Stock index instead of the DataStream Japan stock market index and re-estimate my structural VAR model. Again, this replacement does not qualitatively change my main results.[7]

2.4.7 Relating Results for the U.S. and Japan

In the previous section, I estimate the relationship between oil price shocks and Japanese stock returns and find that the response of real stock returns differs greatly depending on whether the oil price shocks are driven by the supply or demand side in the crude oil market. I now compare my findings with the U.S. market in order to relate my results with those obtained in a large number of studies using U.S. stock market data.[8]

First, the real price of oil imported by U.S. and Japan reacts similarly to the supply and demand shocks, but the magnitude and persistence on the two markets are slight different (Kilian, 2009; Kilian and Park, 2009; Fukunaga, Irakata and Sudo, 2010). For example, an aggregate demand shock from an unexpected increase in global demand for all industrial commodities leads to a maximum of an 8% increase in the real price of oil in Japan in contrast to only a 3% increase using U.S. data. In contrast, an unexpected increase in precautionary demand for oil leads to more persistent increases in real oil prices in the U.S. (for 15 months) than in Japan (i.e., sharply decreases after two months). This might be because Japan is the third-largest oil consumer in the world with almost no domestic sources of oil and relies on imports to meet its consumption needs; therefore, energy security and efficient supply have always been a priority in Japan. Japanese energy policies are designed to mitigate the impact of oil price increases and reduce its foreign oil dependence. It does this by maintaining a large strategic oil reserve that represents more than 150 days consumption; further development

[7] FTSE Japan stock index captures 90% of the Japanese listed companies, which provides a good proxy for the Japan aggregate stock market.

[8] I re-estimate Kilian and Park's (2009) study for the period of January 1988 to December 2009, and include the same dataset i.e., annualized percentage change in global crude oil production, real price of crude oil imported by the U.S., Kilian's real economics index, and CRSP value-weighted market portfolio. I obtain similar results to Kilian and Park (2009). For details on the empirical results, the reader is referred to Kilian and Park (2009).

of nuclear energy to diversify the energy sources; encouraging energy consumption efficiency (International Energy Agency, Japan Energy policies, 2008).

On the other hand, the response of the aggregate Japanese real stock returns to the three different shocks in the global crude oil market that I obtain are similar to Kilian and Park's (2009) findings for the U.S. market. However, the Japanese stock market response to aggregate demand shocks is much stronger (i.e., 2.5%) than that of for the U.S. stock market (a maximum of 0.5% increase) over the initial six months. A potential cause of this difference is that while the aggregate demand shocks stimulate the economy, it also drives the oil price up and affects the economy via different channels (e.g., input-costs channel, income channel, uncertainty and operating costs). Recent studies find that oil price increases have less impact on Japan's real economic activity compared to other oil-importing countries such as the U.S. (e.g., Jimenez-Rodriguez and Sanchez, 2005; Blanchard and Gali 2007). As a consequence, Japanese real stock returns tend to act more positively to the aggregate demand shocks than the U.S.

Third, my variance decomposition shows that aggregate demand shocks play a more important role in explaining the variation (i.e., 24%) for the Japanese real stock returns, compared to 5% in the U.S. market (Kilian and Park, 2009). One possible explanation for this is the composition of the Japanese aggregate stock market. For example, Fukunaga, Irakata and Sudo (2010) who classify the industries into oil-intensive and export-dependent industries, find that the latter have a larger increase in the stock prices with respect to the global demand shocks. The Japanese aggregate stock market indeed contains more export-dependent industries compared to the U.S. market. Therefore, at the aggregate market level, the global demand shocks should also cause a bigger impact on the Japanese aggregate real stock returns than it does for the U.S. stock market.

Finally, Kilian and Park (2009) find that changes in both expected real cash flows and expected real discount rates are responsible for the impact response of U.S. real stock returns to disturbances in the crude oil market. Nevertheless, I find that the response of aggregate Japanese real stock returns to oil supply and demand shocks in the crude oil market is driven by the fluctuations in real cash flows only. This difference may be because Japanese firms have different corporate governance and payout policies compared to U.S. firms. First, the ownership structure of Japanese firms is typically highly concentrated among few corporate stockholders, while the ownership in large U.S. firms is relatively dispersed. Therefore, in contrast to U.S. firms, there is a smaller scope for information asymmetry and agency problems in Japan, and Japanese firms are able to adjust their dividends more often and cut their dividends quicker in respond to poor performance (see for example, Dewenter and Warther, 1998; Chay and Suh, 2009). Second, again in contrast to U.S. firms, cash dividends remain a major form of payout across the firms in Japan. Denis and Osobov (2008) report that the proportion of U.S. firms paying dividends has declined from 61% to 19%, while at Japanese firms changed from 89% to 83% over the period 1989-2002. Finally, since the early 1990s, Japan has had persistent low interest rates and deflation and this may weaken the role of expected real discount rates.

2.5 Conclusion

In this paper, I use a structural VAR approach to study the link between oil price shocks and the Japanese stock market. I find that the response of Japanese real stock returns to oil price shocks differs extensively depending on the specific underlying causes of a higher oil price. For example, oil supply shocks from unanticipated disruptions of crude oil production do not have any significant effect on Japanese real stock returns. Oil-specific demand shocks from unexpected increases of precautionary demand for crude oil caused by concerns about future oil supply shortfalls lower the stock returns in Japan. In contrast, I find a positive relationship between the oil price shocks and the Japanese stock market, when an oil price increase is driven by aggregate demand shocks.

Furthermore, I test whether the reaction of Japanese real stock returns to different shocks in the crude oil market is related to changes in expected cash flows or changes in expected discount rates. I find the responses of the Japanese stock market to all shocks in the crude oil market can be attributed almost entirely to changes in real cash flows.

Finally, I compare and discuss the oil price shocks transmission mechanisms in the U.S. and Japanese stock markets. I find that the Japanese stock market reacts stronger to the unexpected increases in global demand and to the unexpected increases of precautionary demand for oil than the U.S. stock market. In addition, aggregate demand shocks play a more important role in explaining the variation in Japan than U.S. real stock returns. The impact on Japanese stock returns arising from supply and demand shocks in the global crude oil market mainly comes from variations in expected cash flows rather than changes in discount rates, while both changes in cash flows and discount rates are significant factors in the U.S. market. However, further work using Japanese data at the firm level is required to study and explore the channels through which oil price shocks affect Japanese firms. I leave this to future work.

Appendix 2A. Data and Sources Descriptions for Data Used to Obtain Main Results

Variables	Raw Data Series	Transformations	Sources of Data
Changes in global oil production	Global Oil Production	Annualized percentage change	Energy Information Administration Monthly Energy Review
Japanese real stock returns	DataStream Japan Country Index on aggregate stocks	1. Compute the Japanese real stock prices by deflating the nominal price index with U.S. CPI and expressed based on January 1993 dollars; 2. First differences in the logarithms of the real price index.	DataStream
Japanese real dividend growth rate	DataStream Japan Country Index on dividend yield	1. Compute the dividend series by multiplying the dividend yields and aggregate Japan stock prices; 2. Deflate the nominal dividend series; 3. First differences in the logarithms of the real dividend series.	DataStream
Real price of Japanese oil	Japan Crude Cocktail (JCC) in Yen per kiloliter (KL)	1. Translate the JCC price in Yen per KL into Barrel (i.e., 0.159 KL per barrel); 2. Exchange the JCC price in Yen per Barrel into JCC price in dollar price with yen/dollar exchange rate obtained from Federal Reserve Bank of St. Louis; 3. Deflate this nominal price of oil with U.S. CPI.	Trade Statistics of Japan
Global real economic activity	Single-voyage freight rates	See Kilian (2009) for detailed information on how to construct this series.	Kilian's homepage http://www-personal.umich.edu/~lkilian/reaupdate.txt

Appendix 2B. Data and Sources Descriptions for Data Used to Perform Robustness Check

Variables	Data Used in Main Results	Robustness Check Data	Transformations	Source of Robustness Check Data
Oil production	World Oil Production	World Oil Production	Annualized percentage change	Energy Information Administration (EIA), Monthly Energy Review
Global real activity	Kilian's Index	Baltic Dry Index (BDI)	1. Compute the growth rates for BDI and normalize January of 1985 to unity when the data is first introduced; 2. Deflate the nominal index with U.S. CPI; 3. De-trend the real BDI growth rate.	DataStream
Oil price	Japan Crude Cocktail (JCC)	West Texas Intermediate (WTI) crude oil	Deflate the nominal price of oil with U.S. CPI.	EIA, WTI spot prices
Stock index	DataStream Japan Country Index on aggregate stocks	FTSE Japan Stock Index	The stock returns and dividend are calculated calculated similarly as for the DataStream Japan Country Index.	DataStream

Table 1. Statistical summary

Variable	Obs	Mean	Std. Dev.	Min	Max
$\boldsymbol{\Delta}\mathbf{prod}_t$	264	1.760	12.314	-52.664	67.195
$\mathbf{rea}_t$	264	-0.759	22.862	-50.457	55.153
$\mathbf{rpo}_t$	264	-0.301	44.035	-87.001	132.109
$\mathbf{rs}_t$	264	-0.349	6.398	-19.887	23.314
$\mathbf{rd}_t$	264	0.076	3.621	-15.743	12.195

Notes: This table reports the statistical summary of the 4 variables used in the structural VAR. $\Delta prod_t$ is the annualized percentage change of global crude oil production, rea_t is the real economic activity index proposed by Kilian (2009); rpo_t is the real price of oil imported by Japan and expressed based on January 1981 dollar, rs_t is the real Japan stock returns and rd_t is the real Japanese dividend growth rates.

Table 2. Unit root tests

Variables	ADF Test		PP Test		KPSS Test	
	Without Trend	With Trend	Without Trend	With Trend	Without Trend	With Trend
$\mathbf{\Delta prod}_t$	-17.54***	-17.94***	-17.56***	-18.85***	0.11	0.04
$\mathbf{rea}_t$	-2.63***	-3.21	-2.60***	-3.11	0.78***	0.28***
$\mathbf{rpo}_t$	-2.12**	-3.41*	-1.438	-2.62	1.24***	0.41***
$\mathbf{rs}_t$	-14.94***	-14.93***	-14.93***	-14.93***	0.04	0.04
$\mathbf{rd}_t$	-14.49***	-14.50***	-14.41***	-14.41***	0.23	0.10

Notes: This table reports the results of unit roots tests for all five variables that are proposed to use in my VAR model. $\Delta prod_t$ is the first-order difference on global crude oil production, rea_t is the real economic activity index proposed by Kilian (2009); rpo_t is the real price of oil imported by Japan; rs_t is the real Japan stock returns and rd_t is the real Japanese dividend growth rates. I use Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, and report results with and without a trend. The null hypotheses for ADF and PP are 'the series has a unit root I(1)', while the null hypothesis of the KPSS test is 'the series is stationary I(0)'. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 3. Percentage contribution of demand and supply shocks in the crude oil market to the variability of Japanese real stock returns

Horizon Months	**Oil Supply Shock**	**Aggregate Demand Shock**	**Oil-Specific Demand Shock**	**Other Shocks**
1	0.01	1.00	0.06	98.93
2	2.68	0.94	0.68	95.70
3	3.32	1.52	0.91	94.24
12	8.38	5.64	3.38	82.61
∞	12.15	24.08	6.45	57.31

Notes: This table reports the results of the variance decomposition for each supply and demand shock on Japanese real stock returns. It presents the percentage contribution of each shock, namely oil supply shock, aggregate demand shock, oil-specific demand shock, and other shocks, to the overall variability of real stock returns for 1-month, 2-month, 3-months, 12-month and infinity ahead.

Table 4. Percentage contribution of demand and supply shocks in the crude oil market to the variability of Japanese real dividend growth

Horizon Months	**Oil Supply Shock**	**Aggregate Demand Shock**	**Oil-Specific Demand Shock**	**Other Shocks**
1	0.42	1.16	0.51	97.91
2	0.44	1.27	0.70	97.59
3	1.75	1.95	0.76	95.54
12	5.39	11.76	3.21	79.64
∞	8.86	24.37	8.78	57.99

Notes: This table reports the results of the variance decomposition for each supply and demand shock on Japanese real dividend growth. It presents the percentage contribution of each shock, namely oil supply shock, aggregate demand shock, oil-specific demand shock, and other shocks, to the overall variability of real stock returns for 1-month, 2-month, 3-months, 12-month and infinity ahead.

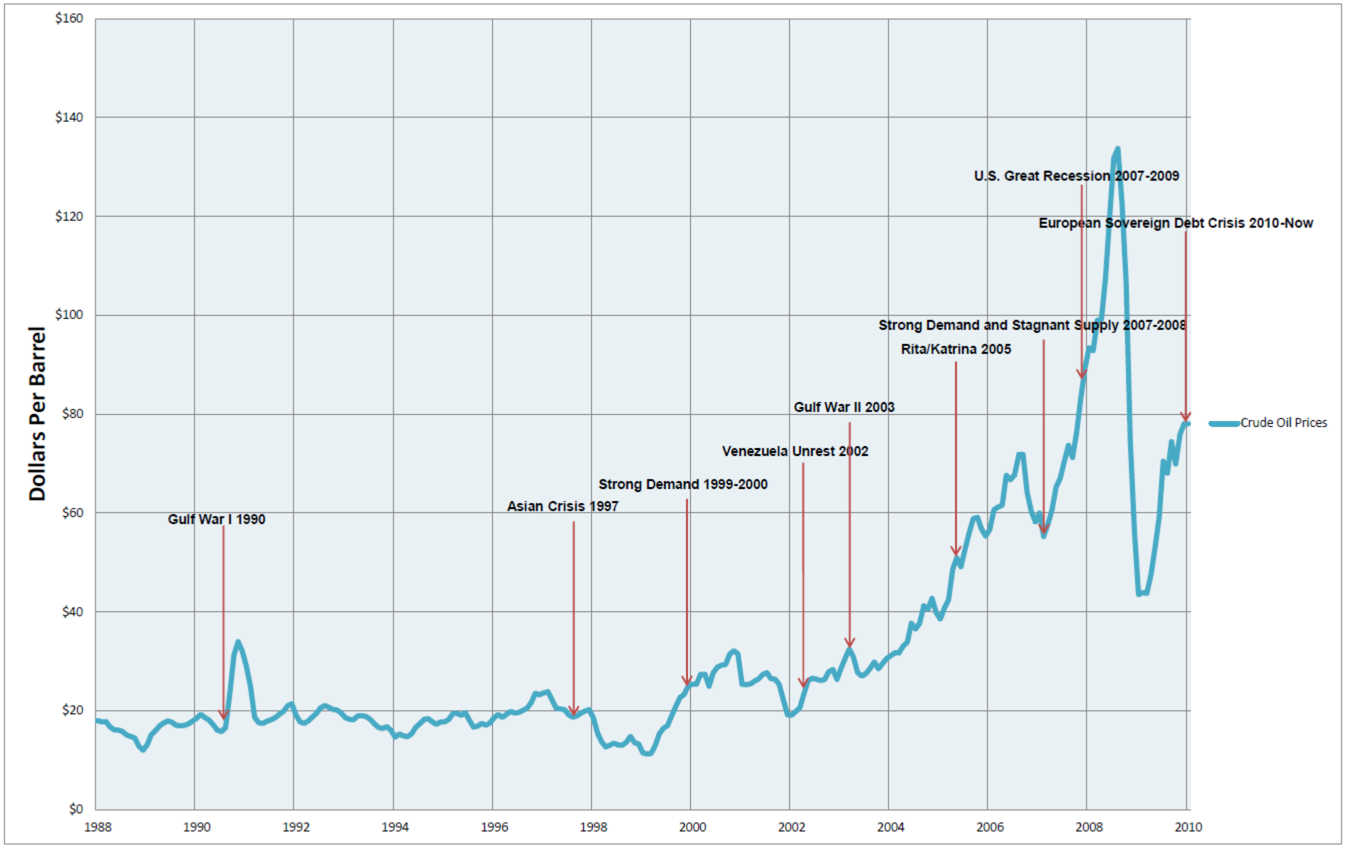
Table 5. Tests of the impact response of Japan real stock returns and dividend growth

Panel A: The Impact Responses of Real Dividend Growth		
	Wald Test Statistic H_0: $\Psi_{0,j} = \sum_{i=0}^{36} p^i \delta_{ij}, j = 1, 2, 3$	**P-Value**
Oil supply shocks	0.1112	0.7387
Aggregate demand shocks	0.0401	0.8413
Oil-market specific demand shocks	0.8385	0.3598

Panel B: The Impact Responses of Real Stock Returns		
	Wald Test Statistic H_0: $\Psi_{0,j} = -\sum_{i=1}^{36} p^i \psi_{ij}, j = 1, 2, 3$	**P-Value**
Oil supply shocks	7.8261	0.0051
Aggregate demand shocks	11.0202	0.0009
Oil-market specific demand shocks	2.8523	0.0912

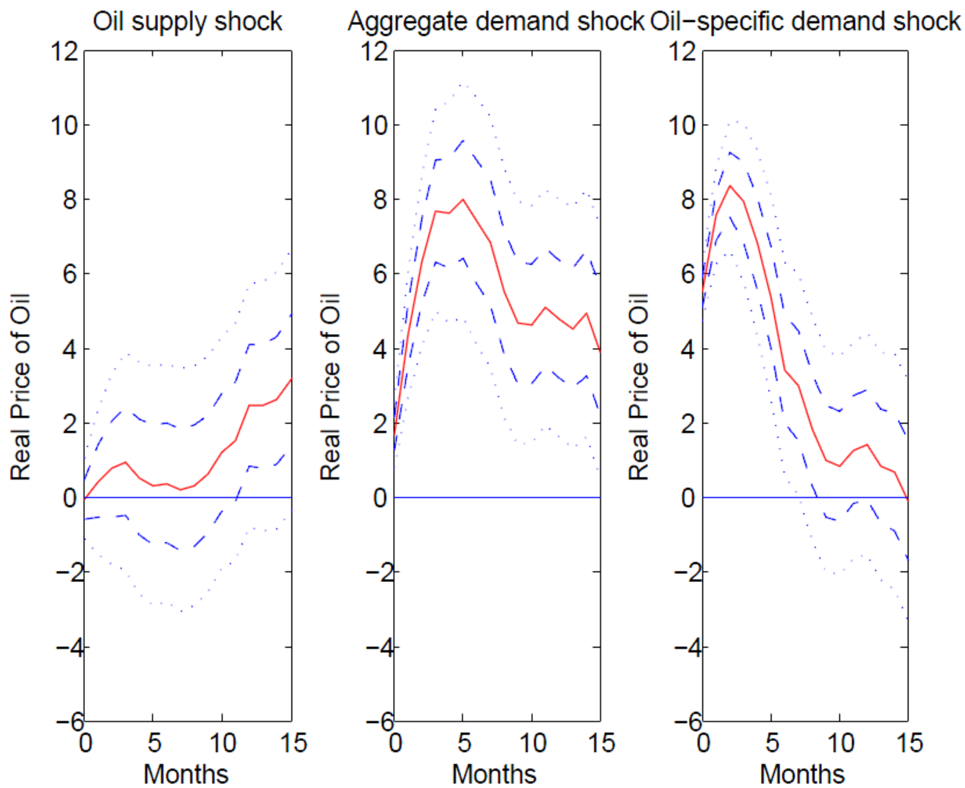
Notes: The Panel A presents the Wald-test statistics and p-values for null hypothesis 'the impact change in real stock returns arising from a given shock of the global crude oil market can be fully attribute to changes in expected real dividend growth'. The Panel B presents the Wald-test results for null hypothesis 'the impact change in real stock returns arising from a given shock from the global crude oil market can be fully attributed to changes in expected returns'. ψ_{ij} denotes the response of real stock returns periods after each oil supply, aggregate demand shock and oil-market specific demand shock, while δ_{ij} denotes the response of real dividend growth to these three shocks.

Figure1. Real price of Japan Crude Cocktail (JCC) from January 1988 to December 2009



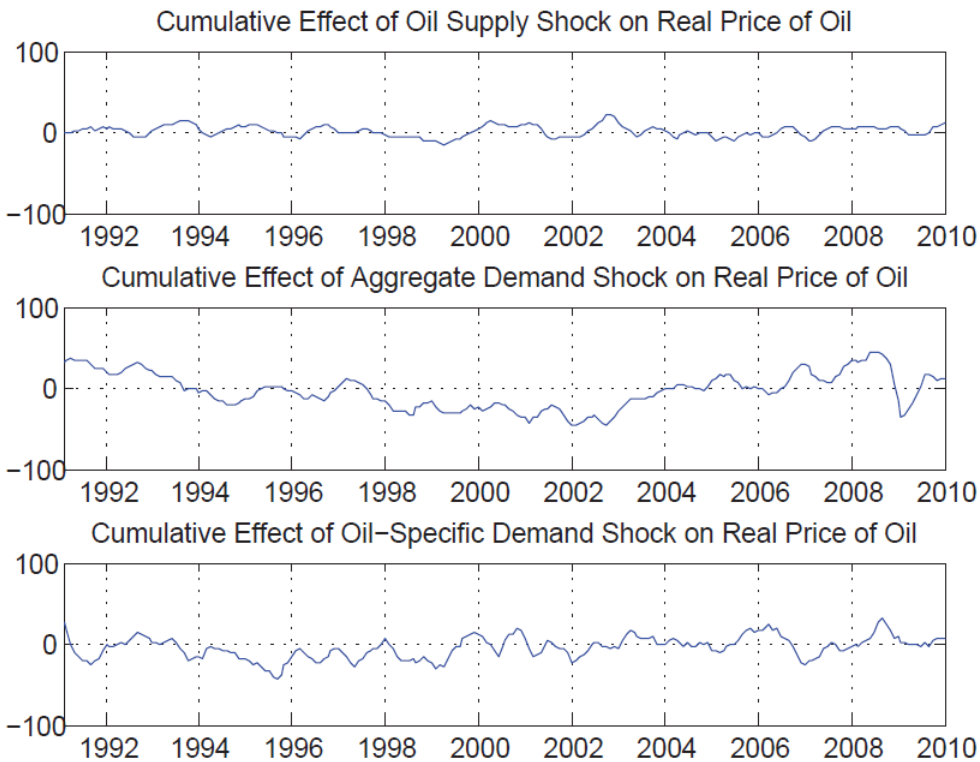
Notes: Figure 1 plots the real oil price imported into Japan. The sample spans the period from January 1988 to December 2009 with x-axis as the year and y-axis as the dollar price.

Figure 2. Cumulative responses of real price of Japan Crude Cocktail (JCC) to three structural shocks with one - and two - standard error bands



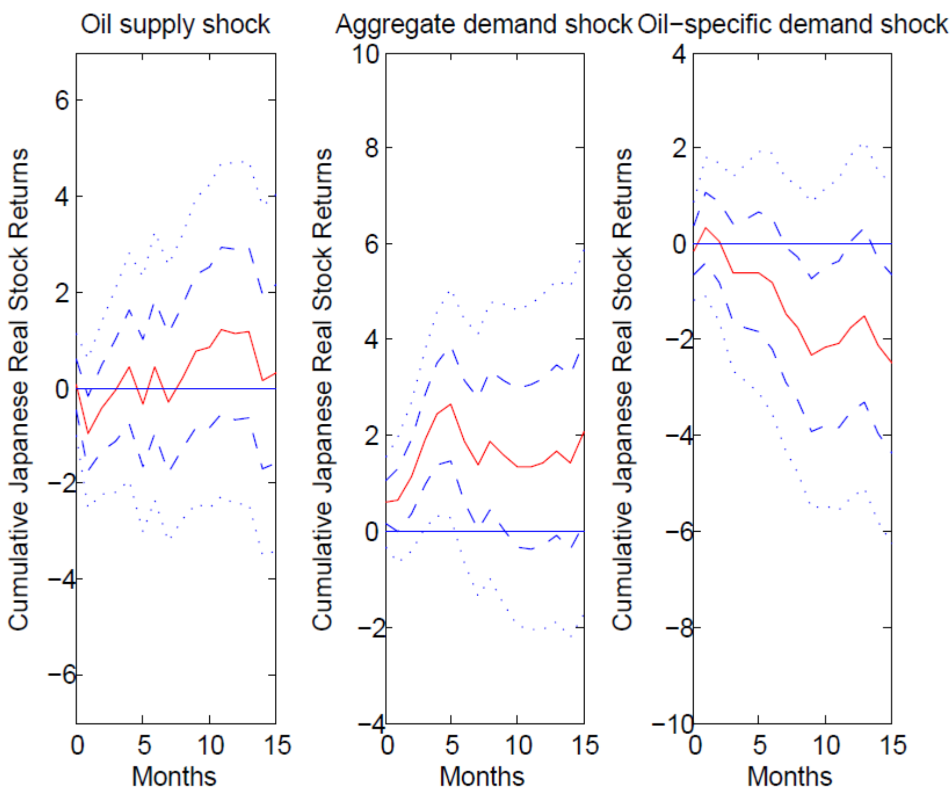
Notes: The three panels in Figure 2 plot the impulse responses of the real price of JCC to each of the three demand and supply shocks that affect the crude oil market. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impact the level of oil price at time $t+s$ for different values of s. Here I limit s to 15 month ahead. All shocks have been normalized to represent an increase in the real price of oil. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 3. Historical decomposition of real price of Japan Crude Cocktail (JCC) from January 1988 to December 2009



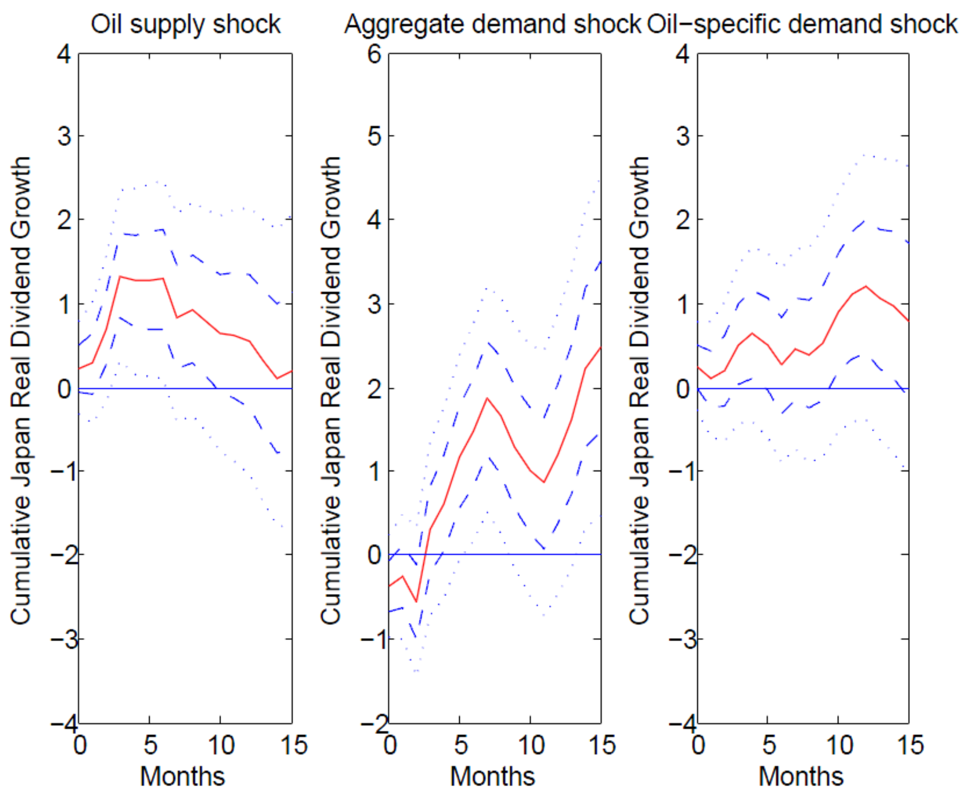
Notes: This figure plots the historical decomposition of fluctuations in the real price of JCC. It shows the cumulative effect of a sequence of structure shocks that affect the real JCC prices spanning the period from January 1988 to December 2009. The estimates are based on the structural VAR model in Eq.1.

Figure 4. Cumulative responses of Japanese real stock returns to three structural shocks with one-and two-standard error bands



Notes: The three panels in Figure 4 plot the cumulative impulse responses of Japanese real stock returns to each of the three demand and supply shocks that affect the crude oil market. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impact the Japanese real stock returns at time $t+s$ for different values of s. Here I limit s to 15 month ahead. The oil supply shock has been normalized to represent a negative one standard deviation shock, while the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shock. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 5. Cumulative responses of Japanese real dividend growth to three structural shocks with one-and two-standard error bands



Notes: The three panels in Figure 4 plot the cumulative impulse responses of Japanese real dividend growth to each of the three demand and supply shocks that affect the crude oil market. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impact the Japanese real dividend growth at time $t + s$ for different values of s. Here I limit s to 15 month ahead. The oil supply shock has been normalized to represent a negative one standard deviation shock, while the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shock. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Chapter 3

Oil Price Shocks and Stock Markets: How Robust Are Results Based on Structural VARs?

3.1 Introduction

The crude oil market is the largest commodity market in the world and total world consumption was 87 million barrels per day in 2010.[1] Crude oil is an important source of energy and any changes in its price are of major concern to governments and private business, as large fluctuations in the price of oil adversely affect the oil importing economies. Specifically, following oil price shocks in the 1970s, oil price movements are considered to be a main source of fluctuation in macroeconomic aggregates. For example, Hamilton (2009b) finds that 10 out of the 11 post-war U.S. recessions were preceded by a sharp increase in the price of crude oil. Oil price increases alone are not a sufficient condition to cause a recession but they affect many aspects of the economy through various transmission channels, such as supply side, demand side and monetary policy (Hamilton, 2003; Kilian, 2009).

There is considerable literature studying the relationship between oil price shocks and the stock market (Jones and Kaul, 1996; Sadorsky, 1999; Park

[1] BP Statistical Review of World Energy June 2011, bp.com/statisticalreview

and Ratti, 2008;). However, pervious literature suffers from two limitations. First, the oil price is often treated as exogenous with respect to the economy. Second, these studies assess the impact of higher oil prices without considering the underlying causes of the oil price increase. Kilian and Park (2009) propose a structural vector autoregression (VAR) model for the global crude oil market and its interaction with the U.S. stock market. Using a structural VAR can control the reverse causality between oil price and stock returns. Further, it can also identify three different shocks to the crude oil market: shock to the global supply of crude oil, shock to the global demand for all industry commodities, and oil-market specific demand shock. Their results suggest that the real price of oil as well as the stock market respond differently to the different causes of the oil price increase.

The purpose of this paper is to test the robustness of structural VAR and to investigate the impact of oil price shocks on the different U.S. stock indices using alternate data. The same methodology is applied in this chapter as in Chapter 2. The difference is that chapter 2 specifically tests the effect of oil price shocks on the Japanese stock market using structural VAR to capture the dynamic relationship, which has not been done before. In this paper, the purpose is to test how robustness the relationship between oil price shocks and U.S. stock markets. Kilian and Park (2009) show that the response of U.S. value-weighted stock indices to oil shocks depends greatly on the different underlying causes of increased prices. I use five different stock indices and two economic indices to conduct a robustness check of these results. More importantly, how firm size affects this relationship are examined and is the main contribution of this paper. The indices are classified as either large firms or small firms. The same model is applied to large-sized and small-sized firms and see if the relationship between oil price shocks and stock market is affected.

I find, in line with Kilian and Park (2009), that the responses of real stock returns of alternate stock indices differ substantially depending on the underlying cause of the oil price increase. For instance, the effect of oil supply shock on U.S. stock returns is statistically insignificant, but an unexpected increase in the global demand for industrial commodities driven by increased global real economic activity will cause a sustained increase in U.S. stock returns. However the magnitude and length of the effect depends on the firm size. The results for an increase in the precautionary demand for oil are a bit mixed. For large firms, it causes persistently negative stock returns. For small firms, it does not have any significant effect. Overall, oil supply and demand shocks combined account for 42% of the long-run variation in U.S. real stock returns, compared with 22% for value-weighted stock returns in Kilian and Park (2009). The response of U.S. stock returns to shocks in oil markets can be attributed to the changes in expected discount rates and changes in expected cash flows, which is in line with Kilian and Park (2009).

The rest of the paper is organized as follows. Section 2 reviews the literature studying the relationship on the oil price and stock market, providing the background for my study. Section 3 introduces the structural vector autoregressive methodology and discusses the identification assumptions and other tests available for structural VAR (SVAR). I also describe the data in this section. Section 4 presents the empirical results and discusses the implication of these results. Finally, Section 5 summarizes and concludes. Appendix 3A provides a summary of the literature studying the relationships of oil price shocks and stock markets.

3.2 Background and Prior Research

3.2.1 Oil Shocks and Stock Returns

Given the importance of crude oil to the world economy, oil price shocks are often considered to have an important effect on the financial markets. For example, Jinjarak (2008) points out that studying the reaction of asset prices to oil price shocks helps to understand whether such price shocks are a major source of fluctuations in the economy. Beaudry and Portier (2004) support this view and provide evidence that stock prices could capture future technological opportunities that affect productivity with substantial delay. Huang, Masulis and Stoll (1996) show the theoretical linkage between oil and stock price.

From the theory of the discounted cash flow method, stock prices are expected future cash flows discounted at a certain rate:

$$P = \frac{E(CF)}{1+R_t}$$

where P is the stock price, CF is the future flow, R_t is the discount rate, and $E(\cdot)$ is the expectation operator. Thus, stock returns are determined both by the expected cash flows and discount rates. We can use this model to understand how oil price changes affect stock prices. For example, oil price shocks have an impact on both expected cash flow and future discount rate. Rising oil prices affect the production cost, which in turn affects the firm's cash flow. But whether this is a positive or negative effect depends on the individual industry, i.e., whether it is an oil-producing industry or an oil-consuming industry. Further, oil price changes affect the discount rate via changes in both expected inflation and the expected real interest rate. For oil-importing countries like the U.S., rising oil price negatively affects the balance of payment, puts downward pressure on the U.S. dollar exchange rate, and then eventually induces inflationary pressures, which may trigger interest rate increases by the central bank. Thus the expected return of the stock increases, which leads to a negative effect on stock returns. Overall, the effect of oil shocks on stock markets are determined by the net effect of oil shocks on changes in expected cash flows and the expected discount rate.

3.2.2 Previous Studies on Oil Price Shocks and Stock Markets

Although considerable research has been carried out to study the relationship between oil price shocks and financial markets, the results are mixed. In the early studies, Kling (1985) reports declining stock prices after shocks in the crude oil prices. However, in some industries oil price shocks have a significant lagged effect on the stock price, which is not consistent with an informationally efficient market. Chen, Roll and Ross (1986) include oil price changes as an economic state variable and systematic factors that influence stock market returns and pricing to address the effect of oil prices on asset pricing. They conclude that, although inclusion of oil price changes reduces the significance of industrial production and increases that of risk premium and term structure, there is no clear relationship between oil price changes and asset pricing. Jones and Kaul (1996) test the reaction of international stock markets to oil price shocks from the perspective of current and future changes in real cash flows and/or changes in expected returns with the postwar quarterly data. Their results suggest that the effect on the U.S. and Canadian stock market of the crude oil price shocks can be completely accounted for by the current and expected future cash flow alone, which indicates that these two stock markets are rationally pricing these shocks. In contrast, U.K. and Japanese stock markets are more volatile than can be explained by a rational model. Jones and Kaul (1996) suggest that oil shocks appear to induce volatility in these two markets. Huang, Masulis and Stoll (1996) examine both the contemporaneous and lead–lag correlation between NYMEX daily returns of oil futures contracts and U.S. stock returns for the period 1979–1983. They find no relationship between stock market returns and oil futures returns, even contemporaneously. The only exceptions are the petroleum stock index and three individual oil stocks where oil futures returns lead by one day. Sadorsky (1999) uses monthly oil price data and applies a VAR model to study the dynamic effect of oil price shocks. He shows that oil price shocks have asymmetric effects on the stock market and this dynamics has been changing over time by comparing the forecast errors of stock returns for two sub-periods. He concludes that oil price movements are important in explaining U.S. stock return movements for the period 1947–1996.

Several studies focus on the effect of oil price shocks on multi-national stock markets. For example, Faff and Brailsford (1999) investigate the sensitivity of Australian industry equity returns to oil price changes and find oil price changes have an important impact on the costs of many firms. Papapetrou (2001) shows that oil prices changes are important in explaining Greek stock price movements and oil price increases reduce the real stock returns. Basher and Sadorsky (2006) contribute to the literature by studying the impact of oil price shocks on 21 emerging stock markets and the Morgan Stanley Capital International (MSCI) world index using daily, weekly and monthly data. They find strong evidence that oil price shocks play a significant role in emerging market stock returns under both unconditional and conditional risk analysis. Park and Ratti (2008) examine the effect of oil price shocks and oil price volatility on the real stock returns of the U.S. and 13 European countries for the period 1986–2005. They find that oil price shocks have a significant impact on the stock returns, especially for the U.S. Driesprong, Jacobsen and Maat (2008) find that changes in oil price predict stock market returns for 12 out of 18 countries and the world market index. This predictability is stronger for developed markets than for emerging markets. They find that a rise in oil prices leads to lower returns, due to underreaction of investors to information in the price of oil. Mohanty et al. (2011) study the link between oil price shocks and stock prices in the Gulf Cooperation Council (GCC) countries and analyze the impact on both the country and industry level. They find that, on the country level, except for Kuwait, there is a positive relationship between oil price shocks and the stock market, while on the industry level, 12 out of 20 industries react positively to the oil price shocks.

All of these studies apply regression based methodology that fails to control the reverse causality between oil price and stock returns and ignores the different underlying causes of oil price increase.[2]

3.2.3 Structural VARs

SVARs are widely used to capture the dynamic relationships among economic variables of interest. Each variable in the SVAR is a linear function of its own lagged value and the lagged value of some other variables. The main advantage of SVARs is the convenience of incorporating the economic theory into the system through the identifying assumptions.

In an important study Kilian and Park (2009) analyze the relationship between oil price shocks and the stock market and address two limitations in existing work. The first is that the price of oil is often treated as exogenous with respect to the economy. In fact, it is widely accepted that the oil price and stock markets respond to the same economic forces. The cause and effect are not well defined in the previous literature when testing the relationship between oil price shocks and the macroeconomy This is because when evaluating the response of the macroeconomy to oil price shocks, the implication is that all other variables are held equal. In fact, in the real world, other factors, such as economic expansion, existing inflation, and changes in the exchange rates and interest rates, could increase or decrease the effect of oil price shocks on stock markets.

The second limitation in existing studies is that they ignore the underlying causes of the oil price changes. Without knowing what drives oil price shocks, it is not possible to predict the effect of higher oil prices. Kilian and Park address this question in detail by separating three underlying causes of the oil price increase; an oil supply shock, a shock to the global demand for all industrial commodities (an aggregate demand shock) and an oil-market specific shock (a precautionary demand shock). The identification helps not only to explain the fluctuation in the oil price but also benefits macro-

[2] Park and Ratti (2008) use an unrestricted VAR model, which treats all the variables including oil price as exogenous. However, the unrestricted VAR model fails to incorporate any economic theory and treats each variable equally and mechanically.

economic policy making. They find that the U.S. stock market responds differently to three different kinds of shock. They find a negative relationship between stock price and oil price only when the price increase is caused by oil-market specific demand shocks. In contrast, positive shocks to the global demand for industrial commodities cause both higher real oil prices and higher stock price. Oil supply side shocks have no significant effect on stock returns.

3.2.4 Oil shocks and the Macroeconomy

The crude oil market is the largest commodity market in the world. The 2011 Statistical Review of World Energy from British Petroleum reports that the total world consumption is around 87.4 million barrels a day, of which United States consumes approximately 22%.[3] Moreover, petroleum is the major source of U.S. primary energy, and it accounted for about 37% of the country's overall energy consumption in 2009.[4] Thus, oil price shocks have received considerable attention from both the financial press and the academic literature.

Oil prices could affect the economy from both supply and demand sides. A higher oil price affects the supply side because oil is a part of inputs, and make the production of goods more costly for firms. This can be in the form of transportation costs, heating bills or even raw input. Oil price shocks also introduce greater uncertainty faced by firms, which may cause them to postpone their investments. Since the energy demand is inelastic, higher oil price means greater spending on energy-related products and less on the other goods, which eventually drives down the discretionary income. Households, like firms, are also affected by the uncertainty caused by oil price shocks, which leads to delayed purchases of certain goods and increases in precautionary saving. In addition, oil price increase may also cause the

[3] BP Statistical Review of World Energy June 2011, bp.com/statisticalreview
[4] U.S. Energy Information Administration, http://www.eia.gov/totalenergy/data/annual/pecss_diagram.cfm

reallocation of labor and capital between oil-intensive industries and less oil-intensive ones. Take the transportation equipment industry as an example, when oil price increases, the capital and labor will flow out of this industry and into others in the economy. This could cause a negative output shock in the short run because of the unemployment.

Putting all these channels together, even though the energy expenditure as a proportion of GDP in U.S. is decreasing, it is plausible that an oil price increase could lead to an economic recession. Hamilton (2008 and 2009b) points out that, after World War II, 10 of 11 recessions in U.S. were preceded by a significant oil price increase. In addition, oil prices are also proven to have an effect on many aspects of the economy. Barsky and Kilian (2004) provide evidence of the link between oil price increases and productivity slowdown. Moreover, they show that inflations have also been affected by oil price shocks historically. Gisser and Goodwin (1986) find that crude oil prices have a significant impact on the employment rate. Blanchard and Gali (2007) find that the effect of price of oil on the economy has changed substantially over time. They argue that, in the last decade, although the global economy experienced two oil shocks as great as those in the 1970s, regardless of the sign and magnitude, the GDP growth and inflation remains relatively stable in most industrialized economies. They attribute these changes to several hypotheses, such as decreasing real wage rigidities, more responsible monetary policy, and declining share of oil in the economy. They conclude that the price of oil and other adverse shocks worked together for the stagflation episodes of the 1970s.

3.2.5 Changing relationship between Oil Shocks and Economy

Recent work focuses on the possible changes in the effects of oil price over time. Blanchard and Gali (2007) argue that the relationship between oil price shock and economic consequence is changing over time and conclude that oil shocks that made a relatively modest contribution to the downturns of the 1970s are even less important today. Hamilton (2009a) argues that the dynamic effect of oil prices has decreased considerably over time although the oil shocks have stay the same. Hooker (2002) finds that, before 1980, oil price shocks contribute substantial pass-through to core inflation while after 1980 oil price shocks only affect the inflation through their direct share in a price index. The change in the reaction of monetary policy to oil shocks could be part of the explanation. Driesprong, Jacobsen and Maat (2008) find declining pass-through from the price of oil to the price level in 34 countries and indicate that the possible explanations are a reduction in the oil intensity economies, a reduction in the exchange rate pass-through, a more favorable inflation environment and demand-pushed oil price.

Hamilton (2009b) argues that the doubled price of oil between June 2007 and June 2008, which is a greater price increase than any previous events in history, is an important factor in the economic recession that happened in the U.S. in the last quarter of 2007. He mentions that, unlike previous episodes, the increased oil price in 2007–2008 results from different factors. First, world oil production declined slightly between 2005 and 2007, due to the production decline from mature oil fields and political instability. Second, because of the economy boom in developing countries, such as China, the demand for oil consistently increases. The economy responses to oil price shocks in 2007 and 2008 were quite similar to previous episodes, with decreases in auto sales and the production of motor vehicles and parts. However, Hamilton indicates that, although the gasoline price could be a possible explanation for the decreased sales of U.S. automobiles in the first half of 2009, falling income is the biggest factor driving sales back down in the fourth quarter of 2008. Moreover, the 2007–2008 shock is similar to 1990–1991, from the aspect of negatively affecting employment in the automobile industry. At the same time, consumer sentiment was deteriorating and consumer spending was slowing down. Moreover, there is also a relationship between oil price shocks and problems in housing. Since oil price shocks make a direct contribution to lower income and higher unemployment, this would depress housing demand.

3.2.6 Hypothesis

This paper uses a structural VAR model introduced by Kilian and Park (2009) and measures the response of different U.S. stock indices to demand and supply shocks in the global oil market. The purpose of this paper is to test the robustness of Kilian and Park's results with alternate stock market variables and different indices of real economic activities. However, the effect of firm size in this study has not been examined before. I classify the 6 stock market indices used in this paper into two groups: large firms and small firms, to test if the responses of small firms to the oil prices shocks are different from that of large firms.

Since all the stock market indices are still from U.S. and the stock returns exhibit very strong correlation in Table 1.1, I would expect the results for different stock indices are similar. However, the individual supply or demand shock may have different effect on large and small firms. That is because large firms are usually distributed in oil-intensive industry, which suffer more when facing oil price shocks. Small firms are experiencing greater volatility to economy expansion in the short run. Similarly, the different indices for real economic activities would have similar results as Kilian and Park (2009) since all three indices used here are derived from shipping rates rather than value-added measures.

3.3 Econometric Methodology

3.3.1 Regression-Based Methods

Jones and Kaul (1992) provide a basic foundation for using regression-based methodology to study the effects of oil shocks on the stock market. Their model is motivated by Campbell (1991), which states that stock returns change over time due to changes in expected returns and current and future expected cash flows. In order to test whether the stock prices overreact to new information from the oil price shocks, the regression is estimated as

$$R_t = \alpha + \sum_{i=1}^{5} a_{1s} X_{it} + \sum_{s=0}^{4} \beta_s OIL_{t-s} + \sum_{s=0}^{4} \gamma_s IP_{t+s} + \eta_t$$

Where R_t is the stock returns, X_{it} is a proxy for expected returns and cash flows, OIL_t is the percentage change of oil price in period t, IP_t is the growth rate of industrial production.

3.3.2 Structural VAR

In this paper, I follow Kilian and Park (2009) and use an SVAR model that relates U.S. stock market variables to measures of demand and supply shocks in the global oil market. The methodology used here is similar to chapter 2.

When we are not confident whether a variable is actually exogenous, an easy way is to treat each variable symmetrically. The SVAR is presented as follows:

$$A_0 z_t = \alpha + \sum_{i=1}^{24} A_i z_{t-i} + \varepsilon_t \qquad (1)$$

where $z_t = [\Delta global\ crude\ oil\ producion, global\ economy\ activity, oil\ price, stock\ returns]'$. The model allows for up to two years worth of lags. The optimal lag number based on Akaike information criterion is 4. However, 4 months are not enough to capture the dynamic effect of oil price shocks on the stock market. Firms need time to adjust production and strategy when facing oil price fluctuations. Hamilton and Herrera (2004) offer evidence in favour of a longer lag length and conclude that for monthly data 12 lags is preferred for studies about the relationship between oil price shocks and economy. Kilian and Park (2009) use 24 lags in their study for the U.S. market and find that impulse responses are still significant after 15 months. Thus in this paper I use 24 lags for my main model.

Take the first line of VAR as example, Eq.1 means we let the time path of changes in global crude oil production be affected by current and past realization of global economy activity, oil price, and stock returns. The contemporaneous terms in the LHS incorporates feedback because the elements of z_t are allowed to affect each other.

In the reduced form,

$$z_t = \beta + \sum_{i=1}^{24} B_i z_{t-i} + e_t, \tag{2}$$

where $\beta = A_0^{-1}\alpha, B_i = A_0^{-1}A_i, e_t = A_0^{-1}\varepsilon_t$.

The error terms e_t are correlated with each other while the structure shocks ε_t are white noise with zero covariance terms, which means that any of the structure shocks are from an independent source. There is no contemporaneous term on LHS in Eq.2. However, what we are interested in are the coefficients in Eq.1, which need to be calculated from Eq.2. It is not a easy job to do so because the VAR is usually not fully-identified. The number of unknown coefficients in Eq.1 is higher than that of the equations built on the relationship between Eq.1 and Eq.2, so we need to impose restriction on the coefficients of the contemporaneous terms, which form matrix A_0 in Eq.1.

3.3.3 Identifying Assumptions

Traditional VAR and Cholesky Decomposition

The traditional VAR approach has been criticized as lacking any economic content. The only role that needs to be decided by researchers is to suggest the appropriate variables to include in the VAR and all the variables are treated symmetrically. After that, the procedure is almost mechanical. If there is little economic content in the input, we could expect little economic content in the results. Thus there is the possibility that the VAR approach could lead to spurious relations by mining the data. It is often not clear how to interpret the coefficients estimated from VAR.

To identify the VAR model, the most popular restriction is the Cholesky factorization. The Cholesky decomposition makes a strong assumption about the underlying structural errors using the lower triangular matrix. However, the test results depend on the ordering of the variables in the VAR. Cooley and Leroy (1985) criticize Cholesky decomposition since the recursive contemporaneous structure is not consistent with economic theory.

Just as an autoregression has a moving average representation, a VAR can be written as a vector moving average (VMA). So from Eq.2, we get

$$z_t = X_t\beta + \sum_{i=0}^{\infty} \Psi_i e_{t-i} \tag{3}$$

where z_t is a 4-variate stochastic process, $X_t\beta$ is the deterministic part of z_t, e_t is a 4-variate white noise process. The impulse responses, variance decomposition and history decomposition are all based on the moving average representation of a vector time series.

There are many equivalent representations for this model, for any nonsingular matrix G, ψ_i can be replaced by $\psi_i G$ and e by $G^{-1}e$. The most frequently used method is Cholesky factorization (Lutkepohl 1991). Suppose $\Sigma = E(e_t e_t^{'})$, if we choose any matrix G so that $G^{-1}\Sigma G^{-1^{'}} = I$, then the new innovations, $\varepsilon_t = G^{-1}e_t$, satisfy $E(\varepsilon_t \varepsilon_t^{'}) = I$. These orthogonalized innovations have the convenient property that they are uncorrelated both across time and across equations. Such a matrix G can be any solution of $GG^{'} = \Sigma$.

Different Identifying Assumptions in SVAR

The VAR methodology is criticized by Cooley and Leroy (1985) by using atheorectical restriction. They argue that a VAR model identified by Cholesky factorization does not use theory and thus cannot be interpreted as a structural model, because different ordering or different lag length could have different results.

In the previous literature, alternative ways have been proposed for looking at the factorization problem, which impose more of an economic structure. The aim of an SVAR is to use economic theory rather than Cholesky decomposition to recover the structural innovations ε_t from the residual e_t.

Bernanke (1986) and Blanchard and Watson (1986) introduce a short-run identification, which assumes the shocks have temporary effects based on contemporaneous restriction. For many problems, this identification is simple zero exclusion restriction.

Since economic theory often does not provide sufficient contemporaneous restrictions, Shapiro and Watson (1988) propose an additional identification method based on restrictions on the long-run properties of economic theory. They consider the shocks to have permanent effects. Blanchard and Quah (1989) introduce another long-term restriction to identify a SVAR model where some variables are stationary and some have unit roots. The shocks can have either a temporary or a permanent effect on the system, and all the shocks are treated like exogenous variables.

The above short-run and long-run restrictions are all parametric restrictions. Recently, another method, which employs sign restriction on impulse response, has received increasing interest from researchers(Faust, 1998; Uhlig, 2005). Fry and Pagan (2010) state that whether one should use parametric restrictions or sign restrictions is mainly determined by the research questions. Since the sign information is weak, it is better to use sign restrictions with a combination of other parametric ones. Moreover, contemporaneous restriction might be useful to impose restrictions on longer lags.

Identifying Assumption used in this Paper

In this paper, I use the recursive short-run restriction suggested by Kilian and Park (2009). The variables in Eq.1 are ordered from most exogenous to most endogenous. The restriction of $a_{i,j} = 0$ means that the response of the i-th variable to the j-th structural shock is zero in the short run:

$$e_t = \begin{pmatrix} e_{1t}^{\Delta global\ oil\ production} \\ e_{2t}^{global\ economy} \\ e_{3t}^{oil\ price} \\ e_{4t}^{stock\ returns} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}^{oil\ \sup ply\ shock} \\ \varepsilon_{2t}^{aggregate\ demand\ shock} \\ \varepsilon_{3t}^{oil-specific\ demand\ shock} \\ \varepsilon_{4t}^{other\ shocks\ to\ stock\ returns} \end{pmatrix} \tag{4}$$

These assumptions originate from the following intuition based on Kilian (2009). First, we assume that, in the short run, global oil supply is rigid because the costs of adjusting oil production are expensive. Hence the crude oil supply cannot respond to changes in demand either driven by the world economy or oil-market specific demand in the short run. Second, if the oil price increases because of increasing demands in the oil market, global economic activity will respond with a delay. This is because oil is an input of production; factories cannot change their production line to a more energy-efficient one in a short time, if oil price has been increased. Third, the change in either world economy demand or the oil market specific demand will result in an instantaneous change in the real price of oil. As a result, shocks to the real price of oil that cannot be explained by oil supply shock and shocks to global demand for industrial commodities can be explained as demand shocks that are specific to the oil market. Oil market specific shock mainly reflects the change of precautionary demand for oil when people are uncertain about future oil supply. Fourth, the oil production, global real activity and the price of oil are treated as predetermined with respect to U.S. real stock returns, which affect these three shocks, but with a delay of at least one month.

In this study, I first estimate the reduced form VAR model by the least-squares method; the resulting estimates are then used to construct the structural VAR representation of the model. Inference is based on a recursive-design wild bootstrap with 2,000 replications (Goncalves and Kilian, 2004).

Wild bootstrap is a model-based resampling technique designed to provide refinement for the linear regression with heteroscedasticity. It is based on the symmetry of the probability distribution function of the residuals. Wild bootstrap has a lower asymptotic risk as an estimator of the true distribution than a normal approximation.

3.3.4 Tests of VAR

The aim of SVAR is to determine the dynamic response of variables to different shocks from the economy. So this methodology does not focus on the analysis of the coefficient from the regression, but the analysis of disturbances.

Impulse Response

Impulse response analysis is used to uncover the dynamic relationship between variables within VAR models. Impulse responses measure the response of $z_{i,t+s}$ to a one-time impulse in $z_{j,t}$ with all other variables at time t or before remaining constant. By imposing restriction on the parameters in the VAR, the shocks can be attributed an economic meaning.

Start form the vector moving average VAR,

$$z_t = X_t\beta + \sum_{i=0}^{\infty} \Psi_i e_{t-i} = X_t\beta + \sum_{i=0}^{\infty} \Psi_i G\varepsilon_{t-i} \qquad (5)$$

The error in the K-step ahead forecast of z_t is $\sum_{i=0}^{K-1} \Psi_i G e_{t-i}$. (6)

The covariance matrix of the K-step forecast is $\sum_{i=0}^{K-1} \Psi_i G G' \Psi_i'$. (7)

Since $GG' = \Sigma$, we can isolate the effect of a single component of ε by rewriting the sum as

$$\sum_{i=0}^{K-1} \sum_{s=0}^{N} \Psi_i G e(s) e(s)' G' \Psi_i' = \sum_{s=0}^{N} \sum_{i=0}^{K-1} \Psi_i G e(s) e(s)' G' \Psi_i' \qquad (8)$$

where $e(s)$ is the s-th unit vector.

This decomposes the variance–covariance matrix of forecast errors into N-terms, each of which shows the contribution of a component of ε over the K-period.

Variance Decomposition

The variance decomposition tells us the proportion of the movements in a time series due to its own shocks and shocks to other variables. In this paper, it quantifies how important $\varepsilon_{1,}$ ε_2, ε_3 have been on average for ε_4.

As we know the K-period forecast error from Eq.5, denote the K-period forecast variance of z_{t4} as $\sigma_{z4}(K)^2$, then

$$\begin{aligned}\sigma_{z4}(K)^2 =& \sigma_{z1}[\phi_{11}(0)^2+\phi_{11}(1)^2+...+\phi_{11}(K-1)^2] \\ &+\sigma_{z2}[\phi_{12}(0)^2+\phi_{12}(1)^2+...+\phi_{12}(K-1)^2] \\ &+\sigma_{z3}[\phi_{13}(0)^2+\phi_{13}(1)^2+...+\phi_{13}(K-1)^2] \end{aligned} \tag{9}$$

Thus, the proportion of $\sigma_{z4}(K)^2$ due to shocks in the ε_1, ε_2, ε_3 is

$$\frac{\sigma_{z1}[\phi_{11}(0)^2+\phi_{11}(1)^2+...+\phi_{11}(K-1)^2]}{\sigma_{z4}(K)^2},$$
$$\frac{\sigma_{z2}[\phi_{12}(0)^2+\phi_{12}(1)^2+...+\phi_{12}(K-1)^2]}{\sigma_{z4}(K)^2},$$
$$\frac{\sigma_{z3}[\phi_{13}(0)^2+\phi_{13}(1)^2+...+\phi_{13}(K-1)^2]}{\sigma_{z4}(K)^2} \quad (10)$$

Historical Decomposition

Historical decomposition decomposes the historical values of the time series data into different projections and shows the accumulated effects of current and past shocks to this data.

Start form the vector moving average VAR,

$$z_{t+j}= X_t\beta+\sum_{i=0}^{\infty}\Psi_i e_{t-i}= X_t\beta+\sum_{i=0}^{\infty}\Psi_i G\varepsilon_{t-i} =\sum_{i=0}^{j-1}\Psi_i\varepsilon_{t+j-i}+[X_{t+j}\beta+\sum_{i=j}^{\infty}\Psi_i G\varepsilon_{t+j-i}] \tag{11}$$

The first sum represents that part of z_{t+j} due to shocks in periods $t+1$ to $t+j$. The second part is the forecast of z_{t+j} based on information available at time t.

3.3.5 Data Set Description

I now provide a brief description on my data used in the empirical analysis. All data used in this paper are monthly and the sample period starts from January 1973 and ends in December 2009. The statistical summary is provided in Table 1.1.

Price of Oil

The nominal oil price is obtained based on the refiner acquisition cost of imported crude oil that is available on the U.S. Department of Energy from 1974 to 2009, and extended backward to 1973 as in Barsky and Kilian (2002). Oil price is then deflated using the U.S. CPI obtained from the website of the Bureau of Labor Statistics and expressed based on January 1981 dollars. In chapter 2, the oil price is measured by the Japan Crude Cocktail which is the oil price imported to Japan. Both oil prices are used to capture the real acquisition cost of refiners.

As plotted in Figures 1.1 and 1.2, we can locate several major events in the oil market. The Yom Kippur War and Arab oil embargo from 1973–1974 caused an increase in the real price of oil. The Iran-Iraq War from 1980 to 1988 caused a more significant jump in the real price of oil. On the demand side, the Asian crisis spanning from 1997 to 1998 led to a sharp drop in the real price of oil. In recent years, the oil price surge between 2003 and 2008 was mainly driven by economic boom around the world, especially unexpectedly high growth in emerging Asia. The main objective of the paper will be to check the robustness of SVARs, which estimate the impact of oil price shock on the U.S. stock market from the various demand and supply shocks of the real price of oil. I will relate the real price of oil to the additional data described below.

Global Oil Production

The monthly global oil production is obtained from the U.S. Department of Energy. I construct the percent change in global production and express it as the annualized percentage change. The changes in global oil production are a good measure of oil supply shocks, which not only reflect the exogenous cartel activities and political struggle among OPEC countries, but also reflect the endogenous response of both OPEC and non-OPEC countries to the fluctuations in the real price of oil (Kilian 2009).

Global Real Economic Activity

Although conventional wisdom suggests that major increases in the price of oil tend to be driven by exogenous political events in the Middle East, if there are no other factors affecting oil price, we would not be able to explain certain price increases in history, such as in 1999/2000, in the absence of any military conflicts in the Middle East. Barsky and Kilian (2004) indicate that exogenous political events, such as cartel activities, wars and embargoes, could indirectly affect the global macroeconomic conditions. Moreover, macroeconomic conditions also affect oil price directly by simply shifting the demand for oil. Barsky and Kilian (2002) point out that the sharp increases in oil price in the 1970s were caused by macroeconomic forces, ultimately by worldwide monetary expansions. Hamilton (2009b) proves that the upward pressure on oil price in 2007–2008 was caused by strong demand confronting stagnating world production. Thus, we also need a measure of global real economic activity because of its effect on the real price of oil.

Kilian and Park (2009) construct an index of global real economic activity using a global index of dry cargo single voyage freight rates, which are not intended as a proxy for global real value added, but rather as a measure of the component of worldwide real activity that is relevant for global industrial commodity markets. They argue that world economic activity is the most important determinant in the demand for transport services. Increases in freight rates may be used as indicators of strong cumulative global demand pressures.

Historical literature has documented a positive correlation between ocean freight rates and economic activity (Isserlis, 1938; Tinbergen, 1959). Klovland (2004) provides evidence that cycles in economic activity are the most important determinants of the demand for transport services and thus short-run behaviour of shipping freight rates. Beverelli, Benamara and Asariotis (2010) argue that economic downturn has a role in suddenly reducing the dry bulk commodity trade.

To carry out the robustness check, there are several empirical proxies available to capture the real economy activity.

1.Dry Cargo Tramp Voyage Shipping Spot Rate (DCTVSSR) This monthly data from January 1970 to February 2009 was mostly collected in UNCTAD's Review of Maritime Transport, various issues.[5] There is a long-term tradition of differentiating the spot voyage charter from the time charter in the related study.

The spot rate is expressed in 1955 dollars per metric ton. I compute the period-to-period growth rates, having normalized January of 1985 to unit. Then I linearly detrend the normalized growth rate to remove the long-run trends in the demand for sea transport rather than the technological advances in ship-building.

2.Baltic Dry Index (BDI) The Baltic Dry Index is a number issued daily by the London-based Baltic Exchange. This index tracks worldwide international shipping prices of various dry bulk cargoes. The BDI index provides an assessment of the price of moving the major raw materials by sea, such as coal, steel, cement and iron ore. Since dry bulk primarily con-

[5] United Nations Conference on Trade and Development.

sists of materials that function as inputs to the production of intermediate or finished goods, it could be seen as one of purest leading indicators of economic activity.

Compared with the DCTVSSR, the BDI is more business-oriented and a latecomer, starting from 1985. However, BDI index is more comprehensive and captures 20 different routes throughout the world and four different sizes of oceangoing dry bulk transport vessel. Bakshi, Panayotovb and Skoulakisc (2011) find that BDI is a great predictor of global stock returns, commodity returns and growth in global economic activity.

Stock Variables

I use an equally-weighted stock index, NASDAQ, S&P 500, large firm portfolio, and small firm portfolio data to carry out the robustness check.

The equally-weighted stock index used here is the Centre for Research in Security Prices (CRSP) equally-weighted market portfolio. Unlike value-weighted stock indices, which have more weight in larger companies and are dominated by a few large stocks, equally-weighted indices simply give each stock an equal weight. An equally-weighted index is more diversified than a value-weighted index, because it is not dominated by large companies. Moreover, investors investing in an equally-weighted index may have higher returns, since small companies generally have a greater growth potential than large companies.

NASDAQ is the largest electronic screen-based equity securities trading market in the U.S., with approximately 3700 companies and the highest trading volume in the world. NASDAQ includes a large number of high technology companies, which cover almost all the new technology industries, such as software, computers, communication, biological technology, retail and wholesale.

S&P 500 is composed of 500 large-cap common stocks actively traded in the U.S. It is the most widely followed index of large-cap U.S. stocks and is considered as a bellwether for the U.S. economy. This index is market-value weighted, in which stocks with higher market capitalization have a greater effect on the index than those with smaller market capitalization.

The large firm portfolio and small firm portfolio are obtain from French's Data library.[6] He constructed 6 U.S. stock portfolios based on size, which include all stocks in NYSE, AMEX and NASDAQ. I use the largest portfolio and the smallest one in this paper.

The real stock return is calculated by subtracting the CPI inflation rate from the log returns of each stock index. The dividend growth rates are constructed from the monthly returns, with $(r(t))$ and without $(r\_0(t))$ dividends, of each stock index (Torous, Valkanov and Yan, 2005). Assuming a \$1 investment in the portfolio at the end of December 1925, $P(0) = 1$, the value of the portfolio at the each of month t, $P(t)$, is constructed according to $P(t) = (1+r\_0(t)) * P(t-1)$. Dividends on the portfolio in month t are given by $((r(t) - r\_0(t)) * P(t-1)$, and by deflating these dividends by the prevailing level of the CPI, we obtain corresponding real monthly dividend payments. The annualize dividend is computed by summing the real monthly dividends for the year preceding month t. The real dividend growth rate is obtained by taking the first difference of real annualized dividend payments.

3.4 Empirical Results and Discussion

3.4.1 Results of Unit Root Tests

Table 1.2 presents the results of the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests for each variable used in this robustness study. The lag length is determined using the Schwarz–Bayes Information Criterion (SBIC). The null hypothesis for ADF and PP is the existence of a unit root $I(1)$, i.e., if the series is stationary $I(0)$, the ADF and PP tests should reject the null hypothesis.

[6] Kenneth R. French's Homepage, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

In contrast, the null hypothesis of the KPSS statistic is that the series is stationary $I(0)$. I use both a constant and a constant with time trend as deterministic terms.

The ADF test (Said and Dickey, 1984) is based on the comparison of calculated statistics. The more negative the test number, the stronger the rejection of the hypothesis that the series has a unit root. The PP test by Phillips and Perron (1998) is different from the ADF test in how it deals with serial correlation and heteroskedasticity in the errors. The KPSS tests introduced by Kwiatkowski, Phillips, Schmidt and Shin (1992) complement the ADF and PP tests by testing both the unit root hypothesis and the stationarity hypothesis.

The conclusions from the ADF test are quite clear: all variables except real oil price are stationary. The results of the SPSS test are in line with the ADF test with the exception that, at both the 5% and 10% significance levels, unit roots cannot be rejected for both the stock return of S&P 500 and the large firm portfolio. Dividend growth rate of the large firm portfolio has a unit root with both the PP and KPSS tests when the deterministic term is the constant with a time trend.

It is worth noting that log real price of oil is not stationary under most of the tests at any critical value. However, this is acceptable for the following reasons. First, economic theory suggests there is a link between cyclical fluctuation of global real activity and the real price of oil (Kilian and Murphy, 2010). If we take the first difference of oil price, it will remove the slow moving component and it will be difficult to find the persistent effect of aggregate demand shocks. This aggregate demand is defined as the demand for industrial commodities including crude oil. Second, even assuming that the real price of oil can be approximately predicted by random walk, it is not clear whether this is a unit root or not. As regards the methodology, the estimated impulse response is robust even if the stationary assumption is violated (Pesavento and Rossi, 2007). The cost of not taking the first difference is a loss of asymptotic efficiency, which leads to a wider error band. However, as long as the impulse responses are reasonably estimated, it is not a concern.

3.4.2 The Short-Run Response of Oil Prices to Oil Shocks

I normalize the oil supply shock to represent one negative percentage shock. The aggregate demand shock and oil-market specific demand shock are also normalized to represent one positive percentage shock. In this way, all three shocks tend to increase the real price of oil. One-standard error and two-standard error bands are indicated by dashed and dotted lines. All intervals are computed based on an appropriate bootstrap method. The impulse responses together with the bootstrap confidence interval are shown in Figures 2–4. The three panels in Figure 2–4 show the impulse response of the real price of oil to each of the three demand and supply shocks that affect the crude oil market, separately, with three different indices of real economic activity; the Baltic Dry Index (BDI), DCTVSSR and Kilian and Park's economic index.

Kilian and Park report that oil production disruption causes a transitory increase in the real price of oil under the one-standard error band. Unexpected global demand expansion causes a delay but sustained increase in the real price of oil. An increase in the oil market specific demand causes an immediate and persistent increase in the real price of oil.

My robustness check using the BDI and DCTVSSR shows a different pattern for the oil supply shock and aggregate demand shock. Data with BDI show that, with the unexpected oil production disruption, the real price of oil has a delayed and sustained increase that is statistically significant based on one standard error band. Data with DCTVSSR show that the oil supply shocks lead to a gradual increase in the first 6 month and then a persistent increase in the real price of oil. For the aggregate demand shock, both data samples represent a sharp increase in the real price of oil within the first 4 months followed by a slow decline for the rest of the time period. These results are statistically significant based on both the one and two-standard error bands. The impact of an oil market specific shock is in line with Kilian and Park, although the increased price declines as time goes by.

3.4.3 The Long-Run Response of Oil Prices to Oil Shocks

Historical decomposition computes the historical effect of a shock and measures the relative importance of shocks over the sample time period. That is, historical decomposition shows the accumulated effects of current and past shocks while impulse response assesses the timing and magnitude of the response to one-time shocks. A great merit of the historical decomposition is that we can follow the demand and supply shocks and their effect on the real price of oil over a long time.

The robustness checks for the historical decomposition of changes in the real price of oil in Figures 5–7 with different indices of real economic activity exhibit similar results which are in line with Kilian and Park (2009). These results suggest that oil price shocks have been driven mainly by the demand shocks rather than the supply shock in their sample period. The first panel in the historical decomposition results indicates that oil supply shocks only contribute a small part historically to the real price of oil, reflecting short and limited swing in the real price of oil in the figure. On the demand side, aggregate demand shock causes a relatively longer and more significant swing in the real price of oil, especially in the newly added period starting in 2007. This result is consistent with Hamilton (2009b) in that the price run-up of 2007–2008 was caused by strong demand confronting stagnating world production. The oil market specific shock cause a sharp increase and decrease in the price of oil, which is consistent with the view that precautionary demand shocks reflect rapid shifts in the market's assessment of the availability of future oil supplies (Kilian, 2009).

3.4.4 The Response of Stock Returns to Oil Shocks

Figures 8–13 depict the impulse response of different stock returns to each of the three demand and supply shocks that affect the crude oil market. Together with the stock index used in Kilian and Park (2009), I use a total of 6 different stock returns for comparison purposes. Compared with the CRSP value-weighted market portfolio used in Kilian and Park, the equally-weighted market portfolio puts more weight on smaller firms. Thus among all 6 indices, the S&P500, value-weighted portfolio and large firm portfolio can be considered to place more weight on the large-sized firms, whereas NASDAQ, the equally-weighted portfolio and the small firm portfolio are composed mostly of small-sized firms.

The main results are in line with Kilian and Park (2009) except the different results for large and small firms. Although generally supply shocks do not have a statistically significant effect on the all the stock returns, shocks from the demand side have different stories for large-sized firms and small-sized firms. Aggregate demand shocks have a longer and stronger effect on the stock returns of small-sized firms than those of large-sized firm. For example, the positive impact of an aggregate demand shock on an equally-weighted market portfolio lasts for 13 months and is statistically significant for the first 12 months based on one-standard error bands. Meanwhile, the same shock has a much weaker and less sustainable effect on S&P500 with a persistence of 12 months and is only statistically significant for the first 9 months based on one-standard error bands. If there is an unexpected global economy expansion, it could have two opposite effects on the U.S. economy. First, the improved business cycle boosts the U.S. economy and in turn increases U.S. stock returns. Second, economy expansion could drive up the oil price, which will eventually slow down the U.S. economy. In the short run, the stimulating effect is more prevailing than the limiting effect, which makes the second panel of Figures 8–13 first rise and then drop down.

The stronger and longer effect on small-sized firms can be explained by the fact that unexpected global economy expansion has a stronger and longer stimulating effect on small firms. This may be because small firms experience greater volatility in response to short run economy expansion.

The oil market specific shock has a negative and persistent impact on the stock returns of large-sized firms, whereas it only has a transitory and even no effect on the stock returns of small-sized firms. The oil-market specific shock captures the changes of precautionary demand shocks that reflect future concerns about oil supply. Small-sized firms are usually distributed in less oil-intensive industries, which is why they suffer less with oil price spikes.

The variance decompositions in the first sections of Tables 2–8 show the average effect of three shocks from the crude oil market on the U.S. stock returns for alternate data samples. My data samples show increased explanatory power than those used in Kilian and Park. In the short run, the effect of these three shocks can be negligible. However in the long run, when BDI is used as the world economic activity index, about 42% of stock returns can be explained by the oil price fluctuation. Among them, 10% of changes in U.S. stock returns can be explained by supply shock, 23% from aggregated demand shock and another 9% from the oil-market specific shock. BDI outperforms other indices and shows a great predictive power for global economic activity.

3.4.5 The Response of Dividend Growth Rates to Oil Shocks

Figures 14–19 show the impulse response of different dividend growth rates to each of the three demand and supply shocks that affect the crude oil market. It is achieved by replacing real stock returns in the last element of z_t with real dividend growth rates, and then re-estimating Eq.1. The results for the oil supply shock are mixed. Higher oil price caused by supply shock statistically lowers the dividend growth rate of S&P500, the large firm portfolio and NASDAQ, whereas for the small firm portfolio and the equally-weighted market portfolio, the effect of supply shock on stock returns can be neglected. The results for the aggregated demand shock are quite clear: positive aggregate demand shocks increase the dividend growth rate. For the oil-market specific shock, the results are similar to those of stock returns. The precautionary demand shock only has a negative effect on large-sized firms and no effect on small-sized firms.

The variance decompositions of U.S. real dividend growth in the second part of Tables 2–8 show that BDI outperforms other indices for economic activity and with it oil price shocks show great explanatory power for dividend growth. In the long run, overall 40% variation of dividend growth can be explained by shocks from the crude oil market, with 20% from each supply and demand side.

3.4.6 Does the Effect of Oil Shocks on Stock Returns Come from Expected Discount Rates or Expected Cash Flows

The contemporaneous approach to explain the movement of stock returns tends to ignore the channels through which oil price shocks affect asset prices. In this study, I aim to fill this gap by testing whether the variations in U.S. real stock returns to specific supply and demand shocks in the crude oil market are driven by fluctuations in cash flows or by discount rates variations.

I do this using Campbell's (1991) stock return decomposition and write the unexpected changes in asset returns from the previous period $(t-1)$ to the current period (t) as follows:

$$rs_t - E_{t-1}(rs_t)$$
$$= \left[E_t\left(\sum_{i=0}^{\infty}\rho^i rd_{t+i}\right) - E_{t-1}\left(\sum_{i=0}^{\infty}\rho^i rd_{t+i}\right)\right] - \left[E_t\left(\sum_{i=0}^{\infty}\rho^i rs_{t+i}\right) - E_{t-1}\left(\sum_{i=0}^{\infty}\rho^i rs_{t+i}\right)\right] \quad (12)$$

where rs_t is the real stock return, rd_t is the real dividend growth rate, E_t is the expectation at time t, and ρ is the discount coefficient that is slightly less than one, which is computed as follows: $\rho \equiv 1/(1+\exp(\overline{d-p})$, where $\overline{d-p}$ is the average log dividend-price ratio.

Revisions of expected future cash flows are written as $\left[E_t\left(\sum_{i=0}^{\infty}\rho^i rd_{t+i}\right) - E_{t-1}\left(\sum_{i=0}^{\infty}\rho^i rd_{t+i}\right)\right]$, and changes of future discount rates are written as $\left[E_t\left(\sum_{i=0}^{\infty}\rho^i rs_{t+i}\right) - E_{t-1}\left(\sum_{i=0}^{\infty}\rho^i rs_{t+i}\right)\right]$. Eq.12 states that stock returns vary through time due to revised expectations about future cash flows and variations in future discount rates. Eq.12 can be written more compactly as:

$$rs_t - E_{t-1}(rs_t) = N_{CF,t+1} - N_{DR,t+1} \qquad (13)$$

where $N_{CF,t+1}$ and $N_{DR,t+1}$ denote the changes in future cash flows, and changes in discount rates respectively.

In order to incorporate the changes in real stock returns arising from a given supply or demand shock in the crude oil market, I reconstruct Eq.13 in terms of the responses to unanticipated disturbances in the crude oil market. First, I normalize all expectations of period $t-1$ in Eq.13 to zero. Then, I write the changes in real cash flows and changes in expected returns relative to the baseline in response to an unexpected disturbance in the crude oil market as follows:

$$rs_t - E_{t-1}(rs_t) = E_t(rs_t) - E_{t-1}(rs_t) = \Psi_{0,j} - 0 = \Psi_{0,j} \qquad (14)$$

$$N_{CF,t+1} = E_t\left(\sum_{i=0}^{\infty}\rho^i\delta_{ij}\right) - E_{t-1}\left(\sum_{i=0}^{\infty}\rho^i\delta_{ij}\right) = \sum_{i=0}^{\infty}\rho^i\delta_{ij} - 0 = \sum_{i=0}^{\infty}\rho^i\delta_{ij} \qquad (15)$$

$$N_{DR,t+1} = E_t\left(\sum_{i=0}^{\infty}\rho^i\varphi_{ij}\right) - E_{t-1}\left(\sum_{i=0}^{\infty}\rho^i\varphi_{ij}\right) = \sum_{i=0}^{\infty}\rho^i\varphi_{ij} - 0 = \sum_{i=0}^{\infty}\rho^i\varphi_{ij} \tag{16}$$

where $\Psi_{0,j}$ is measured by the first element of the impulse response coefficients of real stock returns to a shock j in the crude oil market in month t; $\delta_{ij}(\varphi_{ij}$, respectively) is the impulse response of real dividend growth (real stock returns, respectively) in period i to a given structural shock j in the crude oil market; $j=$ oil supply shock, aggregate demand shock, and oil-specific demand shock.

Finally, I can test whether the impact on real stock returns arising from different supply and demand shocks in the global crude oil market can be fully accounted for by revisions to real cash flows or revisions to expected real returns. In this case, the null and alternative hypotheses can be stated as follows:

$$H_0\colon \Psi_{0,j} = \sum_{i=0}^{\infty}\rho^i\delta_{ij} \approx \sum_{i=0}^{36}\rho^i\delta_{ij} \tag{17}$$

$$H_0\colon \Psi_{0,j} = -\sum_{i=0}^{\infty}\rho^i\varphi_{ij} \approx \sum_{i=0}^{36}\rho^i\varphi_{ij} \tag{18}$$

$$H_1\colon \Psi_{0,j} = \sum_{i=0}^{36}\rho^i\delta_{ij} - \sum_{i=0}^{36}\rho^i\varphi_{ij} \tag{19}$$

Following the practice in the literature I truncate the infinite sum in the above expressions for the purposes of estimation at 36 lags.

The Wald-test statistics and p-values for null hypotheses in Eq.17 and Eq.18 are shown in Panels A and B of Tables 9–15. Most of the results show that both hypotheses cannot be rejected at the 10% significance levels for three shocks. That is, the stock return fluctuation caused by oil price shocks can be fully explained by the changes in future cash flows and the changes in future discount rates, which is in line with Kilian and Park (2009). This result is important to understand how oil price shocks affect stock returns. On one side, oil price shocks have an impact on expected cash flow by increasing the production cost. On the other side, oil prices shock also affect the discount rate via changes in both expected inflation and the expected real interest rate. The exception is in equally-weighted and NASDAQ stock returns. Changes in equally-weighted stock returns caused by oil supply shocks and oil specific shocks can be attributed entirely to fluctuations in expected discount rate. That is, oil supply and oil specific shocks have no effect on the cash flow of firms in the equally-weighted index. Changes in NASDAQ stock returns caused by aggregate demand shocks can be attributed entirely to fluctuations in expected discount rate. Similarly this means aggregate demand shocks could not affect the cash flow of firms in NASDAQ. In a summary, oil price shocks tend to have weaker effect on small firms because they could not affect the cash flow of small firms effectively. The reason is that small firms are usually distributed in the less oil-intensive industries and crude oil is rarely used as the raw input, thus oil price shocks can only have limited effect on the production costs and cash flows.

3.5 Conclusion

This paper studies the impact of oil price shocks on different types of stock indices using a structural vector autoregression (SVAR) approach. SVAR is used to control the reverse casualty between oil price and the stock market and incorporates economic theory into the atheoretical model. I use the newly-developed approach used by Kilian and Park (2009) to classify the oil price shocks into three different types: a supply shock, an aggregated demand shock and an oil-market specific shock. The main purpose of this paper is to study whether the results of SVAR are robust with different stock market variables and indices for global economic activity. I use five different stock indices: an equally-weighted stock index, NASDAQ, a small firm portfolio, a large firm portfolio and S&P500, and two different variables to proxy the world economy activity besides the data used in Kilian and Park: the Baltic Dry Index (BDI) and Dry Cargo Tramp Voyage Shipping Spot Rate (DCTVSSR). BDI shows great explanatory power to capture world-wide economic activity.

I find that oil supply and demand shock have different effects on oil price. While Kilian and Park find that oil supply shock has only a transitory positive effect on the real price of oil within the first year, I find that in my data samples with BDI and DCTVSSR, oil supply shock persistently increases the oil price for more than 15 months. Moreover, in line with Kilian and Park, aggregate demand shock has a delayed and sustained positive impact on oil price, while oil-market specific shock has an immediate and persistent effect on the oil price.

In addition, the three different shocks also have different effects on U.S. stock returns. Higher oil prices triggered by an unexpected oil supply disruption only causes a negligible movement in the stock market. Aggregate demand shock caused by the world economic activity expansion increases stock returns persistently. However the magnitude and length of the effect depends on the firm size. Firm size effect is one of the important contributions of this paper since it is the first paper to examine whether different sized firms have different responses to the oil price shocks. I find that the aggregate demand shock has a longer and stronger effect on the stock returns of small-sized firms compared to those of large-sized firms. Further, oil-market specific shocks have a negative effect on the stock returns of large-sized firms while it has no statistically significant effect on small-sized firms.

Overall, 42% of stock return variation can be explained by the fluctuation in the oil market, with 23% from the demand side and 9% from the supply side. Finally, the stock return variations caused by oil price shocks can be explained by both the changes in expected cash flows and the changes in expected discount rates. This paper contributes to the current literature studying the relationship between oil price shocks and stock markets by highlighting the importance of classifying oil price shocks according to their causes. This is important for policy makers and business owners to allow them to respond differently to movements in the real price of oil and make corresponding decisions on monetary policy, investments and related matters.

Appendix 3A. Summary of Literature on analysing relationships between oil prices and stock markets

Authors Year	Data Period	Market	Methodology	Main Findings/Comments	Types of Relationships
Kaul and Seyhun (1990)	1949-1984	U.S.	Regression Analysis	They found out oil prices movements have a negative effect on the US stock prices.	Negative Relationship
Jones and Kaul (1996)	Quarterly Data from 1947 - 1991	U.S., Canada, Japan and UK	Cash-flow dividend valuation model	They found out oil prices movements have a significant impacts on the U.S. and Canadian Stock prices but not for Japan and UK.	Mixed Relationships
Huang et al. (1996)	Daily	U.S.	Vector Autoregressive (VAR)	The paper studies the linkages between daily oil futures future and U.S. stock returns, but they failed to prove any significant impacts on general market indices such as S&P 500.	No Relationship
Sadorsky (1999)	Monthly data from 1947 to 1996	U.S.	Vector Autoregressive (VAR)	The study investigated the impact on oil price shocks and volatility to the U.S. interest rates, industrial production and real stock returns, he found that after 1986, oil price movements explained a larger fraction of the forecast error variance n real stock returns than interest rates, there is also	Asymmetric Relationships

				evidence on the asymmetric effects for the oil price volatility shock on the economy.	
Papapetrou (2001)	Monthly data from 1989 to 1999	Greece	Vector Autoregressive (VAR)	The paper studied the dynamic interaction between oil prices, real stock prices, interest rates, and real economic activity in Greece, the empirical results showed that oil prices was an important factor for explaining stock prices movements.	Negative Relationships
Ciner (2002)	Using Huang (1996)'s data	U.S.	Linear & Nonlinear causality test	A nonlinear relationship between oil price shocks and stock index returns has been found.	Non-linear Relationship
Hong et al. (2002)				They identified negative relationships between oil price returns and stock markets returns.	Negative Relationship
Hammoudeh and Eleisa (2004)	Daily data from 1994 to 2001	Bahrain, Kuwait, Oman, Saudi Arabia, and the United Arab Emigrates		Only the Saudi Arabia stock market has a bi-directional relationship between oil prices and stock prices.	Mixed vidence
Maghyereh (2004)	Daily data from 1998 to 2004	22 emerging stock markets	VAR	This study aimed to exam the linkages between crude oil price shocks and 22 emerging economies. However, the empirical results failed to support any significant impact on stock index returns in those markets.	Relationship

Basher and Sadorsky (2006)	Daily, weekly and monthly oil prices and market returns from January 1993 to October 2005.	21 emerging stock markets	Multifactor Analysis	They have mixed evidence on the relationships between oil prices shocks and stock markets.	Mixed relationships
Malik and Hammoudeh (2007)	Daily data February 1994 to December 2001	Saudi Arabia, Kuwait and Bahrain	VECH and BEKK	They examined the volatility and shock transmission mechanism among U.S. market to Gulf equity markets; they found only Saudi Arabia market has an bi-direction effects to spillover volatility to the oil market.	Mixed Evidence
Park and Ratti (2008)	Monthly data 1986 - 2005	13 European countries	VAR	They found that oil prices shocks have significant impact on real stock returns in the same month or within one month. Norway as an oil exporter shows a statistically significantly positive response of real stock returns to an oil price increase. While the impact on oil-exporting countries' stock market are negative. For many European countries, but not for the U.S. increased volatility of oil prices significantly depresses real stock returns. The contribution of oil price shocks to variability in real stock returns in the US and most other countries is greater than that of	Mixed Evidence

				interest rate. An increase in real oil price is associated with a significant increase in the short-term interest rate in the U.S. and eight out of 13 European countries within one or two months. Counter to findings for the U.S. and for Norway, there is little evidence of asymmetric effects on real stock returns of positive and negative oil price shocks for oil importing European countries.	
Apergis and Miller (2009)	Monthly data from 1981 to 2007	Australia, Canada, France, Germany, Italy, Japan, UK	Structural VAR	The paper examined how structural shocks that characterize the endogenous character of oil price changes affect stock market returns. The empirical evidence suggested that the international stock market returns did not respond oil market shocks in a large magnitude.	Marginal Evidence
Kilian and Park (2009)	Monthly data from 1973 to 2006	U.S. stock market CRSP value-weighted market portfolio	Structural VAR	They found that the reaction of U.S. real stock returns to an oil price shock differs significantly depending on whether the change in the price of oil is driven by demand or supply shocks in the oil market.	Mixed Evidence

Table 1.1 Statistical summary of all the variables used in structural VAR model

Stock Returns

Variables	**Obs**	**Mean**	**Std.Dev.**	**Min**	**Max**	
S&P500_Rn	433	0.525	4.584	-21.784	15.668	
NASDAQ_Rn	433	0.609	6.472	-27.311	21.983	
Equally-weigted_Rn	433	0.842	5.866	-27.414	29.427	
Value-weighted_Rn	433	0.528	4.728	-22.738	15.418	
Large portfolio_Rn	433	0.488	4.544	-20.7442	17.588	
Small portfolio_Rn	433	0.751	6.364	-29.994	27.384	
Variance-Covariance Matrix	S&P500	NASDAQ	Equally -weigted	Value-weighted	Large portfolio	Small portfolio
S&P500_Rn	1					
NASDAQ_Rn	0.852	1				
Equally-weigted_Rn	0.782	0.872	1			
Value-weighted_Rn	0.986	0.906	0.853	1		
Large portfolio_Rn	0.992	0.848	0.768	0.979	1	
Small portfolio_Div	0.728	0.868	0.963	0.813	0.719	1

Stock Dividend

Variables	Obs	Mean	Std.Dev.	Min	Max	
S&P500_Div	443	0.103	1.624	-10.498	19.728	
NASDAQ_Div	443	0.489	12.815	-59.817	255.364	
Equally-weigted_Div	443	0.463	1.471	-4.506	5.717	
Value-weighted_Div	443	0.112	1.332	-7.250	14.349	
Large portfolio_Div	443	0.074	1.711	-11.058	20.905	
Small portfolio_Div	443	0.295	2.247	-6.639	9.445	
Variance-Covariance Matrix	S&P500	NASDAQ	Equally -weigted	Value- weighted	Large portfolio	Small portfolio
S&P500_Div	1					
NASDAQ_Div	0.659	1				
Equally-weigted_Div	0.246	0.081	1			
Value-weighted_Div	0.953	0.602	0.356	1		
Large portfolio_Div	0.944	0.663	0.236	0.907	1	
Small portfolio_Div	0.213	0.126	0.487	0.273	0.166	1

Economic Index

Variables	**Obs**	**Mean**	**Std.Dev.**	**Min**	**Max**
Kilian Index	443	-0.093	25.932	-57.179	78.115
BDI	300	0.194	14.967	-122.099	65.515
Freight	443	-0.340	75.311	-492.280	720.119
Variance-Covariance Matrix	Kilian Index	BDI	Freight		
Kilian Index	1				
BDI	-0.008	1			
Freight	0.147		1		

Oil Variables

Variables	**Obs**	**Mean**	**Std.Dev.**	**Min**	**Max**
Oil production	443	2.540	18.937	-71.406	112.876
Real oil price	443	3.392	47.248	-114.779	117.3628

Note: This table reports the statistical summary of all the variables used in this study, including the stock return and dividend growth of S&P 500, NASDAQ, equally-weighted index, value-weighted index, large portfolio and small portfolio. There are three different proxy of real economic activities used in this study: Kilian's index, Baltic Dry Index and Dry Cargo Tramp Voyage shipping rate. The variance-covariance matrix is provided for each block of variables.

Table 1.2 Unit root tests on all the variables used in structural VAR model

Stock Returns

Variables	Test	Deterministic terms	Lags	Test value	1% Critical value	1% Critical value	1% Critical value
S&P500_Rn	ADF	c	0	-19.95	-3.44	-2.87	-2.57
		c, t	0	-19.93	-3.98	-3.42	-3.13
	PP	c	8	-30.02	-3.44	-2.87	-2.57
		c, t	8	-30.00	-3.98	-3.42	-3.13
	KPSS	c	8	0.17	074	0.46	0.35
		c, t	8	0.17	0.22	0.15**	0.12**
NASDAQ_Rn	ADF	c	0	-18.30	-3.44	-2.87	-2.57
		c, t	0	-18.29	-3.98	-3.42	-3.13
	PP	c	6	-18.23	-3.44	-2.87	-2.57
		c, t	6	-18.22	-3.98	-3.42	-3.13
	KPSS	c	2	0.10	0.74	0.46	0.35
		c, t	2	0.09	0.22	0.15	0.12
Equally-weighted index_Rn	ADF	c	0	-16.57	-3.44	-2.87	-2.57
		c, t	0	-16.55	-3.98	-3.42	-3.13
	PP	c	5	-16.39	-3.44	-2.87	-2.57
		c, t	5	-16.37	-3.98	-3.42	-3.13
	KPSS	c	0	0.04	0.74	0.46	0.35
		c, t	0	0.05	0.22	0.15	0.12
Value-weighted index_Rn	ADF	c	0	-19.17	-3.44	-2.87	-2.57
		c, t	0	-19.16	-3.98	-3.42	-3.13
	PP	c	6	-19.17	-3.44	-2.87	-2.57
		c, t	6	-19.15	-3.98	-3.42	-3.13
	KPSS	c	6	0.13	0.74	0.46	0.35
		c, t	6	0.13	0.22	0.15	0.12
Large portfolio_Rn	ADF	c	0	-19.82	-3.44	-2.87	-2.57
		c, t	0	-19.80	-3.98	-3.42	-3.13
	PP	c	9	-19.93	-3.44	-2.87	-2.57
		c, t	8	-19.91	-3.98	-3.42	-3.13
	KPSS	c	9	0.18	0.74	0.46	0.35
		c, t	9	0.17	0.22	0.15**	0.12**
Small portfolio_Rn	ADF	c	0	-16.97	-3.44	-2.87	-2.57
		c, t	0	-16.95	-3.98	-3.42	-3.13
	PP	c	10	-16.64	-3.44	-2.87	-2.57
		c, t	10	-16.62	-3.98	-3.42	-3.13
	KPSS	c	6	0.04	0.74	0.46	0.35
		c, t	6	0.04	0.22	0.15	0.12

Stock dividend

Variables	Test	Deterministic terms	Lags	Test value	1% Critical value	1% Critical value	1% Critical value
S&P500_Div	ADF	c	11	-5.08	-3.45	-2.87	-2.57
		c, t	11	-5.03	-3.98	-3.42	-3.13
	PP	c	10	-22.59	-3.44	-2.87	-2.57
		c, t	10	-22.57	-3.98	-3.42	-3.13
	KPSS	c	8	0.17	074	0.46	0.35
		c, t	9	0.06	0.22	0.15	0.12
NASDAQ_Div	ADF	c	0	-21.57	-3.45	-2.87	-2.57
		c, t	0	-21.60	-3.98	-3.42	-3.13
	PP	c	3	-21.56	-3.45	-2.87	-2.57
		c, t	3	-21.60	-3.98	-3.42	-3.13
	KPSS	c	2	0.19	0.74	0.46	0.35
		c, t	2	0.06	0.22	0.15	0.12
Equally-weighted index_Div	ADF	c	2	-4.30	-3.44	-2.87	-2.57
		c, t	2	-4.28	-3.98	-3.42	-3.13
	PP	c	12	-11.95	-3.44	-2.87	-2.57
		c, t	12	-12.00	-3.98	-3.42	-3.13
	KPSS	c	15	0.13	0.74	0.46	0.35
		c, t	15	0.06	0.22	0.15	0.12
Value-weighted index_Div	ADF	c	11	-4.22	-3.44	-2.87	-2.57
		c, t	11	-4.16	-3.98	-3.42	-3.13
	PP	c	12	-22.54	-3.44	-2.87	-2.57
		c, t	12	-22.51	-3.98	-3.42	-3.13
	KPSS	c	12	0.09	0.74	0.46	0.35
		c, t	12	0.05	0.22	0.15	0.12
Large portfolio_Div	ADF	c	11	-5.51	-3.45	-2.87	-2.57
		c, t	11	-5.50	-3.98	-3.42	-3.13
	PP	c	10	-23.29	-3.44	-2.87	-2.57
		c, t	1	-2.00	-3.98**	-3.42**	-3.13**
	KPSS	c	16	0.58	0.74	0.46**	0.35**
		c, t	16	0.40	0.22**	0.15**	0.12**
Small portfolio_Div	ADF	c	23	-5.12	-3.45	-2.87	-2.57
		c, t	23	-5.12	-3.98	-3.42	-3.13
	PP	c	12	-15.67	-3.44	-2.87	-2.57
		c, t	12	-15.66	-3.98	-3.42	-3.13
	KPSS	c	14	0.11	0.74	0.46	0.35
		c, t	6	0.10	0.22	0.15	0.12

Economic index

Variables	Test	Deterministic terms	Lags	Test value	1% Critical value	1% Critical value	1% Critical value
KilianIndex	ADF	c	2	-3.44	-3.45	-2.87	-2.57
		c, t	2	-3.46	-3.98	-3.42	-3.13
	PP	c	4	-3.11	-3.45	-2.87	-2.57
		c, t	4	-3.12	-3.98	-3.42	-3.13
	KPSS	c	16	0.27	0.74	0.46	0.35
		c, t	12	0.27	0.22	0.15	0.12
BDI	ADF	c	0	-13.00	-3.45	-2.87	-2.57
		c, t	0	-12.98	-3.99	-3.42	-3.14
	PP	c	13	-12.48	-3.45	-2.87	-2.57
		c, t	13	-12.45	-3.99	-3.42	-3.14
	KPSS	c	8	0.03	0.74	0.46	0.35
		c, t	8	0.03	0.22	0.15	0.12
Freight	ADF	c	0	-14.18	-3.45	-2.87	-2.57
		c, t	0	-14.16	-3.98	-3.42	-3.14
	PP	c	13	-13.21	-3.45	-2.87	-2.57
		c, t	13	-13.19	-3.98	-3.42	-3.14
	KPSS	c	10	0.06	0.74	0.46	0.35
		c, t	10	0.06	0.22	0.15	0.12

Oil variables

Variables	Test	Deterministic terms	Lags	Test value	1% Critical value	1% Critical value	1% Critical value
Oil production	ADF	c	0	-22.31	-3.44	-2.87	-2.57
		c, t	0	-22.36	-3.98	-3.42	-3.13
	PP	c	19	-22.41	-3.44	-2.87	-2.57
		c, t	21	-22.56	-3.98	-3.42	-3.13
	KPSS	c	21	0.21	0.74	0.46	0.35
		c, t	23	0.04	0.22	0.15	0.12
Real oil price	ADF	c	1	-2.77	-3.44**	-2.87**	-2.57
		c, t	1	-2.82	-3.98**	-3.42**	-3.13**
	PP	c	1	-1.97	-3.44**	-2.87**	-2.57**
		c, t	1	-2.00	-3.98**	-3.42**	-3.13**
	KPSS	c	16	0.58	0.74	0.46**	0.35**
		c, t	16	0.40	0.22**	0.15**	0.12**

Note: This table reports the results of unit root tests for all variables used in the SVAR model. I use Augmented Dickey–Fuller (ADF), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests, and report results with and without a trend. The null hypotheses for ADF and PP are ‘the series has a unit root $I(1)$’, while the null hypothesis for the KPSS test is ‘the series is stationary $I(0)$’.

Table 2.1 Percent contribution of demand and supply shocks in the crude oil market to the overall variability of value-weighted real stock return with BDI

Horizon months	**Oil Supply shock**	**Aggregate demand shock**	**Oil-Specific demand shock**	**Other Shocks**
1	0.27	2.23	2.11	95.39
2	1.79	3.86	4.16	90.19
3	2.73	4.78	5.43	87.06
12	6.28	12.80	6.25	74.67
∞	9.93	22.90	9.36	57.81

Table 2.2 Percent contribution of demand and supply shocks in the crude oil market to the overall variability of value-weighted real dividend growth with BDI

Horizon months	**Oil Supply shock**	**Aggregate demand shock**	**Oil-Specific demand shock**	**Other Shocks**
1	0.89	0.35	1.33	97.43
2	1.03	1.84	2.94	94.19
3	1.26	2.66	2.86	93.22
12	3.51	7.38	4.51	84.60
∞	9.97	20.28	9.94	59.81

Note: This table reports the results of the variance decomposition for each supply and demand shock on U.S. stock return and real dividend growth with BDI as the economic activity index. It presents the percentage contribution of each shock, namely oil supply shock, aggregate demand shock, oil-specific demand shock, and other shocks, to the overall variability of real stock returns and dividend growth for 1 month, 2 months, 3 months, 12 months and infinity ahead.

Table 3.1 Percent contribution of demand and supply shocks in the crude oil market to the overall variability of value-weighted real stock return with dry cargo tramp rate

Horizon months	**Oil Supply shock**	**Aggregate demand shock**	**Oil-Specific demand shock**	**Other Shocks**
1	0.10	0.24	0.59	99.07
2	0.18	1.39	3.11	95.33
3	0.49	1,87	4.66	92.98
12	1.43	7.13	6.14	85.30
∞	5.65	15.18	10.42	68.75

Table 3.2. Percent contribution of demand and supply shocks in the crude oil market to the overall variability of value-weighted real dividend growth with dry cargo tramp rate

Horizon months	**Oil Supply shock**	**Aggregate demand shock**	**Oil-Specific demand shock**	**Other Shocks**
1	0.00	1.07	0.83	98.10
2	0.03	2.77	1.14	96.06
3	0.04	2.72	1.13	96.11
12	1.07	11.15	3.24	84.54
∞	4.18	25.29	6.59	63.95

Note: This table reports the results of the variance decomposition for each supply and demand shock on U.S. stock return and real dividend growth with Dry Cargo Tramp Rate as the economic activity index. It presents the percentage contribution of each shock, namely oil supply shock, aggregate demand shock, oil-specific demand shock, and other shocks, to the overall variability of real stock returns and dividend growth for 1 month, 2 months, 3 months, 12 months and infinity ahead.

Table 4.1 Percent contribution of demand and supply shocks in the crude oil market to the overall variability of equally-weighted real stock return

Horizon months	**Oil Supply shock**	**Aggregate demand shock**	**Oil-Specific demand shock**	**Other Shocks**
1	0.02	1.31	0.19	98.47
2	0.07	1.84	1.48	96.61
3	0.77	3.08	1.59	94.56
12	1.46	5.88	2.35	90.31
∞	4.07	18.52	7.89	69.53

Table 4.2 Percent contribution of demand and supply shocks in the crude oil market to the overall variability of equally-weighted real dividend growth

Horizon months	**Oil Supply shock**	**Aggregate demand shock**	**Oil-Specific demand shock**	**Other Shocks**
1	0.01	0.77	0.79	98.43
2	0.18	1.68	0.72	97.42
3	0.24	3.17	1.11	95.48
12	1.72	16.49	1.28	80.51
∞	6.86	22.98	6.01	64.15

Note: This table reports the results of the variance decomposition for each supply and demand shock on U.S. equally-weighted market portfolio stock return and real dividend growth. It presents the percentage contribution of each shock, namely oil supply shock, aggregate demand shock, oil-specific demand shock, and other shocks, to the overall variability of real stock returns and dividend growth for 1 month, 2 months, 3 months, 12 months and infinity ahead.

Table 5.1 Percent contribution of demand and supply shocks in the crude oil market to the overall variability of NASDAQ real stock return

Horizon months	**Oil Supply shock**	**Aggregate demand shock**	**Oil-Specific demand shock**	**Other Shocks**
1	0.02	1.41	0.95	97.63
2	0.03	1.99	2.54	95.44
3	0.34	2.44	3.12	94.09
12	1.29	4.79	4.84	89.08
∞	3.48	13.14	13.03	70.35

Table 5.2 Percent contribution of demand and supply shocks in the crude oil market to the overall variability of NASDAQ real dividend growth

Horizon months	**Oil Supply shock**	**Aggregate demand shock**	**Oil-Specific demand shock**	**Other Shocks**
1	0.01	0.98	2.64	96.37
2	0.19	1.26	3.03	95.52
3	0.19	1.27	3.05	95.50
12	1.83	7.89	4.56	85.72
∞	3.67	12.99	9.17	74.17

Note: This table reports the results of the variance decomposition for each supply and demand shock on NASDAQ stock return and real dividend growth. It presents the percentage contribution of each shock, namely oil supply shock, aggregate demand shock, oil-specific demand shock, and other shocks, to the overall variability of real stock returns and dividend growth for 1 month, 2 months, 3 months, 12 months and infinity ahead.

Table 6.1 Percent contribution of demand and supply shocks in the crude oil market to the overall variability of small firms real stock return

Horizon months	**Oil Supply shock**	**Aggregate demand shock**	**Oil-Specific demand shock**	**Other Shocks**
1	0.07	0.59	0.00	99.33
2	0.11	1.11	0.06	98.73
3	0.62	2.68	0.24	96.46
12	1.46	5.93	1.66	90.95
∞	3.75	16.17	8.60	71.48

Table 6.2 Percent contribution of demand and supply shocks in the crude oil market to the overall variability of small firms real dividend growth

Horizon months	**Oil Supply shock**	**Aggregate demand shock**	**Oil-Specific demand shock**	**Other Shocks**
1	0.02	0.14	2.17	97.67
2	0.42	0.51	2.78	96.28
3	0.43	0.50	2.75	96.32
12	1.11	6.15	6.03	86.71
∞	3.10	13.99	11.84	71.06

Note: This table reports the results of the variance decomposition for each supply and demand shock on U.S. small firm portfolio stock return and real dividend growth. It presents the percentage contribution of each shock, namely oil supply shock, aggregate demand shock, oil-specific demand shock, and other shocks, to the overall variability of real stock returns and dividend growth for 1 month, 2 months, 3 months, 12 months and infinity ahead.

Table 7.1 Percent contribution of demand and supply shocks in the crude oil market to the overall variability of large firms real stock return

Horizon months	**Oil Supply shock**	**Aggregate demand shock**	**Oil-Specific demand shock**	**Other Shocks**
1	0.02	1.96	1.44	96.58
2	0.08	2.10	2.73	95.10
3	0.35	2.71	3.99	92.95
12	1.81	5.44	5.17	87.57
∞	5.31	10.81	8.94	74.94

Table 7.2 Percent contribution of demand and supply shocks in the crude oil market to the overall variability of large firms real dividend growth

Horizon months	**Oil Supply shock**	**Aggregate demand shock**	**Oil-Specific demand shock**	**Other Shocks**
1	0.00	0.17	0.91	98.92
2	0.28	0.58	0.97	98.18
3	0.57	1.05	1.29	97.09
12	1.55	7.55	2.24	88.67
∞	4.79	12.88	5.49	76.84

Note: This table reports the results of the variance decomposition for each supply and demand shock on U.S. large firm portfolio stock return and real dividend growth. It presents the percentage contribution of each shock, namely oil supply shock, aggregate demand shock, oil-specific demand shock, and other shocks, to the overall variability of real stock returns and dividend growth for 1 month, 2 months, 3 months, 12 months and infinity ahead.

Table 8.1 Percent contribution of demand and supply shocks in the crude oil market to the overall variability of S&P500 real stock returns

Horizon months	**Oil Supply shock**	**Aggregate demand shock**	**Oil-Specific demand shock**	**Other Shocks**
1	0.02	1.59	1.93	96.47
2	0.04	1.59	3.70	94.66
3	0.35	2.07	4.98	92.60
12	1.82	5.43	5.77	86.98
∞	5.77	10.79	9.49	73.96

Table 8.2 Percent contribution of demand and supply shocks in the crude oil market to the overall variability of S&P500 real dividend growth

Horizon months	**Oil Supply shock**	**Aggregate demand shock**	**Oil-Specific demand shock**	**Other Shocks**
1	0.24	0.24	1.42	98.09
2	0.29	0.64	1.53	97.54
3	0.48	2.06	1.79	95.67
12	1.66	7.26	3.92	87.16
∞	4.96	13.53	6.64	74.87

Note: This table reports the results of the variance decomposition for each supply and demand shock on S&P 500 stock return and real dividend growth. It presents the percentage contribution of each shock, namely oil supply shock, aggregate demand shock, oil-specific demand shock, and other shocks, to the overall variability of real stock returns and dividend growth for 1 month, 2 months, 3 months, 12 months and infinity ahead.

Table 9 Tests of the impact response of U.S. value-weighted real stock returns using BDI

Panel A: The impact responses of real dividend growth		
	Wald test statistic H_0: $\Psi_{0,j}=\sum_{i=0}^{36} p^i \delta_{ij}, j=1,2,3$	**p-value**
Oil supply shocks	0.4376	0.5083
Aggregate demand shocks	0.0622	0.8031
Oil-market specific demand shocks	0.0139	0.9061

Panel B: The impact responses of real stock returns		
	Wald test statistic H_0: $\Psi_{0,j}=-\sum_{i=1}^{36} p^i \psi_{ij}, j=1,2,3$	**p-value**
Oil supply shocks	1.3559	0.2443
Aggregate demand shocks	0	0.9983
Oil-market specific demand shocks	0.0188	0.8908

Note: Panel A presents the Wald test statistics and p-values for the null hypothesis 'the impact change in real stock returns arising from a given shock of the global crude oil market can be fully attributed to changes in expected real dividend growth'. Panel B presents the Wald test results for the null hypothesis 'the impact change in real stock returns arising from a given shock from the global crude oil market can be fully attributed to changes in expected returns'. ψ_{ij} denotes the response of real stock returns i periods after each oil supply, aggregate demand shock and oil-market specific demand shock, $j = 1, 2, 3$ while δ_{ij} denotes the response of real dividend growth to these three shocks.

Table 10 Tests of the impact response of U.S. value-weighted real stock returns with dry cargo tramp rate

Panel A: The impact responses of real dividend growth		
	Wald test statistic H_0: $\Psi_{0,j}=\sum_{i=0}^{36} p^i \delta_{ij}, j = 1, 2, 3$	**p-value**
Oil supply shocks	1.3766	0.2407
Aggregate demand shocks	0.0843	0.7716
Oil-market specific demand shocks	0.8689	0.3513

Panel B: The impact responses of real stock returns		
	Wald test statistic H_0: $\Psi_{0,j}=-\sum_{i=1}^{36} p^i \psi_{ij}, j = 1, 2, 3$	**p-value**
Oil supply shocks	0.0418	0.8379
Aggregate demand shocks	0.6658	0.4145
Oil-market specific demand shocks	2.2892	0.1303

Note: Panel A presents the Wald test statistics and p-values for the null hypothesis 'the impact change in real stock returns arising from a given shock of the global crude oil market can be fully attributed to changes in expected real dividend growth'. Panel B presents the Wald test results for the null hypothesis 'the impact change in real stock returns arising from a given shock from the global crude oil market can be fully attributed to changes in expected returns'. ψ_{ij} denotes the response of real stock returns i periods after each oil supply, aggregate demand shock and oil-market specific demand shock, $j = 1, 2, 3$ while δ_{ij} denotes the response of real dividend growth to these three shocks.

Table 11 Tests of the impact response of equally-weighted real stock returns

Panel A: The impact responses of real dividend growth		
	Wald test statistic H_0: $\Psi_{0,j}=\sum_{i=0}^{36} p^i \delta_{ij}, j = 1,2,3$	**p-value**
Oil supply shocks	16.0117	0.0001
Aggregate demand shocks	0.7588	0.3837
Oil-market specific demand shocks	12.8005	0.0003

Panel B: The impact responses of real stock returns		
	Wald test statistic H_0: $\Psi_{0,j}=-\sum_{i=1}^{36} p^i \psi_{ij}, j = 1,2,3$	**p-value**
Oil supply shocks	0.3039	0.5814
Aggregate demand shocks	0.2306	0.6311
Oil-market specific demand shocks	0	0.9955

Note: Panel A presents the Wald test statistics and p-values for the null hypothesis 'the impact change in real stock returns arising from a given shock of the global crude oil market can be fully attributed to changes in expected real dividend growth'. Panel B presents the Wald test results for the null hypothesis 'the impact change in real stock returns arising from a given shock from the global crude oil market can be fully attributed to changes in expected returns'. ψ_{ij} denotes the response of real stock returns i periods after each oil supply, aggregate demand shock and oil-market specific demand shock, $j = 1, 2, 3$ while δ_{ij} denotes the response of real dividend growth to these three shocks.

Table 12 Tests of the Impact Response of NASDAQ Real Stock Returns

Panel A: The impact responses of real dividend growth		
	Wald test statistic H_0: $\Psi_{0,j}=\sum_{i=0}^{36} p^i \delta_{ij}, j=1,2,3$	**p-value**
Oil supply shocks	0.8935	0.3445
Aggregate demand shocks	3.8915	0.0485
Oil-market specific demand shocks	0.6968	0.4039

Panel B: The impact responses of real stock returns		
	Wald test statistic H_0: $\Psi_{0,j}=-\sum_{i=1}^{36} p^i \psi_{ij}, j=1,2,3$	**p-value**
Oil supply shocks	0.0161	0.899
Aggregate demand shocks	0.5339	0.465
Oil-market specific demand shocks	1.2434	0.2648

Note: Panel A presents the Wald test statistics and p-values for the null hypothesis 'the impact change in real stock returns arising from a given shock of the global crude oil market can be fully attributed to changes in expected real dividend growth'. Panel B presents the Wald test results for the null hypothesis 'the impact change in real stock returns arising from a given shock from the global crude oil market can be fully attributed to changes in expected returns'. ψ_{ij} denotes the response of real stock returns i periods after each oil supply, aggregate demand shock and oil-market specific demand shock, $j=1,2,3$ while δ_{ij} denotes the response of real dividend growth to these three shocks.

Table 13 Tests of the impact response of small firms portfolio real stock returns

Panel A: The impact responses of real dividend growth		
	Wald test statistic	**p-value**
	H_0: $\Psi_{0,j}=\sum_{i=0}^{36} p^i \delta_{ij}, j=1,2,3$	
Oil supply shocks	0.697	0.4038
Aggregate demand shocks	0.0297	0.8632
Oil-market specific demand shocks	0.1019	0.7495

Panel B: The impact responses of real stock returns		
	Wald test statistic	**p-value**
	H_0: $\Psi_{0,j}=-\sum_{i=1}^{36} p^i \psi_{ij}, j=1,2,3$	
Oil supply shocks	0.4984	0.4802
Aggregate demand shocks	1.0267	0.3109
Oil-market specific demand shocks	0.1434	0.7049

Note: Panel A presents the Wald test statistics and p-values for the null hypothesis 'the impact change in real stock returns arising from a given shock of the global crude oil market can be fully attributed to changes in expected real dividend growth'. Panel B presents the Wald test results for the null hypothesis 'the impact change in real stock returns arising from a given shock from the global crude oil market can be fully attributed to changes in expected returns'. ψ_{ij} denotes the response of real stock returns i periods after each oil supply, aggregate demand shock and oil-market specific demand shock, $j = 1, 2, 3$ while δ_{ij} denotes the response of real dividend growth to these three shocks.

Table 14 Tests of the impact response of large firms portfolio real stock returns

Panel A: The impact responses of real dividend growth		
	Wald test statistic	**p-value**
	H_0: $\Psi_{0,j}=\sum_{i=0}^{36} p^i \delta_{ij}, j=1,2,3$	
Oil supply shocks	1.0867	0.2972
Aggregate demand shocks	0.1394	0.7089
Oil-market specific demand shocks	0.2503	0.6169

Panel B: The impact responses of real stock returns		
	Wald test statistic	**p-value**
	H_0: $\Psi_{0,j}=-\sum_{i=1}^{36} p^i \psi_{ij}, j=1,2,3$	
Oil supply shocks	0.2861	0.5927
Aggregate demand shocks	1.0794	0.2988
Oil-market specific demand shocks	2.2424	0.1343

Note: Panel A presents the Wald test statistics and p-values for the null hypothesis 'the impact change in real stock returns arising from a given shock of the global crude oil market can be fully attributed to changes in expected real dividend growth'. Panel B presents the Wald test results for the null hypothesis 'the impact change in real stock returns arising from a given shock from the global crude oil market can be fully attributed to changes in expected returns'. ψ_{ij} denotes the response of real stock returns i periods after each oil supply, aggregate demand shock and oil-market specific demand shock, $j=1,2,3$ while δ_{ij} denotes the response of real dividend growth to these three shocks.

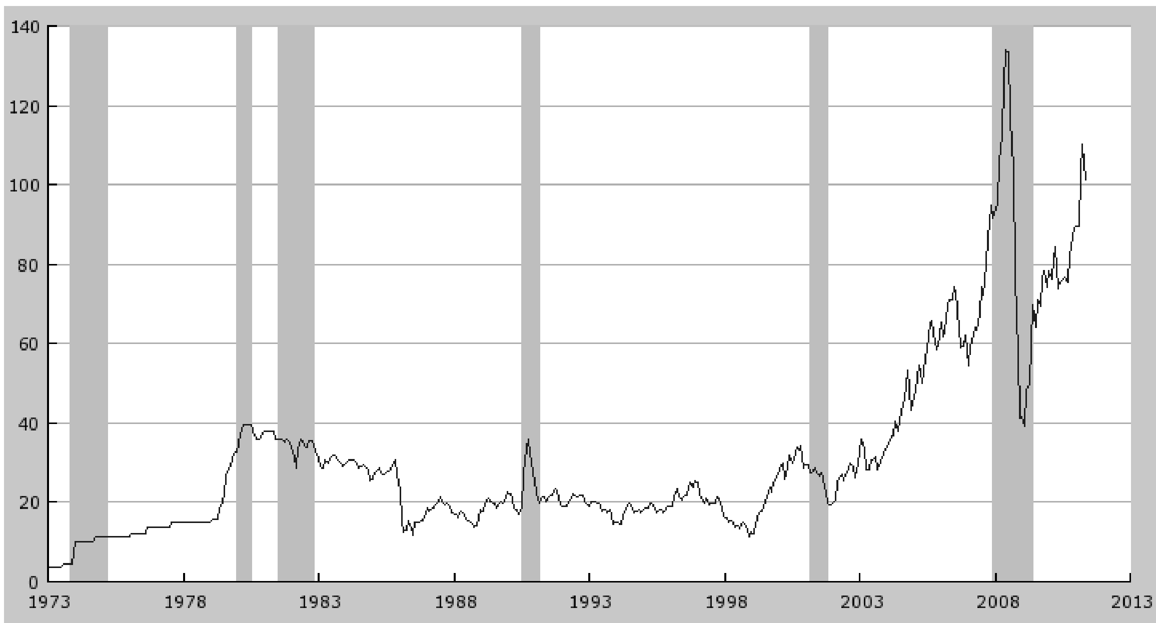
Table 15 Tests of the impact response of S&P500 real stock returns

Panel A: The impact responses of real dividend growth		
	Wald test statistic H_0: $\Psi_{0,j} = \sum_{i=0}^{36} p^i \delta_{ij}, j = 1, 2, 3$	**p-value**
Oil supply shocks	0.5161	0.4725
Aggregate demand shocks	0.0248	0.8748
Oil-market specific demand shocks	0.3389	0.5605

Panel B: The impact responses of real stock returns		
	Wald test statistic H_0: $\Psi_{0,j} = -\sum_{i=1}^{36} p^i \psi_{ij}, j = 1, 2, 3$	**p-value**
Oil supply shocks	0.2937	0.5879
Aggregate demand shocks	1.1274	0.2883
Oil-market specific demand shocks	1.796	0.1802

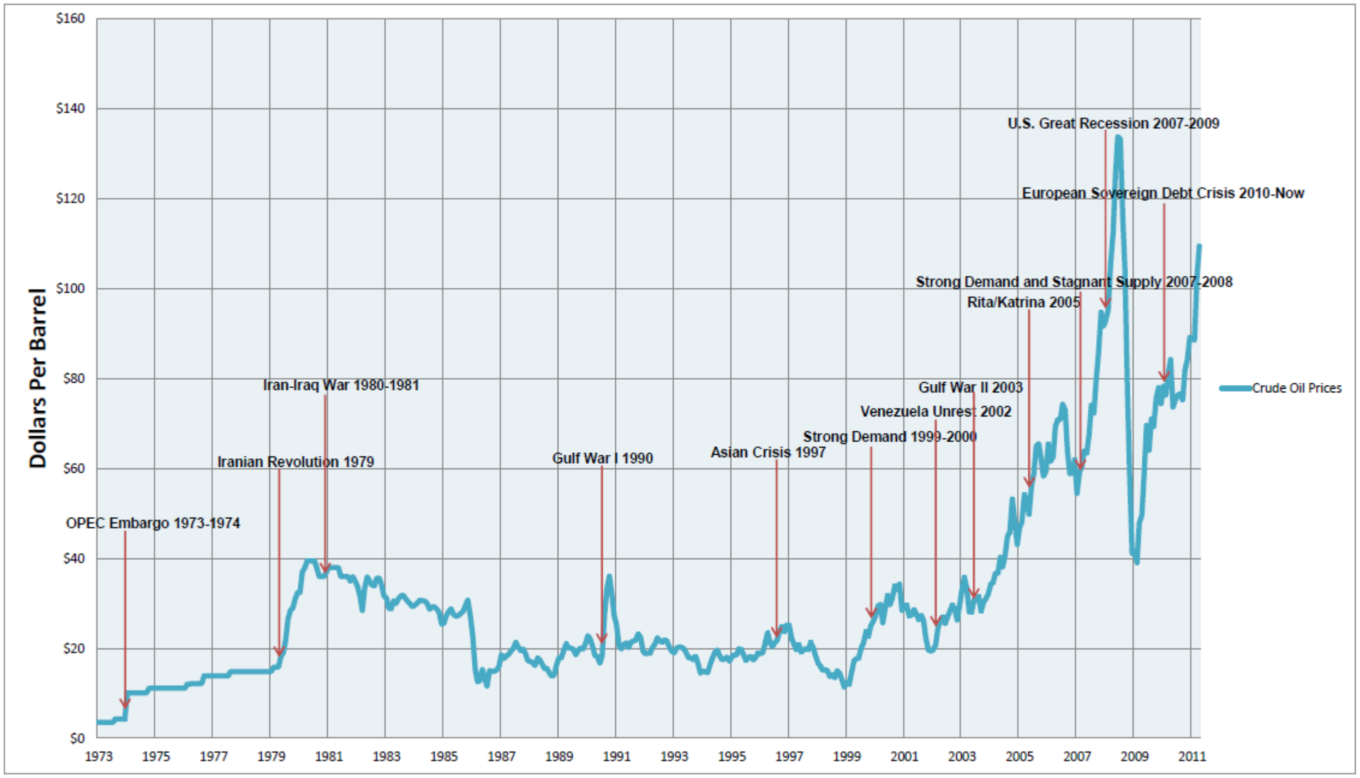
Note: Panel A presents the Wald test statistics and p-values for the null hypothesis 'the impact change in real stock returns arising from a given shock of the global crude oil market can be fully attributed to changes in expected real dividend growth'. Panel B presents the Wald test results for the null hypothesis 'the impact change in real stock returns arising from a given shock from the global crude oil market can be fully attributed to changes in expected returns'. ψ_{ij} denotes the response of real stock returns i periods after each oil supply, aggregate demand shock and oil-market specific demand shock, $j = 1, 2, 3$ while δ_{ij} denotes the response of real dividend growth to these three shocks.

Figure 1.1 Real price of oil and recession from January 1973 to May 2011



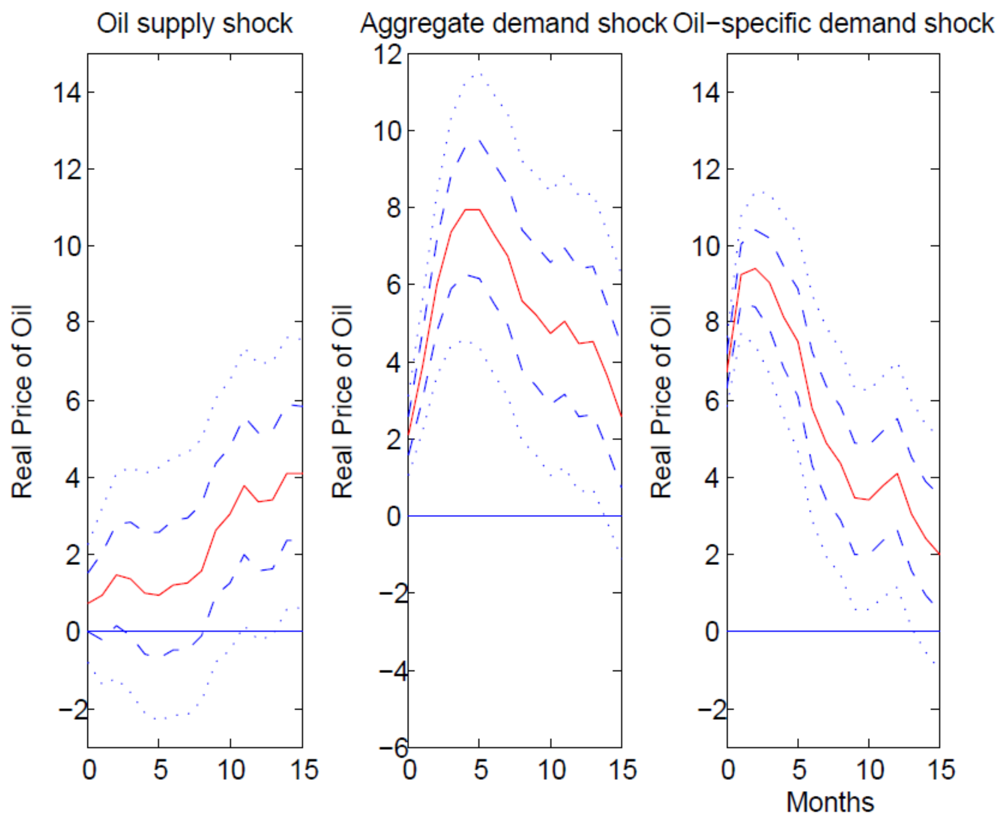
Note: This Figure plots the spot oil price imported into the U.S. The sample spans the period from January 1973 to May 2011. The x-axis is the year, the y-axis is the dollar price per barrel, and the shaded areas are U.S. recessions.

Figure 1.2 Real price of oil and main events from January 1973 to May 2011



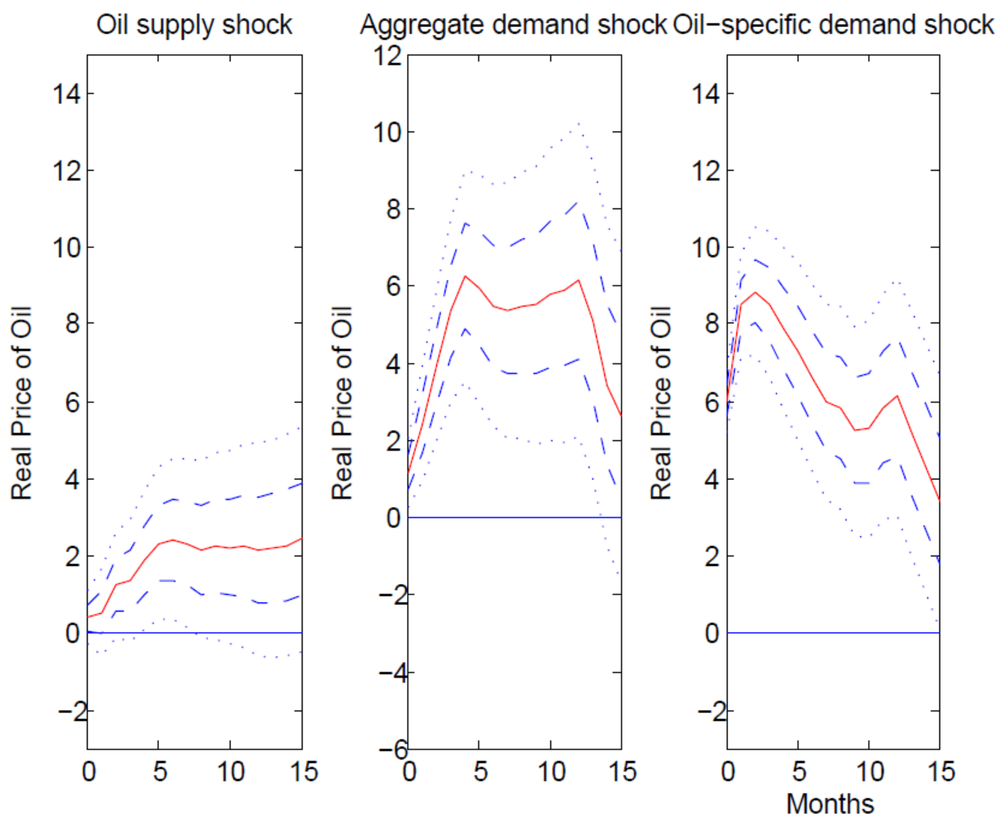
Note: This Figure plots the spot oil price imported into the U.S. The sample spans the period from January 1973 to May 2011. The x-axis is the year, the y-axis is the dollar price per barrel.

Figure 2 Responses of real price of oil to three structural shocks with BDI as the economic activity index



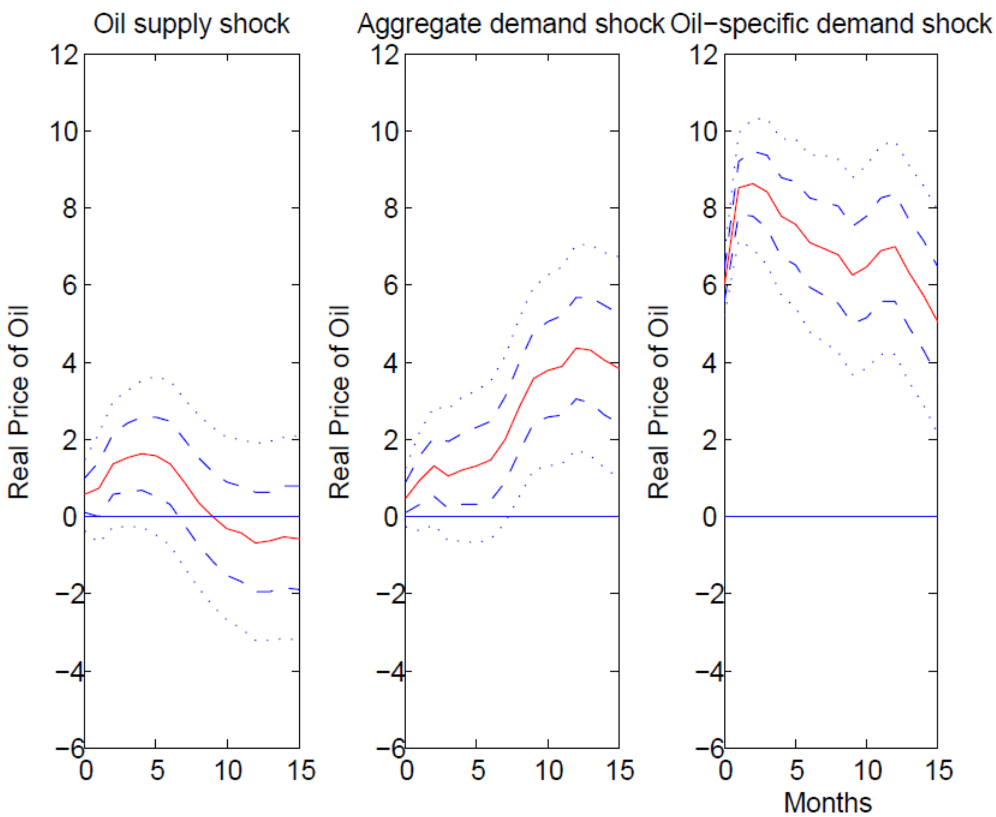
Note: The three panels plot the impulse responses of the real price of oil to each of the three demand and supply shocks that affect the crude oil market with BDI as economic activity index. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impacts the level of oil price at time $t+s$ for different values of s. Here I limit s to a maximum of 15 months ahead. All shocks have been normalized to represent an increase in the real price of oil. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 3 Responses of real price of oil to three structural shocks with dry cargo tramp rate as economic activity index



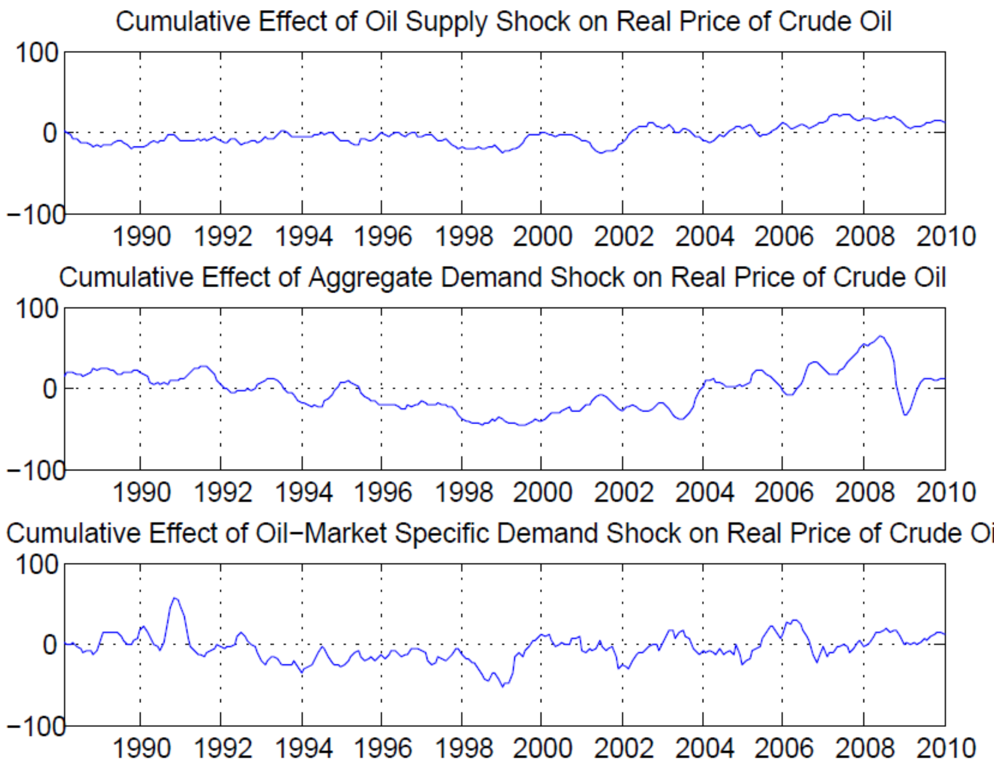
Note: The three panels plot the impulse responses of the real price of oil to each of the three demand and supply shocks that affect the crude oil market with dry cargo tramp rate as economic activity index. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impacts the level of oil price at time $t+s$ for different values of s. Here I limit s to a maximum of 15 months ahead. All shocks have been normalized to represent an increase in the real price of oil. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 4 Responses of real price of oil to three structural shocks in Kilian and Park (2009)



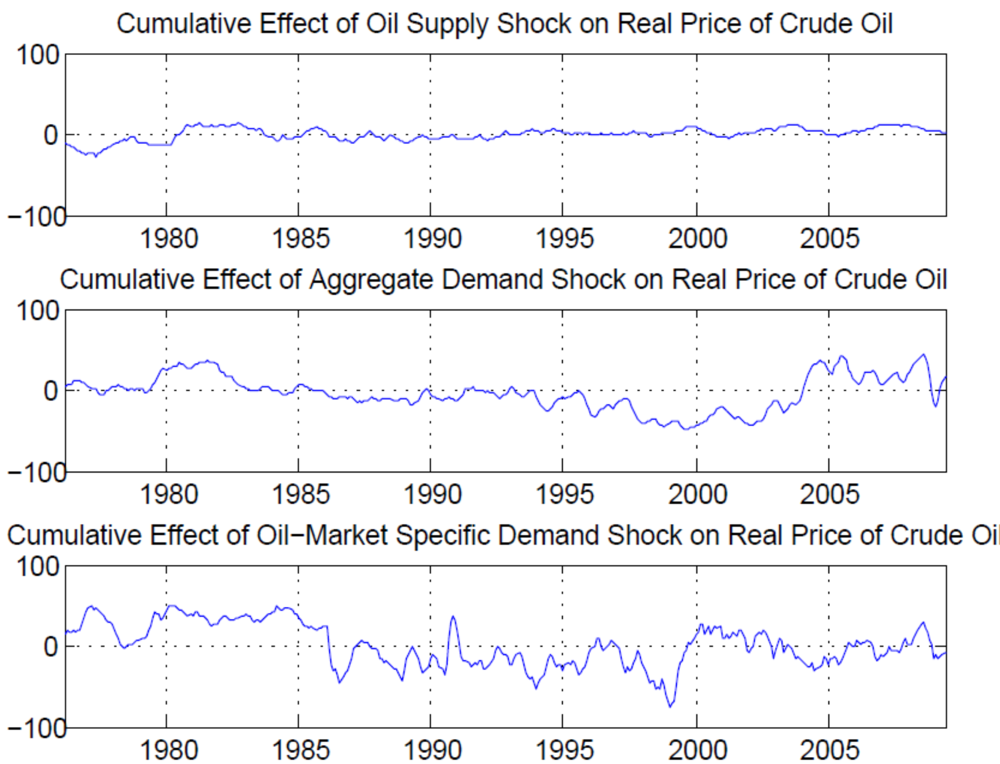
Note: The three panels replicate the impulse responses of the real price of oil to each of the three demand and supply shocks that affect the crude oil market, as detailed by Kilian and Park (2009). The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impact the level of oil price at time $t + s$ for different values of s. Here I limit s to a maximum of 15 months ahead. All shocks have been normalized to represent an increase in the real price of oil. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 5 Historical decomposition of real price of oil from January 1973 to December 2009 with BDI as economic activity index



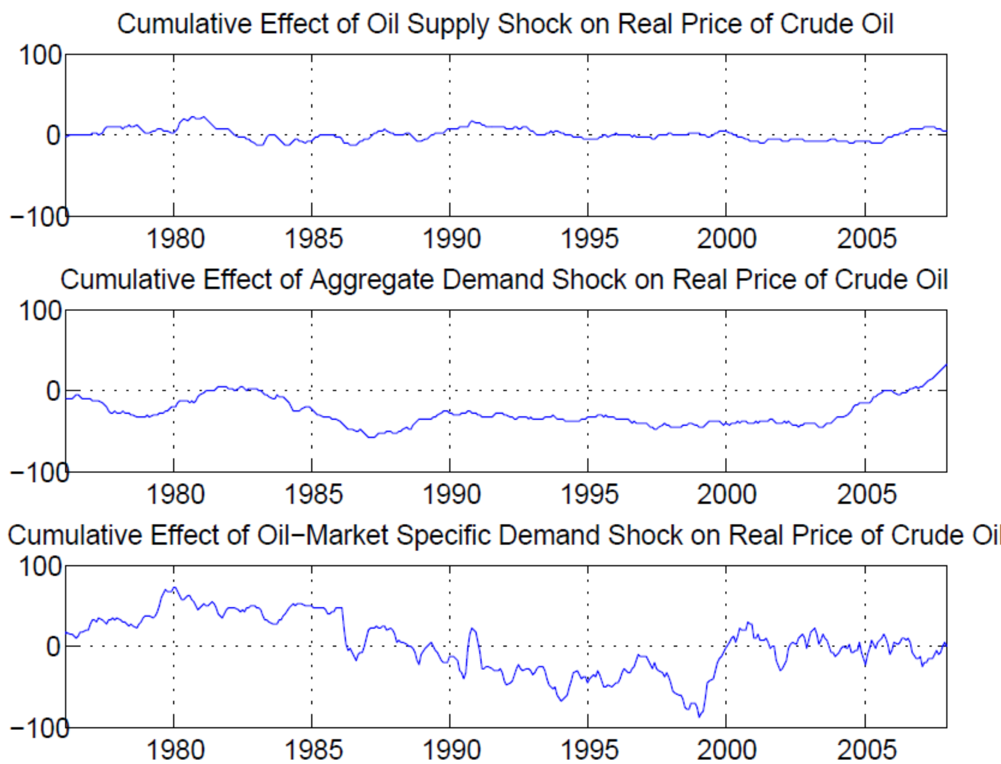
Notes: This figure plots the historical decomposition of fluctuations in the real price of oil with BDI as economic activity index. It shows the cumulative effect of a sequence of structure shocks that affect the real oil prices spanning the period from January 1973 to December 2009. The estimates are based on the structural VAR model in Eq.1.

Figure 6 Historical decomposition of real price of oil from January 1973 to December 2009 with dry cargo tramp rate as economic activity index



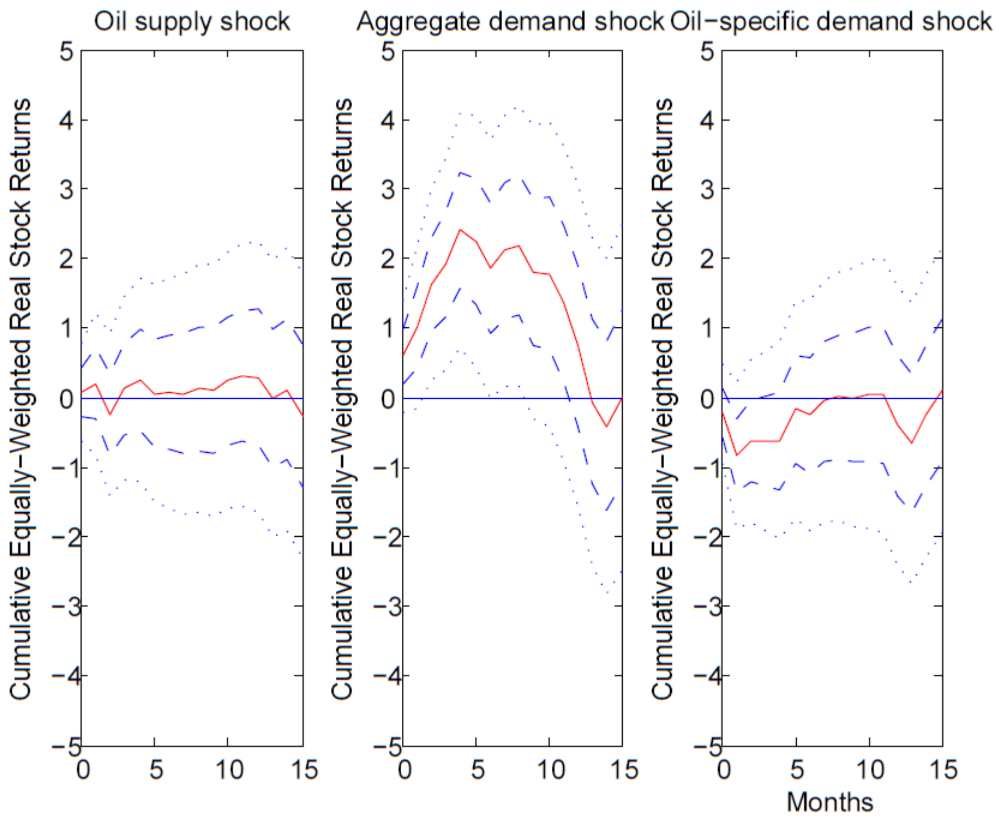
Notes: This figure plots the historical decomposition of fluctuations in the real price of oil with dry cargo tramp rate as economic activity index. It shows the cumulative effect of a sequence of structure shocks that affect the real oil prices spanning the period from January 1973 to December 2009. The estimates are based on the structural VAR model in Eq.1.

Figure 7 Historical decomposition of real price of oil from January 1973 to December 2007 in Kilian and Park (2009)



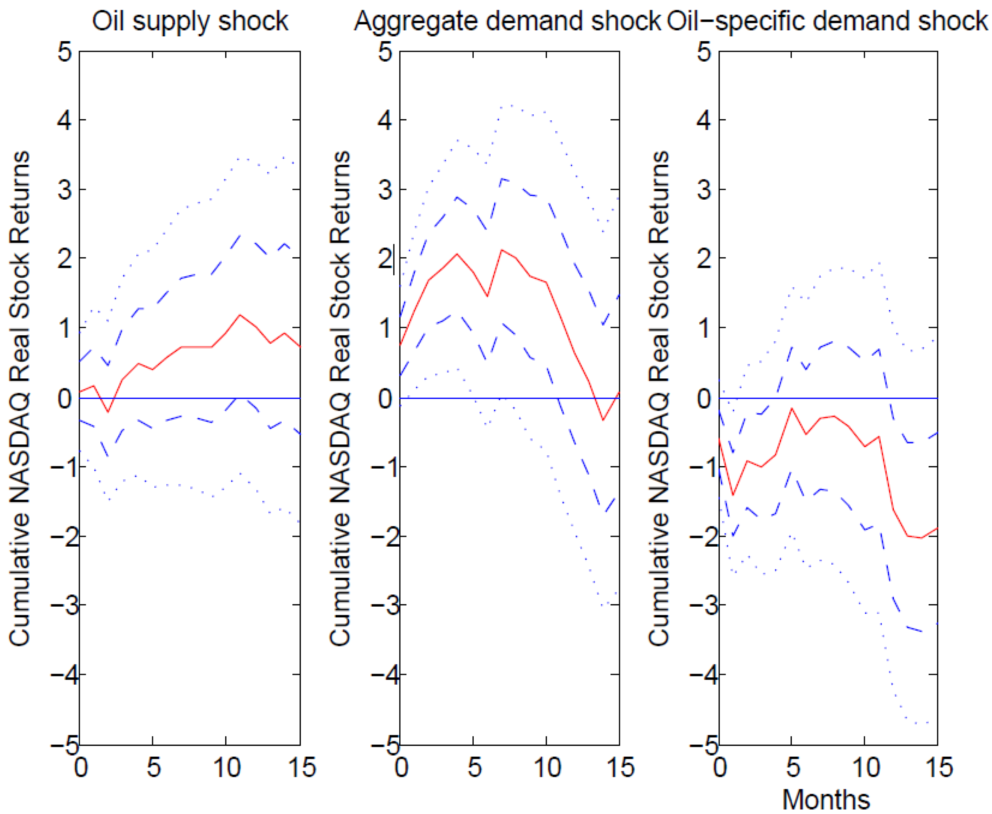
Notes: This figure replicates the historical decomposition of fluctuations in the real price of oil of Kilian and Park (2009). It shows the cumulative effect of a sequence of structure shocks that affect the real oil prices spanning the period from January 1973 to December 2007. The estimates are based on the structural VAR model in Eq.1.

Figure 8 Cumulative responses of equally-weighted real stock returns to three structural shocks with one-and two-standard error bands



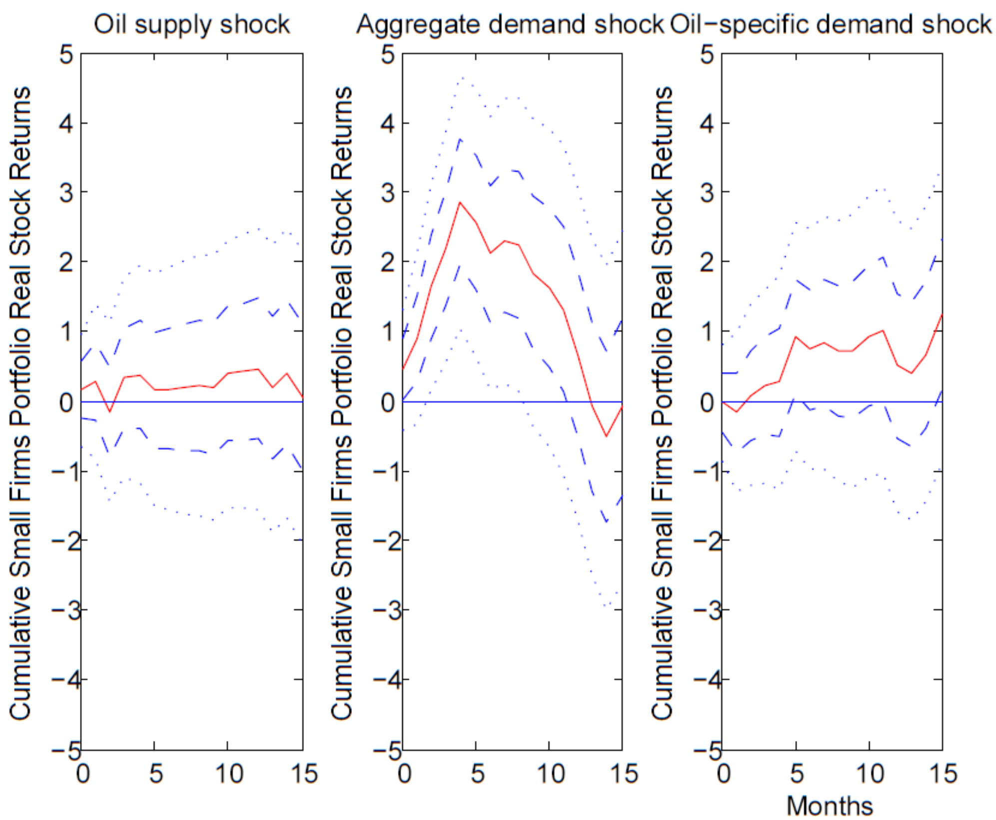
Note: The three panels plot the impulse responses of equally-weighted real stock returns to each of the three demand and supply shocks that affect the crude oil market. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impacts the real stock returns at time $t+s$ for different values of s. Here I limit s to a maximum of 15 months ahead. The oil supply shock has been normalized to represent a negative one-standard deviation shock, while the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shock. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 9 Cumulative responses of NASDAQ real stock returns to three structural shocks with one-and two-standard error bands



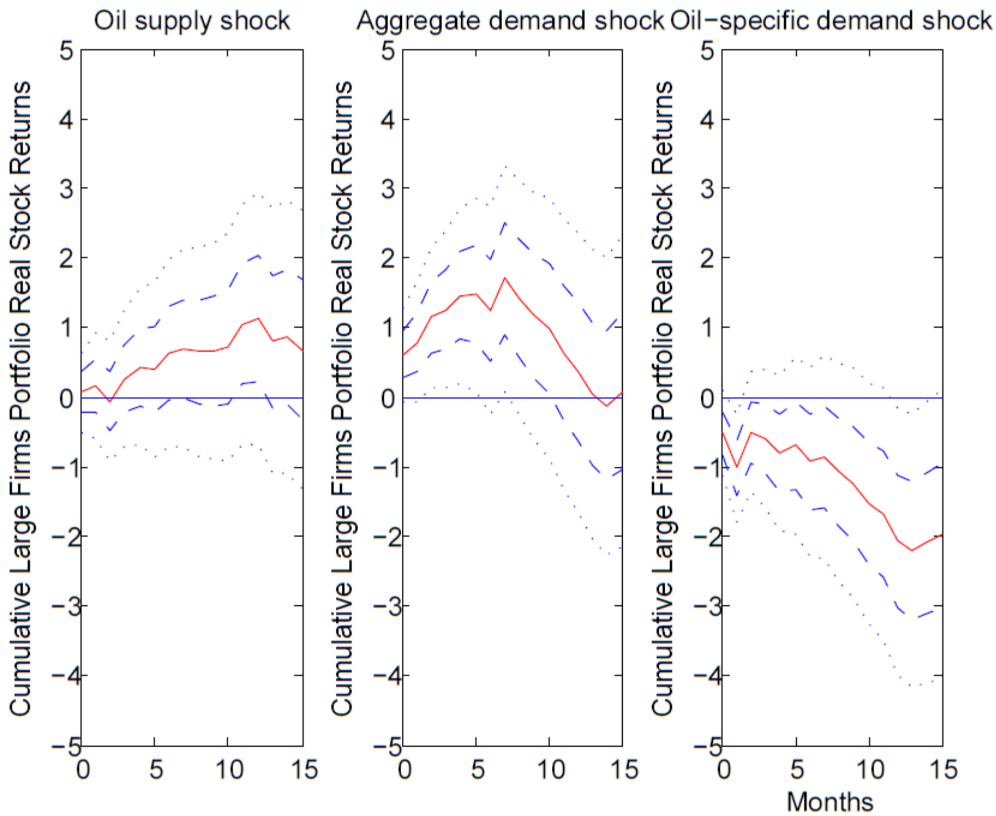
Note: The three panels plot the impulse responses of NASDAQ real stock returns to each of the three demand and supply shocks that affect the crude oil market. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impacts the real stock returns at time $t+s$ for different values of s. Here I limit s to a maximum of 15 months ahead. The oil supply shock has been normalized to represent a negative one-standard deviation shock, while the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shock. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 10 Cumulative responses of small firm portfolio real stock returns to three structural shocks with one-and two-standard error bands



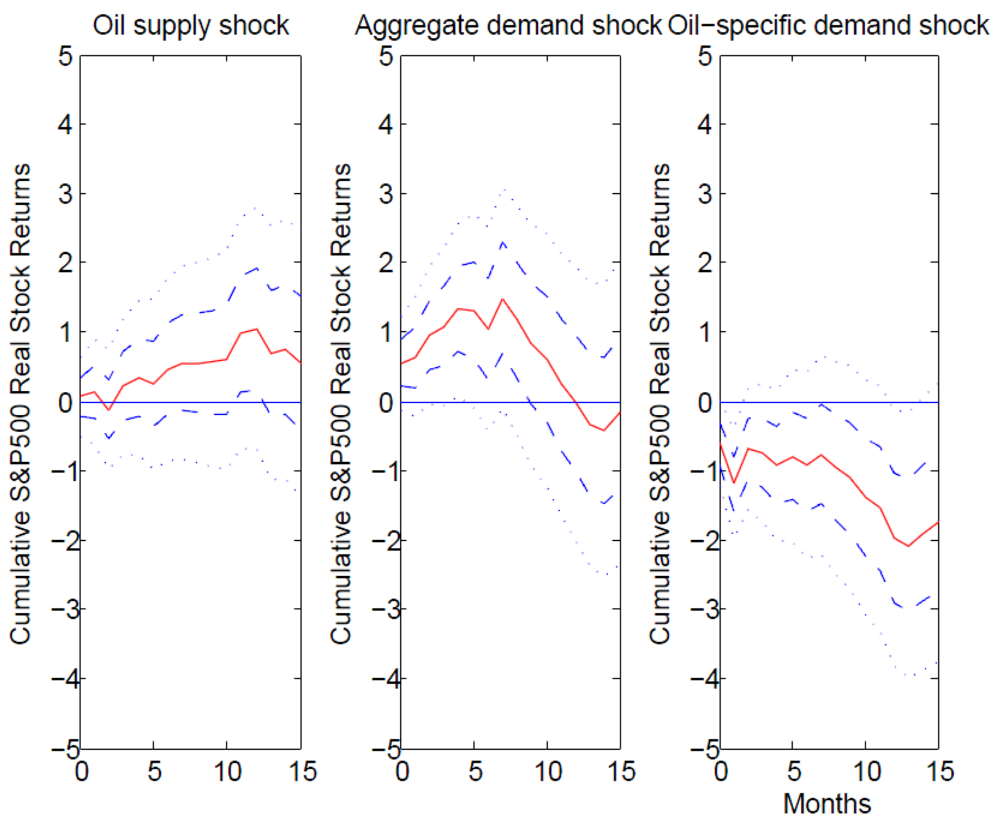
Note: The three panels plot the impulse responses of small firm portfolio real stock returns to each of the three demand and supply shocks that affect the crude oil market. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impacts the real stock returns at time $t + s$ for different values of s. Here I limit s to a maximum of 15 months ahead. The oil supply shock has been normalized to represent a negative one-standard deviation shock, while the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shock. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 11 Cumulative responses of large firm portfolio real stock returns to three structural shocks with one-and two-standard error bands



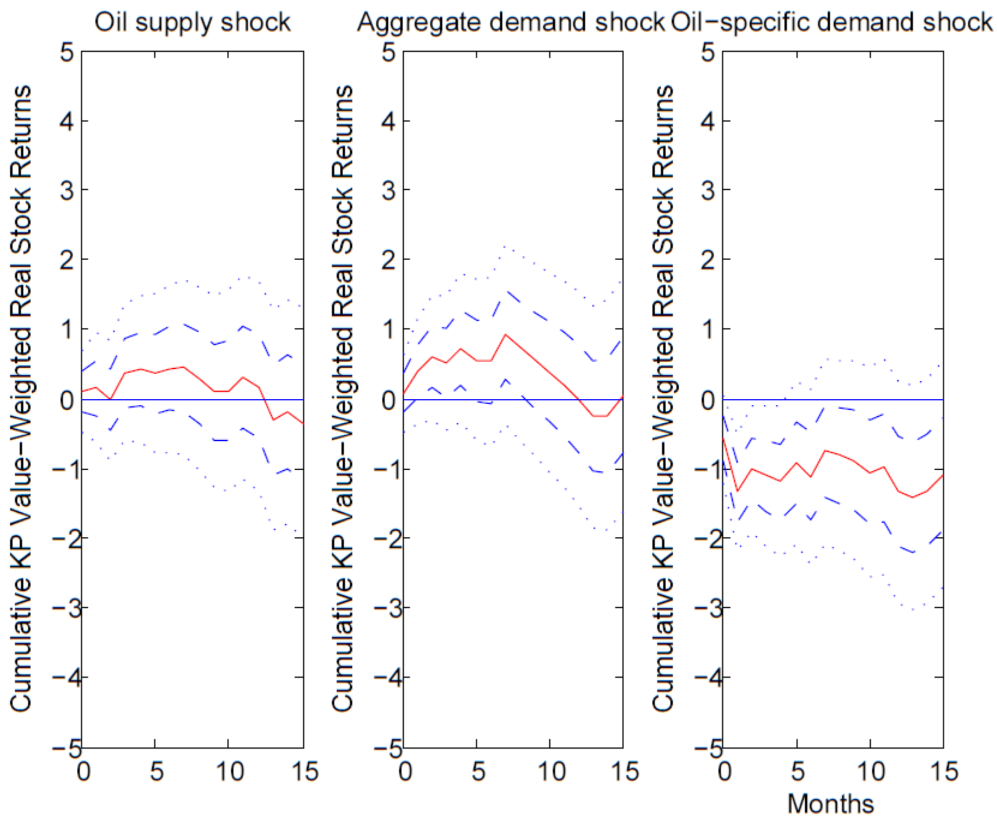
Note: The three panels plot the impulse responses of large firm portfolio real stock returns to each of the three demand and supply shocks that affect the crude oil market. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impacts the real stock returns at time $t+s$ for different values of s. Here I limit s to a maximum of 15 months ahead. The oil supply shock has been normalized to represent a negative one-standard deviation shock, while the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shock. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 12 Cumulative responses of S&P500 real stock returns to three structural shocks with one-and two-standard error bands



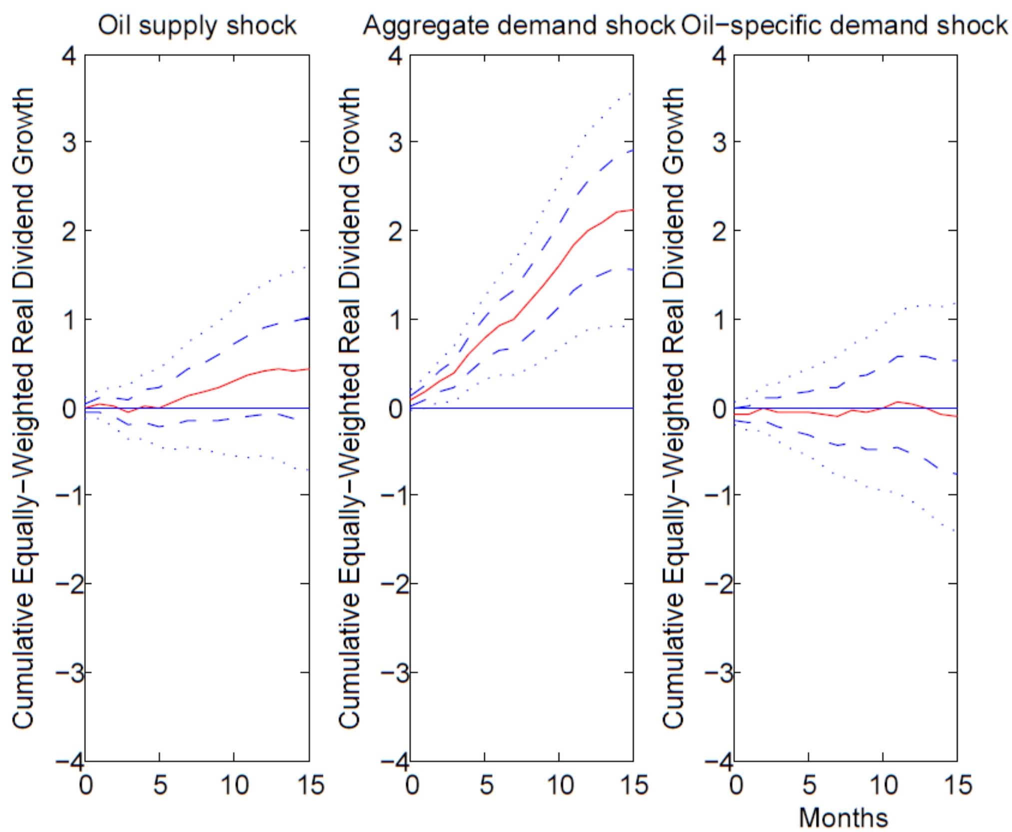
Note: The three panels plot the impulse responses of S&P500 portfolio real stock returns to each of the three demand and supply shocks that affect the crude oil market. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impacts the real stock returns at time $t+s$ for different values of s. Here I limit s to a maximum of 15 months ahead. The oil supply shock has been normalized to represent a negative one-standard deviation shock, while the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shock. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 13 Cumulative responses of value-weighted real stock returns to three structural shocks with one-and two-standard error bands in Kilian and Park (2009)



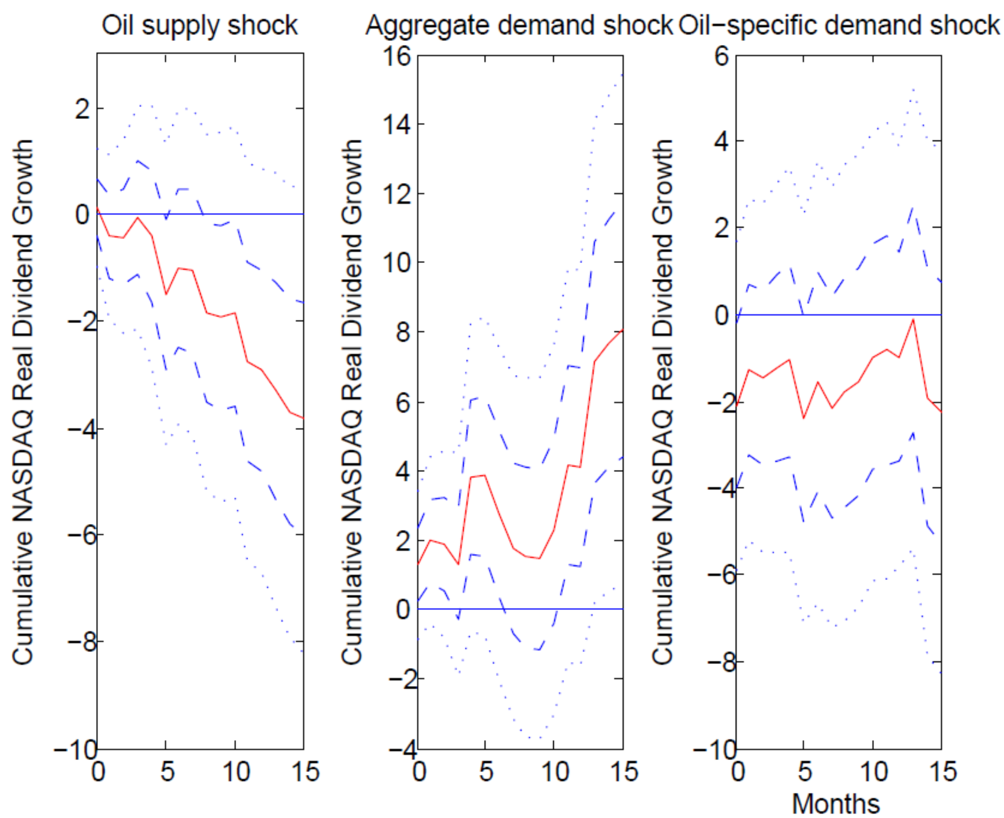
Note: The three panels replicate the impulse responses of value-weighted real stock returns to each of the three demand and supply shocks that affect the crude oil market in Kilian and Park (2009). The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impacts the real stock returns at time $t+s$ for different values of s. Here I limit s to a maximum of 15 months ahead. The oil supply shock has been normalized to represent a negative one-standard deviation shock, while the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shock. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 14 Cumulative responses of equally-weighted real dividend growth to three structural shocks with one-and two-standard error bands



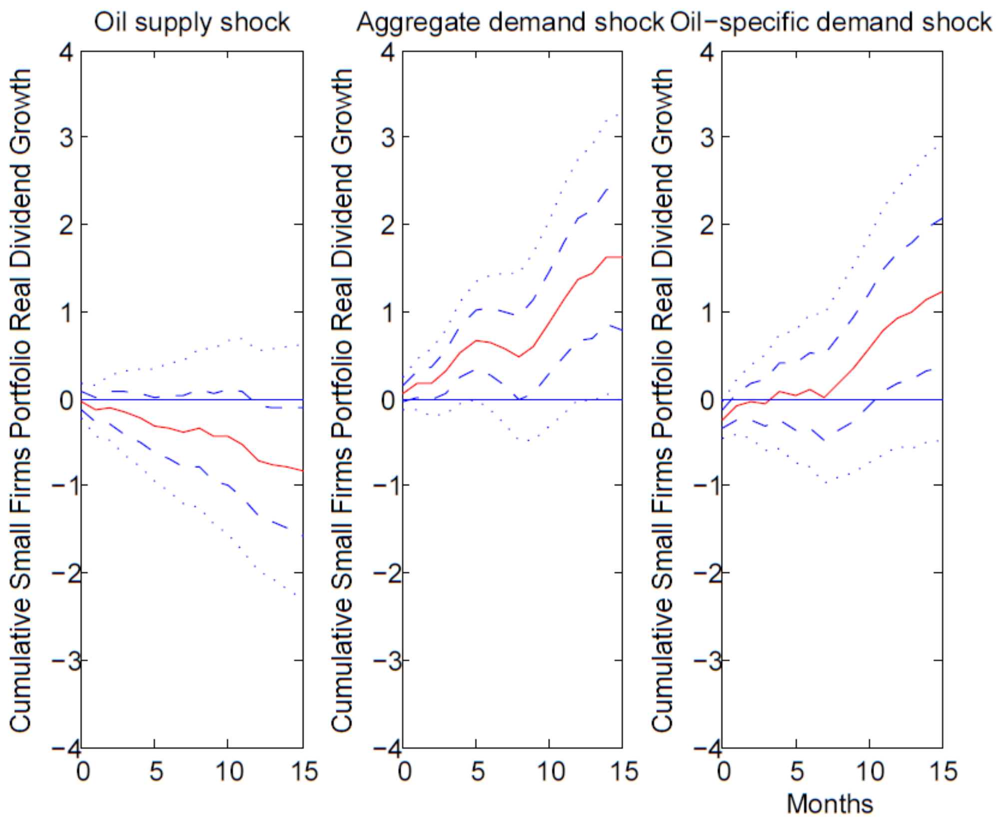
Note: The three panels plot the impulse responses of equally-weighted real dividend growth to each of the three demand and supply shocks that affect the crude oil market. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impacts the real dividend growth at time $t + s$ for different values of s. Here I limit s to a maximum of 15 months ahead. The oil supply shock has been normalized to represent a negative one-standard deviation shock, while the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shock. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 15 Cumulative responses of NASDAQ real dividend growth to three structural shocks with one-and two-standard error bands



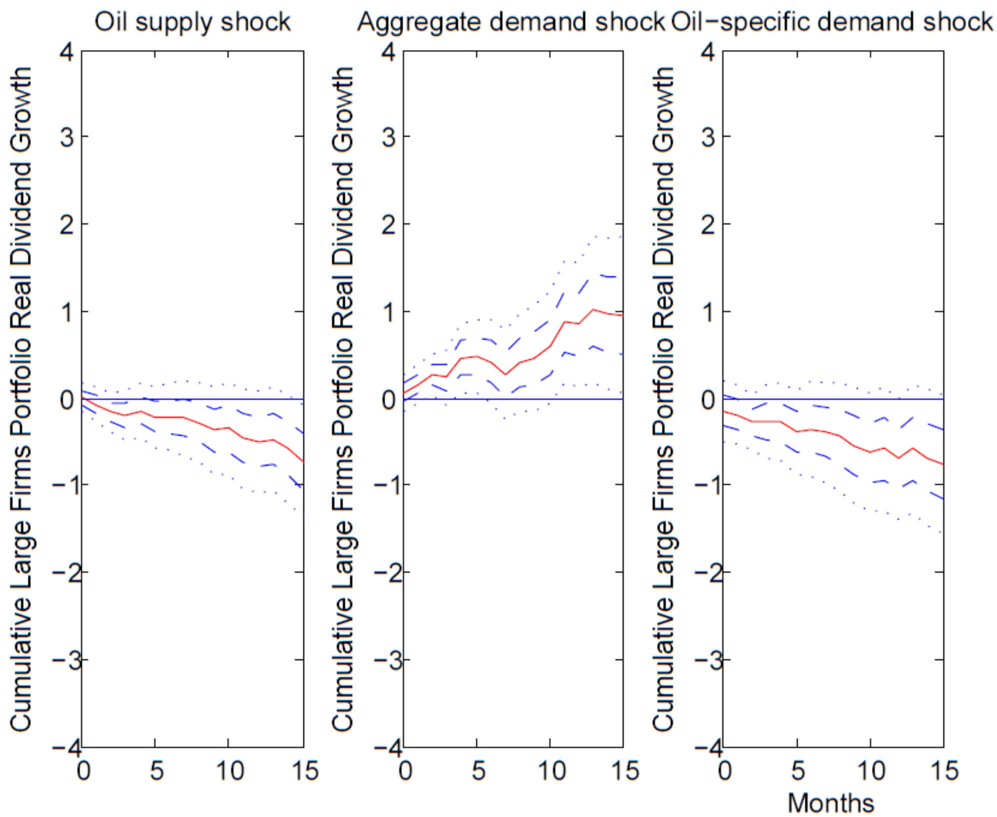
Note: The three panels plot the impulse responses of NASDAQ real dividend growth to each of the three demand and supply shocks that affect the crude oil market. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impacts the real dividend growth at time $t+s$ for different values of s. Here I limit s to a maximum of 15 months ahead. The oil supply shock has been normalized to represent a negative one-standard deviation shock, while the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shock. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 16 Cumulative responses of small firm portfolios real dividend growth to three structural shocks with one-and two-standard error bands



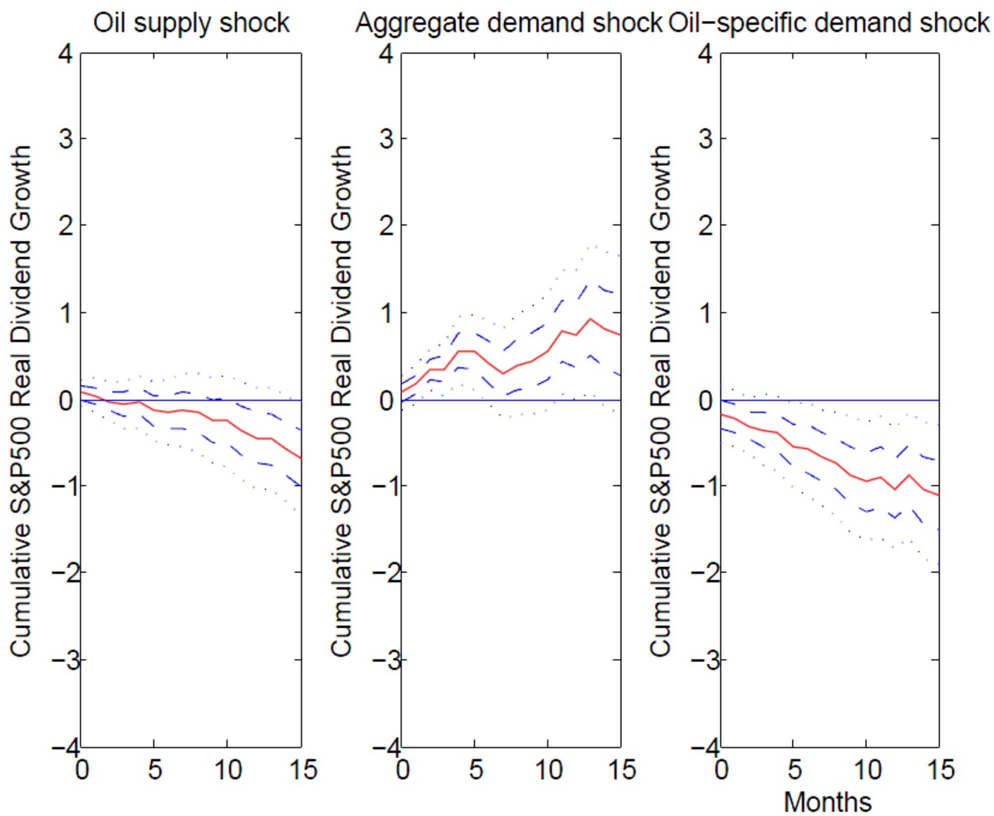
Note: The three panels plot the impulse responses of small firm portfolio real dividend growth to each of the three demand and supply shocks that affect the crude oil market. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impacts the real dividend growth at time $t + s$ for different values of s. Here I limit s to a maximum of 15 months ahead. The oil supply shock has been normalized to represent a negative one-standard deviation shock, while the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shock. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 17 Cumulative responses of large firm portfolio real dividend growth to three structural shocks with one-and two-standard error bands



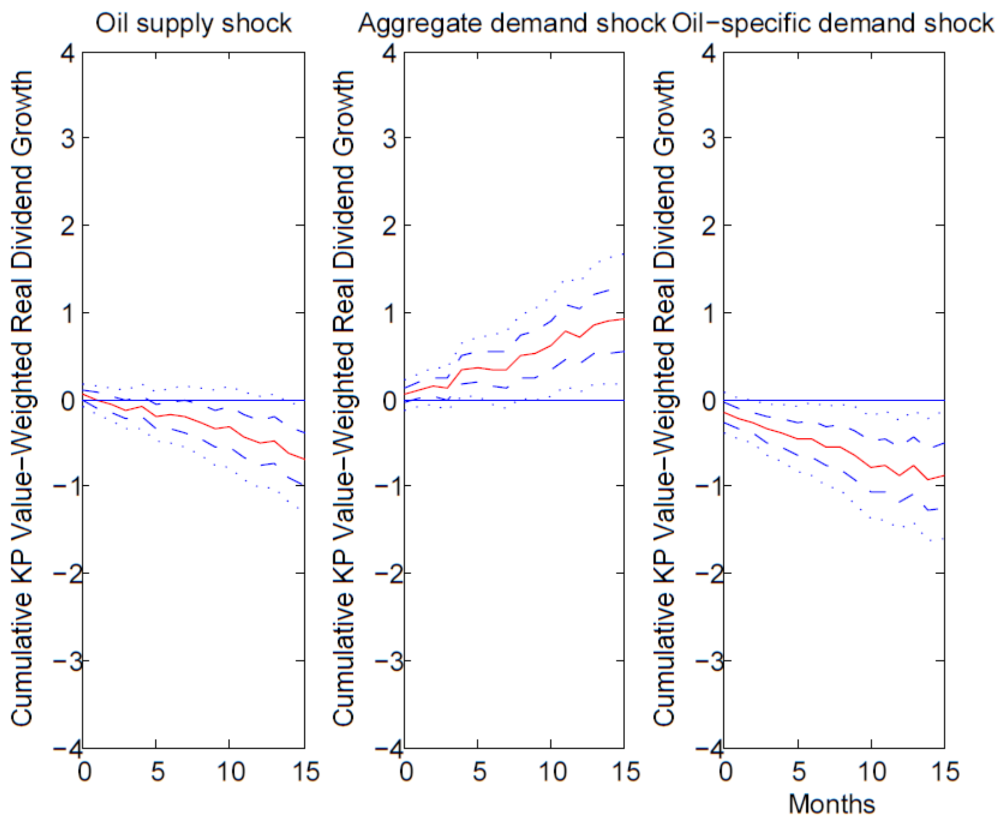
Note: The three panels plot the impulse responses of large firm portfolio real dividend growth to each of the three demand and supply shocks that affect the crude oil market. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impacts the real dividend growth at time $t + s$ for different values of s. Here I limit s to a maximum of 15 months ahead. The oil supply shock has been normalized to represent a negative one-standard deviation shock, while the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shock. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 18 Cumulative responses of S&P500 real dividend growth to three structural shocks with one-and two-standard error bands



Note: The three panels plot the impulse responses of S&P500 portfolio real dividend growth to each of the three demand and supply shocks that affect the crude oil market. The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impacts the real dividend growth at time $t + s$ for different values of s. Here I limit s to a maximum of 15 months ahead. The oil supply shock has been normalized to represent a negative one-standard deviation shock, while the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shock. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Figure 19 Cumulative responses of value-weighted real dividend growth to three structural shocks with one-and two-standard error bands in Kilian and Park (2009)



Note: The three panels replicate the impulse responses of value-weighted real dividend growth to each of the three demand and supply shocks that affect the crude oil market in Kilian and Park (2009). The estimates are based on the structural VAR model in Eq.1. Each panel measures how a unit impulse of structure shocks at time t impacts the real dividend growth at time $t + s$ for different values of s. Here I limit s to a maximum of 15 months ahead. The oil supply shock has been normalized to represent a negative one-standard deviation shock, while the aggregate demand shock and oil-market specific demand shock have been normalized to represent positive shock. The confidence intervals are constructed using a recursive-design wild bootstrap with 2,000 replications.

Conclusion

This thesis studies the interaction between oil price shocks and financial markets on both firm and aggregate levels. Chapter 1 is a firm-level study and empirically tests the relationship between oil price uncertainty and firm-level investment. The purpose of this chapter is to investigate how oil price volatility affects investment for a panel of Japanese firms. This is the first paper to address this relationship in the Japanese market. Chapter 2 uses a structural VAR approach to specifically study the link between oil price shocks and the Japanese stock market for the first time. It also fills the gap by testing whether the variations in Japanese real stock returns to the shocks in the crude oil market are driven by current and future variations in expected cash flows and/or variations in expected discount rate. Chapter 3 tests the robustness of SVAR and investigates the impact of oil price shocks on the different U.S. stock indices using alternate data. More importantly, it determines how firm size affects the relationship between oil price shocks and the stock market.

The results in Chapter 1 show that there is a U-shaped rather than simply a linear relationship between oil price volatility and strategic investment for a sample of Japanese firms. The results are well supported by compound option theory. The U-shaped relationship is robust to a number of different econometric estimations and different measures of volatility. The results from subsamples confirm this U-shaped relationship. Moreover, it shows that oil volatility has a strong and significant effect on investment of oil-intensive firms, whereas oil volatility has no statistically significant effect on that of less oil-intensive firms. For the firms with different size, the negative effect of oil price volatility on investment is stronger and more significant for small firms. These results are stronger than previous research conducted in the U.S. (Mohn and Misund, 2009).

Chapter 2 concludes that the response of Japanese real stock returns to oil price shocks differs extensively depending on the specific underlying causes of a higher oil price, which is in line with Kilian and Park (2009) for the U.S.. Specifically, oil supply shocks from unanticipated disruptions of crude oil production do not have any significant effect on Japanese real stock returns. When an oil price increase is driven by aggregate demand shocks, there is a positive relationship between the oil price shocks and the Japanese stock market. Oil-specific demand shocks from unexpected increases of precautionary demand for crude oil lower the stock returns in Japan. Further, I find the responses of the Japanese stock market to all shocks in the crude oil market can be attributed almost entirely to changes in real cash flows.

The largest contribution of Chapter 3 is that it determines how firm size affects the relationship between oil price shocks and the stock market. For example, aggregate demand shock caused by world economic activity expansion increases stock returns persistently. However the magnitude and length of the effect depends on the firm size. The aggregate demand shock has a longer and stronger effect on the stock returns of small-sized firms than those of large-sized firms. Further, an oil-market specific shock has a negative effect on the stock returns of large-sized firms while it has no statistically significant effect on small-sized firms.

Crude oil is an important input in production process and also used to generate power, and facilitate the advance of economy. Any adverse impact on oil price could bring chaos to the financial market on both firm and aggregate level. The purpose of this thesis is to provide a clear picture about how oil price shocks interact with financial markets and how our policymakers can make effective decisions when facing oil price volatilities.

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