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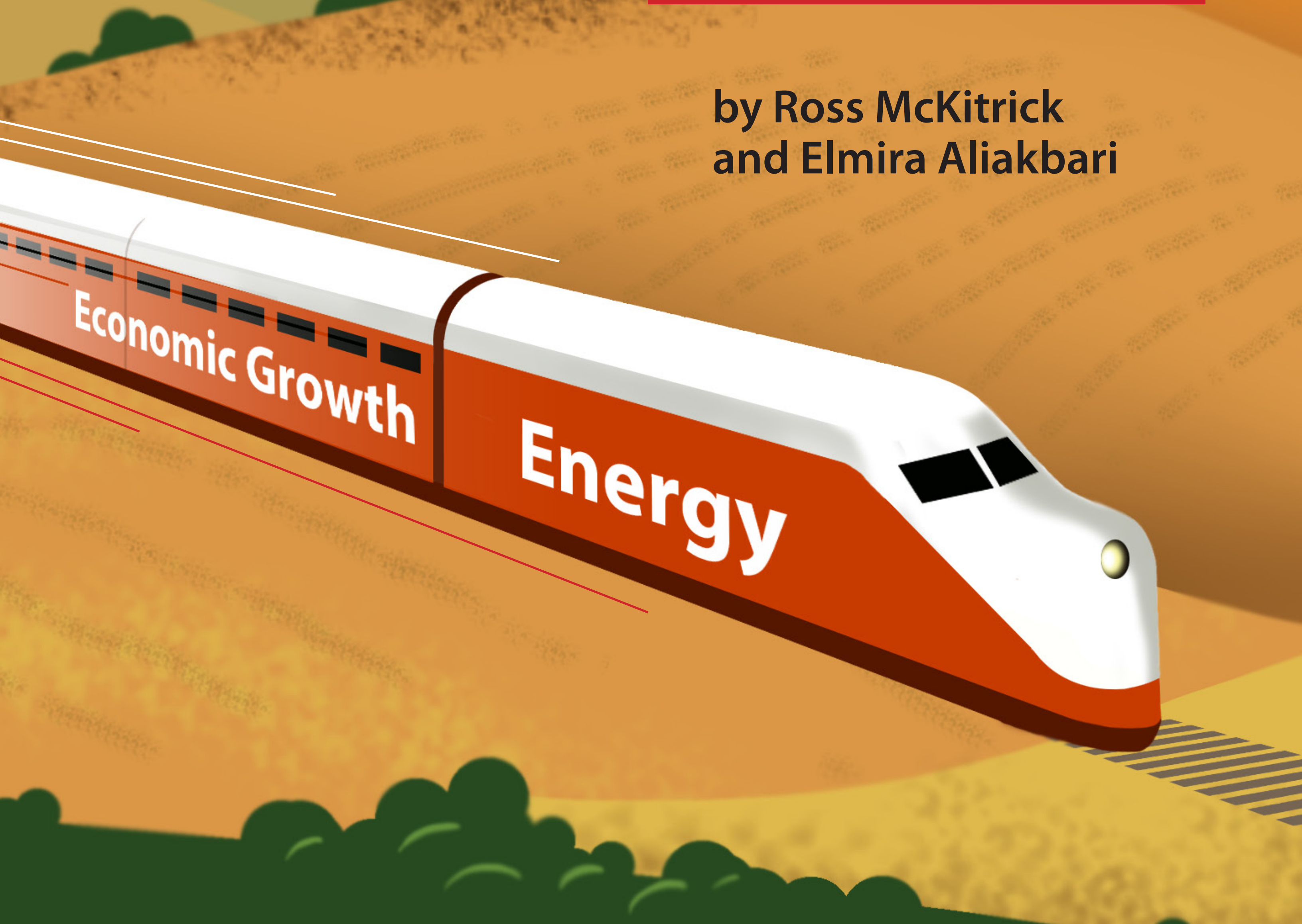
# Energy Abundance & Economic Growth

## International and Canadian Evidence

by Ross McKitrick
and Elmira Aliakbari



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Project Director: Kenneth P. Green

# Contents

# Executive summary

Economic growth in the modern world is fueled by energy. 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 an important research question: Does economic growth cause an increase in energy consumption, or does an increase in energy availability cause an increase in economic activity, or both?

The question has important policy implications. Suppose GDP growth causes increased energy consumption, but isn't dependent on it. In this view, energy consumption is a kind of luxury good (like jewellery), the consumption of which arises from increased wealth. If policymakers wanted to, they could restrict energy consumption without impinging on future economic growth. The alternative view is that energy is a limiting factor, or essential input, to growth. In that framework, if energy consumption is constrained by policy, future growth will also be constrained, raising the economic costs of such policies. If both directions of causality exist, it still implies that energy restrictions will have negative effects on future growth. The final possibility is that energy consumption and GDP are unrelated.

Statistical evidence can be used to establish correlations, but we are asking a question about causality, and as the saying goes, one does not imply the other. In recent decades, new statistical methods have been developed that allow for investigation of a particular kind of causality, and these methods have been applied to the energy-GDP question. The first purpose of this report is to explain what these methods are and how they have been used to examine the connection between growth and energy consumption around the world. The picture that has emerged is that growth and energy either jointly influence each other, or that the influence is one-way from energy to GDP, but in either case the evidence now points away from the view that energy use can be restricted (or, equivalently, prices artificially increased) without constraining future growth. Also, out of all countries studied, Canada has yielded some of the most consistent evidence on this, in that studies done under a variety of methods and time periods have regularly found evidence that energy is a limiting factor in Canadian economic growth.

The second purpose of this paper is to discuss what the evidence indicates for Canada, including new evidence we provide based on our ongoing research on this topic. Our examination of Canadian data, applying the most modern time series econometric methods available, leads us to conclude that energy use in Canada is not a mere by-product of prosperity but a limiting factor in growth: real per-capita income is constrained by policies that restrict energy availability and/or increase energy costs, and growth in energy abundance leads to growth in GDP per capita. 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.

These considerations are important to keep in mind as policymakers consider initiatives (especially related to renewable energy mandates, biofuels requirements, and so forth) which explicitly limit energy availability. Jurisdictions such as Ontario have argued that such policies are consistent with their overall strategy to promote economic growth. In other words, they assert that forcing investment in wind and solar generation systems—while making electricity more expensive overall—will contribute to macroeconomic growth. The evidence points in the opposite direction. Policies that engineer increased energy scarcity are likely to lead to negative effects on future GDP growth.

# 1 Introduction

## 1.1 Growth and energy

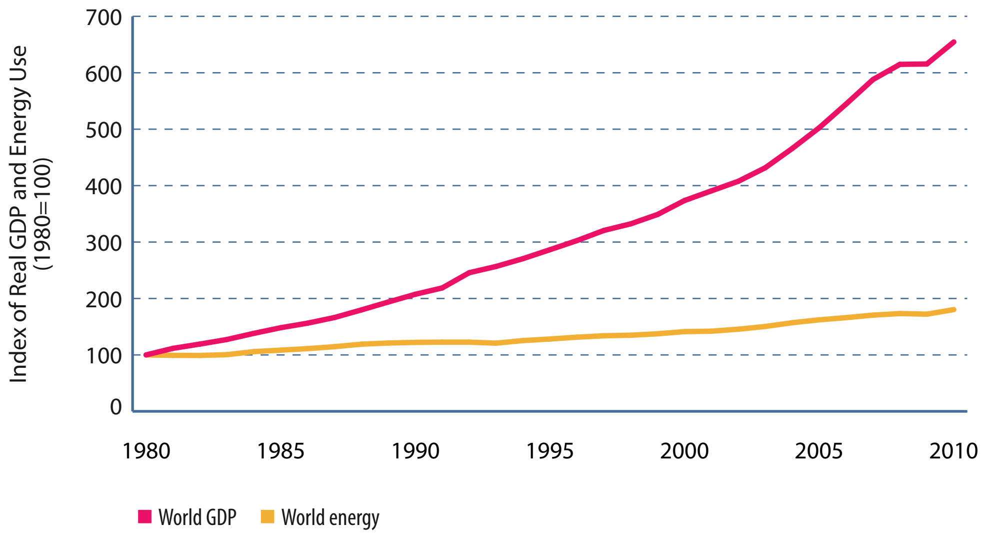
Economic growth in the modern world is fueled by energy. Although the total size of the economy tends to grow faster than total energy consumption, the two nonetheless trend together over the long run. **Figure 1** shows that total world economic output has increased more than sixfold since 1980, while total energy use almost doubled. **Figure 2** shows that for Canada over this period, Gross Domestic Product (GDP) doubled while energy use grew about 50 percent.

Visual inspection of time series data such as these shows that there are clear correlations between energy use and overall economic activity. This raises an important research question centered on which variable drives the other. Does economic growth cause an increase in energy consumption, or does an increase in energy availability cause an increase in economic activity, or both?

The question has important policy implications. Suppose GDP growth causes increased energy consumption, but isn't dependent on it. In this view, energy consumption is a kind of luxury good (like jewellery), the consumption of which arises from increased wealth. If policymakers wanted to, they could restrict energy consumption without impinging on future economic growth. The alternative view is that energy is a limiting factor, or essential input, to growth. In that framework, if energy consumption is constrained by policy, future growth is also constrained, raising the economic costs of such policies. If both directions of causality exist, it still implies that energy restrictions will have negative effects on future growth. The final possibility is that energy consumption and GDP are unrelated, but this seems unlikely either on theoretical grounds or based on historical data.

Statistical evidence can be used to establish correlations, but we are asking a question about causality, and as the saying goes, one does not imply the other. In recent decades, new statistical methods have been developed that allow for investigation of a particular kind of causality, and these methods have been applied to the energy-GDP question. The first purpose of this

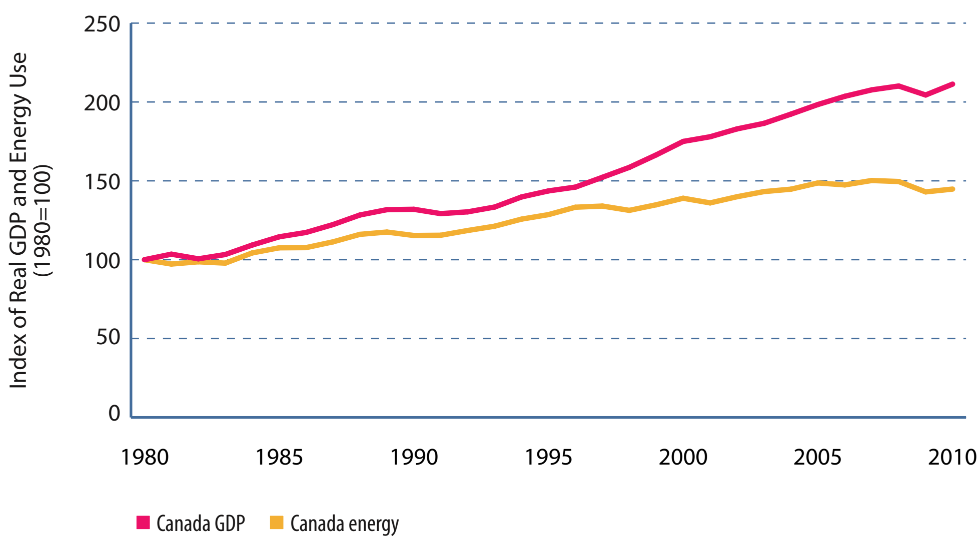
**Figure 1: World energy production and world GDP, 1980–2010**




Note: Underlying GDP data in billions PPP-adjusted $. Energy in Quadrillion BTU. Series scaled by dividing all values by respective 1980 value and multiplying by 100.

Sources: Energy data from EIA.org; GDP from IMF.org.

**Figure 2: Canadian energy production and real GDP, 1980–2010**




Note: Underlying GDP data in billions PPP-adjusted $. Energy in megatonnes oil equivalent. Series scaled by dividing all values by respective 1980 value and multiplying by 100.

Sources: Energy data from BP Statistical Review; GDP data from IMF.org.

report is to explain what these methods are and how they have been used to examine the connection between growth and energy consumption around the world. A great deal of work has been done on this topic, though for reasons we will explain, economists have not yet settled on a single view on the question of how energy restrictions impact growth.

The second purpose is to discuss what the evidence indicates for Canada, including new evidence we provide based on our ongoing research on this topic. Notwithstanding the limitations imposed by data availability and methodological uncertainties, there is convincing evidence that energy and GDP are structurally related in such a way that policies to cut or constrain energy use, including well-meaning conservation programs, are limiting factors on income growth in Canada. Discussions about lackluster growth and productivity in Canada need to take into account the effects of energy policy. In particular, any claim that there are economic benefits attached to interventions in the energy sector that reduce demand, restrict use of conventional sources, and/or mandate use of costlier alternatives are at odds with evidence from Canada and around the world.

## 1.2 Different forms of scarcity

In this paper we will be focusing on the role energy scarcity plays in economic growth. There are several ways that scarcity can be measured. A common way is to think of the quantity of energy being constrained or expanded. When the Arab countries imposed an oil embargo on the west in 1973, they cut back the supply. In recent years, the shale gas revolution in the US has resulted in a large expansion in the quantity of natural gas.

But changes in quantity tend to have an economic impact when they translate into changes in price. The 1973 Arab oil embargo resulted in a sudden jump in the price of gasoline, which then had deep macroeconomic consequences. The opening up of massive shale gas operations has caused the price of natural gas to drop sharply, which has had major economic consequences, especially in North America. While changes to the physical supply may be the initial event, the economic consequences usually flow from a resulting change in price.

In the empirical work on the energy-economy connection, the connection between scarcity and price is taken for granted, and we will likewise do so here. In other words, when we refer to policies that make energy more scarce or abundant, this should be understood as referring not only to policies that expand or contract the physical stocks of energy sources available to the market, but also policies that force energy prices above or below their underlying equilibrium values. A policy that makes energy more expensive than it otherwise would be is as much a scarcity-inducing policy as one that, say, forbids the development of a particular physical supply. And likewise, a policy that removes a price-inflating effect from the market is identical in its economic impact to one that increases the physical supply.

In what follows, we will usually speak in terms of the link between energy supplies and GDP growth, but the reader should bear in mind the implicit equivalence between policies that affect price and those that affect quantity.

# 2 National and international evidence on the energy-GDP link

Before proceeding with this section, the reader should scan Appendix I, which provides a detailed but non-technical overview of some key statistical concepts employed in the research literature. This will not only help in keeping track of the terminology, but will also allow greater precision in understanding the findings of the research literature, since they depend on the use of advanced econometric methods that often have important but subtle points of interpretation.

The key concepts we rely on are summarized as follows.

- *Granger causality*: This is a pattern in time series data in which knowledge of the current value of one variable allows for significantly more accurate forecasts of future values of another variable. If found, such a pattern suggests that some form of causality connects the former variable to the latter, though it is not as secure an inference as one could draw from controlled experiments. In this paper, when we refer to energy *causing* GDP growth or vice-versa, we specifically mean Granger causality.

- *Vector Autoregression (VAR)* and *Vector Error Correction Modeling (VECM)*: These are modeling techniques that can be used to measure Granger causality relationships among groups of variables.

- *Stationarity*: This is a property of time series data which implies a form of stability necessary for standard methods of statistical analysis to yield valid results. Nonstationarity is a property of time series data that, if present, usually precludes application of standard methods. But if all the variables in a model exhibit the same degree of nonstationarity (or, more precisely, *order of integration*) they can be used together in VAR and VECM models.

- *Cointegration*: This is a pattern sometimes observed in economic systems which indicates that a long-term equilibrating mechanism exists between two or more variables.

## 2.1 First generation studies

The relationship between economic growth and energy consumption has been extensively examined during last 30 years. The many papers published so far have yielded what appear to be conflicting and mixed results, but this is partly due to initial use of methods that later came to be seen as unreliable, as well as different choices of the variables to be included in the models (Belke et al., 2011). Many studies have focused on 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.

Mehrara (2006) categorized publications into four "generations." The first used a traditional VAR regression approach to infer a Granger-causal relationship between 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 the late 1970s to the end of 1980s, and stationarity of the data was assumed.

The seminal work on the relationship between income and energy consumption was carried out by Kraft and Kraft in 1978. They applied Sim's methodology to examine causality between energy consumption and economic growth over the period 1947–1974 for the USA. They found that the direction of causality runs from gross national product (GNP) to 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. 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. But Stern (1993) used a longer sample (1947–1990) and found causality going both ways in the US.

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

## 2.2 Second and third generation studies

The two main problems with the first generation papers were that sample lengths were very short, and that nonstationary data were being used in VAR models that presuppose stationarity. Second-generation studies addressed both issues by developing longer data sets and employing univariate Error Correction Models (ECM), which embed a cointegrating component to handle the nonstationarity problem, and later multivariate Vector Error

Correction Models (VECM), also known as the Johansen-Juselius method. The two major studies in this group were Soytas and Sari (2003) and Soytas and Sari (2006). 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 the UK, Japan, Germany, and Canada they were found to cause each other. Ghali and El-Sakka (2004) examined Canada and found bi-directional causality between energy and GDP.

But by now, taking the literature as a whole, it was becoming clear that results tended to be unstable and dependent on the sample period. This led some authors to look for more robust methods.

## 2.3 Fourth and fifth generation studies

A criticism of the VECM methodology was that it only works reliably on very large sample sizes, but data limitations meant that individual countries only had a few decades worth of annual observations to work with. Pesaran and Shin (1999) and Pesaran et al. (2001) proposed methods using so-called Autoregressive Distributed Lag (ARDL) models that were more efficient in small samples and were valid whether or not the series were stationary or cointegrated. Major studies to emerge in this cohort were Lee (2006) and Zachariadis (2007). Lee used a group 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.

The next methodological innovation, coined the fifth generation (Cores and Sanders, 2012), used ARDL methods more efficiently by combining many individual country data sets into one very long international data set called a panel. 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.

This review does not exhaust the literature on either Granger causality testing or the relationship between energy and output. We do not, for instance, address the possibility of endogenous structural breaks, which can affect the power of tests for unit roots (Lee and Strazicich, 2001). Nor do we examine the possibility of nonlinearities in the relationship between energy and the macroeconomy. Hamilton (2011) discusses this issue, looking in particular at models allowing for asymmetries between the effects of oil price decreases and price increases. In general, proper handling of such methodological extensions require longer data sets than are available for our empirical application, and have not yet been fully taken into account in the energy literature. Also, we will be using a panel data set, and the theory governing how to apply these issues in a panel setting has not been derived.

## 2.4 Summary

Over time, as methods have improved and data availability has increased, the evidence has strengthened that energy availability causes income growth, or in other words is a limiting factor for output. It is either the case that growth and energy jointly influence each other, or that the influence is one-way from energy to GDP, but in either case the evidence now points away from the view that energy use can be restricted (or, equivalently, prices artificially increased) without constraining future growth. Also, out of all countries studied, Canada has yielded some of the most consistent evidence on this, in that studies done under a variety of methods and time periods have regularly found evidence of causality either from energy to GDP or in both directions.

The next section explains some new empirical work that exploits the efficiencies of panel methods and the availability of Canadian data at the provincial level to provide new evidence on the link between energy and growth in Canada.

# 3 New Canadian evidence on the energy-GDP link

## 3.1 Data

There are two data sets available through Statistics Canada that can be used for the present purpose. One is an older series spanning 1981–2000, and one is a newer series spanning 1995–2010. Unfortunately, as they are based on different survey methods they cannot be combined to make a single long data set. We report herein the results using the more recent data set (1995–2010) but we have obtained similar results on the older one as well. A more detailed presentation of results from both data sets will be available in a separate paper under preparation (Aliakbari and McKitrick, 2014).

Our data consist of annual provincial-level observations (see **table 1**). Real Gross Domestic Product (GDP) and Real Gross Fixed Capital Formation are both in constant million (2002) dollars. Final Energy Consumption is in terajoules and employment is in thousand persons. Table 1 reports the data sources, variable definitions, and summary statistics. For the actual estimations, all variables were transformed using logarithms, so that coefficients become unitless elasticities.

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 of the province. To avoid generating spurious effects, we removed Newfoundland from the sample and retained the other nine provinces.

### Table 1: Data sources, definitions, and summary statistics

| | Income | Capital | Energy | Labour |
|---|---|---|---|---|
| **Variable Name** | *y* | *k* | *e* | *l* |
| **Definition** | Real Gross Domestic Product | Real Gross Fixed Capital Formation | Total energy use | Employment |
| **Units** | Millions of $2002 constant dollars | Millions of $2002 constant dollars | Terajoules | Thousand persons |
| **Mean** | $124,739.9 | $26241.9 | 807417.3 | 1683.6 |
| **Standard Dev** | $143,780.3 | $28831.2 | 797746.2 | 1873.9 |
| **Minimum** | $3103.0 | $503.0 | 20339.0 | 57.2 |
| **Maximum** | $530475 | $107829.0 | 2643443.0 | 6666.3 |
| **Span of years** | 1995 to 2010 | 1995 to 2010 | 1995 to 2010 | 1995 to 2010 |

Source: Statistics Canada, CANSIM Tables 384-0002, 128-0016, 282-0055.

## 3.2 Methodology overview

Based on the discussion of empirical techniques in Section 2 we implemented the following analytical sequence. Each step is explained subsequently.

- **Step 1**: Test for cross-sectional dependence.
- **Step 2**: Panel unit root tests.
- **Step 3**: Panel cointegration tests.
- **Step 4**: Estimate long-run cointegrating relation.
- **Step 5**: Estimate error correction model to determine direction of Granger causality.

**Step 1** looks at the question of how correlated the data are across provinces. We only have 16 annual observations, but we have 9 provinces, so this gives us 135 data points. However, if all the provinces behave identically, in other words if the data are highly correlated across the provinces, then we would be overstating the richness of our data set by assuming that each provincial series is independent. So in Step 1 we measure the cross-panel correlations and ask whether they are statistically significant, using scores developed by Breusch and Pagan (1980) and Pesaran (2004). The results of these tests will affect the approach we use in Step 2. Both tests strongly reject the null that the panels are independent, which is not surprising. Therefore, subsequent steps take into account the correlations across provinces.

**Step 2** examines the data series for the form of nonstationarity (see Appendix I.3 for more explanation). The importance of this step is that the results determine how the long run equilibrium relationship across the data set can be characterized. If all the data series have unit roots, or in other words are integrated of order 1 (denoted I(1)—see Appendix I.3), then a cointegrating relationship can be estimated to measure the long run equilibrium system in the data. We used the Pesaran (2007) panel unit root test and the results indicate that all four variables have unit roots, and are not I(2), making it possible to proceed to the next step.

**Step 3** involved using panel cointegration tests due to Westerlund (2007), Pedroni (1999, 2004) and Maddala and Wu (1999). These are methods for testing if a linear combination of the variables *cointegrate*, or form a sort of "attractor" to which random deviations tend to return. The Westerlund test takes four forms based on different assumptions about the commonality of linear structures across panels (provinces, in this case). It yielded ambiguous evidence, with two of four indicating cointegration. The Pedroni test likewise takes multiple forms, with four of the seven indicating cointegration. Finally, the Maddala and Wu test takes two forms, both of which strongly rejected the hypothesis of no cointegration (in other words, indicating cointegration is present). Considering the small sample size it is to be expected with these tests that they will tend to have difficulty detecting cointegration, 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.

**Step 4** is very similar to linear regression, but some modifications to the regression model are needed in order to take into account the characteristics of the data as revealed by Steps 1–3. The method is called Dynamic Ordinary Least Squares (DOLS). Since the variables are in logs, the resulting coefficients are elasticities. The estimating equation is as follows:

$$\ln\,(Y_{it}) = \mathrm{a}_0 + a_1 \ln\,(E_{it}) + a_2 \ln\,(K_{it}) + a_3 \ln\,(L_{it}) + [lags] + e_{it} \qquad \textbf{(1)}$$

The [*lags*] term refers to leads and lags of the variables in the model, which are necessary to ensure that the residuals ($e_{it}$) are consistent estimators of the error terms around the long run equilibrium model. Following Hayakawa and Kurozumi (2006) we used two lags and no leads. 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

**Table 2: Results from the Dynamic OLS Regression (Equation 1)**

| Variable name | Coefficient | Estimate | Std error | z-score | Prob>z |
|---|---|---|---|---|---|
| Energy | $a_1$ | 0.116 | 0.058 | 1.99 | 0.046 |
| Capital | $a_2$ | 0.675 | 0.110 | 6.13 | 0.000 |
| Employment | $a_3$ | 0.250 | 0.030 | 8.29 | 0.000 |

Dependent variable: log(GDP)

Adj. R-squared: 0.7984

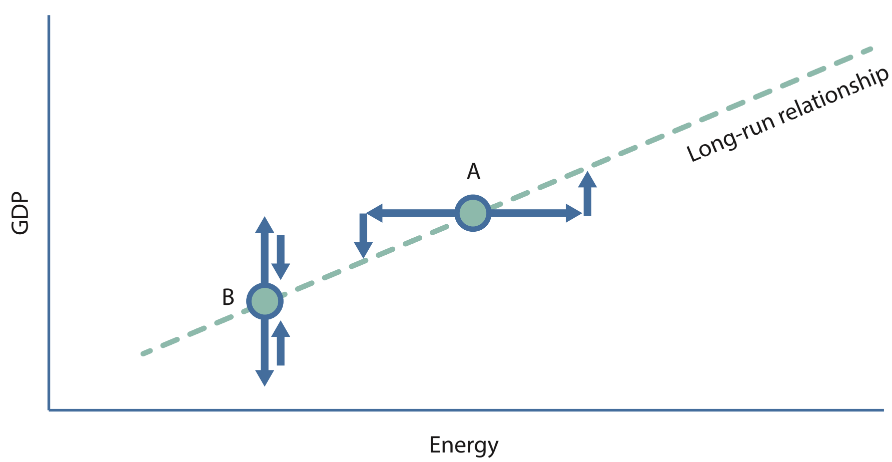
Number of observations: 117

variables, which we confirmed was the case here. **Table 2** reports the results of the DOLS regression. At this stage, the key finding for the present analysis is that the elasticity between energy and real GDP is positive (0.116) and statistically significant (p = 0.0046), indicating that they move together in the long run. More specifically, a ten percent increase in energy availability is associated with a 1.16 percent increase in GDP. But this step does not reveal which direction the causality runs, which leads to Step 5.

**Step 5** quantifies the short-run Granger causality relations among variables, as well as the strength of the "attraction" to the long-run equilibrating relationship. The latter effect is measured as the degree of *endogeneity*. To understand what this means, refer to **figure 3**.

**Figure 3: Endogenous and exogenous variables**

*Schematic illustrates energy as exogenous and GDP as endogenous*



The dashed line indicates the long run cointegrating relationship. The arrows illustrate a situation in which energy is *exogenous* and GDP is *endogenous*. Begin at point A. The horizontal arrow (in the direction of energy) symbolizes a random, up or down external shock to the availability of energy. Suppose an unexpected event increases the abundance of energy (arrow pointing right). The connecting vertical arrow indicates that the system returns to the long run relationship through an adjustment to GDP, in this case going upwards. Since GDP responds to a change in energy, it is said to be endogenous, namely responsive to another variable within the system. Likewise, if an external shock causes energy to drop (arrow pointing left), the connecting arrow indicates that the system moves back to the long run relationship by a negative adjustment to GDP.

Now refer to point B. Suppose there is an external shock to GDP, causing it to go up. This time the connecting arrow simply reverses direction, so that rather than returning to the long run relationship by a horizontal move (increasing energy use), the return merely involves a reduction in GDP back to point B. This is because, in this illustration, energy is exogenous—meaning it is not determined by the other variable in the system but is determined by outside factors. Similarly, if the random shock to GDP causes it to drop (arrow going down from point B) the return to equilibrium does not involve a reduction in energy use, but a rebound in GDP to point B.

The coefficients that emerge from the Error Correction Model indicate that, in the Canadian economy, energy is exogenous and GDP is endogenous, in the form illustrated in figure 2. As found in Step 4, there is a positive long run relationship between energy use and GDP. The VECM model indicates that the error correction term in the energy model is statistically insignificant, but in the GDP model it is significant. This means that, in the short run, increases in GDP do not Granger-cause increases in energy use, but increases in energy abundance do Granger-cause increases in GDP. Likewise, decreases in energy abundance are associated with subsequent decreases in GDP, but the causality does not go in the other direction. These findings are consistent with findings of previous studies as reported in Section 2, and are the same as the results we have obtained on the earlier sample (1980–2000), which are not reported here, but are available in Aliakbari and McKitrick (2014).

The Granger causality tests were also applied to labour and capital. These variables, like GDP, were found to be endogenous, meaning that they respond significantly to GDP changes. This implies that the failure to find significant endogeneity in the energy equation cannot simply be due to not having a large enough sample size, since we were able to detect it for capital and labour. The regressions also detect a short run Granger causality between capital and labour, though not the other way around. This implies that increased capital formation in Canada is associated with increased employment—an interesting finding in light of the general concern about technology causing jobs to disappear.

Details about the estimation are in Appendix II.

# 4 Discussion and conclusions

If energy consumption is just a luxury good, namely a by-product of prosperity but not an input to future growth, policymakers could enact measures to restrict it without limiting future productivity and income. But if energy abundance is a causal input to future GDP growth, policies to restrict energy availability or artificially increase energy prices will act as an economic tourniquet, and GDP growth will be accordingly limited. Evidence from several decades of empirical work raises the distinct likelihood that for many countries, including Canada, there is a long-run equilibrating relationship between GDP and energy. Looking in more detail, there is consistent evidence that changes in energy consumption have a structural effect on future GDP, and possibly vice-versa; but the balance of evidence is that the energy-to-GDP relationship is the primary one. Our examination of Canadian data, applying the most modern time series econometric methods available, lead us to conclude that energy use in Canada is not a mere by-product of prosperity but a limiting factor in growth: real per capita income is constrained by policies that restrict energy availability and/or increase energy costs, and growth in energy abundance leads to growth in GDP per capita. 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.

These considerations are important to keep in mind as policymakers consider initiatives (especially related to renewable energy mandates, biofuels requirements, and so forth) which explicitly limit energy availability. Jurisdictions such as Ontario have argued that such policies are consistent with their overall strategy to promote economic growth. In other words, they assert that forcing investment in wind and solar generation systems, while making electricity more expensive overall, will contribute to macroeconomic growth. The evidence points in the opposite direction. Policies that engineer increased energy scarcity are likely to lead to negative effects on future GDP growth.

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# Appendix I

## Detailed explanations of technical methods

### A.1 Granger Causality

Data analysis often begins with the question of whether two variables are related. Suppose we collect observations at each point in time ($t$) on two quantities $x(t)$ and $y(t)$. A simple step is to compute the correlation coefficient between them, but this tells us only whether they move together. It does not tell us if movements in $x$ cause $y$ to move, or vice versa, or neither. It might, for instance, be the case that they are both driven by an unknown third variable, and their similarity is therefore not a causal relationship at all.

Since correlation does not establish causality, economists began using an alternative concept of causality, originally proposed by Clive Granger (1969). Suppose we want to forecast the future value of $y$, namely $y(t + 1)$, using information available at time $t$. The forecast will contain an error, and if we track the forecasts and errors, we can compute an indicator of the inaccuracy of such forecasts by using the mean squared forecast error. Suppose that we use the information contained in $x(t)$ when estimating $y(t + 1)$, and compare the mean squared forecast errors against an alternative system that ignores $x(t)$. If using $x(t)$ significantly reduces the mean squared forecast errors of $y(t + 1)$ then that implies $x$ has some predictive value for $y$, which in turn implies some form of causal relationship. It may not be the usual kind of causality we see in physical systems, but it is a kind of causality, and economists refer to it as "Granger causality." If we find that $x$ "Granger causes" $y$ but $y$ does not Granger cause $x$, or in other words knowing $x(t)$ significantly improves our forecast of $y(t + 1)$ but knowing y(t) does not help us forecast $x(t + 1)$, this is even more suggestive of a causal structure going from $x$ to $y$.

### A.2 Vector Autoregression (VAR)

Suppose we have variables $x$ and $y$. A simple way to investigate whether there is a Granger causality pattern among them is to form a system of linear regression equations in which we regress $y$ on lagged values of itself and of $x$, and $x$ on lagged values of itself and $y$, then test whether groups of lag coefficients representing lines of Granger causality are significantly different from zero. This is called *Vector Autoregression* (VAR). It is a very common way of building simple time series models; however, it runs into trouble when the data are nonstationary.

## A.3 Stationarity

When we consider the basic statistical tools to relate $x$ and $y$ it is important to understand that they are derived based on the assumption of *stationarity*. This is a somewhat complex concept that boils down to a form of stability in the series. A stationary series tends to revert to its mean over time. Even if a random shock takes place, the effect of the shock must end over time and the series then returns to its mean. That is the intuitive basis of stationarity, but its formal implications go in several technical directions.

- If the series does not revert to its mean but instead follows a trend, we refer to it as "trend stationary" if, once we subtract out the trend, it behaves like a regular mean-reverting stationary series.

- Mean reversion is necessary for stationarity, but it may be the case that a process is so slow to revert to its mean that any sample we collect appears non-stationary. In that case we would look at measures of how slow the mean-reversion process is. These measures are based on the correlations within the series over time (for instance, how well do observations of $x(t)$ correlate to observations of $x(t - 2)$ over the sample length). These are called autocorrelations and covariances. A weaker form of stationarity allows for very slow mean reversion as long as the covariances stay within numerical boundaries that ensure the series must eventually return to its mean.

- There are important cases in economics where mean reversion does not make sense. For example, it would not make sense to suppose that daily closing stock market prices are stationary. If shares in company XYZ close at \$50 one day, and the next morning drop to \$45, and we knew that the share price is strictly mean reverting, it would imply that traders could make a sure profit in the afternoon by buying at \$45 in expectation of a return to \$50. But if everyone expects that, then the price would not have dropped to \$45 in the first place, since no one would sell in the morning at \$45 if everybody knew the stock would be worth \$50 a few hours later. If the stock does fall to \$45, traders must believe it is only worth \$45. Having used all the available information to determine that, it means that the drop in price from \$50 to \$45 was not predictable at the time the share was trading at \$50, making it a random, or unpredictable shock. The fact that the price stays at \$45 (until the next random shock occurs) means that random shocks have a permanent effect on the price. Series in which random shocks have a *permanent* effect are called *random walks*, and they are, by definition, non-stationary.

- Random walks have a few different names depending on the (equivalent) mathematical definitions. They are also called "unit root processes" and "I(1)" processes.

- A random walk does not revert to any one mean value, and it can be shown mathematically that its variance gets larger and larger as the sample length grows, implying that the variance goes to infinity in the long run. But the classical methods used to test for correlations and Granger causality (such as VAR) are based on the assumptions of stationarity and finite variance. If two random walks are used in a VAR model, they will almost always indicate that the series Granger cause each other even if they are completely independent, hence any conclusions we draw will be spurious. Special methods to deal with the problem were developed using cointegration analysis.

## A.4 Cointegration

Suppose we have data on shares XYZ and ABC. We expect both series to be random walks. But both firms may be in the same sector and are affected similarly by random shocks that affect all companies in that sector. If that is the case, while the price of each company individually looks like a random walk, the difference between the two share prices (namely XYZ – ABC) should be stationary. If both companies are about the same size and their shares are both worth about the same, the difference between them might be a mean-reverting stationary series around zero.

When a pair of variables are individually non-stationary, but a linear combination of them (such as the sum, difference, or average) is stationary, we say that the variables are "cointegrated." Cointegration analysis involves looking for linear combinations of nonstationary series such that the combination is stationary.

In the example with the two companies, it would be odd if they were cointegrated over a long time period, since not every random shock affects both firms equally. Eventually we expect shocks to hit just one firm or the other (such as a major sale contract at one, or an unexpected profit miss at the other), and the linear combination will undergo a permanent change. But what if there is some kind of deep connection between the two firms, for instance if one actually owns a substantial share of the other? Then there is a structural, or equilibrium connection and we would expect the cointegrating relationship to be stable over time.

An example of a cointegrating relationship might be spot and future prices of a precious metal. Each one might be a random walk, but they cannot drift too far apart. So we expect the difference between the two prices to be a stationary series, and the two prices to be cointegrated, reflecting the equilibrium they try to maintain with respect to each other.

We can turn the interpretation around. Suppose we have data on some economic variables that appear to follow random walks. But we discover a linear combination of these variables is stationary. That implies that the equation describing the linear combination likely captures a long-run equilibrium relationship among them. Cointegration analysis is therefore used not only to find stationary combinations of variables to support valid correlation analysis, but also to detect long-run equilibrating mechanisms in economic systems. Much of the research described in this study involves analysing whether energy and GDP are cointegrated, and if they are, what the relationship is.

A further step in cointegration analysis involves using the stationary linear combination of variables in a classical model that only works on stationary variables. This is important when the individual variables are nonstationary (and therefore can't be used) but the cointegrated set is stationary, and therefore as long as the variables are used in that combination the classical model is valid. Then the interpretation centres on how the variables outside the cointegrated group relate to the equilibrium system jointly represented by the linear combination within the group. This will be important in understanding how the energy-GDP relationship is analysed.

# Appendix II

## Further details on the Canadian model

### Step 1: Test for cross-sectional dependence

We ran a fixed effects regression of ln(GDP) on the logs of energy, capital and employment and obtained the nine provincial residual series. A Breusch-Pagan LM test of independence yielded a $\chi^2$ score of 92.4 (36 degrees of freedom) which has a p-value of below 0.00001. A Pesaran test had a value of 4.106 which likewise has a p-value of below 0.00001. Thus we concluded cross-sectional dependence is present.

### Step 2: Panel unit root tests

We used the Pesaran (2007) panel unit root test, basing the lag length selection on Akaike and Bayesian Information Criteria. The null hypothesis is non-stationarity (I(1)). The test scores for the logs of, respectively, GDP, energy, capital, and labour had p-values of 0.991, 1.000, 0.946, and 1.000, allowing us to conclude that the four variables are nonstationary. Repeating the tests on the first differences indicated stationarity, so we conclude the series are I(1).

### Step 3: Panel cointegration tests

We applied the Westerlund cointegration test using ln(GDP) as the dependent variable. The null hypothesis is that there is no cointegration. The test returns four Robust P-values, of which two were 0.000 and the others were 0.180 and 0.790. The Pedroni test also uses a null of no cointegration but allows the alternative hypothesis to include individual autocorrelation coefficients across the panels. The group Philips-Perron and Augmented Dickey-Fuller statistics were both very small ($p<0.0005$) indicating cointegration. Also a Kao residual cointegration test rejected the no-cointegration null ($p<0.00001$). Thus we concluded that the variables were cointegrated.

### Step 4: Estimate long-run cointegrating relation

As described in the text above, we used Dynamic OLS with two lags and no leads. The results are shown in table 2.

### Step 5: Estimate error correction model to determine direction of Granger causality

We estimated fixed effects ECM regressions of the following form:

$$\Delta x_t = a_0 + a_1\Delta w_t^1 + a_2\Delta w_t^2 + a_3\Delta w_t^3 + a_4\Delta x_{t-1} + a_5 r_{t-1} + \beta \cdot d_t + e_t$$

where $x_t$ and $w_t^i$ ($i$ = 1, … 3) denote a dependent variable and independent variables made up of logs of GDP, energy, labour, and capital sequentially trading places in $x_t$, $r_{t-1}$ is the lag of the residuals from the cointegrating regression, $\beta \cdot d_t$ is a vector product of province-specific dummy variables and fixed effects coefficients, and $e_t$ is the residual term. The detailed coefficient results are available on request, and are in Aliakbari and McKitrick (2014). Some notable results were as follows:

- We used only one lag as that was indicated by the Akaike Information Criterion as optimal.
- In the model with (delta ln) GDP as the dependent variable, none of the input variables were significant. Only the residual term from the cointegrating regression was significant, as were some fixed effects dummies. The between-province variation explained 98 percent of the variability in the dependent variable.
- In the model with (delta ln) energy as the dependent variable, none of the input variables were significant. Only the lagged dependent variable term was significant. 71 percent of the variance in the dependent variable was explained by the between-province variation.
- In the employment regression, there was a significant positive coefficient on capital, implying a short-run Granger causality running from capital to labour. No other variables were significant except for the cointegrating equation residual. In the capital equation, only the residual term was significant. Between province variation accounted for, respectively, 94 percent and 96 percent of the variation in these two regressions.

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Ross McKitrick is a Professor of Economics at the University of Guelph and Senior Fellow of the Fraser Institute. He specializes in environmental economics. He has published many studies on the economic analysis of pollution policy, economic growth and air pollution trends, climate policy options, the measurement of global warming, and statistical methods in paleoclimatology. His latest book is *Economic Analysis of Environmental Policy*, published by University of Toronto Press (Fall 2010). He has also published numerous invited book chapters, newspaper and magazine essays, and think-tank reports.

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