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“ΜΟΝΤΕΛΟΠΟΙΗΣΗ ΤΗΣ ΔΥΝΑΜΙΚΗΣ ΤΗΣ ΚΑΜΠΥΛΗΣ ΠΕΤΡΕΛΑΪΚΩΝ ΣΜΕ”

Master’s Thesis
September 6, 2004

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Committee:
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“MODELING THE DYNAMICS OF THE TERM STRUCTURE OF PETROLEUM FUTURES”

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CHAPTER 1: INTRODUCTION

In this study, first we examine the dynamics of the term structure of energy commodity futures. Next, apply our findings to forecasting subsequent futures prices. Our raw data consist of crude oil futures traded on the New York Mercantile Exchange (NYMEX) and the International Petroleum Exchange (IPE), and heating oil and gasoline futures traded on NYMEX. We use principal components analysis (PCA) to come up with a reduced number of latent factors that can adequately model their term structure. We then use these factors to forecast the subsequent evolution of futures prices for the commodities under examination.

Modeling the futures curve for energy commodities has gained increasing importance, as it can be used in a number of applications, including hedging, pricing of derivatives, and the valuation of energy-related contingent claims. A number of methods and models have been used to estimate the futures curve and how it evolves over time. These generally follow two approaches. The first approach involves identifying specific economic or financial factors that directly affect futures prices. The disadvantage of this approach is that a lot of these variables exist in theory, but are not observable or measurable in practice (e.g., the convenience yield). The second approach involves dealing only with the data available and manipulating the data in such ways that they would give meaningful information. The forward curve is modeled directly as opposed to being modeled as a function of spot price and convenience yield processes. The drawback of this approach is that, while it may lead to clean-cut and easy-to-use models, there is often no economic interpretation of the variables in play. This study focuses on the second, market-oriented approach rather than the first, traditional approach. The advantage is that we do not postulate ex-ante the factors that drive futures dynamics. Rather, we let the data speak for themselves.

Lautier [2003] provides a general review of term structure models of commodity prices, their ability to describe the price curve empirically observed, and a description of the application of these models on hedging and investment decisions. In her paper, she goes over major research done on the dynamics of futures prices. She describes one-factor stochastic models for a commodity's term structure that can either follow a geometric Brownian motion or a mean-reverting process. She explains how these models can be expanded by the introduction of a second stochastic variable, most commonly the convenience yield or the long-term price, and then she talks about models that add the interest rate as a third factor. Discussing how well these models reproduce the term structure of futures prices, she concludes that one-factor models perform poorly, but the addition of a second factor gives very satisfactory results. Three-factor models are not materially better than two-factor models. Finally, she reviews research conducted on using term structure models to hedge long-term commodity commitments and to make investment decisions that require knowing distant futures prices in order to compute the present value of cash flows associated with the investment.

Moving on to individual work, extensive research has been done following the first of the approaches described above.

Schwartz [1997] examined one-factor, two-factor, and three-factor stochastic models for futures prices of oil, copper, and gold. His one-factor model followed a mean-reverting process for the logarithm of the spot price. The two-factor model added the convenience yield as a second stochastic factor that also followed a mean-reverting process. The three-factor model also included stochastic interest rates. The data he used consisted of weekly futures prices for five contracts on crude oil, high grade copper, and gold (he repeated his analysis using various sets of maturities to check the effect of time, but all of these maturities were less than two years). Oil data ranged from January 2, 1985 to February 17, 1995, copper data from July 29, 1988 to June 13, 1995, and gold data from January 2, 1985 to June 13, 1995. There was also a proprietary dataset on oil futures prices provided by Enron for contract maturities from two months to nine years, which ranged from January 15, 1993 to May 16, 1996. Schwartz then compared the relative performance of the three models by calculating the root mean square errors and mean errors by commodity across several periods of time. He concluded that the one-factor model is often inadequate in reproducing the actual data. The two-factor and three-factor models both clearly outperform the one-factor model, but their relative performance is indeterminate. Finally, the paper applies these models to hedging long-term forward commitments and to making investment decisions under uncertainty.

In subsequent papers, Schwartz studied variations of these models. Miltersen and Schwartz [1998] developed a three-factor model to distinguish between forward and futures convenience yields. They also provided an application on pricing European options using the same data on high grade copper futures traded on the Commodity Exchange of New York (COMEX) as in Schwartz [1997]. They concluded that the introduction of stochastic convenience yields and the time lag between the maturity of the futures contracts and the options can give materially different results when pricing options.

Clewlow and Strickland [1999a] extended Schwartz's one-factor model by using it to derive formulas for pricing derivatives such as standard options on forwards and futures, caps, floors, collars, and swaptions. They also studied trinomial trees consistent with the forward curve and volatility structure and showed how they can be used to price derivatives.

Schwartz and Smith [2000] develop a two-factor model called the short-term/long-term model, which assumes that short-term deviations in spot prices follow a mean-reverting stochastic process and the equilibrium price level follows a Brownian motion process. We should note that the convenience yield does not enter the model, but the authors show that it is equivalent to the stochastic convenience yield models developed in Gibson and Schwartz [1990]. They then show how this model can be used to value futures contracts and European options on futures contracts. Drawing on the same data as Schwartz [1997], they estimate the parameters of the model and demonstrate how it can be applied to real option investment decisions.

Work has also been done on electricity forward curve dynamics. Audet, Heiskanen, Keppo, and Valviläinen [2002] develop a model for forward prices using weekly data from Nord Pool's 52 futures contracts between 1999 and 2001. They then discuss three applications of their model: conditional forecasting of the forward curve, i.e., updating the initial forward curve with spot price predictions and comparing it with the realized forward curve; pricing of forward options; and checking the accuracy of a simplified forward curve model that only uses a finite number of forward curve points.

Ribeiro and Hodges [2004] develop a more technical version of the two-factor model originally suggested by Schwartz [1997]. In their model, the two factors are still the spot price (which follows a geometric Brownian motion) and the instantaneous convenience yield, but there are two important innovations: arbitrage possibilities are ruled out and spot price volatility depends on inventory levels, as predicted by the theory of storage. Their data consists of weekly observations of the seven nearest futures contracts of light, sweet crude oil traded on NYMEX from March 17, 1999 to October 15, 2003. Finally, they compare their model to Schwartz's original model by calculating their mean pricing errors and root mean square errors for all the observations. They conclude that their model outperforms Schwartz's, although not significantly, and that both models are good at reproducing short-term maturity data, but not long-term.

Several papers have also used the second approach to model forward curve dynamics directly, using only available market data. A good deal of research conducted along those lines has used principal components analysis in the estimation of model parameters.

Reisman [1991] examines pricing commodity-related claims. He proposes a model where price processes of futures with several maturities are inputs and the spot price and the convenience yield processes are implied. He then proceeds to show how his results can be used to value commodity claims. Reisman's paper is purely theoretical and has no applications using real data.

Based on Reisman's [1991] model, Schwartz and Cortazar [1994] used PCA in the general framework of valuing commodity-contingent claims. They focused on two copper futures contracts traded on COMEX. The contracts differ in terms of their specifications, mainly the quality of the product to be delivered and their maturities. Schwartz and Cortazar used daily futures return data between January 1978 and January 1990 for the nearest 21 months of the two contracts, grouping them in seven quarterly periods. They then performed PCA to obtain a three-factor model that describes the stochastic movement of futures prices. The three factors accounted for approximately 93%, 4%, and 1% of total variance respectively. The first factor, i.e., the one with the highest loading, was fairly constant across maturities, indicating that shocks cause a parallel shift of the futures return curve. The second factor represented steepness, meaning that shocks cause short-term and long-term contracts to move in opposite directions. The third factor, curvature, represented shocks that affect long-term and short-term contracts in the same way, but medium-term contracts in the opposite way. Finally, they used the factor loadings found in PCA as volatility estimates for pricing Magma Copper Company's publicly traded copper interest-indexed notes issued in 1988.

Clewlow and Strickland [1999b] performed PCA to identify the most important principal components for crude oil and natural gas futures prices. Their data ran from November 1995 to December 1997 and consisted of daily closing futures prices for the nearest 24 monthly contacts for light, sweet crude oil and Henry Hub natural gas traded on NYMEX. They concluded that in the case of light, sweet crude, the first three principal components are significant, whereas for natural gas, the first six principal components are significant. They then went on to use those principal components as the volatility parameters in a multi-factor stochastic model for the evolution of the forward curve, which in turn was used to price European caps on natural gas and European swaptions on crude oil.

In a similar line of research, Tolmasky and Hindanov [2002] applied PCA on crude oil and heating oil. Their data consisted of weekly log returns of the nearest ten futures contracts traded on NYMEX from 1983 to 2000. In the case of crude oil, they also found three components that explain 99.89% of the variance. In line with previous research, the first factor represents a parallel shift or level, the second factor steepness, and the third factor curvature. In the case of heating oil, they concluded that the first three factors (again representing level, steepness, and curvature) explain 99.63% of the total variance. In addition, they examined the effects of seasonality, showing that the correlations among contracts are higher when the commodity is off-season and therefore the level factor becomes more important during that time. However, they did not come up with a definitive answer as to whether seasonality is statistically significant. They then ran PCA on crude oil and heating oil jointly and came up with four factors that explain 99.36% of total variance. Finally, they showed that the results of PCA could be applied as the volatility functions in value-at-risk calculations or option pricing.

Järvinen [2003] extended the analysis to Brent crude oil and pulp. He used weekly NBSK Risi pulp data ranging from June 1998 to October 2001 and monthly data on Brent crude oil ranging from Frebruary 1997 to 2002. The main innovation in this paper is that the forward curve is estimated from the par swap quotes rather than taken directly from the futures market (the par swap price can be interpreted as a present value weighted sum of forward prices).[1] The results of PCA showed a different picture than earlier research. The first factor explained only 62% of total variance for Brent crude and 38% of total variance for pulp. The second factor increased total variance explained to 81% for Brent crude and 63% for pulp, while the addition of a third factor increased the percentages to 89% and 84% respectively. Particularly in the case of pulp, Järvinen suggests a four-factor model in order to satisfy the criterion of choosing factors with eigenvalues greater than one.[2] The greatest difference, however, lies in the effects of the principal components on the curve. The factors do not represent level, steepness, and curvature, but rather show a much more complex behavior, especially for pulp. Järvinen concludes that this may be due to the mean-reverting nature of commodity prices or to the liquidity and reliability of the swap quotes from which he derived the forward curves.

Our study presents two main innovations. First, we extend the empirical investigations done in the field by examining data on four energy commodities: crude oil traded on NYMEX, crude oil traded on the IPE, heating oil, and gasoline. We used PCA to model the dynamics of the term structure of futures prices. We found that the first three components explain more than 95% of total variance for each commodity. Furthermore, the shape and effect of these principal components is similar for all commodities and consistent with the general findings in the literature. The second innovation involves using multiple regression analysis to examine whether the retained principal components have any predictive power for futures prices. We ran this analysis using the retained principal components of all commodities as regressors. The advantage is that we essentially used the whole term structure of futures prices through a few variables only. In addition, by choosing principal components of all commodities as the independent variables, we were able to check for possible spillover effects across commodities. To the best of our knowledge, no previous studies have used principal components to forecast subsequent futures prices. Our results showed that IPE crude oil and heating oil principal components contain information on their respective commodities's subsequent futures prices. On the flip side, this implies the absence of spillover effects.

[1] For more information and additional methods for extracting the forward curve using swap prices, see Järvinen [2002].

[2] To satisfy the criterion of choosing factors that explain 90% of total variance or more, one would need four factors for both Brent crude and pulp.

In the case of NYMEX crude oil and gasoline, however, there was no evidence of a relationship between principal components of any commodity and the next day's futures prices.

This study is organized as follows: Chapter 1 provides a literature review and outlines the contributions of our study. Chapter 2 contains an overview of energy markets and the dataset we will be using. Chapter 3 describes the theory behind principal components analysis and discusses our results from PCA. Chapter 4 examines the forecasting power of principal components across commodities using multiple regression analysis. Chapter 5 concludes.

CHAPTER 2: PETROLEUM MARKETS

2.1 Physical properties of crude oil

The physical properties of crude oil vary depending on the reservoir, field or even region that it has been pumped from. The two main physical characteristics according to which crudes are classified are API gravity and sulfur content.

API gravity is the universally accepted scale adopted by the American Petroleum Institute (API) for expressing the density of the crude.[3] Light crudes, i.e., less dense crudes with a low specific gravity and hence high API gravity, have a greater proportion of the higher-value light hydrocarbons, which are typically easier to recover during the refining process. Heavy crudes, i.e., denser crudes with a high specific gravity and hence low API gravity, have a greater proportion of heavy hydrocarbons, which are less valuable and require further refining in order to break down into lighter, more valuable products such as LPG, naphtha, and straight-run gasoline. There is no clear-cut divisor between light and heavy crudes, but generally, crude oils with gravities above 30^o or 35^o API are considered light and crude oils with gravities below 24^o API are considered heavy.

Sulfur content is the second major physical characteristic that distinguishes crudes. It is important because sulfur compounds released during combustion are harmful pollutants to the environment.[4] Sweet crudes are crudes with a relatively low sulfur content, a property that makes refining easier and the finished product more desirable, and as such are more valuable. Sour crudes are crudes with a relatively high sulfur content, which require additional processing to produce valuable finished products. Again, there is not a universal strict cut-off point that distinguishes sweet from sour crudes. In general, crudes with less than 0.5% sulfur by weight are said to be sweet and crudes with more than 0.5% sulfur by weight are said to be sour.

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[3] API gravity is gravity (weight per unit volume) of oils as measured by the API scale whereby API gravity = (141.5 / Specific gravity) – 131.5. Specific gravity is defined as the ratio of the density of a substance at 60^o Fahrenheit to the density of water at the same temperature.

Other crude oil characteristics include metal content, viscosity, color, and the specific molecular structure of the oil. Such characteristics are important in the use and cost of a particular crude. For example, they help us determine whether a crude is suitable for obtaining products such as lubricants or petrochemicals. Referring to crude oil by its streams (fields of origin) is useful because it summarizes all characteristics.

2.2 Crude oil benchmarks

Crude oil is valued for the products it yields, such as gasoline and heating oil. Since there are more than 150 different types of crude, it is easier to follow just a few crudes that are representative of a specific quality (called benchmarks) and then price other crudes of a similar quality at a premium or discount to the benchmarks.

The US benchmark is West Texas Intermediate (WTI). It is a crude oil of very high quality, having a relatively high natural yield of naphtha and straight-run gasoline. It is light, with an API gravity of 39.6^{o}, and sweet, with a sulfur content of 0.24%. WTI is extracted in Texas and Oklahoma, delivered through pipelines to Cushing, Oklahoma, and refined mostly in the Midwest and the Gulf of Mexico region. Its physical characteristics and convenient location make WTI a premium crude.

Brent is another major crude, used as a benchmark mainly in Europe and Africa. It is also a light, sweet crude (although not as light or sweet as WTI), with an API gravity of 38.5^{o}, and a sulfur content of 0.36%. Brent is actually a blend of crudes extracted from 15 different oil fields in the Brent and Ninian systems in the North Sea and is deliverable at Sullum Voe on Shetland Islands. Brent is typically refined and consumed in Northwest Europe, but it also moves to East Coast and Gulf Coast refineries when price differentials favor exports. Because Brent is of a lower quality than WTI, it is usually priced at a discount to WTI.

There are several other important crudes, such as the OPEC basket, Saudi Arabia's Arab Light or Dubai Crude. While following individual crude oil prices may be sometimes

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[4] After an Environmental Protection Agency regulation passed in 1993, diesel fuel used by vehicles on the highway must contain no more than 0.05% sulfur by weight. In California, this

useful, we should not forget that the oil markets are physically interconnected at a global level and therefore prices of both crudes and products are inevitably correlated and are affected by international political or economic factors.

2.3 Crude oil trading

Crude oil is the world's most actively traded commodity. It is usually traded under contract arrangements, which are tailor-made transactions. However, it is also sold in spot markets (under cargo-by-cargo, transaction-by-transaction arrangements) and in futures markets (under standardized contracts traded on regulated exchanges and settled daily). The two biggest international forums for trading crude oil futures are the New York Mercantile Exchange (NYMEX) and the International Petroleum Exchange (IPE) in London.

Crude oil has been trading on NYMEX since 1983. The NYMEX light, sweet crude oil futures contract is the world's most heavily traded futures contract of a physical commodity in terms of volume and liquidity. It trades in units of 1,000 barrels (equivalent to 42,000 US gallons) and its price is quoted in US dollars and cents per barrel. The minimum price fluctuation is \$0.01 per barrel or \$10.00 per contract. The maximum price fluctuation is \$10.00 per barrel or \$10,000 per contract. However, if any contract is traded, bid or offered at the \$10.00 per barrel limit for five consecutive minutes, trading is halted for five minutes. When trading resumes, the limit is expanded by another \$10.00 per barrel in either direction. If another halt is triggered, the limit will continue to be expanded by \$10.00 per barrel in either direction after each successive five-minute trading halt. Trading is conducted by open outcry from 10:00am until 2:30pm New York time and via an internet-based platform after hours (Mondays through Thursdays from 3:15pm until 9:30am the following day and from 7:00pm on Sundays). There exist contracts for the next 30 consecutive months as well as contracts for delivery in 36, 48, 60, 72, and 84 months (35 futures contracts in total). Trading terminates at the close of business on the third business day prior to the 25th calendar day of the month preceding the delivery month. If the 25th calendar day of the month is a non-business day, trading ceases on the third business day prior to the business day preceding the 25th calendar

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low-sulfur content is also required of distillate fuel oil used off the highway.

day. Settlement is done with physical delivery, although the majority of contracts are actually not executed for physical delivery. The underlying asset can be thought to be WTI, although a number of other streams are also deliverable.[5] The delivery point is Cushing, Oklahoma (free on board seller's facility). The delivery period is a full month, meaning that deliveries must be initiated on or after the first calendar day and completed on or before the last calendar day of the delivery month. Due to the nature of crude oil trading, the WTI spot price is usually at parity to the nearest futures contract. Differences typically arise because the spot price delivery scheduling period does not exactly coincide with the expiration of the futures contracts (it is in fact three days later).[6]

The IPE is the second most liquid crude oil market in the world. The Brent Crude futures contract has been trading on the IPE since 1988. Together with physical (so-called dated) Brent and forward Brent, it forms the Brent blend complex, which is used as a basis for pricing for two thirds of the world's traded crude oil. The trading unit is 1,000 barrels of Brent crude oil. Prices are quoted in US dollars and cents per barrel with a minimum price fluctuation of $0.01 per barrel ($10.00 per contract) and no upper limit for price fluctuation. Trading is conducted by open outcry from 10:02am until 7:30pm London time (5:02am until 2:30pm New York time) and electronically from 2:00am until 10:00pm (9:00pm until 5:00pm New York time). On Fridays, electronic trading ceases at 8:30pm (3:30pm New York time). There exist contracts for the next 12 consecutive months, then quarterly out to a maximum 24months, and then half-yearly out to a maximum 36 months (18 futures contracts in total). Trading terminates at the close of business on the business day immediately preceding the 15th day prior to the first day of the delivery month. If the 15th day is a non-banking day in London (including Saturday), trading ceases on the business day immediately preceding the first business day prior to the 15th day. The contract is traded for physical delivery with an option to cash settle against the IPE Brent Index price for the day following the last trading day of the futures

[5] Deliverable US crudes are crudes with a sulfur content of 0.42% by weight or less and an API gravity between 37^{o} and 42^{o}. Deliverable streams are WTI, Low Sweet Mix, New Mexico Sweet, North Texas Sweet, Oklahoma Sweet, and South Texas Sweet. Deliverable non-US crudes are crudes with an API gravity between 34^{o} and 42^{o}. Deliverable streams are the UK's Brent and Forties and Norway's Oseberg Blend at a $0.30 per barrel discount, Nigeria's Bonny Light and Colombia's Cusiana at a $0.15 per barrel premium, and Nigerian Qua Iboe at a $0.05 per barrel premium.

[6] For example, if a futures contract for October expires on September 22, then from September 23-25 the futures price will track prices for November delivery, whereas the spot price will still

contract.[7] The underlying asset is current pipeline export quality Brent blend as supplied at Sullom Voe.

2.4 Refined products markets and trading

The two most important refined products are gasoline and heating oil, accounting for approximately 40% and 25% of the yield of a crude oil barrel respectively.

Gasoline is the largest single volume refined product sold in the United States, which in turn has the highest gasoline yield per barrel of crude oil in the world. The market for gasoline is very diverse and complex. It involves hundreds of wholesale distributors and thousands of retail outlets and requires a massive distribution infrastructure to move gasoline to every retail outlet. In addition, there are multiple pricing levels ("classes of trade") depending on the point of the distribution chain that the gasoline is sold. Thus, gasoline is sold at refinery gate prices by refiners as it leaves the refinery, at rack prices by refiners or by resellers as it leaves a distribution terminal or at dealer tank wagon prices by refiners or resellers to retailers at the gasoline service station. Refinery gate prices and rack prices are influenced primarily by spot and/or futures prices. Dealer tank wagon prices also reflect other services, such as trademark, credit cards, advertising, and security of supply. In general, however, gasoline prices are determined by crude oil prices since crude oil is the feedstock at refineries.

Both heating oil and gasoline futures trade on NYMEX in contracts of 42,000 US gallons (equivalent to 1,000 barrels). Prices are quoted in US dollars and cents per gallon. The minimum price fluctuation is $0.00001 (¢0.01) per gallon or $4.20 per contract. The maximum daily price fluctuation is $0.25 per gallon or $10,500 per contract for all months. However, if any contract is traded, bid or offered at the $0.25 per gallon limit for five consecutive minutes, trading is halted for five minutes. When trading resumes, the limit is expanded by another $0.25 per gallon in either direction. If another halt is

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reflect prices for October delivery. After September 25, the spot price will also reflect prices for November delivery and it will be again in par with the futures prices.

[7] The IPE Brent Index is the weighted average of the prices of all confirmed 21-day Brent/Forties/Oseberg (BFO) deals throughout the previous trading day for the appropriate delivery months. The IPE Index is issued by the IPE on a daily basis at 12 noon London time.

triggered, the limit will continue to be expanded by $0.25 per gallon in either direction after each successive five-minute trading halt. Trading is conducted by open outcry from 10:05am until 2:30pm New York time and via an internet-based platform after hours (Mondays through Thursdays from 3:15pm until 9:30am the following day and from 7:00pm on Sundays). There exist contracts for the next 18 consecutive months for heating oil and the next 12 consecutive months for gasoline. Trading terminates at the close of business on the last business day of the month preceding the delivery month. Settlement is done with physical delivery, although, as is the case with most futures, the majority of contracts is not executed for physical delivery. The grade and quality of the deliverable heating oil and gasoline generally conform to industry standards for fungible No. 2 heating oil and for Phase II Complex Model Reformulated Gasoline in accordance with Colonial Pipeline Co. specifications for fungible A grade, 87 octane index gasoline respectively. Delivery is free on board seller's facility in New York harbor, ex-shore, although it may also be completed by pipeline, tanker, book transfer or inter- or intra-facility transfer. In the case of heating oil, the buyer may request delivery by truck, if available, at a surcharge. The delivery period begins on the day after the fifth business day of the delivery month and ends on the last business day of the delivery month.

2.5 Properties of petroleum markets

Energy markets, including crude oil markets, behave quite differently than money markets. Both fundamental and quantitative analysis have shown that energy prices respond differently to fundamental micro- or macroeconomic drivers and require different models to best describe their behavior and support derivative valuation and risk management.

The mere fact that energy markets are dealing with a physical product (as opposed to "paper" markets) makes energy price behavior very complex and its modeling extremely hard. The crude oil market, for example, is affected by factors that have to do with extracting the oil from the ground, transferring it, storing it, and actually using (burning) it, which again depends on whether the end user is a utility, a refinery or an industrial producer. Energy markets have many and complex fundamental price drivers, including technology and local or global politics, as opposed to few and simple drivers in money markets.

On the demand side, the physical nature of consumption commodities gives rise to the convenience yield issue. The convenience yield reflects the net benefit of holding a physical asset in your hands, ready for immediate consumption. For industrial users and refineries, it is important that production runs uninterrupted. Therefore, they keep crude oil in inventory, even if it earns no return, because it guarantees them immediate energy supply in case of need. On the flip side, holding a forward contract is less valuable to them, because if they run out of fuel, there is not much they can do. The convenience yield captures the difference in value between holding forwards and holding the actual commodity in storage.[8] It is essentially the premium that crude oil users are willing to pay in order to be sure they have enough energy available to keep production running. The convenience yield is absent from money markets, although it is often thought of as being analogous to a dividend payment.

On the supply side, energy markets are affected by production and storage in a way that financial markets are not. New technological advents in the extraction of crude oil may impact long-term forward prices significantly more than short-term prices. Storage of crude oil and other physical commodities is limited. This resuls in spot prices being much more volatile than forward prices. Moreover, short-term forwards price crude oil that has been extracted and is in storage, whereas long-term forwards price crude oil that is still in the ground and is anticipated to be extracted at some point in the future.

Therefore, we can argue that short-term and long-term petroleum prices have different fundamental drivers. Short-term fundamentals include wars, strikes, extreme temperatures or other acts of God, which would cause an imbalance in short-term supply and demand. Long-term fundamentals include technological improvements (e.g. 3-D seismic testing, deepwater exploration and production) or new productive reservoirs, which would cause an imbalance in the long-term supply and demand, even if such events do not occur as frequently as the events that affect the short term. These

[8] Since forwards cannot be consumed, holding them is less valuable than holding the actual physical asset, i.e. $F_t \leq (S_t+U)e^{r(T-t)}$, where F_t is the forward price at time t, S is the spot price at time t, U is the present value of storage costs, T-t is the time to maturity, and r is the risk-free rate. The convenience yield y then is such that $F_t e^{y(T-t)} = (S_t+U)e^{r(T-t)}$.

different drivers imply that the correlation between short-term forward prices and long-term forward prices is low, whereas in financial markets it is high.[9]

Unlike money markets, energy markets exhibit relatively strong mean reversion. In addition, this mean reversion does not seem to follow economic cycles; rather, it is a function of specific "events" and how quickly these events dissipate or the supply side responds to bring the system back in balance. For example, during the Gulf War, spot and short-term forward prices spiked, while long-term forward prices were much less affected. The difference indicated how quickly the market expected the production side to react in order to restore equilibrium. For this reason, the standard lognormal model used in equity markets is not appropriate for describing crude oil behavior. Instead, we need a mean-reverting model for crude oil spot prices. Research in this field is ongoing, but various attempts have indicated that a log of price mean-reverting model works well for the WTI spot market (Pilipovic [1998]).[10] Given that energy markets are relatively young, it is almost certain that there is still a great deal of research and analysis to be done in modeling crude oil spot prices.

Interestingly enough, unlike other energy assets, such as natural gas and electricity, crude oil prices do not exhibit seasonal patterns.

When it comes to the history of energy markets and energy trading, we should keep in mind that energy markets have only been around for a short period of time. This implies that we do not have a large data set of historical prices. Furthermore, if we exclude near-term futures contracts on NYMEX and the IPE, the oil markets are relatively illiquid. Also, even though the crude oil market in the US is now deregulated, in most parts of the world it remains highly regulated, often with no intention to change. Geography also plays a role: a barrel of oil is priced differently depending on location, whereas for example the stock of a company is worth the same no matter where we may try to sell or buy it.

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[9] In the case of crude oil, the short term can be considered to be three to six months out.

[10] A log of price mean-reverting model assumes that the natural logarithm of the price rather than the price itself reverts to some mean. It is given by the equation $d\tilde{x}_t = a(b-x_t)dt + \sigma d\tilde{z}_t$ where $\tilde{x}_t=\ln(\tilde{s}_t)$. Here s is the spot price, a is the rate of mean reversion, b is the long-term equilibrium of x, and σ is the volatility.

For all of the reasons mentioned above, energy derivatives are much more complex than financial derivatives as difficulties arise in pricing and delivery specifications that meet the needs of all parties involved.

2.6 The dataset

We obtained data on crude oil, heating oil, and gasoline futures trading on NYMEX and crude oil futures trading on the IPE from Bloomberg, which, in turn, gets the data directly from the exchanges. Bloomberg provides raw data on futures contracts for any maturity, but it also rolls over contracts to construct generic series that essentially represent contracts with a fixed time to maturity. Generics use the value of a particular contract month until they roll to the next month in the series. Thus, the first generic (*CL1*) is the nearest futures contract traded on NYMEX at any point in time, the second generic (*CL2*) is the second nearest futures contract traded on NYMEX at any point in time etc. For the purposes of this study, we need to use fixed maturity time series of futures prices. Therefore, we drew our data from Bloomberg's generic contracts. Trading often becomes significantly heavier a few days before a futures contract expires, resulting in increased volatility and potential price spikes. Thus, we have chosen generics to roll to the next contract month seven days prior to expiration to avoid noise in prices due to increased trading activity. There are 35 generics for crude oil futures traded on NYMEX (labeled *CL1*-*CL35*), 18 generics for crude oil futures traded on the IPE (labeled *CO1*-*CO18*), 18 generics for heating oil futures traded on NYMEX (labeled *HO1*-*HO18*), and 12 generics for gasoline futures traded on NYMEX (labeled *HU1*-*HU12*). However, most trading is done in near-term futures; long-dated contracts are relatively illiquid. Therefore, we have only used *CL1*-*CL15*, *CO1*-*CO9*, *HO1*-*HO12*, and *HU1*-*HU11*, for which there is satisfactory liquidity and we can be confident that prices truly reflect market dynamics. Furthermore, even though crude oil futures have been trading on NYMEX since 1983, data is limited (there is no open interest or volume data from May 30, 1983 to June 30, 1986 and again from January 1, 1987 to July 31, 1989) and trading in longer maturity futures did not become available until several years later. For Brent contracts on the IPE as well as for heating oil and gasoline contracts on NYMEX, data doesn't become continuous and abundant until the early '90s. As a result, we have decided to use 11 years of daily data, namely from 1/1/1993 to 12/31/2003.

As mentioned above, prices of different crudes are correlated and so are crude oil prices with refined product prices. This becomes evident by Table 1, which shows correlations of concurrent generics for the four commodities under examination. In addition, Figure 1 plots prices of the nearest maturity contracts for the four commodities over time, which gives a visual representation of the high correlations between petroleum commodity prices. The graphs showing simultaneous price movements of the second, third, etc. nearest contracts of the four commodities show a very similar pattern and are therefore not shown here.

Table 1: Correlation matrix for NYMEX crude oil, IPE crude oil, heating oil, and gasoline futures contracts of the same maturity

	CL	***CO***	***HO***	***HU***
	Panel A: Nearest contract			
CL	1.00	0.99	0.97	0.96
CO	0.99	1.00	0.97	0.96
HO	0.97	0.97	1.00	0.91
HU	0.96	0.96	0.91	1.00
	Panel B: Second nearest contract			
CL	1.00	1.00	0.98	0.96
CO	1.00	1.00	0.98	0.96
HO	0.98	0.98	1.00	0.91
HU	0.96	0.96	0.91	1.00
	Panel C: Third nearest contract			
CL	1.00	1.00	0.98	0.97
CO	1.00	1.00	0.98	0.96
HO	0.98	0.98	1.00	0.92
HU	0.97	0.96	0.92	1.00
	Panel D: Fourth nearest contract			
CL	1.00	1.00	0.98	0.97
CO	1.00	1.00	0.98	0.96
HO	0.98	0.98	1.00	0.93
HU	0.97	0.96	0.93	1.00
	Panel E: Fifth nearest contract			
CL	1.00	1.00	0.98	0.97
CO	1.00	1.00	0.98	0.97
HO	0.98	0.98	1.00	0.93
HU	0.97	0.97	0.93	1.00

Panel F: Sixth nearest contract

CL	1.00	1.00	0.98	0.97
CO	1.00	1.00	0.98	0.97
HO	0.98	0.98	1.00	0.94
HU	0.97	0.97	0.94	1.00

Panel G: Seventh nearest contract

CL	1.00	1.00	0.98	0.97
CO	1.00	1.00	0.98	0.97
HO	0.98	0.98	1.00	0.94
HU	0.97	0.97	0.94	1.00

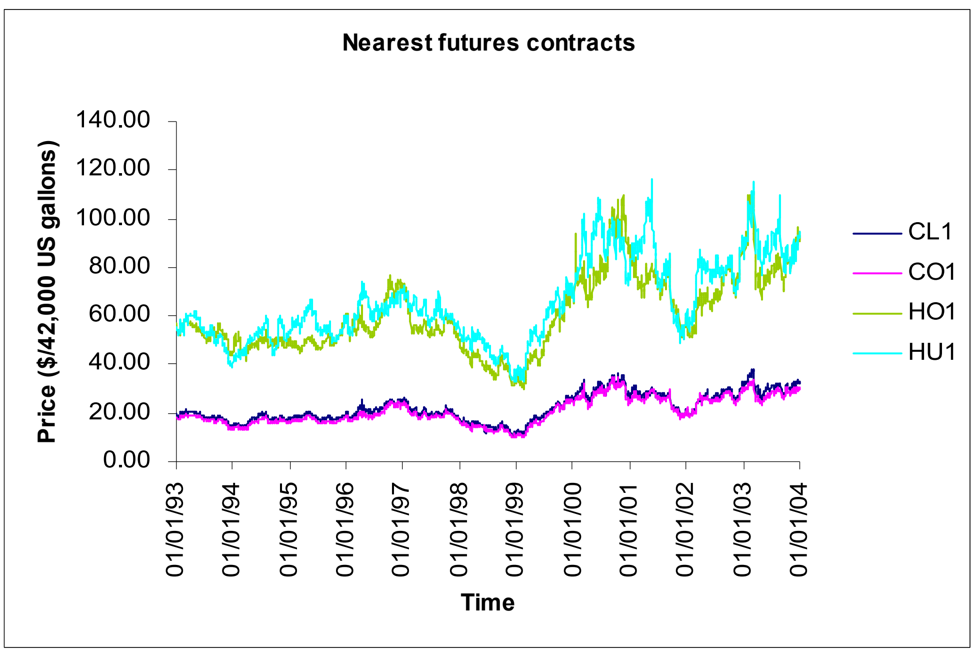
Panel H: Eighth nearest contract

CL	1.00	1.00	0.98	0.97
CO	1.00	1.00	0.98	0.97
HO	0.98	0.98	1.00	0.93
HU	0.97	0.97	0.93	1.00

Panel I: Ninth nearest contract

CL	1.00	1.00	0.98	0.97
CO	1.00	1.00	0.98	0.97
HO	0.98	0.98	1.00	0.93
HU	0.97	0.97	0.93	1.00

Figure 1: Price evolution of the nearest NYMEX crude oil, IPE crude oil, heating oil, and gasoline generic futures contracts from 1/1/93 to 12/31/03



Before we move on, we need to check the series for stationarity since principal components analysis only applies to stationary series (see Frachot, Jansi, and Lacoste [1992]). We checked the AR(1) process and observed autocorrelation in the residuals. We therefore performed an Augmented Dickey-Fuller (ADF) test using four lagged terms on the daily settlement prices of the generic series *CL1-CL15*, *CO1-CO9*, *HO1-HO12*, and *HU1-HU11*. We found that we could not reject the null at the 1% significance level, meaning that the series were non-stationary. However, taking first differences and repeating the test resulted in stationary series. We could easily reject the null at the 1% significance level for all series. Table 2 shows ADF test statistics for levels and first differences for NYMEX crude oil, IPE crude oil, heating oil, and gasoline generic futures. A graphical representation of non-stationary levels versus stationary first differences is shown on Figure 2 for an indicative contract (*CL1*). Appendix A discusses testing for stationarity using the Dickey-Fuller and Augmented Dickey-Fuller tests.

Table 2: ADF test statistic for NYMEX crude oil, IPE crude oil, heating oil, and gasoline generic futures contracts

	ADF test statistic	
	Levels	**First differences**
Panel A: NYMEX crude oil generics		
CL1	0.18	-22.64
CL2	0.07	-22.51
CL3	0.16	-22.26
CL4	0.24	-22.44
CL5	0.30	-22.66
CL6	0.35	-22.90
CL7	0.38	-23.11
CL8	0.42	-23.16
CL9	0.44	-23.29
CL10	0.50	-23.46
CL11	0.53	-23.60
CL12	0.63	-23.84
CL13	0.65	-23.94
CL14	0.71	-24.15
CL15	0.75	-24.41

Panel B: IPE crude oil generics

CO1	-0.78	-22.55
CO2	-0.57	-22.32
CO3	-0.61	-22.21
CO4	-0.58	-22.29
CO5	-0.43	-22.51
CO6	-0.31	-22.69
CO7	-0.33	-22.83
CO8	-0.35	-22.91
CO9	-0.23	-23.05

Panel C: Heating oil generics

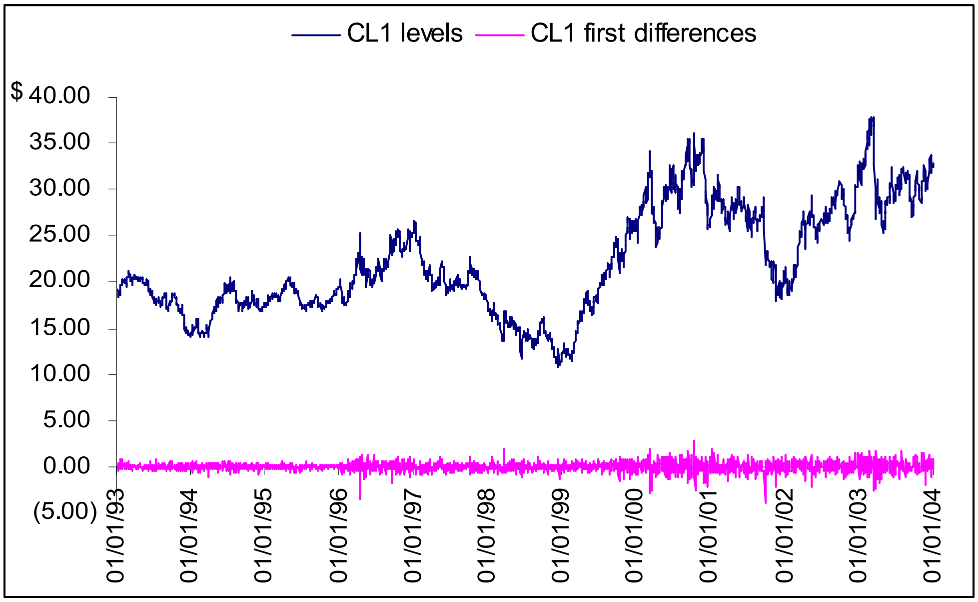
HO1	0.88	-21.02
HO2	1.26	-20.89
HO3	1.25	-20.98
HO4	0.87	-20.94
HO5	0.43	-21.16
HO6	0.01	-21.56
HO7	-0.23	-21.80
HO8	-0.31	-22.01
HO9	-0.15	-22.22
HO10	0.12	-22.38
HO11	0.35	-22.69
HO12	0.75	-24.08

Panel D: Gasoline generics

HU1	-0.32	-21.89
HU2	-0.11	-21.02
HU3	-0.20	-21.08
HU4	0.59	-20.72
HU5	1.16	-21.73
HU6	1.26	-21.42
HU7	1.53	-20.92
HU8	1.25	-21.68
HU9	0.75	-20.79
HU10	0.60	-19.90
HU11	0.13	-18.91

Note: Critical values according to MacKinnon are -1.61 for the 10% significance level, -1.94 for the 5% significance level, and -2.57 for the 1% significance level. The null hypothesis is rejected if the ADF test statistic is less than the critical value.

Figure 2: Evolution of price levels and first differences for nearest NYMEX crude oil generic futures contract



Having decided that we will be using the first difference series in our analysis, the final step in preparing the data involves accounting for illiquidity issues. We have already shown that we excluded illiquid contracts with large blocks of missing data and that we chose the starting date such that trading would be virtually continuous for all maturities chosen. To eliminate further problems arising from thin trading, we excluded datapoints for which volume was less than ten contracts. That way our series is free from the effect of artificial settlement prices that do not reflect true supply and demand.

Summary statistics for our final dataset are shown in Table 3 to Table 6 below. We have added a "Δ" in the generic contract label to indicate that we are dealing with a time series of first differences. Missing datapoints correspond to days for which data was unavailable (e.g. public holidays) or to days that were filtered out subject to the ten-contract volume constraint and were subsequently left out of statistic calculations. Notice that missing datapoints account for only about 7-9% of total for the nearest contracts but as much as 41% for *ΔCL15*, 47% for *ΔCO9*, 42% for *ΔHO12*, and 34% for *ΔHU11*.

Table 3: Summary statistics for NYMEX crude oil generic contracts (first differences)

	ΔCL1	***ΔCL2***	***ΔCL3***	***ΔCL4***	***ΔCL5***	***ΔCL6***	***ΔCL7***	***ΔCL8***	***ΔCL9***	***ΔCL10***	***ΔCL11***	***ΔCL12***	***ΔCL13***	***ΔCL14***	***ΔCL15***
Retained observ.	2647	2644	2644	2642	2642	2631	2626	2611	2555	2465	2398	2288	2149	1870	1699
Missing observ.	222	225	225	227	227	238	243	258	314	404	471	581	720	999	1170
Mean	4.3E-03	3.4E-03	3.6E-03	3.4E-03	3.2E-03	3.4E-03	4.2E-03	3.1E-03	3.2E-03	2.5E-03	5.4E-03	6.1E-03	4.3E-03	7.6E-03	1.3E-03
Median	0.01	0.00	0.00	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mode	-0.04	-0.09	0.00	0.00	-0.02	0.02	-0.02	0.00	0.00	0.00	0.00	-0.07	-0.07	-0.07	0.00
Std. Deviation	0.50	0.45	0.41	0.37	0.35	0.33	0.32	.3050	0.30	0.29	0.28	0.27	0.27	0.26	0.26
Skewness	-0.57	-0.58	-0.46	-0.48	-0.52	-0.51	-0.48	-0.47	-0.46	-0.47	-0.43	-0.41	-0.38	-0.40	-0.66
Kurtosis	5.14	5.51	4.26	4.54	4.94	4.97	4.69	4.47	4.26	4.23	4.28	4.22	3.46	3.57	4.80
Jarque-Bera (JB)	3,043	3,479	2,083	2,358	2,791	2,805	2,491	2,256	2,014	1,916	1,893	1,754	1,116	1,033	1,745
(JB *p*-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Minimum	-3.96	-3.82	-3.00	-3.00	-3.00	-2.88	-2.67	-2.48	-2.32	-2.21	-2.13	-2.08	-2.04	-2.00	-1.97
Maximum	2.81	2.48	2.20	1.92	1.70	1.51	1.31	1.21	1.16	1.10	1.09	1.09	1.03	1.09	1.09

Table 4: Summary statistics for IPE crude oil generic contracts (first differences)

	ΔCO1	***ΔCO2***	***ΔCO3***	***ΔCO4***	***ΔCO5***	***ΔCO6***	***ΔCO7***	***ΔCO8***	***ΔCO9***
Retained observ.	2628	2668	2667	2653	2623	2472	2223	1861	1509
Missing observ.	241	201	202	216	246	397	646	1008	1360
Mean	3.7E-04	3.9E-04	1.1E-05	-4.1E-05	1.3E-04	3.3E-03	1.7E-03	1.0E-03	1.8E-02
Median	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.02
Mode	0.00	0.07	0.00	0.00	0.02	-0.07[a]	0.00	0.00	0.00
Std. Deviation	0.47	0.42	0.39	0.36	0.34	0.33	0.32	0.32	0.30
Skewness	-0.56	-0.52	-0.44	-0.47	-0.49	-0.48	-0.46	-0.55	-0.13
Kurtosis	5.28	4.99	4.71	4.67	4.75	4.77	4.68	4.87	2.83
Jarque-Bera (JB)	3,175	2,869	2,537	2,494	2,564	2,421	2,097	1,918	504
(JB *p*-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Minimum	-3.42	-3.32	-3.12	-2.94	-2.79	-2.66	-2.56	-2.48	-1.88
Maximum	2.80	2.30	2.01	1.80	1.63	1.50	1.45	1.39	1.32

a Multiple modes exist. The smallest value is shown.

Table 5: Summary statistics for heating oil generic contracts (first differences)

	ΔHO1	ΔHO2	ΔHO3	ΔHO4	ΔHO5	ΔHO6	ΔHO7	ΔHO8	ΔHO9	ΔHO10	ΔHO11	ΔHO12
Retained observ.	2612	2594	2598	2594	2582	2582	2537	2421	2307	2159	1904	1651
Missing observ.	257	275	271	275	287	287	332	448	562	710	965	1218
Mean	2.1E-02	2.1E-02	2.4E-02	2.1E-02	1.8E-02	1.1E-02	2.0E-03	-1.8E-04	1.2E-03	5.4E-03	2.2E-03	-8.8E-03
Median	1.0E-02	-1.0E-02	.0000	1.0E-02	.0000	.0000	-1.0E-02	-1.0E-02	-1.0E-02	.0000	-1.0E-02	-2.0E-02
Mode	-0.30	-0.37[a]	-0.25	0.17	0.03	-0.25	-0.25	-0.25	-0.25	-0.25	-0.25	-0.25
Std. Deviation	1.47	1.27	1.16	1.08	1.03	0.99	0.94	0.90	0.88	0.85	0.84	0.84
Skewness	-0.48	-0.24	-0.20	-0.27	-0.43	-0.54	-0.48	-0.40	-0.37	-0.35	-0.32	-0.33
Kurtosis	5.24	3.33	3.12	3.21	4.02	4.44	4.19	3.39	3.20	3.08	3.10	3.30
Jarque-Bera (JB)	3,074	1,223	1,066	1,136	1,807	2,232	1,942	1,215	1,028	892	789	774
(JB *p*-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Minimum	-11.14	-6.80	-6.65	-6.15	-7.85	-8.05	-7.95	-6.80	-6.15	-5.85	-5.55	-5.55
Maximum	7.04	6.23	5.73	5.03	4.73	4.43	4.03	3.74	3.64	3.26	3.31	3.36

a Multiple modes exist. The smallest value is shown.

Table 6: Summary statistics for gasoline generic contracts (first differences)

	ΔHU1	ΔHU2	ΔHU3	ΔHU4	ΔHU5	ΔHU6	ΔHU7	ΔHU8	ΔHU9	ΔHU10	ΔHU11
Retained observ.	2656	2656	2655	2654	2655	2632	2585	2482	2311	2112	1897
Missing observ.	213	213	214	215	214	237	284	387	558	757	972
Mean	1.8E-02	1.5E-02	3.4E-03	1.6E-02	2.1E-02	2.0E-02	2.2E-02	1.9E-02	1.6E-02	1.5E-02	1.0E-02
Median	5.0E-02	3.0E-02	3.0E-02	2.0E-02	2.0E-02	3.0E-02	2.0E-02	2.0E-02	1.0E-02	1.0E-02	.0000
Mode	0.14	-0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Std. Deviation	1.64	1.38	1.21	1.13	1.07	1.03	1.01	0.99	0.97	0.94	0.95
Skewness	-0.86	-0.36	-0.47	-0.29	-0.25	-0.01	-0.03	-0.02	0.07	-0.30	-0.53
Kurtosis	10.05	4.58	4.63	4.33	3.68	5.11	4.99	5.29	6.35	5.62	6.55
Jarque-Bera (JB)	11,451	2,363	2,462	2,098	1,519	2,854	2,665	2,881	3,860	2,799	3,458
(JB *p*-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Minimum	-16.40	-9.25	-9.85	-6.72	-6.37	-6.09	-6.00	-6.60	-7.20	-7.90	-8.25
Maximum	9.68	8.13	6.25	7.33	5.56	8.75	7.36	6.66	7.55	6.48	5.59

CHAPTER 3: PRINCIPAL COMPONENTS ANALYSIS

3.1 Description

Principal components analysis (PCA) is a procedure that linearly transforms a set of correlated variables to a new set of uncorrelated variables (principal components, PC's) with the same dimension. The principal components are orthogonal to each other and sorted in order of decreasing variance. That is, the first principal component is the linear combination of variables that explains the greatest amount of variance of the original variables. The second principal component is orthogonal to the first and explains as much of the variance not explained by the first. The third principal component is orthogonal to both the first and the second and explains the greatest amount of the remaining variance, etc. There is no information lost during this procedure. The new set of principal components reproduces the original variance-covariance structure and the total variance of the principal components equals the total variance of the original variables.

The main use of PCA is to reduce the dimension of the data. From the description of the procedure above, it becomes evident that there can be as many principal components as original variables. In this case, the principal components explain 100% of the variance of the original variables. However, we could drop the principal components that explain a small amount of variance and only keep the first few ones, which still explain most of the variance. This way we achieve compressing the data while losing as little information as possible. The advantages are that we reduce the amount of data and hence make computations simpler and faster, we possibly eliminate noise (as the data not contained in the first few principal components may be mostly due to noise), and we may make visualization possible if the dimension chosen is low.

More formally, assume a set of n variables $x_1,\ldots,x_n$ with variance-covariance matrix $\boldsymbol{C_x}$. Since the goal is to transform this set of variables into a set of uncorrelated variables (i.e., orthogonal), all we need to do is find $\boldsymbol{C_x}$'s eigenvalues and their corresponding eigenvectors. The eigenvalues λ_i and the eigenvectors $\boldsymbol{e_i}$ are nothing but the solutions of the equation $\boldsymbol{C_x e_i} = \lambda_i \boldsymbol{e_i}$ (where i=1,…,n) and can be found by solving the characteristic equation $\| \boldsymbol{C_x} - \lambda \boldsymbol{I} \| = 0$ where $\boldsymbol{I}$ is the identity matrix of the same order as $\boldsymbol{C_x}$.[11]

Adding a time dimension to the above, if we denote time by t=1,…,T, our original variables are n (Tx1) vectors $\boldsymbol{x}$.[12] We want to find linear combinations of these vectors that are orthogonal to each other and maximize variance. If we denote these linear combinations (principal components) by $\boldsymbol{z}$, we have $\boldsymbol{Z}=\boldsymbol{XA}$ where $\boldsymbol{Z}$ is a (Txn) matrix of principal components, $\boldsymbol{X}$ is a (Txn) matrix of the original variables, and $\boldsymbol{A}$ is a (nxn) matrix of coefficients (called loadings). The first-order condition of this maximization problem results in $(\boldsymbol{C_x} - \lambda \boldsymbol{I})\boldsymbol{A}=0$ where λ_i are the Lagrange multipliers, $\boldsymbol{I}$ is a (nxn) identity matrix, and $\boldsymbol{C_x}$ is the variance-covariance matrix. As before, we see that to solve this equation we need to calculate the eigenvalues and the eigenvectors of $\boldsymbol{C_x}$.

If we want to reduce the dimension of the data by keeping only the first k principal components and discarding the rest, we get $\boldsymbol{X_k} = \boldsymbol{Z_k A'_k} + \boldsymbol{u_k}$ where $\boldsymbol{Z_k}$ is a (Txk) matrix of principal components, $\boldsymbol{X_k}$ is a (Txk) matrix of original variables, $\boldsymbol{A_k}$ is a (kxk) matrix of loadings, and $\boldsymbol{u_k}$ is a (Txk) matrix of residuals. The percentage of the original variance that is explained by the k principal components is called communality and can be calculated from the loadings. There is no hard and fast rule for the specification of k. We can choose a fixed number of eigenvectors and their respective eigenvalues or we can choose a fixed percentage of variance explained and use as many eigenvectors/eigenvalues as necessary. Alternatively, we may use formal tests, but we should keep in mind that their results might not be entirely reliable.[13] Finally, the principal components that we can come up with may be just abstract latent variables, but they may also have some economic meaning.[14] A potential economic interpretation of the principal components can be useful in determining how many we should retain.

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[11] We often use the correlation matrix instead of the variance-covariance matrix to standardize the variables in case they have different units of measurement or unequal variances.

[12] The time series of original variables should be stationary, otherwise the results given by PCA can be misleading (see Frachot, Jansi, and Lacoste [1992]).

[13] For more on the various criteria for choosing the right number of principal components, see Basilevsky [1994] and Jackson [1991].

[14] For instance, extensive research has been done on interest rates and using PCA to explain the term structure of interest rates. Three principal components are typically retained, the first one being linked to the concept of duration (see Skiadopoulos [2004]).

3.2 Results of PCA and discussion

We performed PCA for each of the four commodities under examination after adjusting for stationarity and liquidity issues as described above (see Section 2.6). Hence, the original variables are time series of the first differences of select generic contracts (*ΔCL1*-*ΔCL15*, *ΔCO1*-*ΔCO9*, *ΔHO1*-*ΔHO12*, and *ΔHU1*-*ΔHU11*) for the period 1/1/2003 to 12/31/2003. The analysis used the correlation matrix. Data points were excluded listwise if there were missing values for any one variable at any one date. Table 7 shows the cumulative percentage of variance explained by all principal components for each of the commodities.

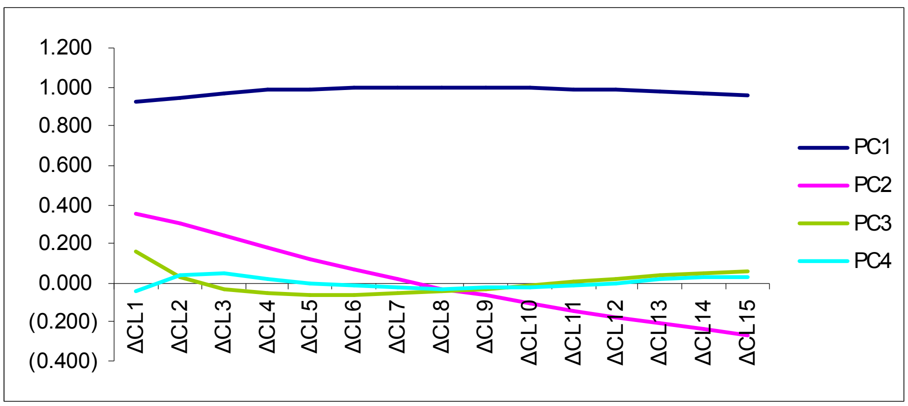
For NYMEX crude oil futures, we can see from Table 7 that the first four principal components explain 99.9% of total variance. Figure 3 plots their loadings. The first principal component corresponds to a nearly parallel shift in futures price differences. The second principal component corresponds to a twist or slope of the curve: a change in the second principal component causes futures prices for contracts expiring in the next seven months to move in one direction and futures prices for contracts expiring in the next eight to 15 months to move in the other direction. The third principal component corresponds to a bowing of the curve: it causes prices of short-maturity and long-maturity futures to move in one direction and prices of mid-maturity futures to move in the other direction. The fourth principal component is probably noise and will be excluded from future analyses.

We should recall that Tolmasky and Hindanov [2002] ran PCA on the nearest ten contracts and had very similar results. They found that 95.9% of total variance was explained by the first component alone (level), 99.5% was explained by the first and second component (level and steepness), and 99.9% was explained by the first three components (level, steepness, and curvature). They also explain that the third principal component is steeper for short expirations than for long ones as a result of the higher correlations among longer expirations.

Table 7: Cumulative percentage of variance explained by each principal component

Principal component	NYMEX crude oil	IPE crude oil	Heating oil	Gasoline
1	95.660	96.012	93.309	86.488
2	99.468	99.026	97.164	92.401
3	99.835	99.625	99.127	95.725
4	99.911	99.815	99.645	96.836
5	99.948	99.895	99.859	97.573
6	99.974	99.935	99.938	98.258
7	99.983	99.964	99.963	98.881
8	99.990	99.984	99.978	99.354
9	99.993	100.000	99.988	99.728
10	99.995		99.993	99.919
11	99.997		99.997	100.000
12	99.998		100.000	
13	99.999			
14	99.999			
15	100.000			

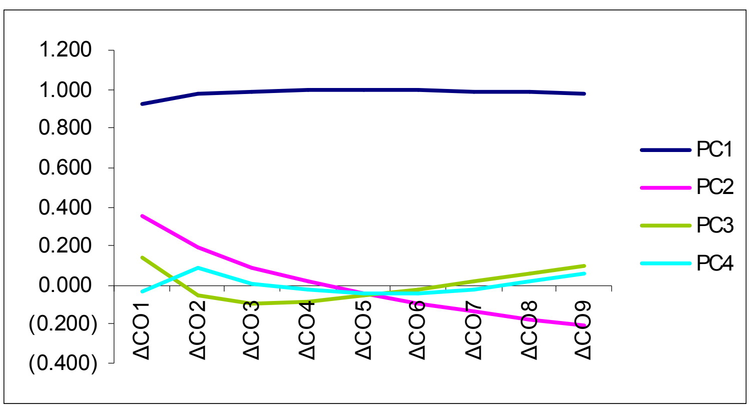
Figure 3: NYMEX crude oil futures – first four PC loadings



As for IPE crude oil futures, Table 7 shows that the first three principal components explain 99.6% of total variance and the fourth one provides only an additional 0.2%. Figure 4 plots loadings for the first four principal components. The picture is strikingly similar to what we had before. The first principal component again corresponds to a parallel shift, the second principal component to a slope of the same direction, and the third principal component to a bowing of the same concavity. In addition to the general shape of the curves, the values of the loadings are very similar to the values of the respective loadings for the NYMEX crude oil PC's. As before, the fourth principal component is probably noise and will be excluded from future analyses.

Our results are in line with the general literature, including Schwartz and Cortazar [1994], Clewlow and Strickland [1999b], and Tolmasky and Hindanov [2002]. In the case of IPE crude oil in particular, the notable exception is Järvinen [2003], who used Brent crude oil swap quotes from 1997 to 2002 to derive the futures curve. His research concluded that the first three principal components explain 89% of total variance. Furthermore, the shape of his loadings was strikingly different. The first factor sloped upwards for maturities of up to 21 months before flattening out and even had an opposite sign for three-month and six-month maturities. The second factor showed a more complex behavior, representing shocks that move contracts with maturities of up to 21 months in one direction and then contracts with longer maturities in the other direction, albeit with a curvature in the middle.[15] The third factor resembled the familiar curvature factor, which moves short-maturity and long-maturity futures in one direction and intermediate ones in the opposite. Finally, the fourth factor's loadings alternated from negative to positive every few months and therefore represented shocks that move futures prices in all directions.

Figure 4: IPE crude oil futures – first four PC loadings



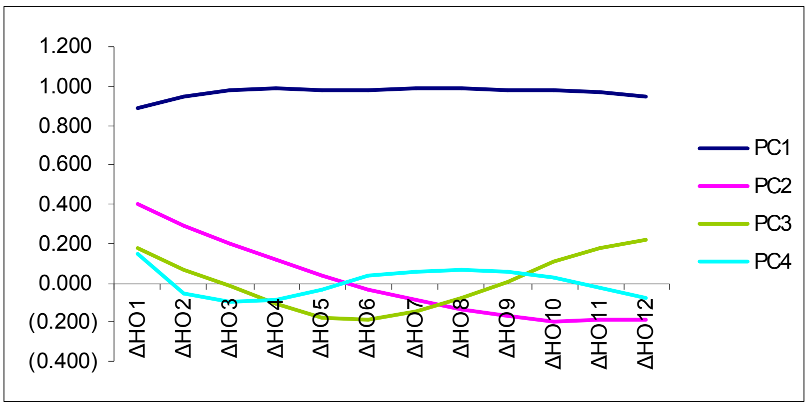
Moving on to heating oil, the picture doesn't change much. This time, the first three components explain 99.1% of total variance (see Table 7). If we wanted to explain the same amount of variance that we did for NYMEX and IPE crude oil, we would need to

[15] Contracts maturing in 42 and 45 months actually moved in the opposite direction, i.e. in the same direction as the short-maturity contracts.

retain the first five components, whose explanatory power is 99.9%. However, there is probably a great deal of noise in the fourth and fifth component. Figure 5 shows loading plots for the first four principal components. The first three principal components are similar in shape and values to the first three principal components retained for NYMEX and IPE crude oil. The fourth one is different and is again discarded as noise.

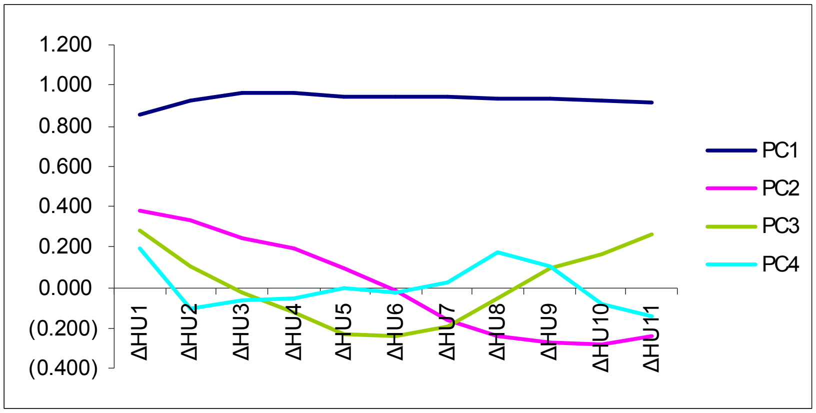
In their research, Tolmasky and Hindanov [2002] found that 95.8% of total variance is explained by the level factor, 99.0% by the level and steepness factors, and 99.6% by the level, steepness, and curvature factors. Their results are very similar to our findings.

Figure 5: Heating oil futures – first four PC loadings



Lastly, performing PCA on gasoline futures shows that the first three principal components account for 95.7% of total variance (see Table 7). The explanatory power of each principal component is lower for gasoline than for the other commodities we examined. For example, the first principal component explains 86.5% of total variance compared to more than 93.0% for the first principal component of the other three commodities. Again, if we wanted a greater amount of variance explained, we would retain more principal components. Figure 6 shows plots of loadings for the first four principal components. Once more, the first three principal components conform to the general findings so far. The fourth one is noisy and will be left out of future analyses.

Figure 6: Gasoline futures – first four PC loadings



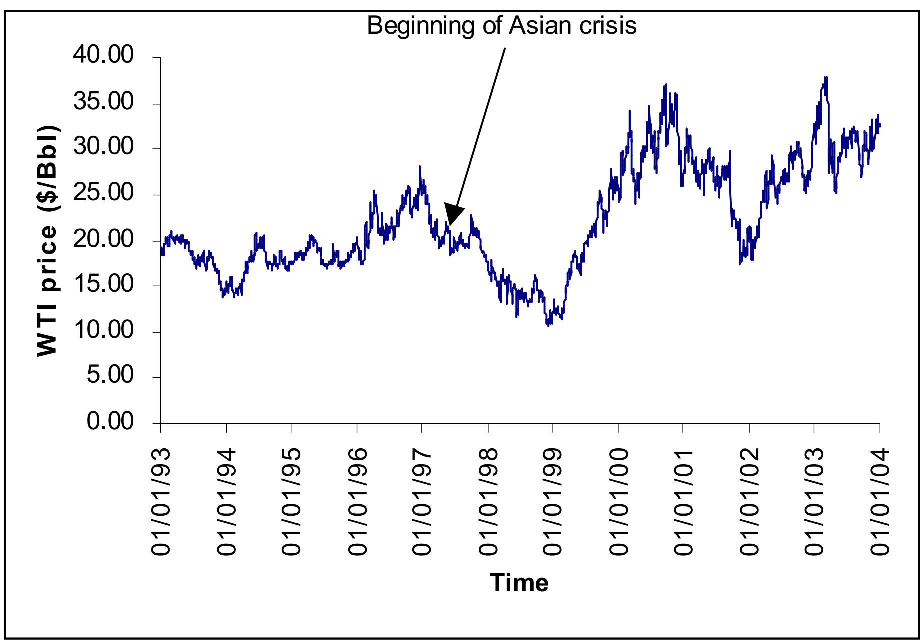
Overall, we found that all four commodities can be modeled by three principal components, representing level, steepness, and curvature in order of importance. Our conclusions are strikingly similar to the general findings in the literature. Clewlow and Strickland [1999b] also found a level factor accounting for most of the variance, which, however, declined slightly over the first eight months before flattening out to become almost constant. Their second factor was negative for the first eight maturities and positive for the remaining 16 and their curvature factor was negative for contracts maturing in the next two months or in more than 14 months and positive for contracts maturing in between.

Principal components analysis has also been used in the interest rate literature to describe the dynamics of interest rates and of implied volatilities. It is generally accepted that government bond returns can also be explained in terms of three factors called level, steepness, and curvature. These broadly look like the principal components we found in this study and function in a similar way (see Skiadopoulos [2004] for a brief overview of PCA applications to interest rates).

3.3 Stability of PCA results

A final checkpoint is the stability of our PCA results over time. Figure 7 shows that crude oil prices (and hence product prices) have fluctuated widely over the period under examination depending on supply and demand conditions as well as global political and economic events. We therefore performed PCA on the four commodities breaking up the period in two subperiods: 1/1/1993 to 5/13/1997 and 5/14/1997 to 12/31/2003, the cutoff point being the day we can identify as the beginning of the Asian crisis.[16] The Asian crisis led to stagnant oil demand, which, combined with increased production in the Middle East, caused oil prices to plummet. It turns out that the results obtained from PCA for each of the two subperiods are not significantly different than the results we obtained for the full length of time. This gives us confidence about the stability of principal component loadings over time. In the upcoming analyses, therefore, we will use the results obtained in the full period between 1/1/1993 and 12/31/2003, choosing the first three principal components for each commodity. Figures 8 to 10 show time plots of principal components for NYMEX crude oil generic futures. Time plots of principal components for the other three commodities look very similar and are therefore not shown here. Table 8 shows summary statistics of the three principal components chosen for each commodity. Finally, Table 9 shows Augmented Dickey-Fuller statistics for these components and the corresponding MacKinnon critical values for the rejection of the null hypothesis of a unit root. As can be seen, the null hypothesis can be rejected at the 1% significance level for all principal components, meaning that they are stationary.

Figure 7: Spot WTI crude oil prices for the period 1/1/93 to 12/31/03



[16] On May 14, 1997, the Thai bhat depreciated dramatically as the country's economic slowdown and political instability urged speculators to proceed to massive sell orders.

Figure 8: Time plot of *CLPC1* for the period 1/1/93 to 12/31/03

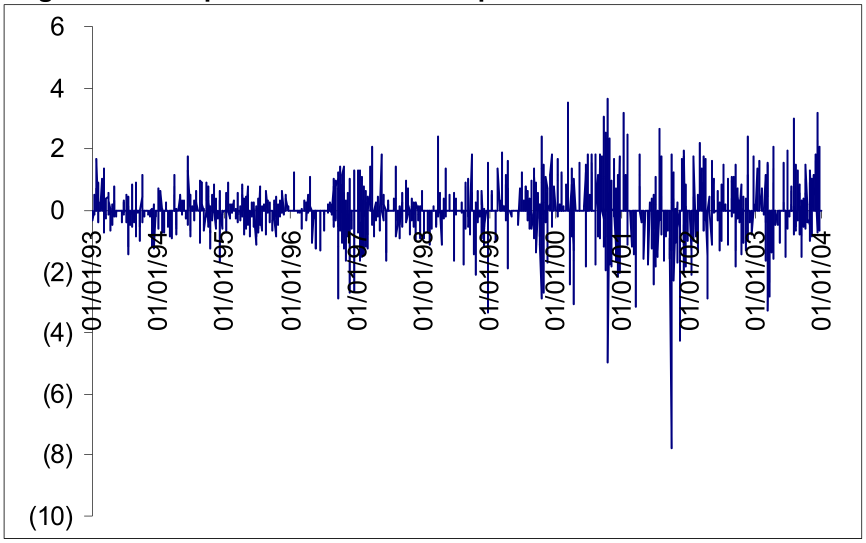


Figure 9: Time plot of *CLPC2* for the period 1/1/93 to 12/31/03

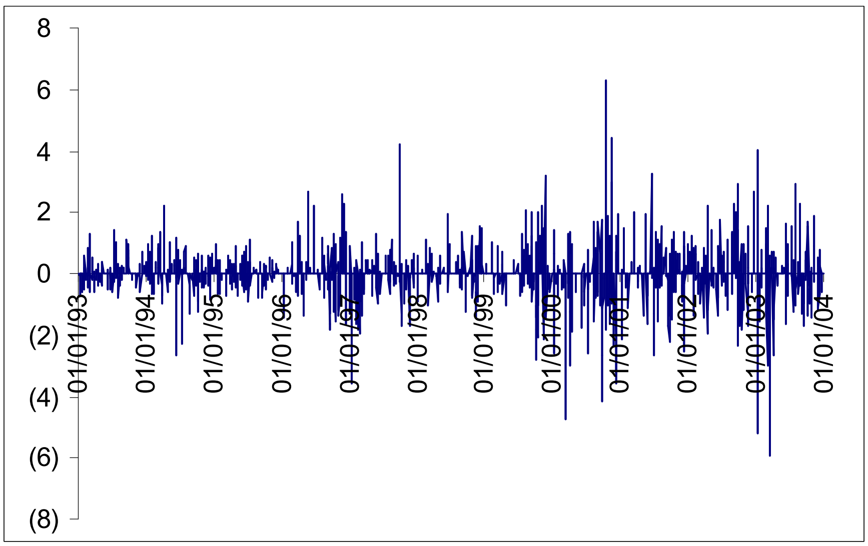


Figure 10: Time plot of *CLPC3* for the period 1/1/93 to 12/31/03

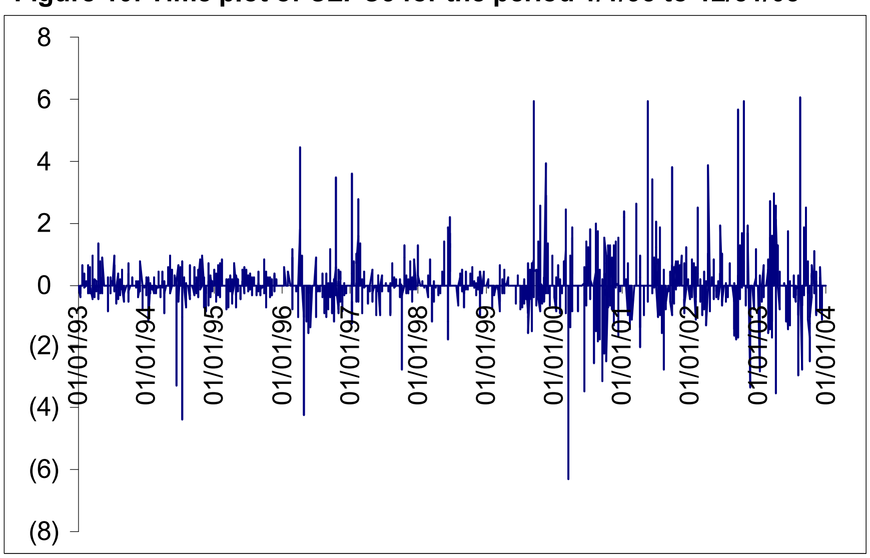


Table 8: Summary statistics of principal components by commodity

	PC1	*PC2*	*PC3*
Panel A: NYMEX crude oil			
Retained observations	962	962	962
Missing observations	1907	1907	1907
Mean	4.1E-16	-7.3E-16	-7.9E-17
Median	2.1E-03	8.8E-03	-4.9E-02
Mode	-7.76[a]	-5.94[a]	-6.30[a]
Std. Deviation	1.00	1.00	1.00
Skewness	-0.65	-0.15	0.92
Kurtosis	5.17	5.60	9.80
Jarque-Bera (JB)	1,125	1,243	3,937
(JB *p*-value)	(0.00)	(0.00)	(0.00)
Minimum	-7.76	-5.94	-6.30
Maximum	3.64	6.29	6.03
Panel B: IPE crude oil			
Retained observations	1014	1014	1014
Missing observations	1855	1855	1855
Mean	-3.4E-16	1.2E-16	2.0E-16
Median	-1.1E-02	5.3E-03	-2.2E-02
Mode	-5.69[a]	-7.13[a]	-5.38[a]
Std. Deviation	1.00	1.00	1.00
Skewness	-0.24	-0.16	0.53
Kurtosis	2.84	5.41	4.97
Jarque-Bera (JB)	346	1,227	1,076
(JB *p*-value)	(0.00)	(0.00)	(0.00)
Minimum	-5.69	-7.13	-5.38
Maximum	4.18	5.15	6.53
Panel C: Heating oil			
Retained observations	1021	1021	1021
Missing observations	1848	1848	1848
Mean	4.6E-16	-4.0E-16	-3.0E-16
Median	-3.1E-02	-1.6E-02	-1.9E-04
Mode	-6.10[a]	-8.79[a]	-8.69[a]
Std. Deviation	1.00	1.00	1.00
Skewness	-0.31	-0.26	1.20
Kurtosis	3.03	13.90	47.39
Jarque-Bera (JB)	400	8,148	94,828
(JB *p*-value)	(0.00)	(0.00)	(0.00)
Minimum	-6.10	-8.79	-8.69
Maximum	3.77	6.32	11.46

Panel D: Gasoline

Retained observations	1897	1897	1897
Missing observations	972	972	972
Mean	-7.6E-16	2.4E-16	-1.3E-16
Median	7.0E-03	1.0E-02	1.3E-02
Mode	-6.06[a]	-15.37[a]	-10.37[a]
Std. Deviation	1.00	1.00	1.00
Skewness	-0.28	-2.85	-1.11
Kurtosis	2.99	40.54	42.44
Jarque-Bera (JB)	726	131,581	141,751
(JB *p*-value)	(0.00)	(0.00)	(0.00)
Minimum	-6.06	-15.37	-10.37
Maximum	4.86	5.58	10.06

a Multiple modes exist. The smallest value is shown.

Table 9: Stationarity tests for principal components

	ADF test statistic	1% critical value
CLPC1	-4.93	-2.60
CLPC2	-3.74	-2.60
CLPC3	-2.68	-2.60
COPC1	-5.89	-2.58
COPC2	-4.30	-2.58
COPC3	-4.42	-2.58
HOPC1	-6.67	-2.58
HOPC2	-3.37	-2.58
HOPC3	-5.08	-2.58
HUPC1	-19.00	-2.57
HUPC2	-16.48	-2.57
HUPC3	-18.39	-2.57

CHAPTER 4: PCA AND FORECASTING POWER

4.1 The regression setup

Having found a limited number of principal components that capture the term structure of futures prices, we can next examine whether they have any forecasting power. The general idea is to check whether one day's principal components can predict the next day's futures prices. To this end, we ran multiple regression analysis. The dependent variables were first differences of futures prices measured at time *t*. The independent variables were the principal components of the commodities found in Chapter 3 measured at time *t*-1. Alternatively, we could have used futures prices as the independent variables. However, the advantage of using principal components instead is that they summarize the term structure of all futures prices. Thus, we get the same information from the regression using only 12 regressors (three per commodity) as opposed to 47 (15 for NYMEX crude, 9 for IPE crude, 12 for heating oil, and 11 for gasoline). Also, by using principal components of all commodities as the regressors, we can check for spillover effects across commodities.[17]

We have used the general-to-specific approach, starting off with all 12 principal components as regressors and dropping the ones that are not statistically significant at the 5% significance level. More formally, we estimated the regressions

$$\Delta F_t^j = c + a_1 CLPC1_{t-1} + a_2 CLPC2_{t-1} + a_3 CLPC3_{t-1} + b_1 COPC1_{t-1} + b_2 COPC2_{t-1} + b_3 COPC3_{t-1} + c_1 HOPC1_{t-1} + c_2 HOPC2_{t-1} + c_3 HOPC3_{t-1} + d_1 HUPC1_{t-1} + d_2 HUPC2_{t-1} + d_3 HUPC3_{t-1} + u \qquad \text{(Equation 1)}$$

where $j = \Delta CL1_t, \ldots, \Delta CL15_t, \Delta CO1_t, \ldots, \Delta CO9_t, \Delta HO1_t, \ldots, \Delta HO12_t, \Delta HU1_t, \ldots, \Delta HU11_t$. From this point onwards, for ease of notation, we will drop subscripts and denote lagged values of NYMEX crude principal components with lag 1 by *CLPC1*, *CLPC2*, *CLPC3*, of IPE crude by *CLPC1*, *COPC2*, *COPC3*, of heating oil by *HOPC1*, *HOPC2*, *HOPC3*, and of gasoline by *HUPC1*, *HUPC2*, *HUPC3*.

[17] We also ran vector autoregression and Granger causality tests. The idea was to run a cross check for our non-structural model by relating all variables to each other, to determine whether we needed a greater number of lags, and finally to make sure that principal components caused changes in futures prices and not vice versa. The results of these tests were not conclusive and are consequently not shown here.

In addition, we checked the correlations among the principal components. It turns out that the first principal components of all commodities are highly correlated to each other (with correlations of around 90%), but all other combinations have relatively low correlations. The high correlations among first principal components could explain the high R^2 values we will see in the regressions below. Table 10 shows the full correlation matrix.

Table 10: Correlation matrix of regressors in Equation 1

	CLPC1	*CLPC2*	*CLPC3*	*COPC1*	*COPC2*	*COPC3*	*HOPC1*	*HOPC2*	*HOPC3*	*HUPC1*	*HUPC2*	*HUPC3*
CLPC1	1.00	0.06	-0.15	0.93	-0.06	-0.14	0.90	0.10	0.10	0.90	-0.07	-0.19
CLPC2	0.06	1.00	0.05	0.22	0.52	-0.38	0.25	0.50	-0.25	0.29	0.41	-0.15
CLPC3	-0.15	0.05	1.00	-0.21	0.25	0.24	-0.16	-0.04	0.02	-0.17	-0.08	-0.11
COPC1	0.93	0.22	-0.21	1.00	-0.05	-0.12	0.91	0.22	0.01	0.89	0.02	-0.17
COPC2	-0.06	0.52	0.25	-0.05	1.00	-0.10	0.02	0.33	-0.06	0.07	0.25	-0.20
COPC3	-0.14	-0.38	0.24	-0.12	-0.10	1.00	-0.15	-0.26	0.17	-0.19	-0.28	0.06
HOPC1	0.90	0.25	-0.16	0.91	0.02	-0.15	1.00	0.24	-0.02	0.92	0.04	-0.17
HOPC2	0.10	0.50	-0.04	0.22	0.33	-0.26	0.24	1.00	-0.16	0.19	0.32	-0.13
HOPC3	0.10	-0.25	0.02	0.01	-0.06	0.17	-0.02	-0.16	1.00	0.09	-0.06	-0.41
HUPC1	0.90	0.29	-0.17	0.89	0.07	-0.19	0.92	0.19	0.09	1.00	-0.01	-0.19
HUPC2	-0.07	0.41	-0.08	0.02	0.25	-0.28	0.04	0.32	-0.06	-0.01	1.00	0.05
HUPC3	-0.19	-0.15	-0.11	-0.17	-0.20	0.06	-0.17	-0.13	-0.41	-0.19	0.05	1.00

Moreover, we used White's test to test for heteroskedasticity. For a description of White's test, see Appendix B. It turned out that most regressions did show the presence of heteroskedasticity at the 5% significance level and the Durbin-Watson statistic for most regressions was either above 2.5 or below 1.5, indicating negative or positive autocorrelation respectively. This required using standard errors corrected for heteroskedasticity. As explained in Appendix B, we have used Newey-West standard errors, which correct for both heteroskedasticity and autocorrelation. Table 11 shows the results of White's test. The test statistic is calculated as n^*R^2 and the corresponding p-values are reported in parentheses next to the test statistic.

Table 11: White's test for ΔF^j_t where $j = \Delta CL1_t, \ldots, \Delta HU11_t$

j	Test statistic	
Panel A: NYMEX crude oil		
ΔCL1	114.9	(0.04)
ΔCL2	111.4	(0.06)
ΔCL3	111.1	(0.07)
ΔCL4	111.9	(0.06)
ΔCL5	112.5	(0.05)
ΔCL6	113.2	(0.05)
ΔCL7	113.7	(0.05)
ΔCL8	114.2	(0.04)
ΔCL9	114.4	(0.04)
ΔCL10	114.0	(0.04)
ΔCL11	111.0	(0.07)
ΔCL12	110.6	(0.07)
ΔCL13	110.5	(0.07)
ΔCL14	105.3	(0.13)
ΔCL15	100.0	(0.22)
Panel B: IPE crude oil		
ΔCO1	132.0	(0.00)
ΔCO2	120.7	(0.00)
ΔCO3	70.7	(0.00)
ΔCO4	28.2	(0.01)
ΔCO5	43.4	(0.00)
ΔCO6	33.5	(0.00)
ΔCO7	8.6	(0.13)
ΔCO8	35.7	(0.00)
ΔCO9	133.3	(0.00)
Panel C: Heating oil		
ΔHO1	339.8	(0.00)
ΔHO2	185.4	(0.00)
ΔHO3	232.0	(0.00)
ΔHO4	251.6	(0.00)
ΔHO5	739.3	(0.00)
ΔHO6	248.7	(0.00)
ΔHO7	662.7	(0.00)
ΔHO8	186.0	(0.00)
ΔHO9	85.2	(0.00)
ΔHO10	346.0	(0.00)
ΔHO11	268.1	(0.00)
ΔHO12	246.8	(0.00)

Panel D: Gasoline

ΔHU1	117.6	(0.03)
ΔHU2	120.4	(0.02)
ΔHU3	118.4	(0.02)
ΔHU4	68.3	(0.96)
ΔHU5	116.4	(0.03)
ΔHU6	113.1	(0.05)
ΔHU7	104.0	(0.15)
ΔHU8	17.2	(0.00)
ΔHU9	19.0	(0.00)
ΔHU10	116.6	(0.03)
ΔHU11	16.1	(0.00)

Note: The White statistic is reported for each commodity across all maturities. The *p*-values of the test are reported within parentheses.

4.2 Regression results

Table 12 presents the results of the regressions per commodity. The first column shows the dependent variable of Equation 1. The next 13 columns show the constant term and the coefficient values of the regressors along with their *t*-statistics in parentheses. The following two columns show the R^2 statistic and the Durbin-Watson statistic for first order serial correlation. Finally, the last column shows the *F*-statistic for testing the null hypothesis that all coefficients (excluding the constant term) are zero. The *F*-statistic's *p*-values are given in parentheses.

From Table 12, we see that for IPE crude oil and heating oil, the principal components of each commodity can be used to forecast subsequent futures prices for any maturity. In most cases, the principal components from the other commodities do not provide any additional information. In the case of NYMEX crude oil and gasoline, the analysis fails to reach the same conclusions. The results from the regressions showed that the principal components of any commodity do not carry any information on NYMEX crude oil or gasoline futures prices.

Table 12: Results from regressing ΔF_t^j (where $j = \Delta CL1_t, \ldots, \Delta HU11_t$) on the retained principal components of the four commodities

j	c (t-stat)	a_1 (t-stat)	a_2 (t-stat)	a_3 (t-stat)	b_1 (t-stat)	b_2 (t-stat)	b_3 (t-stat)	c_1 (t-stat)	c_2 (t-stat)	c_3 (t-stat)	d_1 (t-stat)	d_2 (t-stat)	d_3 (t-stat)	R^2	Durbin-Watson	F-stat (prob)
Panel A: Dependent variables are NYMEX crude oil generic futures contracts																
No significant results found for any maturity.																
Panel B: Dependent variables are IPE crude oil generic contracts																
ΔCO1	0.038	-	-	-0.005	0.476	0.188	0.075	-	-	-	-	-	-	0.999	3.068	98,199
	(54.6)	-	-	(-4.1)	(520.8)	(112.1)	(36.5)	-	-	-	-	-	-			(0.00)
ΔCO2	0.032	-	-	0.013	0.457	0.080	-0.038	-	-	-	-	-	-	0.992	3.086	12,573
	(17.6)	-	-	(3.8)	(191.4)	(18.9)	(-7.2)	-	-	-	-	-	-			(0.00)
ΔCO3	0.025	-	-	-	0.424	0.040	-0.039	-	-	-	-	-	-	0.997	2.656	126,739
	(44.4)	-	-	-	(439.1)	(52.1)	(-32.1)	-	-	-	-	-	-			(0.00)
ΔCO4	0.023	-	-	-0.004	0.395	0.013	-0.028	-	-	-	-	-	-	0.998	3.129	40,503
	(28.0)	-	-	(-3.4)	(396.7)	(9.6)	(-16.0)	-	-	-	-	-	-			(0.00)
ΔCO5	0.021	-	-	-0.005	0.369	-0.012	-0.017	-	-	-	-	-	-	0.997	2.786	38,612
	(24.6)	-	-	(-4.5)	(413.7)	(-8.4)	(-10.4)	-	-	-	-	-	-			(0.00)
ΔCO6	0.019	-	-	-	0.349	-0.032	-	-	-	-	-	-	-	0.996	2.662	122,199
	(31.9)	-	-	-	(394.2)	(-25.5)	-	-	-	-	-	-	-			(0.00)
ΔCO7	0.018	-	-	-	0.332	-0.044	-	-	-	-	-	-	-	0.996	2.774	136,028
	(27.4)	-	-	-	(517.0)	(-68.9)	-	-	-	-	-	-	-			(0.00)
ΔCO8	0.017	-	-	-	0.319	-0.056	0.019	-	-	-	-	-	-	0.998	2.577	152,204
	(45.4)	-	-	-	(521.9)	(-84.5)	(28.3)	-	-	-	-	-	-			(0.00)
ΔCO9	0.015	-	-	-	0.305	-0.064	0.031	-	-	-	-	-	-	0.995	2.823	65,730
	(27.7)	-	-	-	(333.5)	(-46.5)	(18.6)	-	-	-	-	-	-			(0.00)

j	c (t-stat)	a_1 (t-stat)	a_2 (t-stat)	a_3 (t-stat)	b_1 (t-stat)	b_2 (t-stat)	b_3 (t-stat)	c_1 (t-stat)	c_2 (t-stat)	c_3 (t-stat)	d_1 (t-stat)	d_2 (t-stat)	d_3 (t-stat)	R^2	Durbin-Watson	F-stat (prob)
Panel C: Dependent variables are heating oil generic contracts																
ΔHO1	-0.039	-	-	-	-	-	-	1.432	0.669	0.397	-	-	0.222	0.983	2.488	11,490
	(-6.5)	-	-	-	-	-	-	(148.4)	(14.4)	(7.6)	-	-	(4.2)			(0.00)
ΔHO2	-0.040	-	-	-	-	-	-	1.337	0.396	-	-	-	-0.109	0.992	2.436	33,487
	(-8.9)	-	-	-	-	-	-	(196.1)	(22.2)	-	-	-	(-5.3)			(0.00)
ΔHO3	-0.040	-	-	-	0.038	-	-	1.222	0.234	-0.082	-	-	-0.092	0.993	1.060	9,176
	(-7.1)	-	-	-	(2.2)	-	-	(65.9)	(11.2)	(-2.8)	-	-	(-3.6)			(0.00)
ΔHO4	-0.032	-	-	-	0.028	-	-	1.167	0.105	-0.196	-	-	-0.043	0.996	1.100	15,762
	(-8.0)	-	-	-	(2.2)	-	-	(87.6)	(9.2)	(-7.6)	-	-	(-2.1)			(0.00)
ΔHO5	-0.037	-	-	-	-	-	-	1.134	0.043	-0.208	-	-	-	0.994	2.081	56,427
	(-12.2)	-	-	-	-	-	-	(227.5)	(5.3)	(-10.5)	-	-	-			(0.00)
ΔHO6	-0.034	-	-	-	-0.013	-	-	1.096	-0.030	-0.201	-	-0.019	0.044	0.998	1.154	28,558
	(-15.0)	-	-	-	(-2.2)	-	-	(159.3)	(-4.2)	(-11.8)	-	(3.3)	(2.9)			(0.00)
ΔHO7	-0.029	-	-	-	-	-	-	1.043	-0.095	-0.155	-	-	-	0.995	2.741	72,141
	(-13.1)	-	-	-	-	-	-	(196.2)	(-8.3)	(-15.1)	-	-	-			(0.00)
ΔHO8	-0.024	-	-	-	-	-	-	0.997	-0.138	-0.079	-	-	-	0.992	1.688	43,620
	(-8.2)	-	-	-	-	-	-	(284.3)	(-11.6)	(-6.8)	-	-	-			(0.00)
ΔHO9	-0.020	-	-	-	-	-	-	0.959	-0.165	-	-	-	-	0.992	1.664	65,262
	(-7.1)	-	-	-	-	-	-	(253.8)	(-16.3)	-	-	-	-			(0.00)
ΔHO10	-0.019	-	-	-	-	-	-	0.926	-0.179	0.110	-	0.024	-	0.998	2.378	81,719
	(-11.4)	-	-	-	-	-	-	(555.1)	(-46.4)	(14.1)	-	(4.5)	-			(0.00)
ΔHO11	-0.021	-	-	-	-	-	-	0.898	-0.178	0.167	-	-	-	0.998	2.736	136,904
	(-15.5)	-	-	-	-	-	-	(416.7)	(-35.3)	(23.5)	-	-	-			(0.00)
ΔHO12	-0.025	-	-	-	-	-	-	0.875	-0.169	0.202	-	-	-	0.987	1.625	24,945
	(-7.2)	-	-	-	-	-	-	(202.2)	(-11.9)	(13.3)	-	-	-			(0.00)

j	*c* (*t*-stat)	a_1 (*t*-stat)	a_2 (*t*-stat)	a_3 (*t*-stat)	b_1 (*t*-stat)	b_2 (*t*-stat)	b_3 (*t*-stat)	c_1 (*t*-stat)	c_2 (*t*-stat)	c_3 (*t*-stat)	d_1 (*t*-stat)	d_2 (*t*-stat)	d_3 (*t*-stat)	R^2	Durbin-Watson	*F*-stat (prob)
						Panel D: Dependent variables are gasoline generic contracts										
ΔHU1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-	-			-
ΔHU2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-	-			-
ΔHU3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-	-			-
ΔHU4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-	-			-
ΔHU5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-	-			-
ΔHU6	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-	-			-
ΔHU7	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-	-			-
ΔHU8	-	-	-	-	-0.120	-	-	-	-	-	-	-	-	0.012	2.246	-
	-	-	-	-	(-2.9)	-	-	-	-	-	-	-	-			-
ΔHU9	-	-	-	-	-0.105	-	-	-	-	-	-	-	-	0.010	2.275	-
	-	-	-	-	(-2.6)	-	-	-	-	-	-	-	-			-
ΔHU10	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-	-			-
ΔHU11	-	-	-	-	-0.122	-	-	-	-	-	-	-	-	0.015	2.169	-
	-	-	-	-	(-3.0)	-	-	-	-	-	-	-	-			-

In the case of NYMEX crude oil futures price differences, the regressions we ran did not give any significant results. All coefficients were statistically insignificant. As a result, we can infer that knowledge of principal component values for any commodity on any given day are not useful in forecasting the next day's NYMEX crude oil futures prices.

Running the same regressions with IPE crude oil futures price differences as the dependent variables gave a different picture. In this case, all three IPE crude oil futures principal components appear to have a high forecasting power. Their coefficients were statistically significant across all maturities except for *COPC3*, which was statistically significant for all maturities except for *ΔCO6* and *ΔCO7*. This, however, could be just an exception. Likewise, NYMEX crude oil futures third principal component (*CLPC3*) proved significant in forecasting *ΔCO1*, *ΔCO2*, *ΔCO4*, and *ΔCO5*. However, we cannot generalize with confidence that *CLPC3* should be present in all regressions for IPE crude oil futures. It is worth noting that *COPC1* has a large positive coefficient, while the coefficients for *COPC2* and *COPC3* are much smaller in absolute value and their signs are not consistent.

Moving on to heating oil, we get equivalent results, namely we see that the same commodity's principal components have consistently high forecasting power for all maturities except for *HOPC3*, which was left out in the equations for *ΔHO2* and *ΔHO9*. Again, however, these could be mere exceptions. In addition, *COPC1* is statistically significant in three equations, *HUPC3* in four, and *HUPC2* in two. It is likely that a general conclusion for heating oil futures would not include these in the principal components that can be used to forecast future prices. As in the case of IPE crude oil, the coefficient of the first principal component of the commodity that the dependent variable belongs to (in this case *HOPC1*) is always positive and relatively high in value. On the contrary, the other coefficients, including *HOPC2* and *HOPC3*, are more volatile and may be either positive or negative.

Finally, regressing gasoline futures price differences on the retained principal components showed a similar behavior to crude oil. There were no significant regressors for any maturity except for *COPC1* in the case of *ΔHU8*, *ΔHU9*, and *ΔHU11*. However, judging from the small number of equations that they are present, the fact that these equations are for longer-term maturities, the low R^2 statistic, and the small absolute value of the coefficient, we are reluctant to conclude that *COPC1* can be used to forecast gasoline futures prices overall. It is more likely that it just happened to show up in these three equations. In general, it would be safe to conclude that there are no principal components that can help us predict gasoline futures prices.

From all of the above, the conclusion that can be drawn is that in order to forecast futures prices for a commodity, we can look at that particular commodity's principal component values. Principal components of other commodities do not add any information. In other words, there are no major spillover effects. This conclusion holds roughly for IPE crude oil futures and heating oil futures. On the contrary, NYMEX crude oil and gasoline futures prices do not depend on any principal components. It is odd that the results are so different, especially for NYMEX and IPE crude oil futures, which are very highly correlated to each other, but there doesn't seem to be a satisfactory, intuitive explanation.

CHAPTER 5: CONCLUSION

In this study, first we used principal components analysis to model the dynamics of the term structure of futures contracts on four energy commodities: NYMEX crude oil, IPE crude oil, heating oil, and gasoline. Our approach extends the literature developed by Schwartz and Cortazar [1994], Clewlow and Strickland [1999b], Tolmasky and Hindanov [2002], and Järvinen [2003]. Compared to the previous studies, we used a larger dataset in terms of the length of the time series employed combined with the number of commodities under scrutiny. Our results from principal components analysis are in line with the majority of the research done on the term structure of commodity futures prices. We identified three principal components that explain most of the variance in futures prices. Specifically, they account for 99.8%, 99.6%, 99.1%, and 95.7% of total variance for NYMEX crude oil, IPE crude oil, heating oil, and gasoline futures prices respectively. Consistent with the available literature, the first principal component represents a parallel shift in the futures curve, the second one represents a tilt, and the third one represents curvature.

Next, we examined whether the retained principal components have any forecasting power for subsequent futures prices. To this end, we ran multiple regression analysis on the first differences of futures prices for all maturities of the four commodities under examination using the retained PC's as regressors. For any given commodity, we included the retained principal components not only for that commodity, but also for the rest of the commodities. The idea was to check for spillover effects across commodities by testing whether shocks in one commodity affect the others. We thus used a total of 12 regressors, i.e., three principal components per commodity. We found that the IPE crude oil and heating oil PC's can be used to forecast their respective commodities' futures prices. The impact of the other commodities' PC's was not significant in the majority of cases. This indicates that no spillover effects are present. Results on NYMEX crude oil and gasoline were notably different, showing no significant relationship. No principal components of any commodity had a forecasting power for NYMEX crude oil and gasoline futures prices. Further research needs to be done to understand why commodities that are extremely similar (such as IPE crude oil and NYMEX crude oil) gave so different regression results.

APPENDIX A

Testing for stationarity

A stochastic process for a variable y_t is said to be (weakly) stationary if the mean and covariances do not depend on time, i.e. $E(y_t)$ = constant for all t, $Var(y_t)$ = constant for all t, $Covar(y_t, y_{t+n})$ = constant for all t. We can test for stationarity using the Dickey-Fuller (DF) test. The DF test checks for unit roots in the series. For example, an AR(1) process of the form $y_t = \mu + \rho y_{t-1} + u_t$ with $u_t \sim IID(0,\sigma^2)$ is stationary if $|\rho|<1$. If $\rho=1$ (a unit root), the process is non-stationary (in fact, it is a random walk). If $|\rho|>1$, the process is again non-stationary, but it is explosive (i.e. tends to either $+\infty$ or $-\infty$) and is therefore of no concern. The null hypothesis and the alternative of the DF test are $H_0{:}\rho=1$ and $H_1{:}\rho<1$ respectively. The null hypothesis is the presence of a unit root and non-stationarity; the alternative is stationarity.

A generalized version of the test that includes higher order lagged terms is the Augmented Dickey-Fuller (ADF) test. The ADF test is appropriate for any AR(p) process. The reason for using ADF instead of a simple DF test is that, if we use a simple DF test (which is designed for an AR(1) process) for a process that is in fact AR(p), then the errors will be autocorrelated to compensate for the misspecification of the model. Since the Dickey-Fuller distributions assume that the error term is white noise, the autocorrelation will invalidate them. The number of lags to be included should be carefully selected, since too few lags may result in rejecting the null when it is true (due to the presence of some remaining autocorrelation) and too many lags may reduce the power of the test. A generally accepted formula for the selection of lags is $l=\text{int}[12(T/100)^{1/4}]$ where l is the lag length and T is the sample size.

For a more detailed discussion of the Dickey-Fuller and other unit root test, see Harris [1995] and Enders [1995].

APPENDIX B

Testing for heteroskedasticity

There are several tests that one can use to test for heteroskedasticity. The one we have used in this study is White's test. White's test estimates the original regression and then regresses the squared residuals obtained from the original equation on the original regressors, their squared values, and all their cross products (we call this regression the auxiliary regression). Under the null hypothesis of homoskedasticity, $n*R^2$ (where n is the sample size and R^2 is the one obtained from the auxiliary regression) follows the χ^2 distribution with degrees of freedom equal to the number of regressors (excluding the constant term). If White's test statistic exceeds the χ^2 value at a specified significance level, we can reject the null hypothesis and conclude that there is heteroskedasticity. In that case, there exist several methods of correcting the standard errors. In this study, we have used the Newey-West standard errors, which have the advantage of correcting both for heteroskedasticity and for autocorrelation (hence also called HAC or heteroskedasticity- and autocorrelation-consistent standard errors).

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