# Essays in Energy and Environmental Economics

by

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ABSTRACT

**ESSAYS IN ENERGY AND ENVIRONMENTAL ECONOMICS**

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This doctoral dissertation consists of three essays in Energy and Environmental Economics. In the first chapter, an empirical analysis is employed to examine the relationship between energy consumption and economic output in Canada. Using provincial-level Canadian records, this chapter shows that there is a long run equilibrium relationship and a bi-directional Granger causality between energy consumption and economic growth in Canada. These finding have important implications for public policy because they show that constraints on energy consumption may impact future economic growth. In the second chapter, event study methodology and Canadian stock market data are used to assess the impact of seven recent event/announcements regarding the pipelines approval process on the equity returns of energy-related firms. This chapter shows that there is no market reaction (on average) to any of the news events, which implies two possible scenarios: either the market fully anticipated the events and they did not contain any significant new information or these events did not change investor's expectation regarding future profitability and cash flow of Canadian energy firms. In the third chapter, we use a prediction market mechanism to examine the possibility of using derivatives trading as a means of generating objective forecasts of future climate change and the value of marginal damages. This chapter shows that such a market can yield unbiased estimates of the true future climate state. Also, we find that the level of consensus about climate science strongly influences the efficiency with which market uses available information.

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# Chapter 1

# Energy consumption and economic output : Evidence from panel cointegration analysis using sub-national data

## 1.1 Introduction

Energy consumption and economic growth tend to move together over time. Although the total size of the economy tends to grow faster than total energy consumption, the two nonetheless trend together over the long run. This raises the question of whether economic growth causes increases in energy consumption, or increased energy availability causes an increase in economic activity, or both.

Although many studies have examined this question, no single consensus view has emerged yet. The existence and direction of the causality not only provides insights with respect to the role of energy consumption in economic development but also has important implications for public policy. Concerns about global warming and climate change have led to increasing calls for policies to reduce energy use. A country in which causality runs from energy consumption to economic growth will need to be cautious in pursuing conservation measures since any restrictions on energy availability will have negative effects on economic growth. Under these conditions, efforts to address emissions control should aim to avoid, if possible, increasing energy scarcity. On the other hand, if energy consumption is determined by economic growth, policy which aims to reduce energy consumption will not tend to undermine future economic growth. In this case, reducing energy demand using regulatory instruments should not harm growth.

The literature proposes four different hypotheses regarding the possible causality outcomes. The growth hypothesis considers the economy as “energy dependent", implying that energy consumption is an important component in growth as a complement to capital and labour in production. This hypothesis can be interpreted as proposing a uni-directional causality running from energy to growth, such that a decrease in energy consumption or an increase in the costs of energy, as a result of energy conservation policies, will cause a decrease in future real GDP. The conservation hypothesis by contrast, specifies a uni-directional casual relationship running the opposite way from real GDP to energy consumption. In this view, energy consumption is a kind of luxury good, the consumption of which arises from increased wealth. This hypothesis implies that policies which aim to decrease energy consumption, by making energy more costly or less abundant, have little or no adverse effect on growth. The feedback hypothesis corresponds with bi-directional causality which assumes these two variables affect each other simultaneously. This implies that as the economy grows energy demand increases, and vice versa. The last hypothesis is neutrality which assumes that growth and energy do not affect each other. The main rationale for this hypothesis is that the cost of energy is very small relative to the size of GDP so it would be unlikely to have any significant effect on output growth.

The purpose of this paper is to study the causal relationship between energy consumption and economic output in Canada using the concept of Granger causality[1] and a multivariate panel approach. There have been many studies looking at the Energy-GDP relationship internationally, including Canada, but to the best of our knowledge no previous study has taken advantage of Canadian sub-national level data. Hence, the first contribution of our paper is to add to the empirical literature by taking advantage of provincial-level Canadian records. We examine two panels of Canadian provinces, an older one spanning 1981 to 2000 and a newer one spanning 1995 to 2010. Unfortunately, as these datasets are based on different survey methods they cannot be combined to make a single long data set. In addition, most of previous studies have not taken into account recent advances in panel cointegration and panel VAR methods. Unlike most previous studies, we use recently-developed panel econometric techniques consisting of panel unit root, cointegration and Granger causality tests. We also account for the presence of cross section dependencies, a feature of panel data which has been neglected in many previous studies, when verifying the relationship between variables. We utilize a production function framework accounting for labour and capital in order to overcome possible omitted variables bias and implement an appropriate panel error correction model.

The rest of paper is structured as follows. Section 2 provides the literature review on the relationship between economic growth and energy consumption. Section 3 presents theoretical structure, data, methodology and empirical results. Policy implications and concluding remarks are given in Section 4. Appendix 1 and Appendix 2 represent summary statistics by each province.

[1] If two series X and Y both trend together, we say that X "Granger causes" Y if knowing the past values of X lowers the variance of errors associated with forecasts of Y beyond the variance of errors which would be made if the information apart from X had been used (Granger,1969).
$\sigma^2(y_t \mid y_{t-1}, y_{t-2}, ..., x_{t-1}, x_{t-2}, ...) \prec \sigma^2(y_t \mid y_{t-1}, y_{t-2}, ...)$

## 1.2 Literature review

The relationship between economic growth and energy consumption has been extensively examined during the last 30 years and many papers have been published on this topic, yielding conflicting and mixed results. Many studies have focused on developed and industrialized countries since data for them are more available and trustworthy. Results differ among different countries, and even among studies looking at the same country.

In general, the absence of consensus on the relationship between growth and energy consumption is due to the use of different econometric methods and time periods, different energy consumption patterns, country-specific heterogeneity in climate conditions, the stage and structure of economic development within a country, and the presence of omitted variable bias due to using bivariate causality tests (Belke et al. 2011).

Mehrara (2006) categorized publications into four "generations". The first used a traditional VAR regression approach to infer Granger-causal relationship between the levels of energy consumption and GDP. These early studies used the methods proposed in Granger (1969) and Sims (1972), the latter study providing a practical extension of Granger's method. This methodology was applied from late 1970 to the end of 1980s, and stationarity of the data was assumed.

Throughout this paper we use Granger causality and "causality" in the conventional time series sense, which is a weaker concept than ordinary physical causality. Readers should bear the distinction in mind.

The seminal work on the relationship between income and energy consumption was carried out by Kraft and Kraft (1978). They applied Sim's methodology to examine Granger causality between energy consumption and economic growth over the period 1947-1974 for the USA and concluded that the direction of causality runs from the level of gross national product (GNP) to the level of energy consumption. Yu and Hwang (1984) used Sim's method to test the causality between GNP and energy consumption and also between energy consumption and employment. All these variables were in levels. On a sample spanning

1947-1979 they found no causal relationships between energy consumption and GNP for the USA. Yu and Choi (1985) looked at data over the same period and found no causality for the US or the UK. Murray and Nan (1996) used data covering 1970-1990 and found no causality for the US, UK, France or Germany. However, Stern (1993) used a longer sample (1947 to 1990) and found a uni-directional causality running from energy consumption to real GDP.

One of the few consistent findings in the first generation literature was causality running from the level of energy to the level of GDP in Canada. This was observed by Erol and Yu (1987, sample 1950-1982) and by Murray and Nan (1996, sample 1970-1990).

With the emergence of stationary tests, results from VAR analysis came to be seen as spurious, and VECM methods (Engle and Granger 1987) began to be adopted. Second-generation publications considered the presence of a form of nonstationarity called "unit roots" in time series. Engle and Granger (1987) extended the standard Granger causality tests to include the possibility that two non-stationary series might share a common stochastic trend (called cointegrated series). They proposed a two step procedure based on which pair of variables was checked for cointegration. Testing Granger-causality within the context of an error correction model was proposed as a second step in these publications. An example was Glasure and Lee (1997) who found bi-directional causality between GDP and energy consumption for South Korea and Singapore.

Third generation studies used a multivariate ECM approach following Johansen's (1991) method. These publications aimed to remove omitted variable bias associated with second-generation works by taking account of the role of labor, capital, prices, etc. in estimating model. The two major studies in this group were Soytas and Sari (2003) and Soytas and Sari (2006b). Both studies examined a long list of industrialized countries, including Canada, over the intervals 1950-1992 and 1960-2004, respectively. In the 2003 paper, no causality between energy and GDP per capita (or real income) was found for the US, UK or Canada, while for France, Germany and Japan it was found that causality runs from energy to income. In the 2006 study, energy was found to drive income for France and the US, while for UK, Japan, Germany and Canada they were found to cause each other. Ghali and El-Sakka (2004) investigated the relationship between energy consumption and GDP in Canada and found that there is short-run bidirectional causality between energy consumption and GDP growth,[2] concluding also that energy can be considered as a limiting factor to output growth.

Later on, some studies criticized the VECM and /or Johanson-Juselius cointegration procedures due to the fact that they require large samples to yield reliable results, but were being used on relatively short data spans. In response, more recent studies used techniques better suited to small samples called autoregressive distributed lag (ARDL) models with bounds testing (Pesaran and Shin (1999) and Pesaran et al. 2001) as well as the Toda and Yamamoto (1995) test. The advantage of these procedures is that they can be employed without pre-testing the variables for unit roots or cointegration. Major studies to emerge in this cohort were Lee (2006) and Zachariadis (2007). Lee used a panel of 11 countries over 1960-2001 while Zachariadis used seven countries over 1960-2004. Between these two the results were rather inconsistent. Lee found no causality for the UK or Germany, while Zachariadis found partial evidence for Germany and strong evidence (GDP causing energy) for the UK. Lee found evidence of GDP-to-energy causality for France and Japan, but Zachariadis found weak results for France and two-way causality for Japan. For the US, Lee found two-way causality and Zachariadis found none. For Canada, Lee found significant evidence of causality from energy to GDP, while Zachariadis found significant evidence for the other direction.

However, none of these studies took into account time- and country- specific effects. Thus, a fourth generation literature using bivariate panel cointegration tests (Pedroni 1999, 2004) and so-called Panel Error Correction Models began emerging from approximately 2003 onwards. This procedure increases the statistical power of causality tests by combining time series across different countries, allowing for examination of both time series and cross sectional effects. Cores and Sanders (2012) extended Mehrara's classification and considered

[2] In this literature, since all variables, including real GDP and energy consumption, are transformed to their natural logarithms, their first differences are considered to approximate their growth rates.

Multivariate Panel VECM tools as a fifth generation. The two major studies to emerge in this group were Narayan and Smith (2007), covering the G7 countries over 1972-2002, and Lee et al. (2008) covering 22 OECD countries over 1960-2001. Narayan and Smith concluded that, for all G7 countries, energy causes income (real GDP per capita) and Lee et al. concluded that there is two-way causality between them.

## 1.3 Theoretical structure, data, methodology and empirical results

### 1.3.1 Theoretical structure

Mainstream growth models such as Solow-Swan, consider labor and capital as the major factors of production. These theories omit energy because they focus on sources of growth in value-added net output. This implies that energy demand in a given country is derived as a result of macroeconomic conditions, which we have termed the growth-led energy hypothesis.

An alternative view (Stern and Cleveland, 2004) treats energy availability as another factor of production. In this approach, economic growth is a function of energy use and thus is driven by energy consumption, which implies the energy-led growth hypothesis.

Therefore, the economic theory is ambiguous in terms of explaining the direction of causality between energy consumption and economic growth. Many studies have tried to find the direction of this causality empirically. Some studies have adapted the first perspective, the growth-led energy hypothesis, when testing for the causal relationship among energy consumption and economic growth. This modeling is a demand approach that usually adds energy prices as additional variables. However, we want to avoid imposing any particular hypothesis on the data. Therefore, in this study we implicitly measure the relationship between energy consumption and economic output and test the validity of energy-led growth hypothesis, using the following general production function:

$$Y = f(K, L, E) \tag{1.1}$$

where $Y$ is real GDP, $K$ is capital, $L$ is labor and $E$ is energy use. In this study, the causal relationship between energy consumption an output is examined given an implicit assumption of stable long-run relationship among the variables. In other words, the analysis of this paper in terms of investigating the cointegration and Granger causal relationship among the variables may not hold, if there was a major change in the way energy was used in the production function.

### 1.3.2 Data

There are two data sets available through Statistics Canada that can be used for the present purpose. An older series spans 1981-2000 and a newer one spans 1995-2010. Unfortunately, as they are based on different survey methods they cannot be combined to make a single long data set. We therefore analyzed both data sets separately. We provide detailed results based on the more recent data set (1995-2010) and then report results on the older one as well. Since there are many similarities between the two we place details of the older results in the last part of this section (3.7). The newer data set consists of annual provincial-level observations (see Table 1.1). Real Gross Domestic Product (GDP) and Real Gross Fixed Capital Formation[3] are both in constant million (2002) dollars. Final Energy Consumption is in terajoules and employment is in 1000 persons. Table 1.1 reports variable definitions, summary statistics and data sources. Summary statistics by each province are provided in Appendix 1. All variables were transformed using logarithms prior to any estimation.

During the course of the estimations it became clear that Newfoundland was an outlier, possibly due to the large role that the Hibernia oil platform plays in the small economy

[3] Real gross fixed capital formation serves as a proxy for capital following the work by Soytas and Sari (2006, 2007).

Table 1.1: Data sources, definitions, measurement units and summary statistics of Canadian 1995-2010 sample

| Variable Name | Y | K | E | L |
|---|---|---|---|---|
| Definition | Real Gross Domestic product | Real Gross Fixed Capital formation | Final Energy Consumption | Employment |
| Units | \$2002 Constant Dollars | \$ 2002 Constant Dollars | Terajoules | Thousand persons |
| Mean | 124,739.9 | 26,241.87 | 807,417.3 | 1,683.59 |
| Standard Dev. | 143,780.3 | 28,831.19 | 797,746.2 | 1,873.85 |
| Minimum | 3,103.0 | 503.0 | 20,339.0 | 57.2 |
| Maximum | 530,475.0 | 107,829.0 | 2,643,443 | 6,663.3 |
| Span of years | 1995 to 2010 | 1995 to 2010 | 1995 to 2010 | 1995 to 2010 |
| Source | CANSIM tables # 384-0002,128-0016 and 282-005 | | | |

of the province. When testing for Granger causality at the national level, we found that the coefficient on the lagged differenced energy consumption had a significant and negative impact on changes in real GDP in the next period. The only source of this negative impact was Newfoundland, which lead us to conclude this province had a different and atypical pattern from the other provinces. Therefore, to avoid generating spurious effects we removed Newfoundland from the sample (1995-2010) and retained the other nine provinces. This atypical pattern of Newfoundland did not appear to be the case when using the older sample of data (1981-2000), therefore the older dataset includes this province along with other nine provinces. Summary statistics by each province, including Newfoundland, over the period 1981-2000 is reported in Appendix 2.

The sequence of analysis is as follows. First, we test for the existence of cross section dependence in the panel. Then, panel unit root tests are employed to determine the order of integration of the series. If integration of order one is found, then panel cointegration tests are used to investigate the existence of long-run relationships among variables. If the series are cointegrated, the long-run cointegration vector is estimated using panel Dynamic Ordinary Least Squares (DOLS) and Fully Modified Ordinary Least Squares (FMOLS). Existence of cointegration among variables implies that there is Granger causal relationship at least in one direction. Therefore, the final step is to set up a dynamic panel error correction model (ECM) to determine the direction of causality.

### 1.3.3 Cross section dependence

The first generation literature on panel unit root and panel cointegration tests assumed that disturbances in panel data models are cross-sectionally independent, which is a restrictive and unrealistic assumption in many macroeconomic applications. Application of these tests to data with dependent cross sections will lead to low power and size distortions (Banerjee, Marcellino and Osbat, 2000; Strauss and Yigit, 2003).

The second-generation tests were designed to be robust to cross section dependence. Thus, before proceeding to investigate the order of integration and testing cointegration among variables, the hypothesis of cross sectional independence was tested. Cross section dependence might occur due to many reasons such as unobserved common factors, omitted observed common factors, spatial spill over effects, or general residual interdependence that could remain even when all the observed and unobserved effects are taken into account (Breitung and Pesaran, 2005). In this paper, two cross section dependence tests by Breusch and Pagan (1980) and Pesaran (2004) have been applied.

Breusch and Pagan proposed a Lagrange multiplier ($LM$) test that is based on the average of the squared pair-wise correlation of residuals. This $LM$ test exhibits highly desirable statistical properties in the case of panels where the cross section dimension ($N$) is small and the time dimension of the panel ($T$) is adequately large (when $N < T$ as is the case in this study). Both Breusch and Pagan (1980) and Pesaran (2004) tests are based on the estimation of the following panel data model:

$$y_{it} = \alpha_i + \beta' x_{it} + u_{it} \qquad for\ t = 1, ..., T; i = 1, ..., N \tag{1.2}$$

Where $t$ and $i$ index the time and cross section dimensions respectively, $y_{it}$ is real GDP,

$x_{it}$ is a $k \times 1$ vector of regressors (energy consumption, capital and employment), $\overset{\wedge}{\beta}$ is a $k \times 1$ vector of parameters to be estimated and $\alpha_i$ represents the individual intercepts. Under the null hypothesis $u_{it}$ is assumed to be independent and identically distributed across cross-sectional units and over periods. Under the alternative hypothesis, $u_{it}$ could be cross sectional correlated but the assumption of no serial correlation remains (De Hoyos and Sarafidis, 2006). The null hypothesis is therefore $H_0 : Cov(u_{it}\ , u_{jt}) = 0$ for all $t, i \neq j$, and is examined against the alternative $H_1 : Cov(u_{it}, u_{jt}) \neq 0$ for at least one pair of $i \neq j$.

An $LM$ statistic proposed by Breusch and Pagan is given by

$$LM = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\overset{\wedge}{\rho}_{ij}^{\,2} \tag{1.3}$$

Where $\overset{\wedge}{\rho}_{ij}^{\,2}$ is the sample estimate of the pair-wise correlation of residuals and is specified as:

$$\overset{\wedge}{\rho}_{ij} = \overset{\wedge}{\rho}_{ji} = \frac{\sum_{i=1}^{T} e_{it}e_{jt}}{(\sum_{t=1}^{T} e_{it}^2)^{\frac{1}{2}}(\sum_{t=1}^{T} e_{jt}^2)^{\frac{1}{2}}} \tag{1.4}$$

Where $e_{it}$ is the Ordinary Least Squares (OLS) estimate of $u_{it}$ in equation (1.4). The $LM$ statistic is asymptotically distributed as chi-squared with $N(N-1)/2$ degrees of freedom under the null hypothesis.

Pesaran (2004) proposed the following alternative that is based on a simple average of all pair-wise correlation coefficients rather than their squares:

$$CD = \sqrt{\frac{2T}{N(N-1)}}(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\overset{\wedge}{\rho}_{ij}) \tag{1.5}$$

He showed that under the null hypothesis of cross sectional independence $CD \underset{\longrightarrow}{d} N(0,1)$. This test has also been performed in this study for the purposes of comparison.

Table 1.2: Cross section dependence results when series are in levels

| Tests | Breusch-Pagan | Pesaran |
|---|---|---|
| Statistics ( FE model) | 92.375*** | 4.106*** |
| p-value | [0.000] | [0.000] |
| Statistics (RE model) | NA | 4.182*** |
| p-value | NA | [0.000] |

Notes: real GDP (or Y) is the dependent variable in this regression. E, L and K are independent variables. *** indicates the rejection of the null hypothesis of cross sectional independency at the 1% level of significance.

We employed the above two tests to variables in both levels and first differences.

Table 1.2 and Table 1.3 show the results of these tests. In Table 1.2 all variables are in their levels and the dependent variable is real GDP. In Table 1.3 all variables are in first differences and the dependent variable is first differenced real GDP. The results from both tables reveal that we can reject the null hypothesis at the 5% level of significance. Therefore, the remaining tests must be robust to cross-sectional dependency.

Table 1.3: Cross section dependence results when series are in first differences

| Tests | Breusch-Pagan | Pesaran |
|---|---|---|
| Statistics ( FE model) | 57.999 | 4.176 |
| p-value | [0.015]** | [0.000]*** |
| Statistics (RE model) | NA | 4.087 |
| p-value | NA | [0.000]*** |

Notes: First differenced real GDP (or $\Delta$Y) is the dependent variable in this regression. $\Delta$E , $\Delta$L and $\Delta$K are independent variables. *** and ** indicate the rejection of the null hypothesis of cross sectional independency at 1% and 5% level respectively.

### 1.3.4 Panel unit root tests

In this section, the stationarity properties of variables and order of integration of the series is examined using Pesaran (2007) and Breitung and Das (2005) tests. The Pesaran (2007) test employs a factor structure to take into account cross-sectional dependencies. He assumed that variables can be represented by a common factor which can be proxied by the cross section averages of lags and differences on the individual series. His approach is based on the following cross-sectionally augmented Dickey-Fuller regressions (CADF) which controls for the common factor:

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + v_{i,t} \tag{1.6}$$

where $\bar{y}_{t-1} = N^{-1} \sum_{i=1}^{N} y_{i,t-1}$ and $\Delta \bar{y_t} = N^{-1} \sum_{i=1}^{N} \Delta y_{i,t}$ serve as proxies for the effect of unobserved common factor, and $v_{i,t}$ is the regression error.

After having run the above regressions and estimating the t-statistic of the $OLS$ estimate of $\rho_i$ for each cross section individually, a group-mean statistic ($CIPS$) is calculated ($CIPS = \frac{1}{N}\sum_{i=1}^{N} t_i(N,T)$). By comparing the calculated group-mean statistic with critical values, the null hypothesis of non-stationarity of all series ($H_0 = \rho_i \quad for\ all\ i$) is tested under the alternative that only fractions of the series are stationary ($H_A : \rho_i \prec 0\ for\ i = 1, 2, ..., N_1, \rho_i = 0\ for\ i = N_1 + 1, N_1 + 2, ..., N$).

The Breitung and Das (2005) test employs a Seemingly Unrelated Regression (SUR) approach to develop a robust version of the Dickey-Fuller t-statistic under cross-sectional dependency. They consider the following AR(1) model process:

$$y_{it} = \alpha y_{it-1} + \epsilon_{it} \quad \text{where } t = 1, ...T \ \ and \ \ i = 1, ..., N \tag{1.7}$$

or equivalently:

$$\Delta y_{it} = \phi y_{it-1} + \epsilon_{it} \qquad \text{where} \ \ \phi = \alpha - 1 \tag{1.8}$$

They assume the error vector, $\epsilon_t = [\epsilon_{it}, ..., \epsilon_{Nt}]'$, to be $i.i.d$ with $E(\epsilon_t) = 0$ and a positive covariance matrix, $\Omega = E(\epsilon_t\ \epsilon_t') > 0$.

They propose the following t-statistic to test the null hypothesis of a panel unit root, $H_0 : \phi = 0$, against the alternative hypothesis that $\phi < 0$ :

$$t_{robust} = \frac{\sum_{t=1}^{T} y_{t-1}' \Delta y_t}{(\sum_{t=1}^{T} y_{t-1}' \hat{\Omega} \Delta y_t)^{\frac{1}{2}}} \tag{1.9}$$

where $\hat{\Omega}$ is the sample covariance matrix of the residuals and $y_{t-1}' = [y_{1,t-1}, ..., y_{N,t-1}]$. This statistic has a standard normal distribution as $T$ and $N \longrightarrow \infty$.

Table 1.4 displays the Pesaran (2007) statistics and associated p-values with different number of lags for all series in both levels and first differences. The results indicate that all statistics unanimously indicate that GDP, energy and employment are non-stationary variables whose first differences become stationary. The results clearly show that the Pesaran test rejects the null of non-stationarity for the capital in level form when only one lag is included in the model. By adding more lags, this variable also becomes non-stationary in the level form. Using Akaike and Bayesian information criteria, it can be shown that for the case of capital in level forms, the model with more lags (two) is preferred over the model including only one lag, implying that capital, like other variables, can be considered as a non-stationary variable. Results from Table 1.5 are also in accordance with Table 1.4, indicating that all four variables are non-stationary whose first differences become stationary. In general, Table 1.4 and Table 1.5 provide enough evidence that all four variables are panel non-stationary and are integrated of order one but not of order two.

Table 1.4: Pesaran (2007) panel unit root test results

| Number of lags | $q = 0$ | $q = 1$ | $q = 2$ |
|---|---|---|---|
| Series in Levels | | | |
| Y | 0.658 | -0.968 | 2.366 |
| | [0.74] | [0.16] | [0.99] |
| E | 1.761 | 2.252 | 3.486 |
| | [0.96] | [0.98] | [1.00] |
| L | 2.416 | 3.041 | 3.414 |
| | [0.99] | [0.99] | [1.00] |
| K | 0.946 | -2.374*** | 1.609 |
| | [0.82] | [0.009] | [0.94] |
| Series in first differences | | | |
| $\Delta Y$ | -4.054*** | -3.214*** | |
| | [0.000] | [0.001] | |
| $\Delta E$ | -4.175*** | -1.027 | |
| | [0.000] | [0.152] | |
| $\Delta L$ | -4.871*** | -0.493 | |
| | [0.000] | [0.311] | |
| $\Delta K$ | -3.572*** | -4.700*** | |
| | [0.000] | [0.000] | |

** and *** indicate the rejection of the null hypothesis of non-stationarity of all the series at the 5% and 1% level of significance respectively. $\Delta$ represents the first difference operator. Probability values are in brackets and reported underneath the corresponding statistic.

Table 1.5: Breitung and Das (2005) panel unit root test results

| | $Y$ | $E$ | $L$ | $K$ |
|---|---|---|---|---|
| Series in Level | 1.145 | -0.152 | 1.823 | 0.104 |
| | [0.874] | [0.439] | [0.965] | [0.541] |
| First difference | -4.405*** | -3.788*** | -3.434*** | -5.974*** |
| | [0.000] | [0.000] | [0.000] | [0.000] |

Notes: *** indicates the rejection of the null hypothesis of non-stationarity of all the series at the 1% level of significance. Probability values are in brackets and reported underneath the corresponding statistic.

### 1.3.5 Panel cointegration Test

The next step is to investigate whether a long run equilibrium relationship exists among variables. Panel cointegration techniques to test the existence of cointegration among integrated variables have received significant attention in the literature due to the increased power that might be achieved by accounting for both time-series and cross-sectional dimensions. In this study, a second-generation panel cointegration test proposed by Westerlund (2007), which takes into account cross section dependency, is implemented. However, to compare the results obtained from the Westerlund test, two other widely-used cointegration tests, namely Kao (1999) and Pedroni (1999) were also applied.

Westerlund (2007) proposed four new error-correction-based cointegration tests. They are panel extensions of time series cointegration tests developed by Banerjee, Dolado and Mestre (1998). The idea is to consider a conditional error correction model and test whether the error correction term is equal to zero or not. The null (of no cointegration) is rejected if the null hypothesis of no error correction term is rejected. These tests are normally distributed and are general enough to allow for individual-specific short run dynamics, and individual specific intercepts, trend terms and slope parameters. Bootstrap tests were also suggested to handle dependence within as well as across cross-sectional individuals.

All four error-correction tests are based on the following model:

$$\begin{aligned} \Delta Y_{it} &= c_i + \alpha_i (Y_{i,t-1} - \beta_i E_{i,t-1} - \tau_i K_{i,t-1} - \mu_i L_{i,t-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta Y_{i,t-j} \\ &+ \sum_{j=-q}^{p_i} \gamma_{ij} \Delta E_{i,t-j} + \sum_{j=-q}^{p_i} \varphi_{ij} \Delta K_{i,t-j} + \sum_{j=-q}^{p_i} \delta_{ij} \Delta L_{i,t-j} + u_{it} \end{aligned} \tag{1.10}$$

Where $i = 1, \ldots, N$ and $t = 1, \ldots, T$ index cross-sections and time periods respectively. Parameters $p_i$ and $q_i$ represent lag and lead orders in the equation. The parameter $\alpha_i$ is called the error correction term and can be interpreted as a measure of the speed at which the system goes back to the equilibrium relationship after a sudden shock. If $\alpha_i < 0$, the error correction effect exists implying that variables are cointegrated. If $\alpha_i = 0$, the error correction effect does not exist indicating that there is no cointegration among variables. The alternative hypothesis depends on the assumption regarding homogeneity. Two of the tests (called group-mean tests) do not require homogeneity. Group mean test statistics (denoted $G_t$ and $G_\alpha$) are the weighted averages of the estimated error correction coefficient for each cross-section $i$ in the panel. In these two tests, the null hypothesis of no cointegration is tested against the alternative that at least one unit in the panel is cointegrated.

The second pair of tests (called panel tests) assume homogeneity of $\alpha$ for all units and therefore test the alternative hypothesis that the panel is cointegrated as a whole. These two statistics (denoted $p_t$ and $p_a$) pool all information over the cross-sectional dimensions to test the same null hypothesis. Table 1.6 presents the Westerlund (2007) panel cointegration results with critical values computed using a bootstrapping method.

Table 1.6: Westerlund (2007) panel cointegration test results

| Statistic | Value | Robust P-value |
|---|---|---|
| $G_t$ | -1.009 | 0.790 |
| $G_a$ | -3.622 | 0.000*** |
| $P_t$ | -4.720 | 0.180 |
| $P_a$ | -6.747 | 0.000*** |

Notes: *** indicates the rejection of the null hypothesis of no cointegration among four variables at the 1% level of significance. The robust P-values are based on the bootstrapped distribution.

Table 1.7: Kao (1999) panel cointegration test results

| Dependent Variable | ADF | P-value |
|---|---|---|
| Y | -4.91*** | [0.000] |

Notes: *** indicates the rejection of the null hypothesis of no cointegration among four variables at the 1% level of significance.

The results in Table 1.6 indicate that only two statistics out of four reject the null hypothesis of no cointegration among four variables. Results were sensitive to the specification of parameters such as lag/lead lengths. According to Persyn and Westerlund (2008), this sensitivity to choice of parameters might occur in small datasets.

The Kao (1999) test is based on the methodology of Engle and Granger (1987) and tests the existence of a unit root in the residual of a static spurious regression. This residual-based cointegration test assumes the homogeneity of all members in the panel and examines the null hypothesis of no cointegration using an Augmented Dickey Fuller/Dickey Fuller type of test. Table 1.7 reports the result of Kao's residual panel cointegration test which rejects the null of no cointegration at the 1% level of significance.

Pedroni's heterogeneous panel cointegration test, which allows for different individual effects in both intercepts and slopes, can be expressed as follows:

$$Y_{it} = \alpha_{it} + \gamma_i t + \beta_{1i} E_{it} + \beta_{2i} L_{it} + \beta_{3i} K_{it} + \epsilon_{it} \tag{1.11}$$

Where $t = 1, .., T$ indexes time period, and $i = 1, ..., N$ are panel members. Parameter $\alpha_i$ allows the possibility of province-specific fixed effects and the parameter $\gamma_i$ is the deterministic time trend in the model.

To examine whether cointegration exists or not, the following unit root test is conducted on the estimated residuals from the model

$$\epsilon_{it} = \rho_i \epsilon_{it-1} + \omega_{it} \tag{1.12}$$

Pedroni proposed two sets of tests to examine the null hypothesis of no cointegration (i.e. $\rho_i = 1$) in heterogeneous panels. The first set of tests (known as panel cointegration tests) based on the within dimension approach includes four statistics, namely, panel $\nu-$statistic, panel $\rho-$statistic, panel $PP-$statistic and panel $ADF-$statistic. These four pool the autoregressive coefficients across different cross sections (provinces) in order to test for unit roots on the estimated residuals. These statistics allow for heterogeneity across units of the panel and consider common time factors.

The second set of tests (known as groups mean panel cointegration tests) based on the between-dimension approach includes three statistics, namely, group $\rho$, group $PP$, and group $ADF$. These three statistics are based on the average of the individual autoregressive estimated coefficients for each province in a panel. Both types of tests are distributed asymptotically as standard normal. Among all the seven statistics, only the panel $\nu$-statistic is a one-sided test for which large positive values reject the null hypothesis of no cointegration. For the remaining six tests, in contrast, negative values reject the null hypothesis. Table 1.8 reports the results of the Pedroni panel cointegration test. Table 1.8 shows that with respect to the case of including both an intercept and a linear trend in a model, five statistics out of seven reject the null hypothesis of no cointegration.

Table 1.8: Pedroni (1999) panel cointegration test results

| | Statistics (intercept and trend) | Statistics (intercept and no time trend) |
|---|---|---|
| Test | | |
| Within-dimension | | |
| Panel $\nu$-statistic | 2.018** | 1.126 |
| | [0.021] | [0.130] |
| Panel $\rho$-statistic | 1.818 | 0.769 |
| | [0.965] | [0.779] |
| Panel PP-statistic | -2.905*** | -2.192** |
| | [0.001] | [0.014] |
| Panel ADF-statistic | -3.065*** | -2.869*** |
| | [0.001] | [0.002] |
| Between dimension | | |
| Group $\rho$-statistic | 2.558 | 2.081 |
| | [0.994] | [0.981] |
| Group PP-statistic | -4.879*** | -1.888** |
| | [0.000] | [0.029] |
| Group ADF-statistic | -3.326*** | -3.125*** |
| | [0.000] | [0.000] |

Notes: *** and ** indicate the rejection of the null hypothesis of no cointegration at the 1% and 5% level of significance respectively. Probability values are in brackets and reported underneath the corresponding statistic. All seven tests are asymptotically distributed as standard normal. Automatic lag length chosen using the Schwarz Information Criteria.

In general, considering the small sample size, it is to be expected with these tests that they will tend to have low power to reject the null, so the fact that in most cases they detect cointegration leads us to conclude that a long run equilibrating structure is present among the variables. We therefore proceeded to estimate the cointegrating relation.

### 1.3.6 Long-run elasticities

Given the presence of cointegration, the next step is to estimate the long run equilibrium relationship among variables. Using simple OLS to infer a long run relationship in the cointegrated panels will lead to a biased estimator of parameters unless all the regressors are strongly exogenous (Ouedraogo, 2013). Therefore, other estimators such as the Fully Modified Ordinary Least Squares (Pedroni, 2000) or the Dynamic Ordinary Least Squares (Kao and Chiang, 1999) were proposed to estimate the long run relationship. Both these methods remove the endogeneity bias and serial correlation associated with OLS, yielding consistent and efficient estimators. DOLS estimator outperforms the FMOLS, exhibiting both smaller bias and more accurate inference (Kao and Chiang, 1999). According to Kao and Chiang (1999), size distortions from the DOLS estimator are lower than both OLS and FMOLS in finite samples. Nonetheless, we use both FMOLS (Pedroni, 2000 and 2001) and DOLS (Kao and Chiang, 1999) in this paper to estimate the cointegrating vector among variables.

DOLS is a parametric technique which augments the static regression using past and future values of the differenced explanatory variables. By doing so, endogenous feedback effects from the dependent variable to the explanatory variables are absorbed and thereby, consistent estimates of standard errors and valid inferences will be provided. FMOLS is a non parametric approach to deal with problems associated with OLS.

Both DOLS and FMOLS estimations are done using the following equation:

$$Y_{it} = \alpha_i + \beta_i X_{it} + \sum_{q=-q_i}^{qi} \gamma_{iq} \Delta X_{it-q} + \mu_{it} \tag{1.13}$$

Following from equation (1.13), let $\zeta_{it} = (\mu_{it}, \Delta X_{it})$ be a stationary vector of estimated residuals and differences in regressors and let $\phi_{it} = \lim_{T \to \infty} E\left[T^{-1}(\sum_{t=1}^{T}\zeta_{it})(\sum_{t=1}^{T}\zeta_{it})'\right]$ be a long run covariance for the stationary vector which can be decomposed into $\Omega_i = \Omega_i^0 + \Gamma_i + \Gamma_i'$, where $\Omega_i^0$ is the contemporaneous covariance and $\Gamma_i$ is a weighted sum of autocovariances. Therefore, the group mean FMOLS estimator is given as :

$$\beta_{FMOLS} = N^{-1}\sum_{i=1}^{N}\left[\left(\sum_{t=1}^{T}(X_{it} - \bar{X}_i)^2\right)^{-1}\left(\sum_{t=1}^{T}(X_{it} - \bar{X}_i)Y_{it}^{*} - T\hat{\gamma}_i\right)\right] \tag{1.14}$$

Where $Y_{it}^{*} = Y_{it} - \bar{Y}_i - \left(\frac{\hat{\Omega}_{2,1,i}}{\hat{\Omega}_{2,2,i}}\right)\Delta X_{it}$ and $\hat{\gamma}_i = \hat{\Gamma}_{2,1,i} + \hat{\Omega}^0_{2,1,i} - \left(\frac{\hat{\Omega}_{2,1,i}}{\hat{\Omega}_{2,2,i}}\right)\left(\hat{\Gamma}_{2,2,i} + \hat{\Omega}^0_{2,2,i}\right)$.

From equation (1.13), DOLS estimator is given as:

$$\beta_{DOLS} = \sum_{i=1}^{N}\left(\sum_{t=1}^{T}K_{it}K_{it}'\right)^{-1}\left(\sum_{t=1}^{T}K_{it}Y_{it}^{*}\right) \tag{1.15}$$

where $K_{it} = [X_{it} - \bar{X}_i, \Delta X_{i,t-q}, ..., \Delta X_{i,t+q}]$ and $Y_{it}^{*} = Y_{it} - \bar{Y}_i$.

Intercepts and a linear trend are included in both estimations. Linear trends were dropped from the estimations, as the trend coefficients were not significant. With respect to the DOLS estimation, following Hayakawa and Kurozumi (2006), we used two lags and no leads in the equation. Leading values are not needed (and can cause a loss of efficiency) when there is no Granger causality between the residuals and the first differences of the independent variables, which we confirmed was the case here.

Table 1.9 reports the estimate of the long run equilibrium relationship among variables using both DOLS and FMOLS techniques. Since the variables are in logs, the resulting coefficients are elasticities. Results from DOLS estimation indicate that all the coefficients are positive and statistically significant at the 5% level of significance. Our findings indicate that a 1% increase in energy consumption increases real GDP by 0.116 %; a 1% increase in

Table 1.9: Panel DOLS and FMOLS results

| Independent variables | E | L | K |
|---|---|---|---|
| FMOLS | 0.017 | 1.343*** | 0.114*** |
| | [0.395] | [0.000] | [0.000] |
| DOLS | 0.116** | 0.25*** | 0.675*** |
| | [0.046] | [0.000] | [0.000] |

Notes: Y (real GDP) is the dependent variable in both regressions. *** and ** denote statistical significance at 1% and 5% level respectively.

capital increases real GDP by 0.67%; and a 1% increase in employment increases real GDP by 0.25 %. Results from FMOLS estimation indicate that the coefficients of employment and capital are positive and significant while the coefficient of energy consumption is positive but insignificant. More specifically, the results suggest that a 1% increase in employment increases real GDP by 1.343 %; and a 1% increase in capital increases real GDP by 0.114 %.

### 1.3.7 Panel causality analysis

Cointegration among variables implies existence of Granger causality in at least one direction. However, the direction of causality must be identified separately. We use a panel Error Correction Model (ECM) and employ a Pooled Mean Group estimation (PMG) proposed by Pesaran et al. (1999) to examine the short run and Long-run causal relationship among the variables. This estimator allows short run dynamics, more specifically, intercepts, error variances and short-run coefficients, to vary across the cross sections while constrains the long-run relationship to be the same for all groups. Therefore, it relies on both pooling and averaging the coefficients.

Assume that we have the following autoregressive distributed lag (ARDL)$(q, p_1, p_2, p_3)$ dynamic panel specification:

$$Y_{it} = \mu_i + \sum_{j=1}^{q} \lambda_{ij} Y_{i,t-j} + \sum_{j=1}^{p} \delta_{ij}^{'} X_{i,t-j} + u_{it} \tag{1.16}$$

Where $i = 1, \ldots, N$ and $t = 1, \ldots, T$ index cross-sections and time periods respectively. $X_{it}$ is a $3 \times 1$ vector of explanatory variables where $X_{it}^T = \begin{bmatrix} E_{it} & L_{it} & K_{it} \end{bmatrix}$, $\mu_i$ is the group-specific effect, $u_{it}$ is the error term, $\lambda_{ij}$ are scalars, and $\delta_{ij}^{'}$ are the $1 \times 3$ coefficient vectors. Equation (1.16) can be reparametrized to obtain the following error correction equation:

$$\Delta Y_{it} = \mu_i + \psi_i (Y_{i,t-1} - \gamma_i^{'} X_{i,t-1}) + \sum_{j=1}^{q-1} \lambda_{ij}^{*} \Delta Y_{i,t-1} + \sum_{j=1}^{p-1} \delta_{ij}^{*'} \Delta X_{i,t-j} + u_{it} \tag{1.17}$$

Where $\psi_i = -(1 - \sum\limits_{j=1}^{q} \lambda_{ij})$, $\lambda_{ij}^{*} = -\sum\limits_{m=j+1}^{q} \lambda_{im}$ for $j = 1, 2, ..., q-1$, $\gamma_i = \frac{\sum\limits_{j=0}^{p} \delta_{ij}}{(1 - \sum\limits_{j=1}^{q} \lambda_{ij})}$, and $\delta_{ij}^{*} = -\sum\limits_{m=j+1}^{p} \delta_{im}$ for $j = 1, 2, ..., p-1$.

$\gamma_i$ is the vector containing the long-run relationship between variables and the parameter $\psi_i$ is the the error correcting speed of adjustment term.

If the null hypothesis of $\psi_i = 0$ is rejected, there would be an evidence of long-run relationship among the variables. In this case, $\gamma_i$ would be the cointegrating vector which is assumed to be the same for all the panel members ($\gamma_i = \gamma$). We expect the error correcting speed of adjustment to be significantly negative when a long-run relationship among the variables exists, as the negative sign would imply that shocks to the model would generate adjustment toward the equilibrium.

If the null hypothesis of $\psi_i = 0$ is not rejected, then there would be no evidence of a long-run relationship among variables and we conclude that the vector $\gamma$ is not a cointegrating vector. Equation (1.17) is estimated using a maximum likelihood method.

Similarly, the error correction equations for the three remaining variables can be constructed. Therefore, our dynamic ECM take the form:

$$\Delta Y_{i,t} = \mu_{1i} + \psi_{1i} EC_{it-1} + \sum_{j=1}^{h} \lambda_{11ij} \Delta Y_{i,t-j} + \sum_{j=1}^{h} \delta_{11ij} \Delta E_{i,t-j} + \sum_{j=1}^{h} \delta_{12ij} \Delta L_{i,t-j} + \sum_{j=1}^{h} \delta_{13ij} \Delta K_{i,t-j} + u_{1it} \tag{1.18}$$

$$\Delta E_{i,t} = \mu_{2i} + \psi_{2i} EC_{it-1} + \sum_{j=1}^{h} \lambda_{21ij} \Delta Y_{i,t-j} + \sum_{j=1}^{h} \delta_{21ij} \Delta E_{i,t-j} + \sum_{j=1}^{h} \delta_{22ij} \Delta L_{i,t-j} + \sum_{j=1}^{h} \delta_{23ij} \Delta K_{i,t-j} + u_{2it} \tag{1.19}$$

$$\Delta L_{i,t} = \mu_{3i} + \psi_{3i} EC_{it-1} + \sum_{j=1}^{h} \lambda_{31ij} \Delta Y_{i,t-j} + \sum_{j=1}^{h} \delta_{31ij} \Delta E_{i,t-j} + \sum_{j=1}^{h} \delta_{32ij} \Delta L_{i,t-j} + \sum_{j=1}^{h} \delta_{33ij} \Delta K_{i,t-j} + u_{3it} \tag{1.20}$$

$$\Delta K_{i,t} = \mu_{4i} + \psi_{4i} EC_{it-1} + \sum_{j=1}^{h} \lambda_{41ij} \Delta Y_{i,t-j} + \sum_{j=1}^{h} \delta_{41ij} \Delta E_{i,t-j} + \sum_{j=1}^{h} \delta_{42ij} \Delta L_{i,t-j} + \sum_{j=1}^{h} \delta_{43ij} \Delta K_{i,t-j} + u_{4it} \tag{1.21}$$

Where $\Delta$ is the first-difference operator; $j$ is the lag length (determined by Schwarz Criterion); EC is the error correction term; $\psi_i$, $\lambda_i$ and $\delta_i$ are adjustment parameters and $u_t$ is the serially uncorrelated error term with mean zero.

Two sources of causation can be identified using the panel error correction models. First weak Granger Causality can be evaluated by testing for significance of the coefficients on the lagged differenced explanatory variables in equations (1.18), (1.19), (1.20) and (1.21). Masih and Masih (1996) and Asafu-Adjaye (2000) interpreted weak Granger causality as "short-run" causality in the sense that the dependent variable responds only to short-term shocks to the stochastic environment. Thus, in terms of short-run causality in equation (1.18), causality running from energy consumption, employment and capital to real GDP is examined respectively, based on the following null hypotheses $H_0$: $\delta_{11j} = 0 \ \forall_j$, $H_0$: $\delta_{12j} = 0$

$\forall_j, H_0$: $\delta_{13j} = 0\ \forall_j$. In particular, in terms of short run causality we followed Santana-Gallego et al. (2011) and Salim et al. (2014 ) who assumed the estimated parameters to be equal for all the cross sections and considered the null hypothesis to be $H_0$: $\delta_j = 0\ \forall_j$ rather than being $H_0$: $\delta_{ij} = 0\ \forall_{ij}$. Similarly, in equation (1.19), short run causality running from real GDP, employment and capital to energy consumption is examined based on $H_0$: $\lambda_{21j} = 0\ \forall_j, H_0$: $\delta_{22j} = 0\ \forall_j, H_0$: $\delta_{23j} = 0\ \forall_j$. Likewise, in equation (1.20), short run causality running from real GDP, energy consumption and capital to employment is tested based on $H_0$: $\lambda_{31j} = 0\ \forall_j, H_0$: $\delta_{31j} = 0\ \forall_j, H_0$: $\delta_{33j} = 0\ \forall_j$ respectively. Finally, in equation (1.21), the same type of causality running from real GDP, energy consumption and employment to capital is tested based on $H_0$: $\lambda_{41j} = 0\ \forall_j, H_0$: $\delta_{41j} = 0\ \forall_j, H_0$: $\delta_{42j} = 0\ \forall_j$. Standard Wald tests can be used to test various null hypotheses as all variables are represented in stationary form.

An ECM also measures another source of causation through the error correction term (EC) in this case called Long-run causality, and it is tested using the significance of the coefficient on the respective error correction term (denoted by $\psi$). As mentioned, this coefficient is called the speed of adjustment and indicates how fast deviations from the long-run equilibrium are eliminated following changes in each variable. A statistically significant ECT determines the long run causality going from all of the explanatory variables toward the dependent variables. (Dergiades and Tsoulfidis, 2010).

The PMG estimator has many advantages over other approaches developed to estimate dynamic panels. This estimator is robust to the choice of lags orders and outliers (Pesaran et al., 1999). Besides this estimator is efficient and consistent when the regressors in the model are endogenous (Fayad, 2010; Salim et al., 2014). This is an important characteristic, as we are examining the causality relationship among the variables. Besides, PMG estimator is super consistent even when the size of sample is small (Jalil, 2014). There are many other candidates for estimating dynamic panels, such as GMM (Arellano and Bond, 1991) estimator and IV estimators (Anderson and Hsiao, 1982). However, these estimators are

Table 1.10: Results of panel Granger causality test

| Dependent variables | Independent variables (sources of causation) | | | | |
|---|---|---|---|---|---|
| | Short-run | | | | Long-run |
| | $\Delta Y$ | $\Delta E$ | $\Delta L$ | $\Delta K$ | $ECT$ |
| Eq. 1.18, $\Delta Y$ | - | 1.89 (-0.0778) [0.172] | 0.009 (-0.0254) [0.922] | 4.39 $^{**}$(0.0495) [0.038] | -0.0554$^{***}$ [0.0000] |
| Eq. 1.19, $\Delta E$ | 0.17 (-0.1177) [0.677] | - | 0.64 (0.3492) [0.424] | 1.94 (0.1135) [0.166] | -0.5557$^{***}$ [0.0010] |
| Eq. 1.20, $\Delta L$ | 6.48$^{**}$ (0.262) [0.0125] | 0.66 (-0.0244) [0.4153] | - | 0.08 (-0.0076) [0.7667] | 0.0095 [0.4999] |
| Eq. 1.21, $\Delta K$ | 2.40 (0.9084) [0.1245] | 0.074(0.0866) [0.7851] | 2.33 (-1.707) [0.1301] | - | -0.3226$^{***}$ [0.0031] |

Notes: With respect to short-run causality column, partial F-statistics are reported with their corresponding probability values in brackets underneath them. Figures in parenthesis are the estimated coefficients. With respect to long-run causality column, ECT represents the estimated coefficients of the error correction terms. Probability values associated with the coefficients of the error correction terms are reported below them in brackets. *** and ** denote statistical significance at 1% and 5% level respectively.

appropriate for panels in which the number of cross sections is relatively large (panels with N>T). Since in our panel, the number of time periods is relatively large (T>N), PMG estimator is employed to examine the direction of causality.[4]

Table 1.10 shows the panel Granger causality test results. Using the Schwarz Criterion (SC), the optimal lag length of one year is chosen.

In terms of equation (1.18), the impact of capital on real GDP in the short-run is positive and statistically significant at 5% level. This suggests that in the short-run capital Granger cause economic output. Neither energy consumption, nor employment has a statistically significant effect in the short-run on real GDP. Moreover, the ECT is negative and significant at the 1% significance level, but with a relatively slow speed of adjustment toward long run equilibrium. The significance of the ECT implies that there is a long run causal-

[4] In the liturateure of dynamic panel data, Seemingly Unrelated Regression Equations (SURE) approach is recommended for panels with a relatively large magnitude of time periods (T>N) only if N is reasonably smaller than T.

ity running from energy consumption, employment and capital to real GDP. The negative sign of ECT implies convergence toward the long-run equilibrium. In regards to equation (1.19), it appears that there is no short run Granger causality running from real GDP, employment or capital to energy consumption. However, the error correction term is negative and statistically significant which implies that this variable is responsive to deviations from long-run equilibrium and confirms the long-run causality running from real GDP, capital and employment to energy consumption. The speed of adjustment toward equilibrium in energy consumption equation appears to be much faster than in the case of economic output. In terms of equation (1.20), real GDP has positive impact on employment in the short run whereas energy consumption and capital are statistically insignificant. Moreover, the incorrectly signed and insignificant ECT suggests that a change in employment would not respond to deviations from the long-run equilibrium in the previous period. With respect to equation (1.21), the impact of energy consumption, real GDP and employment on capital are insignificant in the short run. The ECT is negative and statistically significant and it appears that the speed of adjustment toward equilibrium is much faster than in the case of economic output.

In summary, with respect to the main question of interest here, the results strongly suggest that there is a bi-directional Granger causality between energy consumption and real GDP in Canada in the long run. This means that Canada is an energy-dependent country for its economic growth and conservation policies would adversely affect Canada's economic growth in the long run. In addition, as the Canadian economy grows energy demand also increases in Canada.

### 1.3.8 Analysis on older data set

#### Data

The older dataset consists of annual data on the 10 provinces of Canada for the period 1981 to 2000. This dataset also includes Newfoundland which had appeared to be an outlier in the newer dataset. The dataset (see table 1.11) contains real GDP per capita (Y) in constant 2002 dollars, real gross fixed capital formation per capita (k) in 2002 constant dollars, final energy consumption per capita (E) in terajoules and employment (L) in thousands employed. All variables except employment were transformed into per capita terms since real GDP appeared to be stationary in its level form but became non-stationary when it was transformed to a per capita variable. To yield consistency, we transformed all variables (except employment) to per capita terms. Table 1.11 reports variable definitions, summary statistics and data sources. As before, all variables were transformed using logarithms prior to any estimation.

Table 1.11: Data sources, definitions, measurement units and summary statistics of Canadian 1981-2000 sample

| Variable Name | Y | K | E | L |
|---|---|---|---|---|
| Definition | Real Gross Domestic Product Per capita | Real Gross Fixed Capital formation Per capita | Final Energy Consumption Per capita | Employment |
| Units | $2002 Constant Dollars | $ 2002 Constant Dollars | Terajoules | Thousand persons |
| Mean | 0.026642 | 0.00486 | 0.22671 | 1,272.184 |
| Standard Dev. | 0.00616 | 0.00183 | 0.06594 | 1,513.328 |
| Minimum | 0.01586 | 0.00194 | 0.12215 | 46.6 |
| Maximum | 0.04768 | 0.01335 | 0.41457 | 5,814.9 |
| Span of years | 1981 to 2000 | 1981 to 2000 | 1981 to 2000 | 1981 to 2000 |
| Source | CANSIM tables # 384-0002,282-0002,051-0001 and 128-0002 | | | |

***Analysis***

We follow the same sequence as before, beginning with the tests for cross section dependence. Table 1.12 shows that both tests strongly reject the null hypothesis at the 1% level of significance. Table 1.13 confirms the robustness of this result to first differenced variables.

Table 1.12: Cross section dependence results when series are in level

| Tests | Breusch-Pagan | Pesaran |
|---|---|---|
| Statistics ( FE model) | $205.048^{***}$ | $6.066^{***}$ |
| p-value | [0.000] | [0.000] |
| Statistics (RE model) | NA | $8.414^{***}$ |
| p-value | NA | [0.000] |

Notes: Y (real GDP per capita) is the dependent variable in this regression. E, K and L are independent variables. *** indicates the rejection of the null hypothesis of cross sectional independency at the 1% level of significance

Table 1.13: Cross section dependence results when series are in first differences

| Tests | Breusch-Pagan | Pesaran |
|---|---|---|
| Statistics ( FE model) | 78.341 | 2.641 |
| p-value | [0.000]*** | [ 0.0015]*** |
| Statistics (RE model) | NA | 3.248 |
| p-value | NA | [0.0012]*** |

$\Delta Y$ (first differenced real GDP per capita) is the dependent variable in this regression. $\Delta E$, $\Delta L$ and $\Delta K$ are independent variables. Notes: *** indicates the rejection of the null hypothesis of cross sectional independency at the 1% level of significance

The Pesaran (2007) and Breitung and Das (2005) panel unit root tests were therefore applied. Table 1.14 displays Pesaran (2007) statistics with different number of lags for all series in both levels and first differences. Almost all statistics indicate that energy consumption per capita and employment are non-stationary whose first differences become stationary. The results clearly show that the Pesaran test rejects the null of non-stationarity for real GDP per capita in level form when zero lags or one lag is included in the model. However, by adding more lags, this variable also becomes non-stationary in the level form. Using Akaike and Bayesian information criteria, it can be shown that the model with two lags is preferred over all other models for the case of real GDP in level forms, implying that real GDP like the other two variables can be considered as a non-stationary variable. With respect to capital, the optimal number of lags using Akaike and Bayesian criteria is two, based on which the null hypothesis of non-stationarity of all series is rejected. Therefore, based on the Pesaran unit root test, it can be concluded that capital, unlike the other three variables, is panel stationary in this dataset. Results from the Breitung an Das (2005) unit root test, however, indicate that all variables including capital are non-stationary whose first differences become stationary. Therefore in terms of capital we have mixed findings. In general, results from

Table 1.14 and Table 1.15 provide enough evidence that three out of four variables are panel non-stationary and are integrated of order one but not of order two. As we found mixed results for the case of capital, we excluded capital from the model in the next step, where we investigate the existence of long-run relationships. In other words, since cointegration refers to a linear combination of nonstationary variables, capital, will be excluded from the model.

Table 1.14: Pesaran (2007) panel unit root test results

| Number of lags | $q = 0$ | $q = 1$ | $q = 2$ |
|---|---|---|---|
| Series in levels | | | |
| Y | -3.173*** | -3.991*** | -0.923 |
| | [0.001] | [0.000] | [0.178] |
| E | -1.566 | -0.372 | 2.129 |
| | [0.059]* | [0.355] | [0.983] |
| L | -0.218 | 0.560 | 0.672 |
| | 0.414 | [0.712] | [0.749] |
| K | -0.186 | -1.838** | -1.713** |
| | 0.426 | [0.033] | [0.043] |
| Series in first differences | | | |
| $\Delta Y$ | -7.540*** | -7.764*** | |
| | [0.000] | [0.000] | |
| $\Delta E$ | -8.641*** | -5.012*** | |
| | [0.000] | [0.000] | |
| $\Delta L$ | -5.925*** | -2.377*** | |
| | [0.000] | [0.009] | |
| $\Delta K$ | -6.353*** | -3.526*** | |
| | [0.000] | [0.000] | |

*, ** and *** indicate the rejection of the null hypothesis of non-stationarity of all the series at the 10%, 5% and 1% level of significance respectively. $\Delta$ represents the fist difference operator . Probability values are in brackets and reported underneath the corresponding statistic. Linear trend is included in the regressions of series in levels.

Table 1.15: Breitung and Das (2005) panel unit root test result

| | $Y$ | $E$ | $L$ | $K$ |
|---|---|---|---|---|
| Level | 0.1529 | 0.1210 | 0. 0312 | -0.0187 |
| | [0.5608] | [0.5481] | [0.5124] | [0.4926] |
| First difference | -1.8702** | -1.9543** | -2.7502*** | -2.6280*** |
| | [0.0307] | [0.0253] | [0.0030] | [0.0043] |

Notes: *** and ** denote the rejection of the null hypothesis of non-stationarity of all the series at the 1% and 5% level of significance respectively. Probability values are re in brackets and reported underneath the corresponding statistic.

Table 1.16 reports the result of the Westerlund (2007) panel cointegration tests among real GDP per capita, energy consumption per capita and employment. The results of all cointegration tests are obtained from the following equation:

$$\Delta E_{it} = c_i + \alpha_i (E_{i,t-1} - \beta_i Y_{i,t-1} - \mu_i L_{i,t-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta E_{i,t-j} + \sum_{j=-q}^{p_i} \gamma_{ij} \Delta Y_{i,t-j} + \sum_{j=-q}^{p_i} \sigma_{ij} \Delta L_{i,t-j} + u_{it} \tag{1.22}$$

Table 1.16: Westerlund (2007) panel cointegration test results

| Statistic | Value | Robust P-value |
| --- | --- | --- |
| $G_t$ | -3.565 | 0.000*** |
| $G_a$ | -10.823 | 0.000*** |
| $P_t$ | -10.031 | 0.000*** |
| $P_a$ | -10.337 | 0.000*** |

Notes: *** indicates the rejection of the null hypothesis of no cointegration among four variables at the 1% level of significance. The robust P-values are based on the bootstrapped distribution.

The results in Table 1.16 indicate that all four statistics strongly reject the null hypothesis of no cointegration among three variables. It is worth mentioning that adding capital as a fourth variable to the specified model in equation (1.22) causes all four cointegration test statistics reported in Table 1.16 to become highly insignificant. This can be another reason to justify the exclusion of capital from the long run relationship. The cointegration results reported in Table 1.16 were not sensitive to the specification of parameters like before. Table 1.17 and Table 1.18 report the results of Kao and Pedroni tests respectively. All these panel cointegration tests reject the null hypothesis of no cointegration among three variables. We therefore proceeded to estimate the cointegration relation.

The Kao and Chang (1999) DOLS and Pedroni (2000) FMOLS estimators were used to estimate the cointegration vector among variables as before. Table 1.19 represents the results. Following Hayakawa and Kurozumi (2006), we used two lags and one lead for the DOLS estimation. We included one lead in the model since there was evidence of Granger causality between the residuals and the first differences of the independent variables.

Table 1.17: Kao (1999) panel cointegration test results

| Dependent Variable | ADF | P-value |
|---|---|---|
| E | –1.565* | [0.058] |

Notes: * indicates the rejection of the null hypothesis of no cointegration among four variables at the 10% level of significance.

Table 1.18: Pedroni (1999) panel cointegration test results

| | Statistics (intercept and time trend) | Statistics (intercept and no time trend) |
|---|---|---|
| Test | | |
| Within-dimension | | |
| Panel $\nu$-statistic | -0.2413 | 0.9896 |
| | [0.5953] | [0.1612] |
| Panel $\rho$-statistic | 0.6084 | -0.5580 |
| | [0.7286] | [0.2884] |
| Panel PP-statistic | -2.4077*** | -2.7818*** |
| | [0.0080] | [0.0027] |
| Panel ADF-statistic | -2.5658*** | -3.2463*** |
| | [0.0051] | [0.0006] |
| Between dimension | | |
| Group $\rho$-statistic | 1.6300 | 0.4973 |
| | [0.9485] | [0.6905] |
| Group PP-statistic | -3.3572*** | -3.5809*** |
| | [0.0004] | [0.0002] |
| Group ADF-statistic | -3.7377*** | -4.3726*** |
| | [0.0001] | [0.0000] |

Notes: *** indicates rejection of the null hypothesis of no cointegration at the 1% level of significance. Probability values are in brackets and reported underneath the corresponding statistic. All seven tests are asymptotically distributed as standard normal. Automatic lag length chosen using the Schwarz Information Criteria.

Table 1.19: Panel DOLS and FMOLS results

| | Y | L |
|---|---|---|
| FMOLS | 0.5229*** | -0.3059** |
| P-value | [0.000] | [0.0315] |
| | | |
| DOLS | 1.3970*** | -0.0524 |
| P-value | [0.000] | [0.754] |

Notes: E is the dependent variable in both regressions. *** and ** denote statistical significance at 1% and 5% level respectively.

Given that variables are expressed in logarithms, the coefficients can be interpreted as elasticity estimates as before. Results from the DOLS estimation indicate that the coefficient of real GDP per capita is positive and significant while the coefficient of employment is negative and insignificant. More specifically, a 1% increase in real GDP per capita increases energy consumption per capita by 1.39 %. Results from the FMOLS estimation indicate that both coefficients are statistically significant. More specifically, a 1% increase in real GDP per capita increases energy consumption per capita by 0.52 %; and a 1% increase in employment decreases energy consumption by 0.05 %. But this step does not reveal the direction of causality: that requires estimation of the ECM.

The dynamic ECM (equations 1.18 to 1.21) is estimated using PMG estimator (Pesaran et al., 1999) described before. Table 1.20 shows the panel Granger causality test results. Using the Schwarz Criterion, an optimal lag length of one year is chosen.

With respect to capital, only short run Granger causality running from this variable to the other three variables can be verified (since this variable was stationary and as a result was excluded from the long run dynamics). In terms of equation (1.18), neither energy consumption, employment nor capital have a statistically significant effect in the short-run on real GDP. Moreover, the ECM is incorrectly signed and statistically insignificant, which implies that real GDP is not responsive to deviations from equilibrium. In regards to equation (1.19), it appears that neither employment, capital nor real GDP has any significant effect on energy consumption in the short run. Moreover, the ECM is negative and sta-

Table 1.20: Results of panel Granger causality test

| Dependent Variables | Independent variables (sources of causation) | | | | |
|---|---|---|---|---|---|
| | Short-run | | | | Long-run |
| | $\Delta Y$ | $\Delta E$ | $\Delta L$ | $\Delta K$ | $ECT$ |
| Eq. 1.18, $\Delta Y$ | - | 0.2549 (-0.0304) | 0.0453 (-0.0384) | 0.4922 (-0.0260) | 0.0407 |
| | - | [0.6144] | [0.8317] | [0.4841] | [0.6130] |
| Eq. 1.19, $\Delta E$ | 1.9368 (0.1247) | - | 0.2561 (0.0961) | 0.2167 (-0.0148) | -0.5999$^{***}$ |
| | [0.1662] | - | [0.6136] | [0.6423] | [0.0000] |
| Eq. 1.20, $\Delta L$ | 12.424$^{***}$ (0.2500) | 1.5401 (0.0577) | - | 0.8679 (0.0135) | -0.1424$^{**}$ |
| | [0.0006] | [0.2167] | | [0.3531] | [0.0142] |
| Eq. 1.21, $\Delta K$ | 1.50 (0.3758) | 0.21 (0.0869) | 0.96 (0.4680) | - | - |
| | [0.2225] | [0.6503] | [0.3281] | - | - |

Notes: With respect to short-run causality columns, partial F-statistics are reported with their corresponding probability values in brackets underneath them. Figures in parenthesis are the estimated coefficients. With respect to long-run causality column, ECT represents the estimated coefficients of the error correction terms. Probability values associated withcoefficients of the error correction terms are reported below them in brackets. *** and ** denote statistical significance at 1% and 5% level respectively.

tistically significant which implies this variable is responsive to deviations from long run equilibrium and confirms the long-run causality running from real GDP and employment to energy consumption. In terms of equation (1.20), real GDP as before has a positive and significant impact on employment in the short run whereas energy consumption and capital are statistically insignificant. Moreover, the ECM is negative and statistically significant which suggest that a change in employment would respond to deviations from the long-run equilibrium in the previous period. The speed of adjustment toward equilibrium appears to be much lower than in the case of the energy consumption equation. With respect to equation (1.21), the impact of energy consumption, real GDP and employment on capital in the short run are insignificant.

## 1.4 Conclusion and policy implications

Understanding the relationship between economic growth and energy consumption is vital for policy makers in order to formulate effective energy and environmental policies. Thus, the main purpose of this study was to examine the existence and direction of Granger-causality between energy consumption and economic output in Canada. Panel data sets of Canadian provinces over the periods 1995-2010 and also 1981-2000 were examined. Employment and gross fixed capital formation (as a proxy for capital) were included in the model along with energy consumption and economic output. Panel unit root and cointegration techniques were implemented to investigate the long run relationships among variables. Standard results for non-stationarity of all four variables based on the newer dataset and three out of four variables based on the older dataset were found. The results of panel cointegration tests revealed that there is a long-run equilibrium relationship between variables. Furthermore, a panel vector error correction model was estimated to analyze Granger causality among variables. The empirical results obtained from the newer dataset suggest that there is a bi-directional causality between energy consumption and real GDP in the long run. Our findings based on the older series suggest that there is a uni-directional causality running from real income to energy consumption. Since the strong evidence of long-run causality running from energy consumption to real GDP based on the newer dataset was found, the empirical results lead us to conclude that there is a bi-directional causality between energy use and economic output in Canada. Thus, policies favouring the abundant availability of energy are important for sustaining strong economic growth, and policies that deliberately limit energy availability will likely have negative macroeconomic consequences.

## 1.5 Appendix 1

Table 1.21: Summary statistics by each province, newer dataset spanning 1995-2010

| Province | Variable Name | Y | K | E | L |
|---|---|---|---|---|---|
| | Definition | Real Gross Domestic Product | Real Gross Fixed Capital Formation | Final Energy Consumption | Employment |
| | Units | 2002 Constant $ | 2002 Constant $ | Terajoules | Thousand persons |
| Prince Edward Island | Mean | 3736.87 | 731.687 | 23611.31 | 64.475 |
| | SD | 391.62 | 153.403 | 1414.015 | 4.4218 |
| | Minimum | 3103 | 503 | 20339 | 57.2 |
| | Maximum | 4302 | 950 | 25774 | 70.6 |
| Nova Sotia | Mean | 26233.19 | 5328.81 | 169942 | 421.475 |
| | SD | 2799.65 | 952.305 | 7855.736 | 27.6495 |
| | Minimum | 21539 | 3225 | 158493 | 375.9 |
| | Maximum | 29693 | 6325 | 183828 | 452.5 |
| New Brunswick | Mean | 20950.56 | 4357.18 | 175179.9 | 336.893 |
| | SD | 2318.30 | 1127.808 | 10805.2 | 19.0286 |
| | Minimum | 17329 | 2743 | 149325 | 305.8 |
| | Maximum | 24370 | 6116 | 190897 | 359.5 |
| Quebec | Mean | 238087.7 | 45678.5 | 1533589 | 3540.53 |
| | SD. | 26726.9 | 11148.5 | 69633.2 | 276.597 |
| | Minimum | 192782 | 28456 | 1415023 | 3132.7 |
| | Maximum | 271109 | 62072 | 1626349 | 3915.1 |
| Ontario | Mean | 463999.2 | 86039.9 | 2516127 | 6005.7 |
| | SD | 58996.05 | 17146.9 | 89506.6 | 538.28 |
| | Minimum | 360017 | 54210 | 2386828 | 5100 |
| | Maximum | 530475 | 107829 | 2643443 | 6666.3 |
| Manitoba | Mean | 36890.7 | 6747.06 | 253626.1 | 566.53 |
| | SD | 4197.29 | 1498.23 | 9409.99 | 33.521 |
| | Minimum | 29881 | 4395 | 237474 | 516.5 |
| | Maximum | 43453 | 9523 | 270805 | 619.8 |
| Saskatchewan | Mean | 36267.4 | 8760.06 | 379828.6 | 482.237 |
| | SD | 3433.26 | 2499.36 | 30076.8 | 22.2541 |
| | Minimum | 30500 | 5381 | 343411 | 454.6 |
| | Maximum | 41424 | 13711 | 445050 | 524.3 |

Table 1.21- continued

| Province | Variable Name | Y | K | E | L |
|---|---|---|---|---|---|
| | Definition | Real Gross Domestic Product | Real Gross Fixed Capital formation | Final Energy Consumption | Employment |
| | Units | 2002 Constant $ | 2002 Constant $ | Terajoules | Thousand persons |
| Alberta | Mean | 155450 | 48469.3 | 1340395 | 1719.044 |
| | SD | 26183.7 | 16655.5 | 174369.2 | 233.782 |
| | Minimum | 114363 | 23741 | 1095904 | 1364.9 |
| | Minimum | 189940 | 74730 | 1679167 | 2053.7 |
| British Columbia | Mean | 141043.6 | 30064.19 | 874457.8 | 2015.43 |
| | SD | 18806.1 | 7443.167 | 25622.6 | 164.64 |
| | Minimum | 112901 | 22144 | 826093 | 1785.6 |
| | Minimum | 165792 | 42055 | 915709 | 2266.4 |

## 1.6 Appendix 2

Table 1.22: Summary statistics by each province, older dataset spanning 1981-2000

| Province | Variable Name | Y | K | E | L |
|---|---|---|---|---|---|
| | Definition | Real Gross Domestic Product Per capita | Real Gross Fixed Capital Formation Per capita | Final Energy Consumption Per capita | Employment |
| | Units | 2002 Constant $ | 2002 Constant $ | Terajoules | Thousand persons |
| Newfoundland and Labrador | Mean | 0.02022 | 0.00455 | 0.19717 | 192.68 |
| | SD | 0.00311 | 0.00104 | 0.01183 | 8.5608 |
| | Minimum | 0.01586 | 0.00304 | 0.1795 | 179 |
| | Maximum | 0.02732 | 0.00715 | 0.22550 | 206.9 |
| Prince Edward | Mean | 0.02113 | 0.00333 | 0.14820 | 54.39 |
| | SD | 0.00270 | 0.00083 | 0.01687 | 4.4126 |
| | Minimum | 0.01689 | 0.00194 | 0.12215 | 46.6 |
| | Maximum | 0.02626 | 0.00479 | 0.17835 | 62.8 |
| Nova Scotia | Mean | 0.02253 | 0.00401 | 0.18027 | 367.14 |
| | SD | 0.002131 | 0.00079 | 0.01103 | 25.547 |
| | Minimum | 0.01849 | 0.00302 | 0.16934 | 321.1 |
| | Maximum | 0.02699 | 0.00615 | 0.21128 | 411.7 |
| New Brunswick | Mean | 0.02150 | 0.00364 | 0.19981 | 290.07 |
| | SD | 0.00258 | 0.00081 | 0.01813 | 24.886 |
| | Minimum | 0.01687 | 0.00262 | 0.17836 | 248.4 |
| | Maximum | 0.02660 | 0.00570 | 0.23596 | 331.6 |
| Quebec | Mean | 0.02580 | 0.00412 | 0.1930 | 3035.46 |
| | SD | 0.00248 | 0.000748 | 0.00782 | 204.462 |
| | Minimum | 0.02190 | 0.00267 | 0.17992 | 2640.1 |
| | Maximum | 0.03151 | 0.00542 | 0.20599 | 3401.5 |
| Ontario | Mean | 0.03206 | 0.00524 | 0.22363 | 4959.7 |
| | SD | 0.00302 | 0.00101 | 0.00976 | 445.56 |
| | Minimum | 0.02686 | 0.00344 | 0.20995 | 4198.6 |
| | Maximum | 0.03916 | 0.00697 | 0.24489 | 5814.9 |
| Manitoba | Mean | 0.02582 | 0.00392 | 0.21492 | 505.39 |
| | SD | 0.00244 | 0.00069 | 0.00669 | 24.099 |
| | Minimum | 0.02174 | 0.00257 | 0.19921 | 460.3 |
| | Maximum | 0.03092 | 0.00519 | 0.22974 | 552.2 |

Table 1.22-continued

| Province | Variable Name | Y | K | E | L |
|---|---|---|---|---|---|
| | Definition | Real Gross Domestic Product Per capita | Real Gross Fixed Fixed Capital Formation Per capita | Final Energy Consumption Per capita | Employment |
| | Units | 2002 Constant $ | 2002 Constant $ | Terajoules | Thousand persons |
| | Mean | 0.02743 | 0.00552 | 0.31723 | 454.27 |
| Saskatchewan | SD | 0.00417 | 0.00104 | 0.03699 | 12.039 |
| | Minimum | 0.02207 | 0.00457 | 0.26966 | 430 |
| | Maximum | 0.03489 | 0.00802 | 0.36971 | 472.9 |
| | Mean | 0.03816 | 0.00883 | 0.37077 | 1297.59 |
| Alberta | SD | 0.00515 | 0.00204 | 0.02763 | 137.616 |
| | Minimum | 0.03037 | 0.00654 | 0.31815 | 1133.8 |

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# Chapter 2

# Pipeline uncertainty and the market returns of Canadian energy firms

## 2.1 Introduction

This paper uses the event study approach to examine the impact of uncertainty over getting Alberta's oil into market on the equity returns of Canadian energy firms. Canadian energy companies have been facing several barriers in recent years in transporting their oilsands crude into markets. The decision about the application for the Keystone XL pipeline, which would carry crude oil from Alberta to the US Gulf coast, was first unexpectedly delayed by president Obama in 2011 due to concerns about ecological damage in Nebraska. Since then, this project has created many disputes between Canada and the US. In addition to negative environmental impacts and concerns about climate change, different economic and political issues have also made the project controversial and long-delayed. Therefore, the prolonged pipeline dispute has caused Canadian firms to consider new options to get their crude into markets.

The proposal for the Energy East pipeline in 2013 was an alternative to the Keystone XL project. This pipeline, if completed, would carry more than one million oil barrels per day from Western Canada to Eastern Canada. However, this project is also facing opposition by environmentalists and First Nations people and is still under review. There have also been some other pipeline proposals with the aim of targeting Asian markets for Alberta's crude. The Northern gateway pipeline, which would carry 500,000 barrels of oil from Edmonton to BC, was first announced in 2006 and approved by the Canadian government in June 2014 with some conditions. Kinder Morgan also proposed a competing project to expand the current Transmountain pipeline in order to increase the pipeline's capacity to carry more oil barrels from Edmonton to BC. They claimed that this expansion would cost less and reduce opposition compared to the Northern gateway. However, in April 2013, the NDP's leader, Adrian Dix, adopted an unexpected and unfavorable position toward this application during an election campaign and announced that the NDP would not approve any pipeline which would make Vancouver a major oil exporting centre. Overall, Table 2.1 lists the events and announcements considered in this study along with their date of release according to Wall Street Journal. In general, an equity price of a firm can be thought of as the discounted value of expected future earnings of that firm. In this study, the events/projects chosen are large enough that we expect them to affect the firms' future earnings and consequently firms' equity prices.

We collect weekly equity prices for Canadian energy companies for the period January 2011 to March 2015, which encompasses all seven events of interest. We consider two samples in this study. The first sample consists of 40 energy services out of 45 firms listed in Toronto Stock Exchange website. The second sample encompasses a panel of the 20 largest oil producers which provide the majority of production. We use multivariate regression models with inclusion of dummy variables and employ several joint tests in order to assess the impacts of the considered events on equity returns. Our results indicated no significant market reaction to any of the selected events. Our findings did not change when we applied the same analysis on daily returns with a two year estimation period and different event windows. Therefore, our results imply two possible scenarios: first, the selected events

Table 2.1: Summary of the events

| Events | Description | Date |
|---|---|---|
| 1 | Obama administration's announcement of delaying any decision on Keystone XL project for the first time | November 10, 2011 |
| 2 | Kinder Morgan Energy Partners LP's announcement of Trans Mountain pipeline expansion | April 12, 2012 |
| 3 | U.S. presidential election | November 6, 2012 |
| 4 | NDP leader's, Adrian Dix, anti-pipeline announcement | April 22, 2013 |
| 5 | British Columbia provincial election | May 14, 2013 |
| 6 | TransCanada's announcement of Energy East pipeline project as an alternative to Keystone XL | August 1, 2013 |
| 7 | Canadian government acceptance of Northern Gateway pipeline | June 17, 2014 |

did not contain a significant amount of new information and had been fully anticipated by investors in the market, and second, occurrence of these events did not change investors' expectations regarding the future profitability and cash flow of Canadian energy firms. To the best of our knowledge, this is the first study that assesses the impact of Alberta's uncertainties on the market value of Canadian energy firms.

In the next section, we review the literature. The dataset and the methodology used in this study are presented in Section 3. Section 4 contains empirical results based on weekly returns of both types of energy firms. Section 5 contains empirical results based on daily returns of both types of energy firms. The last section presents the conclusion. Appendix 1 and Appendix 2 list the name of companies sampled and descriptive statistics of the datasets.

## 2.2 Literature Review

### 2.2.1 Event study analysis

An event study is an empirical procedure which examines security price reactions to some events or announcements. McWilliams and Siegel (1997) defined this methodology as an approach which "determines whether there is an abnormal stock price effect associated with an unanticipated event." This methodology has been used to address two major questions in the literature (Binder,1998). First, it measures market efficiency and examines how quickly information is incorporated into security prices. Second, it assesses the effect of some events on the wealth of the security holders under the assumption of a semi-strong form of market efficiency, which states that publicly available information will be incorporated into security prices immediately.

This methodology has a long history. The first published paper using this method is associated with James Dolley (1933) who measured the impact of stock splits on stock prices by examining nominal price changes at the time of the split. He used a sample of 95 splits for the period 1921 to 1931 and found that price decreased in only 26 cases while it increased in 57 cases. Subsequent users of this methodology were Myers and Bakay (1948), Baker (1956, 1957 and 1958) and Ashley (1962) who made some improvements by separating out confounding events and removing general stock market price movements (MacKinlay, 1997). Later, two pioneering papers by Fama et al. (1969) and Ball and Brown (1968) introduced the current form of the methodology which has become the basis for many studies.

Ball and Brown (1968) examined the information content of annual accounting data on stock prices. They calculated income forecast errors, which is the actual change in income minus the expected change, and defined it as negative news when it was negative and vice versa. They examined the release of news and found that bad news would result in negative impact in stock returns residuals around the annual report announcement date. Similarly, with respect to the positive forecast error, they found positive abnormal returns around the announcement day.

Fama et al. (1969) measured the effect of stock splits on stock prices using a sample of monthly returns from 1926 to 1960. A market model which relates the return of an equity to the return of the market portfolio was estimated for each individual firm, with data including the period during which the events had occurred ( the estimation period contained event periods). Then, abnormal returns were measured as the residuals from the market model estimation during the event period. Finally, the residual during the event period were cross-sectionallly averaged and a test statistic based on the cross sectional estimate of the standard deviation was constructed in order to test the hypothesis that average abnormal returns were equal to zero. They found no abnormal returns after a split announcement, therefore they concluded that stock prices quickly incorporated all the information.

Subsequent studies separated the estimation period from the event period and estimated the market model with data prior to (or after) the event window, as it was pointed out that including the event period in the estimation period would result in biased coefficient estimates of market models. However, this traditional approach was still based on strong assumptions which considered asset returns to be jointly multivariate normal and identically and independently distributed (i.i.d). Security returns can not be independent when the events occur at the same time for all firms (calender clustering) and firms are from the same or related industries (industry clustering). In fact, King (1966) found that abnormal returns estimated as residuals of a market model are contemporaneously correlated for firms in the related industries. In addition, there is also a potential of auto correlation across time for a given firm. Fama (1976) showed that abnormal returns (market model residuals) have different variances across firms (the heteroskedasticity problem). Collins and Dent (1984) showed that in some cases, considerable bias exists when cross-sectional dependency and heteroskedasticity across firms are not taken into account[1]. Warner and Brown (1980, 1985) in two seminal papers, used simulation procedures on large random samples of monthly

[1] Binder (1998) and Henderson (1990) have great surveys on the methodology and its statistical problems and solutions.

(1980) and daily (1985) security returns in order to asses the impact of potential concerns such as clustering and cross-correlation, non-normality of returns and biases in OLS estimates of market model parameters when non-synchronous trading exist. With respect to normality, they found that daily stock return for an individual firm is highly differing from normal distribution, whereas monthly returns did not exhibit such behavior. Non-normality of daily stock returns had been recognized in the literature for a long time (Fama, 1965 and 1976; Officer 1972, Bloom 2011), which might cast doubt on credibility of event studies conducted using daily stock data without addressing non-normality. With respect to cross-sectional dependency, they argued that failure in taking into account (positive) dependency will result in the variance of the mean abnormal returns being underestimated, implying too many rejections of the null hypothesis. Among all the papers dealing with estimation issues, these two papers are among the most significant.

In sum, the event study methodology has been widely used and has many applications in economics, accounting and finance. Various types of events such as stock splits, mergers and acquisitions, earning announcements, regulatory changes and macro economic announcements have been studied with event studies. We now look specifically at studies that have been conducted on energy firms.

### 2.2.2 Event studies on the energy sector

There have been several studies to assess the relationship between energy firm values and environmental policies using the event studies approach. Colwell and Noseworthy (2009) used a standard event study methodology to verify the effect of environmental events on the value of shareholders wealth based on a sample of oil and gas companies listed in the 2006 Fortune 500 list. Using daily stock price data, first they considered all firms as a group and found that negative news about the environmental performance of a company caused significant negative abnormal returns. However, when they separated the sample based on market capitalization, they realized that significant negative abnormal returns exist only for companies with lower market capitalization, meaning that the market only punishes smaller firms. Thus, they concluded that market capitalization and the financial stability of the firm are important factors in determining the degree to which negative environmental news affects the shareholders wealth.

Dezhu Ye et al. (2013) used an event study approach to investigate the effect of the carbon emission rights trading scheme (CERTS) of China introduced in 2011 on Chinese energy-related firms. Using daily return data on 768 firms, their results showed that this event had a significant positive effect on the financial performance of energy firms, as CERTS enables emission rights to be traded and considered firm assets (Dezhu et al. 2013). They further investigated the effect of energy-saving efforts on firm value and investors behaviors and found that energy-saving efforts of a firm has a positive impact on its market value.

Following the Japanese nuclear disaster in Fukushima-Daiichi in 2011, several papers examined the effect of this event on nuclear and alternative energy firms. Frestle et al. (2012) investigated the effect on daily stock prices of French, German, U.S. and Japanese nuclear and alternative firms in both short run and medium run. Using a three factor model and multivariate regression, they found a significant impact on stock prices of Japanese, French and German nuclear firms a day after the incident, no significant effect on the U.S. companies. Their results also indicated an increased volatility in Japanese nuclear stocks following the event implying uncertainty about future policy implications. Betzar et al. (2013) examined the impact of the German government's decision to phase out nuclear power in response to the Fukushima disaster on shareholder wealth of German nuclear, conventional and renewable energy firms. For the purpose of comparison, they also considered a group of energy firms in other European countries that were unaffected by this policy change, in order to investigate their market reaction as well. They found insignificant abnormal returns on the day of the earthquake for all German firms. However, they found highly significant negative abnormal returns for nuclear and conventional firms on the day of policy change and highly positive abnormal returns on the same date for renewable energy firms. With respect to other European firms included in their sample, their results revealed no significant effect either on the day of the earthquake or on the day of the policy change. However, they could find slightly positive effects around 10 days following the disaster. Thus, they concluded that shareholders wealth of energy companies were affected by the policy change and not by the disaster itself.

## 2.3 Data and methodology

### 2.3.1 Data

We consider two samples in our study. The first consists of 40 energy services companies out of 45 listed in Toronto Stock Exchange (TSX) website. Appendix 1 represents a list of all the companies included in the dataset. We had to exclude 5 energy services companies from our dataset as they had relatively short spans of data. The second sample encompasses major Calgary-based oil producers listed in TSX website. Although there are numerous oil and gas companies, the majority of production is done by the companies included in our study[2]. Appendix 2 represents a list of oil producers in our dataset. Weekly equity prices[3] for the period January of 2011 to March 2015, which encompasses all seven events of our interest, were obtained from Yahoo Finance website. Weekly returns were then calculated using the following formula:

$$R_t = \frac{P_{t+1} - P_t}{P_t}$$

Daily equity prices, for both energy services and oil producers, for the period January 2011 to January 2015 were collected using the same website as before. With respect to

[2] These companies are chosen using the edition 2013 of Forbes Global 2000 and also the Alberta oil magazine's ranking, which were based on companies mix of revenues, sales, profits, assets and market values.

[3] We use close prices adjusted for dividends and splits

energy services companies, our sample includes all companies listed in Appendix 1 except Akita Drilling Ltd. We had to exclude this company as its daily prices had some missing values. With respect to oil producing companies, our daily sample includes all 20 major oil producers listed in Appendix 2. Daily returns then were calculated in a similar way as they were before.

### 2.3.2 Event study approach and hypothesis testing

Traditional event studies are based on a cross-section independency assumption among abnormal returns. However, this assumption can not be made when firms of the same industry share the same event date. Ignoring contemporaneous correlations in event-date clustered analysis of returns may cause substantial downward bias in the variance and standard deviation and thereby overstate the $t-$statistic, implying the overrejection of a true null hypothesis (Collin and Drent 1984; Kothari and Warner 2007; Kolari and Pynnonen 2010).

In this paper, we use a multivariate regression model methodology (MVRM) with an application of Zellner's (1962) seemingly unrelated regression (SUR).[4] Gibbons (1980) first suggested this methodology for use in event studies, and later Schipper and Thompson (1983, 1985) and Binder (1985a, 1985b) developed it. The basic approach is to consider a system of returns equations with dummy variables defined over the event periods (or on an individual event date) to capture abnormal returns[5] and estimate the equations jointly using feasible generalized least squares. In this paper the following system of equations is estimated jointly:[6]

[4] The event study analysis conducted in this study focuses on the mean equity price effects. We have not examined return variances in this study.

[5] Karafiath (1988) and Salinger (1992) have shown that dummy variable apporoach where estimation period encompasses event period is equivalent to the returns approach which seperates event period from estimation period.

[6] We also conducted the analysis using the market model type of regressions (return on a risk free asset was deleted from the model). Our results were robust to this type of regression and only negligible changes were found.

$$
\begin{aligned}
R_{1t} - R_{0t} &= \alpha_1 + \beta_1(R_{mt} - R_{0t}) + \sum_{b=1}^{y} \gamma_{1b} D_{bt} + u_{it} \qquad (2.1)\\
R_{2t} - R_{0t} &= \alpha_2 + \beta_2(R_{mt} - R_{0t}) + \sum_{b=1}^{y} \gamma_{2b} D_{bt} + u_{2t}\\
&.\\
&.\\
&.\\
R_{Nt} - R_{0t} &= \alpha_N + \beta_N(R_{mt} - R_{0t}) + \sum_{b=1}^{y} \gamma_{Nb} D_{bt} + u_{Nt}
\end{aligned}
$$

where $R_{it}$ is the return on equity $i$ in period $t$, $i = 1, 2, ...., N$

$R_0$ is the weekly return on the three-month Canadian Treasury Bills in period $t$

$\alpha_i$ and $\beta_i$ are regression parameters for firm $i$, $i = 1, 2, ...., N$

$R_{mt}$ is the weekly return on the market index, which is S&P/TSX Composite Index, in period $t$

$D_{bt}$ represents dummy variables which equal to one if the $y^{th}$ event occurred during the $t^{th}$ week and zero otherwise.[7]

$\gamma_{bi}$ reflects the abnormal return for firm $i$ on event $y$

$u_{it}$ is regression residual for firm $i$ during the $t^{th}$week

Zellner's SUR model assumes that residuals are identically and independently distributed (i.i.d) within each equation but not across them. In other words, residual variances are allowed to differ across firms but are constant within firms. This technique also assumes that

[7]For each event (y=1,2,...7), we also defined dummy variables on both pre and post event week in order to capture abnormal returns induced due to information leakage or market's delay in reacting to the new information.

contemporaneous covariances of residuals across firms are not zero, while the noncontemporaneous covariances across them are all equal to zero ($E(u_{it}, u_{jt}) = \sigma_{ij}$ for $i \neq j$ whereas $E(u_{it}, u_{j,t-q}) = 0$). The SUR model is estimated using a two step procedure. In the first step, all equations are estimated by Ordinary Least Squares and the estimated residuals are used to construct a consistent estimator of the error variance-covariance matrix. In the second step, feasible generalized least squares regressions are implemented using the estimator of the variance-covarience matrix.

Since all return generating equations have exactly the same explanatory variables, Ordinary Least Squares (OLS) for each equation will result in the same estimated coefficients and standard errors as feasible generalized least squares. Thus, the advantage of using MVRM approach is in hypothesis testing since heteroskedasticity and contemporaneous dependency of the residuals are taken into account. (Binder, 1985)

The first hypothesis to be tested is whether the average abnormal returns to the $y^{th}$event equal zero ($H_{1b} : \frac{1}{N}\sum_{i}^{N}\gamma_{ib} = 0$). Hughes and Ricks (1984b) prove that when individual firms form an equally weighted portfolio, an $F$-test of $H_{1b}$ is equivalent to the $t^2$ test of the hypothesis that $\gamma_{portfolio}$ equals zero. Therefore, to test $H_{1b}$ that measures the average market reaction to the specific event, we form an eqaully weighted portfolio of equities and estimate the following equation using OLS:

$$R_{pt} = \alpha_p + \beta_p R_{mt} + \sum_{b=1}^{\gamma}\gamma_{pb} D_{bt} + u \tag{2.2}$$

In fact, constructing a portfolio of returns is advantageous since the variability of the portfolio returns captures all cross section dependency and also cross section heteroskedasticity that might exist.

The second hypothesis to be tested is that for a particular event, all abnormal returns are equal to zero ($H_{2b} : \gamma_{ib} = 0 \ \forall i, b$). These joint hypotheses are tested using Wald and Likelihood ratio tests.

Table 2.2: Regression estimates of the market reaction to the events

| | $\alpha$ | $\beta$ | E1 | E2 | E3 | E4 | E5 | E6 | E7 |
|---|---|---|---|---|---|---|---|---|---|
| estimated coefficients | .0163 | 1.016 | .0011 | -.0158 | -.0036 | .0043 | .0132 | .0006 | .0034 |
| $t-$value | 1.01 | 58.08 | .05 | -.76 | -.017 | .21 | .63 | .03 | .0208 |
| P.value | .313 | .000*** | .95 | .44 | .86 | .83 | .52 | .97 | .87 |

*** denotes significance at 1 percent

## 2.4 Empirical results

### 2.4.1 Results based on energy services companies

Table 2.2 shows the first hypothesis testing results. As explained, the t-statistics in this regression enables the direct test of the hypothesis that average market reaction to the $y^{th}$ event is equal to zero ($y = 1, 2, ..., 7$). The results presented in Table 2.2 indicate that none of the average abnormal returns are significant, meaning that the events considered in this study did not have any effects on equity returns on average.[8] Therefore, we conclude that there was no average market reaction to any of the 7 events.

The fact that abnormal returns on average were equal to zero implies two possible scenarios: first, the events we have considered may have been fully anticipated by market agents and did not contain any considerable new information; second, if the market agents had not already fully anticipated the events and announcements, then our results would suggest that market agents did not expect those events to have any economic consequences for the energy firms. In others words, these events did not change market agents' expectations regarding future profitability and cash flow of the affected firms.

Even though the average abnormal returns are equal to zero, some of the individual abnormal returns could be different from zero. Therefore, in order to test the hypothesis that there is no market reaction for any firm to the $y^{th}$ event ($y = 1, 2, ..., 7$), we estimated

[8]The coefficients on dummay variables defined on each event's per and post week, were all insignificant. We just found positive slightly significant (at 10 percent level) abnormal return in a week after the acceoptance of Northern gateway pipeline by the Canadian govenrment.

seemingly unrelated regressions (SUR) and took advantage of a covariance matrix of residuals to construct joint tests. Table 2.3 represents the individual parameter estimates for each of the firms, using SUR estimations.

Table 2.3: Individual parameter estimates

| firm | $\alpha$ | $\beta$ | E1 | E2 | E3 | E4 | E5 | E6 | E7 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | -.0598 | .9344 | .0764 | -.0258 | -.0202 | .0181 | -.0088 | .0470 | -.0316 |
| P-value | .014** | .000*** | 0.015** | .414 | .522 | .565 | .779 | .137 | .317 |
| 2 | -.0035 | .9919 | .0266 | -.0077 | -.0098 | -.0177 | -.0079 | .0029 | .0095 |
| P-value | .849 | .000*** | .27 | .749 | .685 | .465 | .744 | .905 | .694 |
| 3 | .0092 | 1.002 | .1087 | .0056 | -.0240 | -.0070 | .1153 | -.0304 | -.0060 |
| P-value | ..775 | .000*** | .010** | .892 | .568 | .867 | .006*** | .469 | .886 |
| 4 | -.0745 | .9261 | .1878 | .1008 | -.0754 | -.1091 | .0854 | .0934 | .0257 |
| P-value | .128 | .000*** | .003*** | 0.111 | .234 | .085* | .178 | .141 | .684 |
| 5 | .0112 | 1.013 | -.0150 | -.0133 | .0197 | .0236 | -.0026 | -.0214 | -.0317 |
| P-value | .769 | .000*** | .761 | .788 | .691 | .634 | .957 | .666 | .521 |
| 6 | .0299 | 1.027 | -.0313 | .0323 | .0208 | .0394 | .0211 | -.0006 | -.0009 |
| P-value | .428 | .000*** | .520 | .507 | .670 | .420 | .666 | .989 | .984 |
| 7 | .0082 | 1.008 | -.0355 | -.0656 | .0353 | -.0273 | .0230 | -.0703 | .0506 |
| P-value | .834 | .000*** | .486 | .197 | .489 | .591 | .652 | .168 | .321 |
| 8 | -.0459 | .9552 | .0321 | -.0358 | -.0221 | -.0240 | .0418 | -.0162 | .0316 |
| P-value | .245 | .000*** | .529 | .483 | .665 | .638 | .413 | .751 | .535 |
| 9 | -.0193 | .9806 | .0485 | -.0001 | .0004 | -.0286 | -.0003 | .0180 | -.0442 |
| P-value | .490 | .000*** | .180 | .996 | .989 | .429 | .993 | .620 | .222 |
| 10 | -.0074 | .9839 | -.1009 | -.0166 | -.0593 | .0329 | -.0306 | -.0037 | -.0392 |
| P-value | .918 | .000*** | .281 | .859 | .527 | .726 | .744 | .968 | .676 |
| 11 | -.0254 | .9741 | .0962 | -.0079 | -.0525 | .0106 | .0473 | .0001 | .0547 |
| P-value | .507 | .000*** | .052* | .872 | .290 | .831 | .341 | .998 | .270 |
| 12 | .0967 | 1.106 | .0269 | .0176 | -.0775 | -.1267 | -.1309 | -.1083 | -.0710 |
| P-value | .181 | .000*** | .774 | .850 | .409 | .176 | .163 | .249 | .448 |
| 13 | 1.158 | 2.250 | -.0543 | .0119 | .1194 | -.0054 | .0946 | .0630 | .0890 |
| P-value | .000*** | .000*** | .868 | .971 | .716 | .987 | .773 | .847 | .785 |
| 14 | .1136 | 1.126 | -.0767 | .0004 | -.1065 | .0493 | .0197 | -.0886 | -.0939 |
| P-value | .037** | .000*** | .276 | .995 | .131 | .484 | .780 | .209 | .182 |
| 15 | -.1469 | .8319 | -.2073 | -.0217 | -.1388 | -.2008 | -.1015 | -.1837 | .3648 |
| P-value | .292 | .000*** | .250 | .904 | .443 | .266 | .574 | .309 | .043** |
| 16 | -.1093 | .8728 | .0235 | .0966 | .0024 | -.0367 | .0459 | .0067 | -.0307 |
| P-value | .066* | .000*** | .760 | .210 | .975 | .634 | .552 | .931 | .690 |
| 17 | .0078 | 1.008 | .0233 | -.0187 | -.0665 | .0955 | -.0007 | .0068 | .0036 |
| P-value | .852 | .000 | .668 | .732 | .224 | .080* | .990 | .901 | .947 |
| 18 | .0066 | 1.001 | .0261 | -.0139 | .0334 | .0128 | -.0093 | .0998 | .0333 |
| P-value | .942 | .000*** | .823 | .905 | .775 | .913 | .936 | .395 | .776 |
| 19 | -.0776 | .9191 | -.0533 | -.0668 | .0514 | .2547 | .2050 | .1384 | .0026 |
| P-value | .054* | .000*** | .306 | .199 | .324 | .000*** | .000*** | .008*** | .960 |
| 20 | -.0205 | .9758 | -.0853 | -.0292 | .0013 | .0259 | .0373 | .0642 | -.0446 |
| P-value | .544 | .000*** | .052* | .505 | .975 | .555 | .396 | .144 | .309 |

Table 2.3-continued

| firm | $\alpha$ | $\beta$ | E1 | E2 | E3 | E4 | E5 | E6 | E7 |
|---|---|---|---|---|---|---|---|---|---|
| 21 | .0759 | 1.083 | -.0354 | -.0724 | -.0330 | -.0217 | -.0055 | .0463 | -.0366 |
| P-value | .04** | .000*** | .476 | .145 | .507 | .663 | .912 | .352 | .461 |
| 22 | -.0189 | .9773 | .0444 | -.0596 | -.0168 | -.0365 | .0015 | -.0052 | -.0020 |
| P-value | .408 | .000*** | .133 | .044** | .569 | .217 | .958 | .859 | .945 |
| 23 | .0221 | 1.029 | .0331 | -.0721 | .0633 | -.0624 | .2050 | .0352 | -.0124 |
| P-value | .669 | .000*** | .622 | .282 | .346 | .353 | .002*** | .601 | .852 |
| 24 | -.0334 | .9715 | .0298 | -.0024 | .0394 | -.0373 | .0808 | .0279 | .0010 |
| P-value | .460 | .000 | .610 | .966 | .502 | .524 | .169 | .635 | .986 |
| 25 | -.0443 | .9498 | -.0476 | -.0287 | -.0035 | .0088 | -.0299 | .0884 | -.0069 |
| P-value | .097* | .000*** | .169 | .407 | .920 | .799 | .389 | .011** | .842 |
| 26 | -.0761 | .9062 | -.0122 | -.1018 | .1561 | -.0475 | .0079 | -.0807 | .0495 |
| P-value | .326 | .000*** | .903 | .309 | .120 | .636 | .937 | .421 | .621 |
| 27 | .0117 | 1.013 | -.0082 | -.0537 | .0077 | .0446 | -.0212 | -.0187 | .0156 |
| P-value | .752 | .000*** | .865 | .266 | .873 | .356 | .661 | .698 | .745 |
| 28 | .0901 | 1.097 | -.0140 | -.0029 | -.0066 | .0275 | .0012 | .0086 | -.0197 |
| P-value | .035** | .000*** | .800 | .957 | .905 | .620 | .983 | .876 | .722 |
| 29 | -.0476 | .9449 | .0283 | -.0322 | .0185 | -.0039 | .0625 | .0590 | -.0187 |
| P-value | .198 | .000*** | .554 | .500 | .700 | .934 | .192 | .219 | .695 |
| 30 | .0291 | 1.034 | -.0152 | .0075 | -.0051 | -.0000 | .0059 | -.0117 | -.0220 |
| P-value | .424 | .000*** | .747 | .872 | .914 | .998 | .900 | .804 | .640 |
| 31 | .0073 | 1.002 | -.0374 | .0261 | .0109 | .0440 | -.0100 | -.0114 | -.0119 |
| P-value | .833 | .000*** | .407 | .563 | .809 | .330 | .824 | .800 | .792 |
| 32 | -.0436 | .9520 | .0260 | -.0087 | .0156 | -.0126 | -.0030 | -.0173 | -.0101 |
| P-value | .100 | .000*** | .448 | .799 | .650 | .714 | .930 | .615 | .768 |
| 33 | -.0778 | .9158 | .0233 | -.0408 | -.0275 | .1210 | -.0367 | -.0778 | .0687 |
| P-value | .031** | .000*** | .616 | .381 | .556 | .009*** | .431 | .096* | .140 |
| 34 | -.0644 | .9330 | .0447 | -.0080 | .0232 | .1768 | .0123 | .0100 | .0024 |
| P-value | .409 | .000*** | .658 | .936 | .818 | .080* | .903 | .921 | .981 |
| 35 | -.0017 | .9970 | .0102 | -.0737 | -.0993 | -.0255 | -.0013 | .0317 | .0025 |
| P-value | .948 | .000*** | .763 | .031** | .004** | .456 | .969 | .354 | .939 |
| 36 | -.0333 | .9688 | .0028 | -.0203 | .0028 | .0293 | -.0310 | -.0370 | -.0429 |
| P-value | .422 | .000*** | .957 | .705 | .958 | .585 | .564 | .492 | .425 |
| 37 | .0041 | 1.004 | -.0126 | -.0056 | .0133 | -.0381 | -.0187 | -.0362 | -.0288 |
| P-value | .913 | .000*** | .798 | .909 | .788 | .441 | .705 | .464 | .559 |
| 38 | .0489 | 1.051 | .0103 | -.0756 | .0170 | -.0130 | .0139 | .0188 | -.019 |
| P-value | .203 | .000*** | .836 | .128 | .732 | .793 | .779 | .705 | .688 |
| 39 | .0179 | 1.021 | -.0618 | .0590 | .0528 | .0500 | -.0453 | -.0792 | -.0452 |
| P-value | .757 | .000*** | .409 | .430 | .482 | .504 | .545 | .291 | .546 |
| 40 | -.0627 | .9290 | .0187 | -.0106 | -.0055 | -.0069 | -.0100 | .0587 | .0030 |
| P-value | .028** | .000*** | .611 | .774 | .880 | .850 | .786 | .113 | .935 |

*, ** and *** denote significance at 10 percent, 5 percent and 1 percent respectively

Table 2.4 represents the multivariate hypothesis testing results using Wald (both F and Chi-squared tests) and Likelihood ratio tests. As is demonstrated in Table 2.4, the null hypothesis of abnormal returns being jointly equal to zero is rejected in three cases based on all three test statistics. Specifically, the Obama administration delaying the Keystone

Table 2.4: Multivariate hypothesis testing: All abnormal returns equal zero

| | Wald (F-test) | Wald (Chi-squared test) | Likelihood ratio |
|---|---|---|---|
| $H_{21}$ :event 1 | 1.82 | 75.88 | 65.03 |
| | .0012*** | .0005*** | .0074*** |
| $H_{22}$ :event 2 | .85 | 35.31 | 32.70 |
| | .742 | .681 | .786 |
| $H_{23}$ :event 3 | .92 | 38.33 | 35.28 |
| | .618 | .545 | .682 |
| $H_{24}$ :event 4 | 1.86 | 77.47 | 66.20 |
| | .0008*** | .0003*** | .0057*** |
| $H_{25}$ :event 5 | 1.72 | 71.80 | 61.99 |
| | .0032*** | .0015*** | .014** |
| $H_{26}$ :event 6 | 1.29 | 53.99 | 48.19 |
| | .1018 | .068* | .175 |
| $H_{27}$ :event 7 | .80 | 33.36 | 31.03 |
| | .812 | .761 | .844 |

*** denotes significance at 1%, ** denotes significance at 5%, and * denotes significance at 10%

XL (event 1),[9] The NDP leader's anti-pipeline talk (event 4), and the BC provincial election (event 5) induced some abnormal returns for at least one firm. The null hypothesis of joint zero abnormal returns for the case of the Energy East proposal (event 6) was rejected (at 10 percent level) only based on one test statistic. However, with respect to the other remaining events, which were the 2012 U.S. presidential election (event 3), the acceptance of the Northern gateway by Canadian government (event 7) and also the announcement of Trans Mountain pipeline expansion (event 2), no significant results were found, meaning that we could not reject the null of zero abnormal returns for all firms. These results confirm the findings in Table 2.3 where individual parameter estimates indicated that the abnormal returns associated with event 1, event 4 and event 5 were significant for a small number of firms.

[9] We also checked the event on July 21, 2010 where the Environmntal Protection Agency said the draft environmental impact study for Keystone XL was inadequate and should be revised. That event produced some negative abnormal returns for at least one firm.

### 2.4.2 Results based on oil producers

Table 2.5 shows the regression estimates for the portfolio of 20 leading oil producers companies. Similar to the previous section, Table 2.5 indicates that none of the average abnormal returns are significant.[10] Therefore, there was no average market reaction to any of the included events.[11]

Table 2.5: Regression estimates of the market reaction to the events

| | $\alpha$ | $\beta$ | E1 | E2 | E3 | E4 | E5 | E6 | E7 |
|---|---|---|---|---|---|---|---|---|---|
| estimated coefficients | .0480 | 1.054 | .0146 | -.0023 | .0129 | -.0011 | .0151 | -.0054 | -.0133 |
| $t-$value | 2.30 | 46.55 | .54 | -.09 | .48 | -.04 | .56 | -.20 | -.49 |
| P.value | .022** | .000*** | .58 | .93 | .63 | .96 | .57 | .84 | .62 |

** and *** denote significance at 5 percent and 1 percent respectively

Similar to the results in previous section, these findings imply two possible scenarios: first, the events we have considered may have been fully anticipated by market agents and did not contain any new information; second, if the market agents had not fully anticipated the events and announcements, then our results would suggest that market agents did not expect those events to have any economic consequences for the energy firms. In others words, these events did not change market agents' expectations regarding future profitability and cash flow of the affected firms.

As before, in order to test the hypothesis that there is no market reaction for any firm to the $y^{th}$ event $(y = 1, 2, ..., 7)$, we estimated seemingly unrelated regressions (SUR) and took advantage of a covariance matrix of residuals to construct joint tests. Table 2.6 represents the individual parameter estimates for each of the firms using SUR estimations.

[10] Results on dummy variables defined on each event's pre and post week were all insignificant too.

[11] Most of the oil producer companies considered in our sample are also part of the constituents of the market index, meaning that the implicit assumption of no correlation between abnormal returns and market index will be violated. However, event studies are not concerend with this matter as in largely capitalized markets the resulting distortions are negligible (Lopatta and Kaspereit, 2014). In order to statistically check on whether this distortion exists in our analysis, we regressed the excess market index returns on the event dummy variables. We found insignificant coefficients implying that there is no distortion in our analysis.

Table 2.6: Individual parameter estimates

| firm | $\alpha$ | $\beta$ | E1 | E2 | E3 | E4 | E5 | E6 | E7 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | .0154 | 1.016 | .0816 | -.0284 | .0320 | -.0378 | .0371 | -.0513 | -.0094 |
| P-value | .535 | .000*** | .011** | .377 | .321 | .240 | .250 | .111 | .769 |
| 2 | .0546 | 1.062 | -.0007 | .0318 | .0615 | .0229 | .0096 | -.0183 | -.0039 |
| P-value | .102 | .000*** | .986 | .460 | .155 | .594 | .824 | .671 | .928 |
| 3 | .0329 | 1.041 | .0148 | -.0070 | .0055 | .0254 | .0015 | .0158 | -.0091 |
| P-value | .298 | .000*** | .715 | .863 | .892 | .533 | .969 | .698 | .822 |
| 4 | .0261 | 1.028 | .0154 | -.0048 | -.0138 | -.0163 | .0215 | -.0321 | .0076 |
| P-value | .244 | .000*** | .592 | .867 | .633 | .573 | .457 | .268 | .791 |
| 5 | .0031 | 1.005 | -.0021 | .0273 | -.0134 | -.0164 | -.0112 | -.0161 | .0110 |
| P-value | .883 | .000*** | .938 | .326 | .631 | .555 | .688 | .562 | .693 |
| 6 | .0292 | 1.032 | .0607 | .0075 | .0322 | .0281 | .0043 | .0208 | -.0062 |
| P-value | .255 | .000*** | .067* | .819 | .332 | .397 | .896 | .532 | .852 |
| 7 | .1328 | 1.147 | -.0032 | .0292 | .0342 | .0179 | .0073 | .0166 | .0010 |
| P-value | .000*** | .000*** | .941 | .512 | .443 | .688 | .870 | .710 | .982 |
| 8 | -.0059 | .9961 | .0035 | .0098 | .0368 | -.0390 | .0410 | -.0116 | -.0392 |
| P-value | .834 | .000*** | .923 | .789 | .318 | .289 | .266 | .752 | .286 |
| 9 | .0338 | 1.039 | .0092 | -.0491 | -.0482 | .0214 | .0096 | .0327 | .0106 |
| P-value | .815 | .000*** | .815 | .213 | .223 | .587 | .807 | .408 | .787 |
| 10 | .0560 | 1.065 | .0027 | -.0139 | .0464 | .0037 | .0091 | .0557 | .0267 |
| P-value | .205 | .000*** | .962 | .807 | .417 | .948 | .873 | .331 | .640 |
| 11 | .0066 | 1.005 | .0320 | -.0017 | -.0319 | -.0038 | .0044 | -.0309 | -.0456 |
| P-value | .730 | .000*** | .199 | .944 | .202 | .877 | .859 | .216 | .067 |
| 12 | .0142 | 1.015 | .0419 | .0190 | -.0070 | -.0164 | -.0038 | -.0249 | -.0033 |
| P-value | .372 | .000*** | .042** | .355 | .735 | .425 | .852 | .227 | .870 |
| 13 | .2512 | 1.279 | .0053 | -.0055 | -.0345 | .0042 | .0707 | -.1082 | -.0744 |
| P-value | .003*** | .000*** | .961 | .959 | .754 | .969 | .520 | .325 | .497 |
| 14 | .0549 | 1.063 | .0205 | .0435 | .0536 | -.0424 | .0084 | .0187 | -.0080 |
| P-value | .160 | .000*** | .684 | .390 | .289 | .402 | .867 | .712 | .873 |
| 15 | .0552 | 1.063 | .0213 | -.0393 | -.0002 | .0374 | .0193 | .0154 | .0096 |
| P-value | .088* | .000*** | .609 | .347 | .996 | .371 | .645 | .713 | .817 |
| 16 | .1163 | 1.136 | .0389 | -.0125 | .0386 | .0366 | .0921 | .0374 | -.0198 |
| P-value | .014** | .000*** | .523 | .836 | .528 | .548 | .132 | .540 | .744 |
| 17 | .0335 | 1.036 | .0043 | .0098 | -.0225 | .0457 | -.0311 | -.0128 | -.0083 |
| P-value | .088* | .000*** | .863 | .697 | .376 | .071* | .221 | .614 | .742 |
| 18 | .0636 | 1.071 | -.0166 | .0024 | .0294 | -.0367 | .0172 | .0058 | -.0250 |
| P-value | .225 | .000*** | .805 | .972 | .664 | .588 | .799 | .931 | .712 |
| 19 | -.0266 | .9673 | -.0690 | -.0574 | .0087 | -.0440 | -.0094 | -.0058 | -.0240 |
| P-value | .000*** | .384 | .081* | .147 | .826 | .265 | .811 | .884 | .544 |
| 20 | .0135 | 1.012 | .0313 | -.0081 | .0513 | -.0136 | .0056 | -.0148 | -.0562 |
| P-value | .557 | .000*** | .295 | .786 | .087* | .649 | .850 | .621 | .06* |

*, ** and *** denote significance at 10 percent ,5 percent and 1 percent respectively

Table 2.7: Multivariate hypothesis testing: All abnormal returns equal zero

| | Wald (F-test) | Wald (Chi-squared test) | Likelihood ratio |
|---|---|---|---|
| $H_{21}$ :event 1 | 1.85 | 38.56 | 35.44 |
| | .0122** | .0076*** | .0179** |
| $H_{22}$ :event 2 | .65 | 13.49 | 13.08 |
| | .8805 | .8555 | .8740 |
| $H_{23}$ :event 3 | 1.30 | 27.17 | 25.57 |
| | .1660 | .1306 | .1805 |
| $H_{24}$ :event 4 | 1.30 | 27.17 | 25.57 |
| | .1661 | .1307 | .1806 |
| $H_{25}$ :event 5 | .61 | 12.76 | 12.39 |
| | .9080 | .8875 | .9019 |
| $H_{26}$ :event 6 | 1.31 | 27.36 | 25.74 |
| | .1601 | .1255 | .1746 |
| $H_{27}$ :event 7 | .89 | 18.63 | 17.86 |
| | .5978 | .5460 | .5967 |

***denotes significance at 1%, ** denotes significance at 5 %

Table 2.7 represents the multivariate hypothesis testing results using Wald (both F and Chi-squared tests) and Likelihood ratio tests. As is demonstrated in Table 2.7, the null hypothesis of abnormal returns being jointly equal to zero is rejected only in one case: the Obama administration delaying the Keystone XL (event 1) induced some abnormal returns for at least one firm. This finding is consistent with individual parameter estimates reported in Table 2.6 where the abnormal returns associated with event 1 became significant for a few firms.

## 2.5 Analysis using daily returns

In this section we examine whether our findings depend on the time frequency of our dataset.

Employing the methodology explained in section 3 and using daily returns data, we examine the average market reaction to any of the selected events. We consider a two year estimation period with different event windows (3 days and 10 days). As explained, we form an equally weighted portfolio and estimate equation (2.2) using OLS. A two year estimation period of

January 2011 to January 2013, which encompasses the first three events, was considered to examine the average market reaction to these events. A two year estimation period of January 2013 to January 2015, which encompasses the remaining four events, is considered to examine the market reaction to the remaining four events. With respect to the portfolio of energy services companies, we had to exclude Akita Drilling Ltd. from the sample as its daily records had some missing values. Therefore, we consider the remaining 39 energy services listed in Appendix 1. Table 2.8 shows the regression estimates for the portfolio of 39 energy services companies when considering a three day event window (-1,0,+1). Table 2.9 shows the regression estimates for the portfolio of 20 leading oil producers listed in Appendix 2 when considering a two year estimation period and a three day event window (starting one day before and ending one day after the specified event date).

Table 2.8: Regression estimates of the market reaction to the events based on the portfolio of energy services companies and a three day event window (-1,0,+1)

| | E1 | E2 | E3 | E4 | E5 | E6 | E7 |
|---|---|---|---|---|---|---|---|
| estimated coefficients | 0.0004 | -0.00579 | -0.0026 | 0.00177 | 0.00320 | 0.0055 | 0.00356 |
| $t-$value | 0.10 | -1.19 | -0.55 | 0.40 | 0.72 | 1.23 | 0.80 |
| P.value | [0.921] | [0.235] | [0.583] | [0.693] | [0.473] | [0.218] | [0.426] |

Table 2.9: Regression estimates of the market reaction to the events based on the portfolio of oil producing companies and a three day event window (-1,0,+1)

| | E1 | E2 | E3 | E4 | E5 | E6 | E7 |
|---|---|---|---|---|---|---|---|
| estimated coefficients | 0.0008 | -0.0025 | -0.0079 | 0.0029 | 0.0030 | 0.0057 | -0.0023 |
| $t-$value | 0.10 | -0.30 | -0.93 | 0.44 | 0.55 | 1.04 | -0.42 |
| P.value | [0.917] | [0.763] | [0.355] | [0.659] | [0.584] | [0.299] | [0.673] |

The results presented in Table 2.8 and Table 2.9 indicate that none of the estimated average abnormal returns are significant, meaning that the events considered in this study did not have any effects on equity returns on average.

Now, we increase the event window to 10 days (-4,0,+5). Table 2.10 shows the regression estimates for the portfolio of 39 energy services companies when considering a two year estimation period and a 10 day event window. Table 2.11 shows the regression estimates for the portfolio of 20 leading oil producers listed in Appendix 2 when considering a two year estimation period and a 10 day event window.

Table 2.10: Regression estimates of the market reaction to the events based on a portfolio of energy services companies and a ten day event window (-4,0,+5)

| | E1 | E2 | E3 | E4 | E5 | E6 | E7 |
|---|---|---|---|---|---|---|---|
| estimated coefficients | 0.0075 | -0.0044 | -0.0009 | -0.001 | 0.0026 | 0.0026 | 0.0014 |
| $t-$value | 1.55 | -1.58 | -0.35 | -0.43 | 1.00 | 1.02 | 0.59 |
| P.value | 0.123 | 0.115 | 0.728 | 0.664 | 0.317 | 0.307 | 0.556 |

Table 2.11: Regression estimates of the market reaction to the events based on a portfolio of oil producing companies and a ten day event window (-4,0,+5)

| | E1 | E2 | E3 | E4 | E5 | E6 | E7 |
|---|---|---|---|---|---|---|---|
| estimated coefficients | -0.0104 | -0.0000 | -0.0073 | 0.0000 | 0.003 | 0.00178 | 0.0008 |
| $t-$value | -1.22 | -0.01 | -1.57 | 0.02 | 0.94 | 0.56 | 0.29 |
| P.value | 0.223 | 0.992 | 0.118 | 0.984 | 0.348 | 0.579 | 0.772 |

As before, our results indicate no significant average reaction to any of the selected events. As explained in Section Two, non-normality of daily stock returns has been recognized in the literature for a long time and it has been indicated that daily data in reality is heavy tailed. Therefore using traditional statistics ($t-$test), we should expect to find biased downward

$p-$values meaning that we reject the null hypothesis too frequently. However, in this study, even under these circumstances, we still could not reject the null hypothesis and all the coefficients on the dummy variables are still insignificant. Therefore, there is no need to get bootstrapped $p$-values as has been suggested in the literature (Hein and Westfall, 2004) to deal with non-normality.

## 2.6 Conclusion

Using an event study approach, we examined the impact of uncertainties over getting Alberta's oil into market on the equity prices of Canadian energy firms. We selected seven events/and or announcements that appeared in the Wall Street Journal. Weekly equity prices for the period January 2011 to March 2015, which encompasses all seven events of our interest, were collected for both energy services and oil producing companies. Employing a seemingly unrelated regressions model, and also several joint tests on both groups of energy firms, our results indicated no significant market reaction to any of the selected events. Our results did not change when we applied the same analysis on daily returns with a two year estimation period and different event windows. Therefore, our findings imply two possible scenarios: first, the selected events did not contain a significant amount of new information and had been fully anticipated by investors in the market, and second, occurrence of these events did not change investors' expectations regarding the future profitability and cash flow of Canadian energy firms; In other words, if the market agents had not already fully anticipated the events and announcements, then our results would suggest that market agents did not expect those events to have any economic consequences for the energy firms.

## 2.7 Appendix 1

Table 2.12: Panel A-Energy services companies with their descriptive statistics

| Firms | Name | Mean equity Price | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| 1 | Akita Drilling Ltd. | 11.578 | 2.559 | 8.29 | 17.05 |
| 2 | AltaGas Ltd. | 32.955 | 8.784 | 18.14 | 51.39 |
| 3 | Badger Daylighting Ltd. | 15.916 | 11.158 | 4.43 | 41.69 |
| 4 | Bri-Chem Corp | 2.375 | .9363 | .76 | 4.26 |
| 5 | Calfrac Well Services Ltd. | 13.650 | 2.766 | 8.05 | 20.79 |
| 6 | Canadian Energy Services & Technology Corp | 5.121 | 2.498 | 2.53 | 11.03 |
| 7 | Canyon Services Group Inc. | 10.864 | 2.132 | 7.03 | 19.11 |
| 8 | Cathedral Energy Services Ltd. | 4.711 | 1.202 | 2.16 | 8.13 |
| 9 | Ensign Energy Services Inc. | 14.687 | 1.848 | 8.7 | 18.89 |
| 10 | Enterprise Group ,Inc. | .4419 | .3185 | .11 | 1.15 |
| 11 | Essential Energy Services Ltd. | 2.020 | .3905 | 1.27 | 2.85 |
| 12 | Foraco International SA | 1.958 | 1.362 | .18 | 4.95 |
| 13 | GASFRAC Energy Services Inc. | 4.046 | 3.663 | .01 | 14.01 |
| 14 | Geodrill Limited | 1.59 | .9184 | .48 | 3.69 |
| 15 | Hanwei Energy Services Corp. | .1370 | .0820 | .05 | .43 |
| 16 | High Arctic Energy Services Inc. | 2.417 | 1.350 | .9 | 5.42 |
| 17 | Horizon North Logistics Inc. | 5.188 | 1.610 | 1.93 | 8.92 |
| 18 | Hyduke Energy Services Inc. | .6090 | .214 | .31 | 1.36 |
| 19 | Logan International Inc. | 5.458 | 1.396 | 3.01 | 8 |
| 20 | McCoy Global Inc. | 4.290 | 1.290 | 2.39 | 7.12 |
| 21 | Major Drilling Group International Inc. | 9.921 | 2.966 | 5.31 | 17.05 |
| 22 | Mullen Group Ltd. | 20.796 | 3.887 | 14.06 | 29.93 |
| 23 | North American Energy Partners Inc. | 5.847 | 2.408 | 2.33 | 13.21 |
| 24 | Orbit Garant Drilling Inc. | 2.997 | 1.821 | 1 | 6.19 |
| 25 | Pason Systems Inc. | 18.19 | 6.201 | 10.67 | 33.9 |
| 26 | Petrowest Corporation | .6363 | .3374 | .16 | 1.4 |
| 27 | PHX Energy Services Corp. | 9.498 | 2.426 | 5.66 | 15.92 |
| 28 | Precision Drilling Corporation | 9.996 | 2.314 | 6.08 | 15.72 |
| 29 | Pulse Seismic Inc. | 2.674 | .776 | 1.55 | 4.58 |
| 30 | Savanna Energy Services Inc. | 6.694 | 1.224 | 2.17 | 8.91 |
| 31 | Secure Energy Services Inc | 12.468 | 5.383 | 5.53 | 26.67 |
| 32 | ShawCor Ltd. | 38.425 | 8.878 | 21.59 | 58.73 |
| 33 | Strad Energy Services Ltd. | 3.633 | .5299 | 2.56 | 4.75 |
| 34 | Telsa Exploration Ltd. | 2.572 | .5022 | .85 | 3.45 |
| 35 | Total Energy Services Inc. | 16.030 | 2.907 | 11.07 | 23 |
| 36 | Trican Well Service Ltd. | 14.072 | 3.798 | 4.38 | 23.87 |
| 37 | Trinidad Drilling Ltd. | 7.612 | 1.929 | 4.22 | 12.36 |
| 38 | Western Energy Services Corp. | 7.432 | 1.314 | 4.8 | 11.16 |
| 39 | Xtreme Drilling and Coil services Corp. | 3.267 | 1.261 | 1.02 | 5.79 |
| 40 | ZCL Composites Inc. | 4.774 | 1.471 | 2.78 | 7.28 |

## 2.8 Appendix 2

Table 2.13: Panel B-Oil producers companies with their descriptive statistics

| Firms | Name | Mean equity price | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| 1 | ARC Resources Ltd. | 23.638 | 3.679 | 16.657 | 31.964 |
| 2 | Baytex Energy Inc. | 38.825 | 6.200 | 15.243 | 47.846 |
| 3 | Bonavista Energy Corporation | 14.995 | 4.120 | 5.912 | 23.332 |
| 4 | Canadian Natural Resources Ltd. | 34.801 | 5.929 | 25.051 | 48.156 |
| 5 | Cenovus Energy Inc. | 29.744 | 2.494 | 19.843 | 35.141 |
| 6 | Crescent Point Energy Corp. | 34.776 | 3.400 | 21.099 | 44.454 |
| 7 | Canadiaon Oil Sands Ltd. | 18.769 | 3.255 | 7.817 | 26.501 |
| 8 | Encana Corp. | 20.557 | 3.577 | 14.030 | 30.149 |
| 9 | Enerplus Corporation | 17.318 | 4.393 | 10.005 | 25.117 |
| 10 | Gran Tierra Energy Inc. | 6.270 | 1.317 | 2.75 | 9.16 |
| 11 | Husky Energy Inc. | 26.268 | 4.020 | 19.227 | 35.777 |
| 12 | Imperial Oil Ltd. | 45.219 | 5.008 | 35.158 | 57.422 |
| 13 | Lightstream Resources Ltd. | 7.819 | 3.148 | .76 | 15.647 |
| 14 | MEG Energy Corp. | 36.624 | 7.646 | 14.16 | 52.68 |
| 15 | Pengrowth Energy Corp. | 6.109 | 1.679 | 2.987 | 9.81 |
| 16 | Penn West Petroleum Ltd. | 10.799 | 4.260 | 1.885 | 20.427 |
| 17 | Suncor Energy Inc. | 33.853 | 4.946 | 24.431 | 45.361 |
| 18 | Talisman Energy Inc. | 11.979 | 3.132 | 4.348 | 21.571 |
| 19 | Tourmaline Oil Corp. | 36.708 | 9.713 | 19.96 | 58.33 |
| 20 | Vermilion Energy Inc. | 49.339 | 10.239 | 35.043 | 75.045 |

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# Chapter 3

# Information aggregation in a prediction market for climate outcomes

## 3.1 Introduction

A policymaker wanting to address the climate change issue faces many forms of uncertainty, of which this paper examines novel solutions to two of the most acute: uncertainty regarding marginal damages of greenhouse gases, and uncertainty over bias in the selection of information for presentation to policymakers. Uncertainty over marginal damages derives from uncertainty over Equilibrium Climate Sensitivity (ECS), or the projected long term climate response to doubling the concentration of CO2 in the atmosphere, after enough time has passed for all components of the climate system to adjust. A widely-cited survey by Roe and Baker (2007) of model-generated ECS estimates showed a range spanning 1.7—7.0 oC. Applying this distribution and a 3 percent discount rate, Integrated Assessment Models (IAMs) generate a range of marginal damage estimates spanning -\$22 to \$727 per tonne of CO2 (Inter-Agency Working Group, 2013). Hence, just based on mainstream climate and economic modeling, all we appear to be able to say is that the optimal climate policy target is somewhere between a small subsidy for CO2 emissions and an effective prohibition on fossil fuels.

Past attempts to reduce this uncertainty are reviewed in Section 2. The approach considered herein involves a temperature-indexed carbon tax (McKitrick, 2010) that, on an ex post basis, generates a price path highly correlated with the unobservable true marginal damages trajectory. Firms subject to the tax must then form expectations about its likely path and plan their investments accordingly. To facilitate expectations-formation, Hsu (2011) proposed pairing the tax with a sequential futures market for tradable certificates, each of which would exempt the holder from paying the tax on a tonne of emissions in a specified future year. He conjectured that since firms have a financial incentive to get the forecasts right, the price path thus generated would provide the most objective and unbiased forecast possible of future marginal damages and, by implication, future climate warming. We refer to the temperature-indexed pricing rule as a state-contingent carbon tax, and the trading system as a futures market for exemption permits.

If the incentives work as conjectured, the paired tax-permit system would resolve the first form of uncertainty and in the process neatly address the second. Since most damages are either projected to occur far in the future or are based on counterfactual claims about contemporary meteorological conditions, they cannot be directly measured and typically must rely on arbitrary selections from black-box model simulations (Pindyck, 2013). Policymakers therefore rely on selection by experts of forecasts or counterfactual simulations from among the wide range currently available, which raises the possibility of selection bias, since scientists will be aware that their assessments have policy implications (Lawson 2008, InterAcademy Council 2010, Johnson 2012). A prediction market that generates a state-contingent carbon tax path based on expectations among agents with a financial incentive to get their forecasts right would potentially resolve this problem by providing unbiased projections. For this to be the case, the auction price must not only be an unbiased forecast of the actual future price (and hence of the actual future climate state), but must also make efficient use of all available information.

This paper investigates the conditions under which such an outcome would hold. We study a prediction market implementing the McKitrick (2010) and Hsu (2011) state-contingent carbon tax/prediction market system using an auction model developed by Kyle (1985) and Foster and Viswanathan (1996, herein FV96). Three types of traders are assumed to participate. Risk-neutral firms subject to the emissions tax are assumed to have private access to noisy signals about the likely future climate state and hence the likely future tax rate, and to make bids for permits based on their profit-maximizing strategies. Also, an unspecified number of uninformed traders generate noise in the market by trading based on purely random signals about the future climate state rather than informative private signals. A market maker who only sees the aggregate order flow but does not observe individual bids or the number of uninformed traders clears the market in each round of bidding, thereby generating a price signal which is incorporated into information sets by traders in subsequent trading rounds. Employing a proposition due to FV96 we confirm part of the conjecture of Hsu (2011) for the case of risk-neutral traders: such a prediction market would yield an unbiased forecast of the future tax rate, and hence the state of the climate.

It is less clear that the prediction market would efficiently use all available information. An interesting result is that one's belief about the level of consensus around climate science would strongly influence one's interpretation of the market outcome. The question of the degree of consensus in climate science, and what specific points experts actually agree on, is itself controversial (Tol, 2014). We find that, even in the presence of noisy uninformed traders, the market price will converge to a sufficient statistic (in other words, an expectation that efficiently uses all available information) if, at the start of trading, private signals of informed traders are highly correlated. In other words if there really is a strong consensus on the scientific issues, so that traders seeking credible information are effectively drawing the same signals regardless of source, then the trading process we describe will yield a price path that incorporates all relevant information and no trader would be able to improve on the market price forecast using his or her private information set. Conversely, to argue that the prediction market fails to take account of all relevant information about the future path of the climate requires the assumption that there is no current consensus about climate science.

The FV96 framework assumes traders are risk-neutral. We provide a preliminary extension to their framework to include risk-averse firms. We show that risk-aversion slows down the convergence process, so the market outcome is more susceptible to the influence of uninformed traders.

The intuition for using a trading process to predict climate outcomes is based on the literature on prediction markets, which were first proposed in 1988 by researchers at the University of Iowa interested in predicting US presidential outcomes (Segol, 2012). The markets were designed based on the informational role of prices and the efficient market hypothesis suggested by Hayek (1945) and Fama (1970). Prediction markets have the ability to produce credible forecasts since markets are able to aggregate dispersed information and reveal it by incorporating it into prices in a way that gives participants an incentive to be objective in their expectations. If a trader believes a security related to a future event is underpriced, he or she has an incentive to buy more of the asset, and doing so will push up the price and bring it closer to the correct value. Therefore, the price of a tradable asset reveals the expectation of all events that may affect the value of the asset. Although market efficiency assumptions have been exposed to some critiques, especially from behavioral economists, researchers (Wolfers and Zitzewitz, 2004; Berg et. al., 2008) have shown that prediction markets perform well and generate accurate forecasts. In particular, these markets outperform polls for the longer horizons.

The paper is organized as follows. Section 2 provides the literature review on this topic. Section 3 presents the model, assumptions, and definitions. Section 4 describes the linear equilibrium of the model and its necessary and sufficient conditions. Section 5 proposes the results. Section 6 extends the existing model to include risk aversion. Conclusion briefly summarizes the findings.

## 3.2 Literature review

There is a large and growing literature in climate change focusing on pricing carbon emissions as a way of addressing the global warming externality. Using classical theory, this price should be equal to marginal social damages from emissions. However, in the context of global warming, there is significant uncertainty regarding the magnitude that greenhouse gas emissions contribute to global warming and the magnitude of the impact that global warming has on the economy. In other words, there is considerable uncertainty with respect to the magnitude of the social damages (or social costs of carbon), and hence developing the optimal policy has proved to be challenging.

Nordhaus (1991, 1993a,b) introduced a dynamic integrated model of climate science and economics (DICE) to help understand the mechanisms connecting $CO_2$ emissions, atmospheric concentration, changes in temperature and changes in output and consumption and their effects on welfare. Using an optimal growth model, and given some parameter values and critical assumptions, they found the optimal path for emission abatement and the associated carbon tax. Ever since, many Integrated Assessment Models (IAMs) have been developed. However, the major problem with them is the assumption that all the key parameters in the model are known. In fact, different parameter values or functional forms would result in very different estimates of social costs and consequently different optimal abatement policies, which make these models almost useless as policy tools (Pindyck, 2015). In addition, in the context of global warming, it would be expected that uncertainty would be diminished over time; therefore, models which try to identify the optimal policy path should take into account new information to be released overtime to update the optimal policy. However, IAMs fail to account for new information, in that once the optimal policy path given critical parameter values and functional forms are identified, the path is set permanently without any updates.

To consider the effect of uncertainties, Kelly and Kolstad (1999) incorporated Bayesian learning about the relationship between temperature changes and greenhouse gas levels in to the existing DICE model. In their model, there is a social planner who chooses the optimal amount of emission control based on prior beliefs regarding the relationship. Then, based on an observed temperature realization, beliefs are updated and actions are adjusted. The main result of their model was that it would take between 90 and 160 years for the uncertainty to resolve sufficiently to reject an incorrect parameter value. In other words, it takes 90 to 160 years till we realize whether the chosen policy was correct or not. Leach (2007) characterized the same model but he added a second source of uncertainty, which was uncertainty over persistence of temperature changes. He found that it can take several hundred to several thousand years until uncertainty is resolved sufficiently to reject an incorrect policy stance.

McKitrick (2011), as mentioned, proposed a novel idea, called the state-contingent pricing rule, to overcome the inherent uncertainties. He proposed a pricing rule that ties the emissions tax linearly to an observed measure of the climate state, namely average temperature. Using this approach, prices are continually updated automatically, exploiting the arrival of new information, and emitters must therefore form expectations about the future tax path. This approach also could address the uncertainty over the severity of climate change. If global warming turns out to be rapid, then taxes on emissions will go up rapidly. However, if it does not happen, the taxes will not go up. Since agents affected by the policy will have to act based on expectations, they will need to base forward-looking investments on forecasts of climate outcomes. In addition, this policy has a higher chance of getting implemented compared to other instruments being proposed because different parties with divergent views on climate change would each expect to get their preferred outcome in the future.

However, since investment plans are based on expected future tax liabilities and future prices, investors would not know their future tax liabilities. Therefore, it would be essential to create a way of getting accurate and credible information for forecasting future liabilities and prices.

Hsu (2011) proposed the idea of integrating the state-contingent pricing rule with a market for permits that exempt holders from paying the tax in a future period. This would both regulate emissions optimally and get credible information about future tax rates. The idea of using the prediction market, where emitters can buy a permit to cover future tax liabilities, would motivate buyers to seek information and reveal that information when trading permits over time. Therefore, permit prices could provide the best possible forecasts regarding future tax rates, as long as the trading process yields objective, unbiased price expectations. This, in turn, would yield unbiased forecasts of the future temperature path. Our model herein focuses on this question and characterizes the properties of prices in trading outcomes.

## 3.3 The model

Following McKitrick (2011), at a future date $T$, a state variable $s_T$, which is a non-manipulable measure of the climate state,[1] will be revealed. Based on this observation, the policy maker will impose a tax rate $\tau_T(s_T)$. $\tau_T(s_T)$ is unique, so $s_T \Rightarrow \tau_T$ and vice versa. Following Hsu (2011), instead of paying the tax in year $T$, firms have the option to submit emission permits that they already purchased in previous years over multiple auctions. Each permit allows a one tonne exemption from paying the tax, so a firm can either pay the tax on each tonne of emissions or submit a permit. We assume permits dated for one vintage $T$ can not be banked for use in another year. Therefore, the spot price of a permit $p_T$ in future year $T$ must equal the tax rate, so $p_T = \tau_T(s_T)^2$. Since the functional form of $\tau_T$ is known, the permit price also reveals $s_T$.

[1] McKitrick proposes the mean temperature of tropical troposphere as measured by weather satellites as the state variable.

[2] Since $\tau_T$ is a linear and known function of $s_T$, trading in contracts for the future carbon tax would yield the same finding as trading in contracts for the future global temperature.

Now at current time $t$ consider a market for tradable permits for vintage year $T$. We assume there are three types of traders in this market who will trade a specific permit over $h = 1, 2, ..., k$ auction rounds. First, there are $M$ risk-neutral traders who possess disparate private information about the true climatic state in period $T$, and then about the true price of a permit. Each trader's initial private information is denoted $g_{i0}(T)$ where $i = 1, 2, ..., M$. The private signal can consist both of publicly-available information and privately acquired information. Second, there are several uninformed traders who do not possess any private information and trade as a single entity in this market. This means that a single aggregate bid emerges from this group. The assumption that uninformed traders are present allows the results to be robust to the possible presence of agents who act on signals that have no valid informational content. As we will discuss below, the assumption is also necessary to avoid the Grossman-Stiglitz (1980) paradox that, if only informed traders are present in a market, information will not actually be collected and used. Third, there is a set of risk-neutral market makers who can be considered as large private financial institutions whose role is to clear the market at zero expected profit. The market makers are responsible for facilitating trades in this market.

At the beginning of the first auction round ($h = 1$), $M$ informed traders receive different noisy signals regarding the true state variable in a future date $T$. They each form different expectations about the future price, $\hat{p}_{iT}$. Then, informed traders and uninformed traders simultaneously choose the number of permits they want to buy and submit their quantities (market orders) to the market makers. We show the informed traders' market orders and the uninformed traders' aggregate market order as $q_{ih}(\hat{p}_{iT})$ and $u_{Th}$ respectively. Since we are only considering a single vintage period $T$, wherever the $T$ subscript is not needed we will suppress it for clarity. At this stage, when choosing their permit quantity, the only information informed traders have is their initial signals, so their information set is $\Omega_{ih}(g_{i0})$. Market makers observe the aggregate quantities ($y_h = \sum_{i=1}^{M} q_{ih} + u_h$) without seeing individual orders separately, and they set a price determined by a competitive process that yields zero expected profits for the market makers, implying that it becomes equal to $E[p_T|y_h]$.[3] Everyone observes the price and the total quantities traded. Next, market makers trade a quantity $m_h$ that clears the market, meaning that $m_h = -y_h$.

In the subsequent auctions, informed traders will trade based on their initial signals and what they learn by observing previous rounds[4]. In other words, their information set consists of their initial signals, past prices, past market orders, and past quantities traded by themselves, which we write as $\Omega_i(g_{i0}, p_{-h}, y_{-h}, q_{i,-h})$, where $-h$ denotes all previous rounds. Market makers do not observe the individual quantities; when they receive the aggregate quantities, they update their beliefs regarding their estimate of $p_T$ and set the price accordingly. Hence, their information set consists of the current and past aggregate order flows and also past prices, $\Omega_{MM}(y_h, y_{-h}, p_{-h})$. The process of trading goes for $k$ rounds where $k$ is some finite, large number. At this point when considering the trading process for the vintage year $T$, we ignore information spillovers that might exist from climatic prediction markets for other vintages. However, this information can be considered part of the publicly-available information used by traders and therefore would not have any effect on our model.

In this set-up, we have taken into account strategic behavior of the informed traders given their private information, meaning that they are not price takers and they consider the effects of their actions on the price and informational content of the price when choosing their actions. Since we have a finite number of traders participating in this market, the assumption of price taking behaviour is not reasonable. For instance, if information is costly to obtain, there might be some big energy firms in this market, such as the American Electric Power Company (AEP) that may be able to invest sufficient amounts to acquire exclusive information, which would lead them to not behave as a price taker.

The described set up is a trading environment applied in well-known financial markets such as the New York Stock Exchange (NYSE) and Tokyo Stock Exchange. The most close

[3] The market maker's expected profit is $E(\pi) = -y_k\ (E(p_T) - p_k)$, *where* $k$ refers to the last round of the auctions. Therefore at each auction round $h$ where $h \neq k$, a price equal to the expected value of a permit given the observed order flow, $p_h = E(p_T|y_h)$, would yield zero expected profits for market makers.

[4] Buying permits on a future market helps investors hedge against costs of future climate policy.

application of this set up is the NYSE call auction opening where market makers indicate a price range, traders submit their market orders, and at last market makers adjust the initial prices.

In this description, choosing the number of permits to make available for a vintage year $T$ is a critical matter. The number of available permits should be large enough to create a real market so that traders would have enough incentive to obtain information and engage trading. However, the quantity of permits can not be so large as to exceed the emission level associated with the tax that period. The excessive amount of permits would drive prices down below the tax rate, causing the whole hybrid process to fail (Hsu, 2011). In order to avoid generating too many permits, we first need to have an estimate of the emission level in a future year $T, e_T$. To find an estimate of $e_T$, we should take into account potential future policies and advances that might cause future emission reduction. Next, we set the number of available permits to be only a fraction of $e_T$. This way, the number of available permits always remains lower than the expected level of emissions, which eliminates the possibility that permits become too abundant. As a result, the price path of a permit can generate the expectation of future tax rates.

In this model, inclusion of an appropriate discount rate in weighting future profits will not change the result. In the case of having long-term prediction market, we expect traders to predict and discount their future tax liability, so that the price of a permit reveals the discounted expected liability.

Following FV96, we assume that the price of a permit for future year $T$ is a random variable with normal distribution with known mean $\rho(T)$ and variance $\Sigma(T)$, so $p_T \sim N(\rho, \Sigma)$. The "true" price of a permit is a realization of the random variable $p_T$ that is fixed and unknown to all the traders prior to $T$, however, informed traders observe a noisy signal regarding this true value.

We assume that the signal vector about the true price of a permit $g = [g_{10}, g_{20}, ..., g_{M0}]$, received by $M$ informed traders, is drawn from a multivariate normal distribution with variance-covariance matrix $\Psi_0$ and zero means. The form of all distributions, including $p_T$, is known to all traders in this prediction market. We assume that all signals have the same initial variance $\Lambda_0$, the initial covariance $\Omega_0$ between any two signals is the same, and the cross covariance with the true price of the permit $c_0$ is the same for all signals. As shown in the Appendix, these three assumptions imply:

$$E(p_T|g_{10}, g_{20,}...., g_{M0}) = \rho + \theta\bar{g} \tag{3.1}$$

Where $\bar{g}$ is the average signal and $\theta$ is a constant. This means that a constant multiple of the average signal, $\theta\bar{g}$, is a sufficient statistic for all the information known by traders (all the signals) to predict $p_T$. In other words, $\theta\bar{g}$ uses all the available information (all the signals), and knowing any other functions of $g_{10}, g_{20,}...., g_{M0}$ will not improve the estimate of $p_T$. As mentioned before, the normal distribution of random variable $p_T$ with mean $\rho$ and variance $\Sigma$ is known to all participants. Therefore, all that is needed to predict $p_T$ is $\theta\bar{g}$. In fact, knowing $\theta\bar{g}$ would provide us with the best estimate regarding the true value of the permit $p_T$ as it is a sufficient statistic for all the available information. This assumption simplifies the complex model and will be used in the following discussion.

It is noteworthy to clarify the model using a numerical example. Suppose in 2016, an auction is held for year 2020 permits. $P_{2020}$ is a draw form $N$ (25,50), where $\rho$ equals 25 and $\Sigma$ equals 50. This information is common knowledge. The actual $P_{2020}$ will be 25+ $\varepsilon$. No one knows the actual $P_{2020}$, however, informed traders have private signals about $\varepsilon$. Therefore, informed traders using their signals, will have different expectations regarding $P_{2020}$, such as 20, 22, 25, 27, 29. Now, suppose that a price $p_k$ emerges from an auction:

If both $p_k$ and $\rho + \theta\bar{g}$ equal a same amount, for instance \$25.50, then the emerged price is a sufficient statistic for all the available information (or equivalently used all the available information).

If $\rho + \theta\bar{g} = 25.50$ but $p_k \neq \rho + \theta\bar{g}$ and equals for instance to 25.80, then the auction price has not used all the available information. What we will show is :

Both $p_k = 25.50$ and $p_k = 25.80$ are unbiased forecasts of $P_{2020}$ given the order flow. The difference between these two prices reflects how much of their private signals firms choose to reveal through trading activity. By looking at the price $p_k$, there is no way to know whether it is a sufficient statistic. This is a property that can be inferred based on structure of information, namely correlation of signals (this will be discussed in section 5).

Uninformed traders submit a quantity $u_h$ at round $h$ that has a normal distribution with mean zero and variance $\sigma_u^2$. We assume uninformed traders' order $u_h$ to be independent of all the other random variables. They have no private information and nothing can be learned about $p_T$ from their actions during the trading process.

The $i^{th}$ informed trader, given his private information and what he learns from past prices, submits a quantity $q_{ih}$ at round $h$. Market makers observe the aggregate quantity $y_h$ submitted by both informed and uninformed traders, update their beliefs regarding the initial signals using $\overset{\wedge}{g}_{ih} = E[g_{i0}|y_1, ..., y_h]$,[5] and set the competitive price at period $h$ using $p_{hT} = E[p_T|y_1, ..., y_h]$, meaning that market makers earn zero profits on average, by assumption.

In this market, information gets fully aggregated if the market price contains information from all market traders so that each informed trader finds his own private information $g_{ih}$ redundant. In other words, private information gets fully aggregated if a round $h$ occurs in which:

$$p_{hT} = E[p_T|y_1, ..., y_h] = E(p_T|g_{10}, g_{20,}...., g_{M0}) = \rho + \theta\bar{g} \tag{3.2}$$

Therefore, if price becomes equal to $\rho+\theta\bar{g}$, it becomes a perfect aggregator of information and consequently an ideal estimate of $p_T$. In this case, price contains all the available

[5] Market makers need to update their estimate regarding initial signals so that they can have a better estimate of the true price of a permit $p_T$. In particular, price, which is the market makers' updated estimate of $p_T$ given their observed order flow, is related to the market makers' estimate of signals in the following way (FV96)

$p_{hT} = \frac{\theta}{M} \sum_{i=1}^{M} \overset{\wedge}{g}_{ih}$

information and becomes fully revealing, without containing any error in predicting $p_T$.[6] Note that traders do not necessarily know if the observed price $p_{hT}$ satisfies (2) or not. They only observe the price in this market, not the underlying "true" price $\rho + \theta\bar{g}$. As a result, the magnitude by which the price at an auction, which is also an estimate of $p_T$, differs from $\rho + \theta\bar{g}$, shows the level of price noise, and is of interest in this paper. We define the noise $\Sigma_h$ as following:

$$\Sigma_h = Var(\rho + \theta\bar{g} - p_{hT}) \tag{3.3}$$

$\Sigma_h$ measures the magnitude of noise at round $h$ in a price system when conveying information regarding the expected price of the permit. In other words, it measures price informativeness at each round $h$ in the climate prediction market. If $\Sigma_h$ equals zero, that would mean that price at round $h$ has become exactly equal to $\rho + \theta\bar{g}$, meaning that all the information has been aggregated and incorporated into the price. In other words, the auction price is an unbiased estimate of the true value $p_T$, though it contains some noise and the magnitude of this noise shows the extent to which prices become informative in this market.[7]

After $h$ rounds market makers observe $(y_1, ..., y_h)$ and learn about private signals, so at round $h$, the informed player $i^{th}$ has an informational advantage relative to market makers that is equal to:

$$g_{ih} = g_{i0} - E[g_{i0}|y_1, ..., y_h] \tag{3.4}$$

FV96 also define the following variance covariances in order to measure the remaining information :

$$\Lambda_h = Var(g_{i0}, g_{j0}|y_1, ..., y_h) = Var(g_{ih}, g_{jh}) \tag{3.5}$$

[6] In particular, we assume that the ideal estimate of $p_T$, $\rho + \theta\bar{g}$, is indeed equal to $p_T$.

[7] FV96 assumed $\rho$ to be equal to zero so that they defined $\Sigma_h$ as the variance of $(\theta\bar{g} - p_{hT})$.

$$\Omega_h = Cov(g_{i0}, g_{j0}|y_1, ..., y_h) = Cov(g_{ih}, g_{jh}) \tag{3.6}$$

## 3.4 The Equilibrium

We have used the FV96 and Kyle (1985) auction model to characterize a permits trading system that would implement the Hsu (2011) exemption certificate proposal. Now we need to characterize the equilibrium that emerges and explore the properties of the resulting prices as they relate to the question of whether such a market would yield valid climate forecasts. Following Kyle (1985) and FV96, a Bayesian Nash equilibrium exists if there is a vector of of strategies $(q_1, q_2, ..., q_M, p)$ such that:

1. For each trading round $h = 1, 2, ..., k$ and for every informed trader $i$, $i = 1, 2, ..., M$, an alternative strategy $q_i^{'} = (q_{i1}^{'}, q_{i2}^{'}, ..., q_{ih}^{'})$ would result in a lower or equal expected profit for firm $i$ given his information set, the pricing rule, and strategies of the other informed traders :

$$E(\pi_h(q_1, q_2, ..., q_i^{'} ..., q_M, p)|g_{i0}, q_{i,-h}, y_{-h}) \leq \tag{3.7}$$

$$E(\pi_h(q_1, q_2, ..., q_i ..., q_M, p)|g_{i0,} q_{i,-h}, y_{-h})$$

*i.e.* The optimal strategy of trader $i$ at period $h$ should be best no matter what strategies he played in previous periods

2. Price at round $h = 1, 2, ..., k$ becomes equal to the expected value of the permit given the observed order flow up to $h$, and given the strategies of the informed traders.

$$p_{hT} = E[p_T|y_1, y_2, ..., y_h] \ for \ h = 1, 2, ..., k \tag{3.8}$$

This is a market efficiency condition that makes price become an unbiased estimate of the future price and hence future tax rate. This condition can be viewed as a result of a Bertrand auction among at least two risk-neutral market makers who can observe only the total quantities in the market. The Bertrand auction would result in a price which yields zero profits for market makers, indicating that price becomes equal to the permit's expected value.

FV96 used dynamic programming and backward induction to characterize a linear equilibrium in this setting. Proposition 1 restates their result in the context of the application developed herein, showing the existence of an equilibrium.

Proposition 1

There exists a recursive linear Markov equilibrium that satisfies conditions 1 and 2. The equilibrium occurs where all informed traders $i = 1, 2, ..., M$ submit bids of the form $q_{ih} = \beta_h g_{ih}$ for all trading periods $h = 1, 2, ..., k$, and prices become equal to $p_h = p_{h-1} + \lambda_h y_h$, where the parameters $\beta_h$ and $\lambda_h$ are defined as follows:

$$\beta_h = \frac{\eta_h - \lambda_h \Psi_h}{\lambda_h [1 + (1 + \phi_h(M-1))(1 - ((\lambda_h \Psi_h / \theta))]}$$

$$\gamma_h = \frac{(1 - 2\mu_h \lambda_h)(1 - (\lambda_h \beta_h (M-1)/\theta))}{2\lambda_h(1 - \mu_h \lambda_h)}$$

$$\alpha_{h-1} = (\eta_h - \lambda_h \beta_h [1 + (M-1)\phi_h])\beta_h + \alpha_h \left[1 - \frac{\lambda_h \beta_h}{\theta}[1 + (M-1)\phi_h]\right]^2$$

$$\begin{aligned} \Psi_{h-1} \quad = \quad & (\eta_h - \lambda_h \beta_h [1 + (M-1)\phi_h])\gamma_h - \lambda_h \gamma_h \beta_h + \beta_h (1 - \frac{\lambda_h \beta_h (M-1)}{\theta}) \\ & + \Psi_h \left(1 - \frac{\lambda_h \beta_h}{\theta}[1 + (M-1)\phi_h]\right)\left(1 - \frac{\lambda_h \beta_h (M-1)}{\theta} - \lambda_h y_h\right) \end{aligned}$$

$$\mu_{h-1} = -\lambda_h \gamma_h^2 + \gamma_h \left(1 - \frac{\lambda_h \beta_h (M-1)}{\theta}\right) + \mu_h \left(1 - \frac{\lambda_h \beta_h (M-1)}{\theta} - \lambda_h \gamma_h\right)^2$$

$$\begin{aligned} \delta_{h-1} &= \delta_h + \frac{\alpha_h \lambda_h^2}{\theta^2} \sigma_u^2 + \alpha_h \frac{\beta_h^2 \lambda_h^2}{\theta^2} [(M-1) Var(g_{jh-1} | g_{i0}, y_1, ..., y_{h-1}) \\ &\quad + \alpha_h \frac{\beta_h^2 \lambda_h^2}{\theta^2} [[(M-1)(M-1)] Cov(g_{jh-1}, g_{rn-1} | g_{i0}, y_1, ..., y_{h-1})] \end{aligned}$$

$$Var(g_{jh-1} | g_{i0}, y_1, ..., y_{h-1}) = \frac{\Lambda_{h-1}^2 - \Omega_{h-1}^2}{\Lambda_{h-1}}$$

$$Cov(g_{jn-1}, g_{rh-1} | g_{i0}, y_1, ..., y_{h-1}) = \frac{\Omega_{h-1}(\Lambda_{h-1} - \Omega_{h-1})}{\Lambda_{h-1}}$$

$$\phi_h = \frac{\Omega_{h-1}}{\Lambda_{h-1}}$$

$$\eta_h = \frac{\theta}{M} [1 + (M-1)\phi_h]$$

$$\Sigma_h = (1 - \frac{M \lambda_h \beta_h}{\theta}) \Sigma_{n-1}$$

$$\Lambda_h = \Lambda_{h-1} - \frac{M}{\theta^2} \frac{\lambda_h \beta_h}{\theta} \Sigma_{h-1}$$

$$\Omega_h = \Omega_{h-1} - \frac{M}{\theta^2} \frac{\lambda_h \beta_h}{\theta} \Sigma_{h-1}$$

Where $\alpha_h = \Psi_h = \mu_h = \delta_h = 0$

A second order condition ensuring that the informed traders' utility is maximized also holds :

$$\lambda_h(1 - \mu_h \lambda_h) > 0$$

Proof: see proof of proposition 1, FV96 Appendix

The stated conditions are the necessary and sufficient conditions for the Markov equilibrium to hold. The stated recursions were solved numerically in FV96 using a backward induction algorithm and the equilibrium parameters were calculated for different correlation structures between the initial signals.

Before proceeding to the next section, it is worth clarifying the role of uninformed traders in this model. As stated in the above equilibrium, prices are a linear function of the order flows and become equal to:

$$p_h = p_{h-1} + \lambda_h y_h \tag{3.9}$$

Considering $h$ to be equal to one, we will have:

$$p_1 = p_0 + \lambda_1 y_1 = \rho + \lambda_1 (\sum_{i=1}^{M} \beta_1 g_{i1} + u_1) \tag{3.10}$$

$\Longrightarrow$

$$p_1 = \rho + \lambda_1 (\beta_1 M \frac{\sum_{i=1}^{M} g_{i1}}{M} + u_1) \tag{3.11}$$

$\Longrightarrow$

$$p_1 = \rho + \lambda_1 (\theta \bar{g} + u_1) \tag{3.12}$$

Therefore, in the equilibrium, as stated before and can be seen from equation (3.12), price is a noisy signal of $\theta \bar{g}$ - a sufficient statistic for all the available information- and the source of the noise is coming from the uninformed traders' market order, $u_1$. More specifically, uninformed traders in this model act as a camouflage for informed traders' information and help informed traders hide their information from market makers when trading with them. If we remove uninformed traders from the model, the price becomes fully revealing as it incorporates and reveals all the available information. In other words, removing uninformed traders from the model implies that prices in financial markets always reveal all the available information perfectly. This would create a paradox pointed out by Grossman and Stiglitz in 1980. When the equilibrium price is always a perfect aggregator of information, no traders would have any incentive to collect costly information as they know they can not earn a return on their information gathering. Therefore, no one would gather information on which prices are based.

## 3.5 Results

In this section, we present four properties of the market outcome that emerge from the analysis of the Bayesian Nash trading equilibrium.

*1. The auction price* $p_{kT}$=$E[p_T|y_1, y_2, ..., y_k]$, *is an unbiased estimate of the true future price* $p_T$ and hence of $s_T$.

The unbiasedness of the price holds because:

$$E(p_{kT}) = E[E[p_T|y_1, y_2, ..., y_k]] = E[p_T] \tag{3.13}$$

Therefore, the unbiasedness condition $E(p_{kT} - p_T) = 0$ holds. In any specific outcome, prices are not necessarily equal to the true value, because they contain some noise, but the average of the existing noise is equal to zero.

*2. The stronger the scientific "consensus" about global warming, the more accurate will be the auction price signals.*

More formally, the higher the correlation of signals among traders, the closer the auction price gets to $\rho+\theta\bar{g}$, meaning it is a sufficient statistic, or one that uses all available information efficiently.

This was demonstrated by FV96 through numerical simulations of the equilibrium conditions. FV96 considered the case of four auctions (k=4) and three informed traders (M=3) in order to solve the model. They fixed the total available information and examined four different information structures among traders. Specifically, they considered four cases for the initial correlation among signals: very high positive (0.9999), which corresponds to identical information, low positive (0.1818), zero, and low negative (-0.2857). The evolution of $\Sigma$, which is the variance of the noise in this market, was computed for the four different cases. Figure 1 is taken form FV96. It shows how $\Sigma$ changes, or in other words how informative prices become, after four auctions under different signal structures.

As Figure 1 shows, the higher the initial correlation, the lower the terminal variance and therefore the higher the price informativeness. The amount of reduction in sigma is very dramatic when traders have identical information, indicating that most of the information gets released after running only four rounds. But even when there is no initial agreement ($corr = 0$) the variance falls by more than half after four rounds. Results from Figure 1 imply that traders with almost identical information in the prediction market would face more competition and trade more intensely in early rounds, causing more information to get released. However, traders with more heterogenous information face less competition because part of their information is unique and gives them some monopoly power. As a result, they have less incentive to trade aggressively in early auctions, causing less information to get released over four auctions. The least amount of information gets released in the negative correlation case. The intuition is that with negatively correlated beliefs, each trader believes that the action of other traders will pull the price in the wrong direction. Therefore, each trader has a tendency to wait and let others trade larger quantities to amplify the mispricing. As a result, all informed traders will trade small quantities in early periods with the hope of trading larger quantities and earning greater profits in future periods. In other words, the more heterogenous information they have, the more likely they are to wait in early periods.

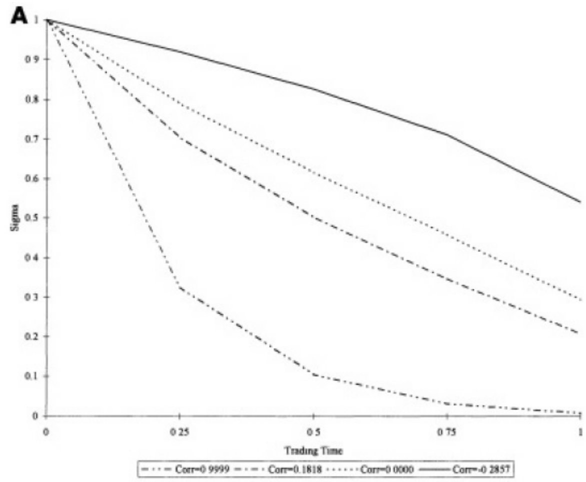


Figure 3.1: Evolution of sigma with 4 periods (Source: FV96)

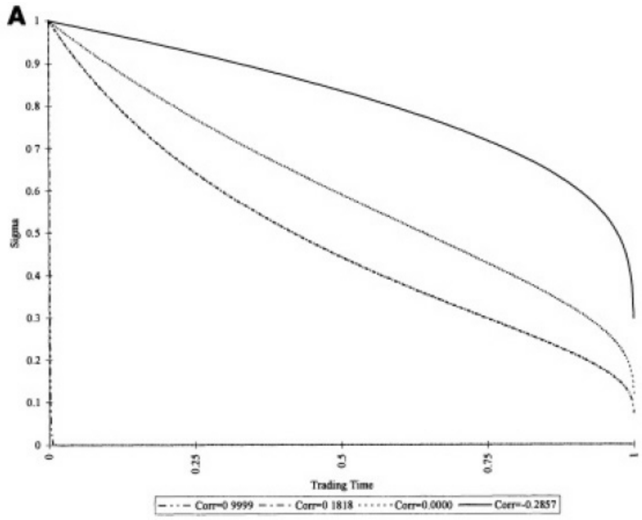


Figure 3.2: Evolution of sigma with 800 periods (Source: FV96)

*4. An auction price $p_{kT}$ is a sufficient statistic (equation 3.1 holds) for $p_T$ only when informed traders have almost identical private information regarding the state variable.*

It was shown before that $\theta\bar{g}$ is a sufficient statistic for the available information to predict $p_T$ (equation 3.1). In other words, $\theta\bar{g}$ contains all the information about $p_T$ ; once $\theta\bar{g}$ is known, no further information can be gained on $p_T$ by knowing any individual signals, $g_1, g_2, ..., g_M$. Therefore, an auction price $p_{kT}$ becomes a sufficient statistic for $p_T$ when it becomes equal to $\rho + \theta\bar{g}$. As was shown in Figures 1 and 2, $p_{kT}$ becomes equal to $\rho + \theta\bar{g}$ or equivalently the level of noise becomes equal to zero even after only 4 trading rounds when informed traders had almost identical information in the market. But with weaker correlation signals, $\sum$ converges to zero but it remains still positive even after running 800 auctions. This means that repeated trading rounds may not compensate for information heterogeneity if prior beliefs are sufficiently uncorrelated.

In summary, the climate prediction market we have described for a future period $T$ yields an unbiased estimate of the true future price, and hence of the climate state. Also, the level of consensus about climate science strongly influence the effectiveness of the market. The higher the level of consensus, or the higher the correlation of information signals prior to trading, the more accurate the price forecast is after trading. Adding more rounds of trading helps increase the accuracy of prices even when signals are uncorrelated. Finally, the auction price becomes a sufficient statistic, meaning that it uses all the available information, only when there is a very high level of consensus about the future climate state. Put another way, the argument that the price emerging from the permits auction systematically ignores important information about the future climate relies on the assumption that there is no scientific consensus. Belief in the existence of a strong consensus on climate science implies that the price emerging from the market we have described would be as accurate as possible, because it uses all available information.

## 3.6 Extension to risk averse firms

The previous results rely on the assumption that traders are risk-neutral. Here I extend the framework by considering $M$ informed agents who possess different private information and who are risk averse, using the following CARA (constant absolute risk aversion) utility functions with "$A$" as a risk aversion coefficient:

$$U(W_{N+1}) = -e(-AW_{N+1})$$

where $W_{N+1}$ represents terminal wealth. The following proposition establishes the existence of a trading equilibrium in this case.

Proposition 2

There is an equilibrium where informed traders submit the optimal order $q_i$ that is a linear function of initial signals and is given by:

$$q_i = \beta g_{i0}$$

and the price is set according to the following linear rule:

$$p = \chi(\sum_{i=1}^{M} q_i + u) = \lambda y$$

where $\beta$ and $\lambda$ are given by:

$$\beta = \frac{\eta}{2\lambda + \phi\lambda(M-1) + A\vartheta}$$

$$\lambda = \frac{\frac{\beta M}{\theta}\sum_0}{(\frac{\beta M}{\theta})^2\sum_0 + \sigma_u^2}$$

Proof.

The $i^{th}$ informed trader maximizes his expected utility given his initial signal and given the assumption that other traders follow their optimal strategies. Therefore, at round $h = 0$, he solves the following problem:

$$\underset{q_i}{Max} E\left[-e(-AW_1) \mid g_{i0}\right] = -E\left[e(-AW_0 - Aq_i(p_T - p)) \mid g_{i0}\right] = \tag{3.14}$$

$$-e^{-AW_0} E\left[e(p_T - \lambda q_i - \lambda \sum_{i \neq j} q_j - \lambda u)(-Aq_i) \mid g_{i0}\right]$$

given that $p = \lambda(\sum_{i=1}^{M} q_i + u)$ and $\sum_{i \neq j} q_j = \beta g_{j0}$

We assume that all informed traders have the same initial wealth $W_0$. Using the Linear-Normal-Exponential model properties, we will have the following :

$$E\left[e(p_T - \lambda q_i - \lambda \sum_{i \neq j} q_j - \lambda u)(-Aq_i) \mid g_{i0}\right] = \tag{3.15}$$

$$e^{E\left[(p_T - \lambda q_i - \lambda \sum_{i \neq j} q_j - \lambda u)(-Aq_i) | g_{i0}\right] + \frac{1}{2} Var\left[(p_T - \lambda q_i - \lambda \sum_{i \neq j} q_j - \lambda u)(-Aq_i) | g_{i0}\right]}$$

Therefore maximizing (3.14) is equivalent to maximizing :

$$E\left[(p_T - \lambda q_i - \lambda \sum_{i \neq j} q_j - \lambda u)(-Aq_i) \mid g_{i0}\right] + \frac{1}{2} Var\left[(p_T - \lambda q_i - \lambda \sum_{i \neq j} q_j - \lambda u)(-Aq_i) \mid g_{i0}\right] \tag{3.16}$$

Since the expression in (3.16) is a monotone increasing transformation of the expression in (3.15).

From (3.16):

$$E\left[(p_T-\lambda q_i-\lambda\sum_{i\neq j}q_j-\lambda u)(-Aq_i)\mid g_{i0}\right]=-Aq_i\left\{E\left[p_T\mid g_{i0}\right]-\lambda q_i-\lambda\sum_{i\neq j}E\left[\beta g_{j0}\mid g_{i0}\right]\right\} \tag{3.17}$$

Multivariate normality implies that both $E\left[p_T\mid g_{i0}\right]$ and $E\left[g_{j0}\mid g_{i0}\right]$ are linear in $g_{i0}$, therefore (3.17) becomes equal to :

$$-Aq_i[\eta g_{i0}-\lambda q_i-\lambda\beta(M-1)\varphi g_{i0}]$$

where

$$\eta=\frac{Cov(p_T,g_{i0})}{Var(g_{i0})}=\frac{Cov(\theta\bar{g},g_{i0})}{Var(g_{i0})}=\frac{\theta Cov(\frac{\Sigma g_{i0}}{M},g_{i0})}{Var(g_{i0})}=\frac{\frac{\theta}{M}\left[\Lambda_0+(M-1)\Omega_0\right]}{\Lambda_0}=\frac{\theta}{M}\left[1+\frac{(M-1)\Omega_0}{\Lambda_0}\right]$$

and

$$\varphi=\frac{Cov(g_{j0},g_{i0})}{Var(g_{i0})}=\frac{\Omega_0}{\Lambda_0}$$

and

$$Var\left[(p_T-\lambda q_i-\lambda\sum_{i\neq j}q_j-\lambda u_i)(-Aq_i)\mid g_{i0}\right]=A^2q_i^2\left[Var(p_T\mid g_{i0})+\lambda^2\beta^2Var(\sum_{i\neq j}g_{j0}\mid g_{i0})+\lambda^2\sigma_u^2\right]=A^2q_i^2\vartheta$$

where

$$\vartheta=\left[Var(p_T\mid g_{i0})+\lambda^2\beta^2Var(\sum_{i\neq j}g_{j0}\mid g_{i0})+\lambda^2\sigma_u^2\right]$$

Therefore, the $i^{th}$ informed player's problem is to maximize

$$-Aq_i[\eta g_{i0} - \lambda q_i - \lambda\beta(M-1)\varphi g_{i0}] + \frac{1}{2}A^2 q_i^2 \vartheta$$

with respect to $q_i$.

*FOC.*

$$-A\left[\eta g_{i0} - \lambda q_i - \lambda\beta(M-1)\varphi g_{i0}\right] + (-\lambda)(-Aq_i) + A^2\vartheta q_i = 0$$

$$q_i(2A\lambda + A^2\vartheta) = A\eta g_{i0} - A\lambda\beta(M-1)\varphi g_{i0}$$

$$q_i = \frac{\eta - \lambda\beta(M-1)\varphi}{2\lambda + A\vartheta} g_{i0}$$

Therefore $q_i$ is a linear function of the initial signal and $\beta$ is given by:

$$\beta = \frac{\eta}{2\lambda + \phi\lambda(M-1) + A\vartheta}$$

Now with respect to the price:

$$p = E\left[p_T \mid y\right] = E\left[p_T \mid \sum_{i=1}^{M} q_i + u\right] = E[p_T \mid \sum_{i=1}^{M} \beta g_{i0} + u] = \lambda y$$

As both $p_T$ and $y$ ($y = \sum_{i=1}^{M} \beta g_{i0} + u$) are normally distributed, $E\left[p_T \mid y\right]$ becomes linear in $y$ and $\lambda$ is given by:

$$\lambda = \frac{Cov(p_T, y)}{Var(y)}$$

Where $y = \sum_{i=1}^{M} \beta g_{i0} + u = \beta M \left( \frac{\sum_{i=1}^{M} g_{i0}}{M} \right) + u = \frac{\beta M}{\theta}(\bar{g}\theta) + u$

$\Longrightarrow$

$$\lambda = \frac{Cov(p_T, \frac{\beta M}{\theta}(\bar{g}\theta) + u)}{Var(\frac{\beta M}{\theta}(\bar{g}\theta) + u)} = \frac{Cov(\bar{g}\theta, \frac{\beta M}{\theta}(\bar{g}\theta) + u)}{Var(\frac{\beta M}{\theta}(\bar{g}\theta) + u)} = \frac{\frac{\beta M}{\theta} Var(\bar{g}\theta)}{(\frac{\beta M}{\theta})^2 Var(\bar{g}\theta) + Var(u)} = \frac{\frac{\beta M}{\theta}\sum_0}{(\frac{\beta M}{\theta})^2 \sum_0 + \sigma_u^2}$$

This completes the proof.

To check how informative prices become after only having one auction, we need to find $\sum_1$ which is equal to $Var(p_T \mid y)$ by definition.

$$\Sigma_1 = Var(p_T \mid y) = Var(\theta\bar{g} \mid y) = \Sigma_0(1 - corr^2_{\theta\bar{g},y}) =$$

$$\Sigma_0\left(1 - \frac{Cov(\theta\bar{g}, y)^2}{var(\theta\bar{g})var(y)}\right) = \Sigma_0\left(1 - \frac{Cov(\bar{g}\theta, \frac{\beta M}{\theta}(\bar{g}\theta) + u)^2}{\sum_0 Var(\frac{\beta M}{\theta}(\bar{g}\theta) + u)}\right) = \Sigma_0(1 - \frac{(\frac{\beta M}{\theta})^2 \sum_0^2}{\sum_0 \left[(\frac{\beta M}{\theta})^2 \sum_0 + \sigma_u^2\right]})$$

$Therefore,$

$$\Sigma_1 = \Sigma_0(\frac{\sigma_u^2}{(\frac{\beta M}{\theta})^2 \Sigma_0 + \sigma_u^2})$$

### 3.6.1 Comparison with the case of having risk-neutral traders

As was proved, the $i^{th}$ informed risk averse trader would trade $q_i = \beta g_{i0}$ in the first auction where $\beta = \frac{\eta}{2\lambda + \phi\lambda(M-1) + A\vartheta}$. Since $A\vartheta$ in the denominator is a positive term, comparing the optimal demand in the case of risk averse traders with the case of risk-neutral traders would indicate that risk averse traders would trade smaller amounts, causing prices to be less informative. As it was shown, $\Sigma_1$ is given by:

$$\Sigma_1 = \Sigma_0 (\frac{\sigma_u^2}{(\frac{\beta M}{\theta})^2 \Sigma_0 + \sigma_u^2}) = \Sigma_0 (\frac{\sigma_u^2}{(\frac{\beta M}{\theta})^2 \Sigma_0 + \sigma_u^2}) = \Sigma_0 \left[ \frac{\sigma_u^2}{(\frac{\eta}{2\lambda + \phi\lambda(M-1) + A\vartheta})^2 (\frac{M}{\theta})^2 \Sigma_0 + \sigma_u^2} \right]$$

Therefore, as shown in the above equation, $\frac{\partial \Sigma_1}{\partial A}$ is positive and is given by:

$$\frac{\partial \Sigma_1}{\partial A} = \frac{\partial \Sigma_1}{\partial \beta} . \frac{\partial \beta}{\partial A} = \frac{-2(\frac{M}{\theta})^2 \Sigma_0 \beta (\Sigma_0 \sigma_u^2)}{\left[(\frac{\beta M}{\theta})^2 \Sigma_0 + \sigma_u^2\right]^2} . \left( \frac{-\vartheta\eta}{[2\lambda + \phi\lambda(M-1) + A\vartheta]^2} \right)$$

$$= \frac{2(\frac{M}{\theta})^2 \Sigma_0^2 \sigma_u^2 \vartheta \eta \beta}{\left[(\frac{\beta M}{\theta})^2 \Sigma_0 + \sigma_u^2\right]^2 [2\lambda + \phi\lambda(M-1) + A\vartheta]^2}$$

As traders become more risk averse, they would trade smaller quantities and as a result, the permit price would become informative at a slower rate. In other words, we expect to see lower rate of reduction in $\sum$ when adding risk aversion to the model.

## 3.7 Conclusion

In this paper we developed the idea of integrating the state contingent pricing rule with tradable permit markets as a way of obtaining an accurate forecast of the future climate state. We modeled trading of permits that exempt emitters from paying a tempurature-indexed tax among traders with different private information and investigated price formation in this market. With risk neutral traders, we used FW96 framework to show how information in this market gets efficiently aggregated and incorporated into prices, making them unbiased forecasts of the future climate outcomes. Also, we demonstrated that the initial structure of private information plays an important role in the level of competition among traders and consequently the extent to which prices become informative in this market. In particular, the higher the level of scientific consensus (meaning the higher the correlation of private signals), the more competition traders face, causing more information to get released. With almost identical information, it takes only four auction rounds until all the information gets incorporated into the market price. On the other hand, traders with more heterogenous information face less competition as they have some monopoly power. They trade less intensely, causing less information to get released over time. We showed that in this case adding multiple rounds of bidding would help increase the price informativeness. We also extended the existing model to include risk averse traders. In this case, they trade smaller quantities and as a result, the permit price would become informative at a slower rate. These results are important because they provide a feasible mechanism for addressing two serious impediments to climate policy formation. First, the combined state contingent tax /exemption permit auction would yield a forward-looking price path that correlates to the unobservable intertemporal marginal damages path, without a regulator needing to know the current form of the underlying state function connecting the climate to emission (McKitrick, 2010; Hsu, 2011). Second, the permits auction will yield unbiased predictions of the future climate state and the corresponding optimal emission price, thus resolving the uncertainty over credibility of information sources. The mechanism outlined herein also has the potential to make the most efficient use possible of all available information.

## 3.8 Appendix

**Proof of equation 3.1 :**

let $X$ and $Y$ be two random variables with normal distributions. The conditional expectation of $X$ given $Y = y$ is the following formula:

$$E[X|Y = y] = m_X + \Sigma_{XY}\Sigma_{YY}^{-1}(Y - m_Y) \tag{3.18}$$

where $m_X = E[X]$, $m_Y = E[Y]$, *and* $\Sigma$ is the covariance matrix.

Given the above formula and the normality assumptions we will have:

$$E(p_T \ |g_{10}, g_{20,}...., g_{M0}) = m_{p_T} + \Delta_0^{'}\Psi_0^{-1}(g - m_g)^{'} \tag{3.19}$$

$p_T$ has a normal distribution with mean $\rho_0$ and variance $\Sigma_0$. In the above equation, $g$ is the vector of signals with zero means. The diagonal elements of $\Psi_0^{-1}$are all $\Lambda_0$ (initial variance of signals) and the off diagonal elements of $\Psi_0^{-1}$ are all $\Omega_0$ (initial covariance between any two signals). $\Delta_0$ is the covariance vector between signals and the true price of a permit with $c_0$ as its element, meaning that $\Delta_0^{'} = [c_0, c_0, ..., c_0]$. Therefore the entries of the matrix $\Delta_0^{'}\Psi_0^{-1}$ are all the same and equal to $c_0[\Lambda_0 + (M - 1)\Omega_0]$. We show the term $c_0[\Lambda_0 + (M - 1)\Omega_0]$ by $\varsigma$. Thus,

$$E(p_T|g_{10}, g_{20,}...., g_{M0}) = \rho_0 + \varsigma \sum g_{i0} = \rho_0 + M.\varsigma\left(\frac{\sum g_{i0}}{M}\right) = \rho_0 + \theta\bar{g} \tag{3.20}$$

Where $\theta = M.\varsigma$, which is a set of weights implied by conditioning on the signals.

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