Three Papers on the Political Consequences of Oil Prices

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Three Papers on the Political Consequences of Oil Prices

by

Adriana Crespo Tenorio

A dissertation presented to the
Graduate School of Arts and Sciences
of Washington University in
partial fulfillment of the
requirements for the degree
of Doctor of Philosophy

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Adriana Crespo Tenorio

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Para Samuel, mi constante
Given the importance of oil in any country’s energy needs, it should not be surprising that the increasing volatility of oil prices in the past decades is a challenge for most political systems. While the political and economic impact of natural resource wealth in general is strongly debated, the political consequences of these sudden shifts have gone understudied. This dissertation examines the relationship between politics and oil from a new perspective. First, I implement a Bayesian meta-regression model to assess the state of research on the natural resource curse, finding that the measurement of resources is one of the most important sources of the debate. In the second part of the dissertation, I turn to discussing the impact of fuel prices on politics. I argue that at the domestic level, rational leaders feel pressured to compensate for oil price shocks because they are held accountable for these shifts by their constituents. This hypothesis is tested using Bayesian multilevel models that allow state and time-varying information to be matched to individual survey responses for a sample of voters in nine American states between 2008 and 2009.
shows that fuel prices are related to appraisals of the economy only during electoral periods. The results also provide evidence that the degree to which voters use fuel prices to evaluate the president’s performance varies greatly across party lines. At the global level, I posit in the final chapter that cross-country cooperation in other issue areas is pursued to mitigate the economic impact of oil price volatility. By developing a Bayesian bivariate Poisson change-point model and implementing it using MCMC methods, I find that fuel price shifts are related to increased trade networks, especially for oil-exporting countries.
Chapter 1

Introduction

Research in political science and political economy has long been concerned with the interaction between economic conditions and political institutions and actors. Natural resources and oil are obviously no exception. In economics, scholarly works have focused on the economic consequences of natural resource ownership and dependency on countries’ economies. From the political economy perspective, natural resource ownership provides an opportunity for local political actors to extract rents, to use natural resources as motors for development (and sources of funding for populist policies), or to gain leverage in the international arena vis-à-vis states who do not own such resources.

The recent experience of oil price fluctuations following the turn of the century has encouraged many new questions about fossil fuels in areas like environmental sciences, life sciences and engineering, but political science and political economy have lagged in this discussion. To be sure, political economy research has focused on the
supply-side of the fossil fuel market: extensive research has studied the consequences of dependence on natural resources for the countries who produce them. However, most countries in the world fall on the demand side of the market: they depend on foreign acquisitions of fossil fuels. For these countries, economists have noted that their inelastic short-run demand makes oil price volatility a serious threat to their macroeconomic performance. Specifically, countries must work to finance their demand for this good when other countries are looking to do the same.

The goals of the dissertation are to provide a fresh perspective to the natural resource literature in political economy, and to showcase the advantages of Bayesian statistics for social science data analysis. Together, the three papers are meant to provide a broad yet thorough analysis of how fuel prices can be incorporated into existing political economy theories. Regarding the first goal, the emergence of alternative energy sources and new actors in the fossil fuel market prompts new questions about the consequences of these developments for international cooperation emerge. These questions are at the heart of each paper in this dissertation.

Methodologically, each chapter in the dissertation leverages on the flexibility of Bayesian methods. For instance, likelihood-based the meta-regression methods used in Chapter 2 depend on assumptions about the sampling distribution of the observed data and asymptotic properties of the estimators. Exchangeability in Bayesian modeling relaxes one of these assumptions, thus treating the observations in the meta-regression in a more realistic setting without underestimating the underlying heterogeneity in the data-generating process of the observations. The use of prior distributions in Bayesian modeling is also an important advantage. A bivariate Poisson model is developed in Chapter 3. The estimation of multidimensional models in traditional
approaches is cumbersome, and few data structures are supported. Thanks to conjugate prior distributions, the Bayesian estimation of this model is greatly simplified.

The rest of the dissertation proceeds as follows. Chapter 2 explores existing literature that links natural resources to political institutions and economic outcomes. Large amounts of scholarly work in political science and economics have studied the relationship between natural resource wealth, political institutions, and economic development. While in the past it was generally agreed that natural resources were a “curse”, recent research has cast doubt on this claim. Using Bayesian meta-analytical tools, Chapter 2 explores the state of research in this topic. Meta-analysis and meta-regression methods are discussed and then applied to over 1000 regression models for the effect of natural resource abundance and dependence on levels of democracy and economic growth. The results of this exercise ultimately cast doubt on the existence of a resource curse, more on methodological than substantive grounds. Specifically, the chapter raises questions about measurement choices. Chapter 2 shows that natural resource ownership matters for macroeconomic outcomes. More importantly, this quantitative overview of the literature proves that natural resource income—and not natural resource abundance per se—can many times be a curse.

The impact of oil price changes on the international political environment has gone understudied, and Chapter 3 takes steps to address this gap in the literature. In this chapter, I argue that through economic interdependence, countries rely on other cooperative regimes—trade and investment—to palliate the economic shocks that uncooperative regimes—oil prices—represent for their economies. Increasing volatility should challenge countries’ capacities to cope domestically with the sudden increase (decrease) in oil expenditure (revenue). How do countries cope with this situation?
To answer this question, Chapter 3 introduces a Bayesian multidimensional Poisson change-point model. In the period under study, both oil prices and the number of agreements signed each year have increased dramatically, suggesting a fundamental change in the average oil price-level and the number of treaties. In addition to the novel application of this Bayesian model, Chapter 3 provides a more nuanced and precise understanding of the impact of oil wealth on international cooperation.

What motivates national governments to intervene in the fuel market gaps examined in Chapter 3? Chapter 4 approaches the domestic political economy of fuel price changes. Even though national leaders’ ability to affect gasoline prices in the immediate or short term is limited, oil and other fossil fuel prices are a sensitive issue in elections. Much has been said about the relationship between macroeconomic phenomena and government survival. After all, the idea that politicians can be held accountable for policy outcomes is at the heart of the concept of democratic government. At the same time, this dissertation has talked about the undeniable impact of fuel prices on the national economy and the limited role of national political leaders in the fuel market. Given these two ideas: that politicians are accountable for the economy and that they have little to do with fuel prices, it is puzzling that gas prices would appear as an issue in political campaigns at all. The main argument put forth in Chapter 4 is that fuel prices indeed matter in politics, because they are used by the public as an indicator of the state of the economy. Incumbents, then, face domestic pressure to palliate the adverse economic effects of fuel price shocks, even if they cannot intervene immediately and directly.
The study of fossil fuels is important because nearly every inhabitant of this planet participates in the world oil market one way or another, and on a daily basis. Although political institutions and fuel prices may not move at the same pace, it is not necessarily true that institutions escape the influence of the fossil fuel market. The resource curse literature makes this clear for oil-producing nations. Ultimately, the chapters in this dissertation should motivate further research on the demand-side politics of oil.
Chapter 2

What do we know about Natural Resources, Democracy, and Economic Growth?

Many countries depend on imports to produce a wide array of goods, from essential services like power to luxury goods like jewelry. One would be inclined to believe that because of the lack of control over the supply of the inputs for these goods and the costs of obtaining them from abroad, these countries are unlucky, and worse off than countries that produce these resources in their own territories. However, the wealthiest countries in the world depend on imports of important resources like minerals, metals and fuels while in many of the poorest countries these resources are abundant. This phenomenon is commonly called the natural resource curse.
Large amounts of scholarly work in political science and economics have studied the relationship between natural resource wealth, political institutions, and economic development. Despite the growth of research on these topics, the debate is far from settled. From the 1980’s to the turn of the century, there was strong evidence in favor of a curse (Ross, 1999): natural resource wealth can stymie economies, support bad governments, and prevent political stability. However, a growing amount of research has found either no evidence of an effect or even the possibility that natural resource wealth is a blessing. What conclusions can we draw from this vast body of work, and how can we explain the differences in results?

The first objective of this chapter is to condense and weigh existing knowledge and evidence on the resource curse. Specifically, Bayesian meta-analysis will assess the average, overall effect of natural resource wealth on institutional quality and growth levels. Meta-regression analysis is another useful tool to quantitatively evaluate extant research on a given topic. They are analogous to qualitative approaches like literature reviews, since they have the same goal of assessing the state of scientific knowledge on a subject. However, the massive amounts of information that must be processed in some scholarly debates complicate an objective and accurate evaluation of all articles (Wolf, 1986, 10). Meta-analysis especially helpful when, as in the case of the resource curse, an objective and thorough qualitative analysis of the plethora of articles on a topic is infeasible. Although notable efforts have been made to assess the state of the resource curse literature, meta-analysis is absent from this body of work.

The second objective of this chapter is to seek the sources of this debate. The results of similar research endeavors often differ across models, sample sizes, and time. Occasionally, these differences are nuanced, but other times results are diametrically
opposed. Bayesian meta-regression methods will be used to explore how differences in research design, measurements, and samples contribute to the differences in results. Using meta-regression analysis, we will be able to understand the conclusions that can be drawn from thirty years of research.

Once we review the general hypotheses put forth in the resource curse literature in the next section, section three will explain the meta-regression methodology and model. The fourth section describes the dataset of over fifty articles on the resource curse. Section five applies meta-analysis to the data and discusses the results. Our final section discusses avenues for further research given the current state of knowledge.

2.1 Theoretical Overview: the Current State of Research

The goal of this section is to overview the state of natural resource curse literature and point out some of the most important schisms in it. As mentioned earlier in the dissertation, a large amount of research in political science and economics has studied the resource curse. In the thirty years since the earliest articles on the topic were published, the common wisdom has wavered between confirming and denying that natural resources affect any of these outcomes negatively. This, together with inconclusive results in several of the most important works in this literature, makes reaching a solid conclusion a challenging endeavor, although several authors (Frankel, 2010; Isham et al., 2005; Ross, 2004; Rosser, 2006; Sachs and Warner, 2001) have provided overviews.
Sachs and Warner (2001) explain that research on the “natural resource curse”, the “Dutch disease” or the “paradox of the plenty” was originally motivated by a need to “understand the roots of failure in natural resource-led development” (Sachs and Warner, 2001, 828) in the post-war era. This chapter focuses on two of the main sub-literatures: natural resources and economic growth, and natural resources and political regime types. We refer to the former as the economic resource curse and the latter as the political resource curse.

Before reviewing these two outcomes, the important debates on the definition and operationalization of natural resource wealth must be discussed. First, there are important divisions over what constitutes a resource, and whether all resources are a curse. Second, the resource curse is broadly defined as the impact of natural resource wealth on a political economy, but often times the terms wealth, abundance, and dependence have been used interchangeably when these three concepts may not be comparable.

Oil and fuels are by far the most well-known curse. For example, the foundational work by Gelb (1988) only considers countries that produce hard minerals or oil as resource-rich countries. However, the most widely used measure of resource wealth, the ratio of primary exports to Gross National Product (GNP), includes primary agriculture, fuels, and minerals (Sachs and Warner, 1997a). Sachs and Warner and many articles that used this measure consistently found evidence of a curse (examples include Atkinson and Hamilton, 2003; Boschini, Pettersson and Roine, 2013; Bruckner, 2010), but others have also used this data and found the opposite to be true (Mehlum, Moene and Ragnar, 2006). Collier and Hoeffler (2005) also take a broad definition

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1 Although there are some subtle differences between these three terms, in this chapter we use them interchangeably.
of natural resources and find evidence in favor of a curse in terms of institutions and political stability.

In contrast, studies with narrower definitions of natural resources have not found solid results. Several studies considered only mineral wealth and confirmed the evidence in favor of a curse (Brunnschweiler and Bulte, 2008). Nevertheless, Alexeev and Conrad (2009) separate mining from hydrocarbons and find evidence that they are both beneficial in the long term for GDP levels and political institutions. Leite and Weidmann (1999) disaggregate the Sachs and Warner measure and find that while fuel and metal ores have a negative impact on corruption, food and agricultural exports have the opposite, albeit statistically insignificant, effect. Isham et al. (2005, 159), however, find that cocoa and coffee are associated with weaker institutions. How can we explain these differences?

One vein of research on the causes of the resource curse suggested that the unstable prices of natural resources complicate economic development (Rosser, 2006). We should expect, then, that natural resources with more unstable prices should be a graver curse than resources in stable markets. Ross (2006, 295), for example, finds that trade shocks are associated with the onset of civil conflicts. Another course of research distinguishes diffuse from point resources, with the latter referring to natural resources extracted from a concentrated geographic or economic area (Isham et al., 2005). Sala-i Martin and Subramanian find that “the lobbying for and allocation of the rents associated with such resources” (Sala-i Martin and Subramanian, 2003, 9) makes “point-source” natural resources more pernicious than diffuse resources. Empirical evidence in Sala-i Martin and Subramanian (2003), Isham et al. (2005) and (Ross, 2001) supported this distinction.
Some suggest that “lootable” resources like diamonds or narcotics (Ross, 2006) are more damaging than non-lootable resources such as forestry. In the civil war sub-literature, it has been argued that rebel groups are more likely to have access to lootable resources during a conflict, and lootable resources can be used by rebel groups for economic support (Lujala, Petter Gleditsch and Gilmore, 2005). In the political-economic sub-literature, Mehlum, Moene and Ragnar (2006) argue in favor of the distinction between lootable and non-lootable resources because the latter, exemplified by agriculture and land, are less taxable than lootable resources. In addition, some institutional settings may facilitate the diversion of rents from lootable resources into activities that benefit inefficient industries or small social groups, blocking economic growth and sustaining low-quality institutions (Mehlum, Moene and Ragnar, 2006).

In summary, when thinking on the paradox of the plenty, social science research has accounted for some of the variation in empirical support by refining the term “natural resource”. Literature nowadays would agree that not all natural resources are curses (Frankel, 2010). However, it is still possible that some natural resources operate differently in different classifications. For example, narcotics are lootable resources, but they are not necessarily “point-source”. The implications of this type of distinction have not yet been explored, but we may speculate that they affect countries’ political institutions but not economic development. Arezki and Bruckner (2009), for example, found that oil rents worsen some political institutions but improve other aspects of the political economy. Most importantly, studies have found contradictory evidence of the natural resource curse even when definitions of natural resources are similar. Since minerals and fuels are the most commonly measured resource, we focus on them in the analysis that will follow.
A parallel line of research has explored how the definition and operationalization of resource wealth affects our assessments of the paradox of the plenty. Natural resource abundance, dependence and wealth are often used interchangeably (see Sachs and Warner, 2001, 832; Wantchekon, 2002, 70) but the choice is not trivial. The term “natural resource abundance” is a statement about an economy’s endowment of natural resources. In contrast, “natural resource dependence” makes a claim about natural resources relative to a country’s economic structure. Moreover, the underlying mechanisms that link abundance and dependence to economic and political outcomes, as well as their policy implications, are not equivalent.

Consider the most widely-used measure in the literature: primary exports as a share of GNP or Gross Domestic Product (GDP).\(^2\) While it is clear that a country without natural resource endowments cannot export them, it need not be the case that resource-wealthy countries always export them. This measure thus makes a strong assumption: that natural resource abundance is directly correlated with natural resource exports (Brunnschweiler, 2008). Moreover, Brunnschweiler (2008) points out that GDP per capita, as opposed to GDP, is the standard indicator for economic wealth. Even when per capita measures of natural resources are used, they are often compared directly to exports/income measures. This comparison implies that abundance and dependence are equivalent. Finally, a related measure is the share of natural resources (particularly oil and minerals) in a country’s total exports (Rowley and Smith, 2009; Sala-i Martin and Subramanian, 2003), and it is most commonly used as a specification to test the robustness of resource curse results. However, the

\(^2\)While GDP counts only the goods and services produced within a given country’s territory, GNP takes the goods and services produced by residents, assets and capital of a country, regardless of their location. For the purposes of this chapter, they are taken as equivalent measures of country income.
degree of an economy’s openness, trade diversification (Murshed and Serino, 2011) as well as price fluctuations (Frankel, 2010) for the resource could easily misrepresent a country’s resource wealth.

The challenge in explicitly modeling resource abundance is to decide whether abundance is comparable across states and across resources, and whether it should be measured by the stocks (i.e., oil reserves) or flows (i.e., oil income) of resources per capita. Several measurements have been proposed. Haber and Menaldo (2010); Ramsay (2011); and Ross (2009) measure abundance as oil income per capita; Bearce and Laks Hutnick (2011) and Kurtz and Brooks (2011) use energy production per capita; and Stijns (2005) and Brumenschweiler and Bulte (2008) measure abundance in terms of reserves and assets. Finally, binary indicators for natural resource exports and/or production imply that the mere possession of natural resources, regardless of the structure of the economy, are a curse.

But is natural resource abundance a more faithful operationalization of the natural resource wealth that curses economies? In much of the literature, resource abundance is admittedly the sine qua non of the resource curse, but not a causal mechanism itself. As Rosser explains,

\[\ldots\] the main problem with natural resource abundance is not that it leads to economic dependence on natural resources or a skewed export structure per se but that it creates rents – that is, excess earnings above normal profits. (Rosser, 2006, 10)

Rentier state theories of the Dutch disease bypass debates on abundance and dependence, and focus on natural resource rents. In this theory the importance of natural
resource rents for a government, and not its importance in the economy as a whole, is identified as the source of the curse. Governments whose revenues come mostly from resource rents have less incentives to create wealth (Auty, 2007, 629), collect taxes (Ross, 1999), are freed from accountability (Bearce and Laks Hutnick 2011, 703; Ross 1999), and have resources to repress opposition (Herb, 2005). Rents are often defined as the difference between the cost of resource extraction and the income from these resources (Collier and Hoeffler, 2005, 11). Herb (2005) measures the share of rents in government revenue and others measure the share of rents in GDP. The latter operationalization makes an assumption that the composition of a government’s revenue is proportional to the composition of the economy in general, which need not be the case.

The goal of examining these different measures is not necessarily that one is better or carries more validity than the other. Rather, we wish to point out the important differences between the main concepts of resource curse literature. To explore the existence of a Dutch disease and the causal mechanisms behind it, the link between theory and empirics must be analyzed more carefully. We cannot discard the idea that failure to address these issues would explain at least some of the heterogeneity in empirical support for the resource curse.

Heterogeneity is also present in the explanations that have been offered for the curse. Research on the paradox of the plenty in the social sciences began in economics. Gelb (1988); Gylfason, Herbertsson and Gylfi (1999); and Sachs and Warner (1995) were among the first to present empirical evidence that natural resource wealth is associated with reduced economic growth. In their seminal study, Sachs and Warner (1995) find that the development strategy followed by Latin American countries based
on commodities was key to explaining the difference in economic development between this region and East Asia (see also Ross, 1999, 310–312). Several quantitative, large-sample studies followed (Rosser, 2006) with similar results (Auty, 2001; Gylfason, Herbertsson and Gylfi, 1999; Leite and Weidmann, 1999).

Nevertheless, these results have been challenged by an equally large body of work that finds weak evidence that resource wealth is associated with slowed growth (Collier and Hoeffler, 2005; Herb, 2005; Stijns, 2005), or even evidence to the contrary (Alexeev and Conrad, 2009). Rosser (2006) and Frankel (2010) point out that evidence in favor of the resource curse is challenged the most by the lack of robustness of the evidence vis-a-vis alternative measures of wealth and natural resources.

A second group of studies emphasizes a conditional relationship between resource wealth and economic growth. For example, Atkinson and Hamilton (2003) conclude that natural resources combined with low savings rates were characteristic of the countries most afflicted with the curse. Most conditional relationships, however, have to do with institutions. More importantly, researchers have been concerned with how the pre-existing institutional setting influences a country’s economic and institutional performance (Bhattacharyya and Hodler, 2010; Boschini, Pettersson and Roine, 2007; Dunning, 2008) when natural resources are available or become available.

Political science literature has mainly approached the resource curse through the relationship between resource abundance and political institutions. Several studies on the influence of natural resource wealth on regime duration and regime transitions. Ulfelder (2007) and Al-Ubaydli (2012) apply rentier state theory to find that democratic transitions are less likely in resource-rich countries. In particular, resource-rich dictators have a source of income that will not be hurt by repression, which lengthens
their survival in power. The results of Smith (2004) concur with this result, showing that authoritarian regimes in oil-dependent countries are less likely to fail.

Evidence that “natural resource abundance is associated with low levels of democracy” (Rosser, 2006, 268) has been provided in the political resource curse literature by several time-series cross-sectional studies (Jensen and Wantchekon, 2004; Ramsay, 2011; Ross, 2001; Wantchekon, 2002). For Arezki and Bruckner (2009) the effect is mixed: while oil rents significantly increase corruption, they also improve civil liberties. Dunning (2008) proposes that, conditioned on the level of inequality generated in the non-resource economy and on a low level of resource dependency in the economy, resource wealth can actually promote democracy (Dunning, 2008, 101). In their seminal paper, Haber and Menaldo (2010) and find no evidence of a resource curse.

To sum up, research in political science and economics agrees that natural resource abundance, economic development, and political institutions are closely linked. However, many questions remain open regarding the story behind the resource curse, as the heterogeneity of results in both fields makes evident. In his review, Ross once suggested the main weakness of the resource curse in political science was the “failure of political scientists to test their own hypotheses” (Ross, 1999, 322). Fourteen years later, the state of the literature is somewhat the opposite: with a plethora of empirical tests, were still lack a clear response to the link between resource abundance and political regime.
2.2 The Literature in Numbers

This section presents the information discussed above from a new perspective. Some of the most important works in the natural resource curse literature were discussed in the previous section, but more contributions have been made. In an effort to include a wider range of articles in our assessment of the state of the literature, in this section we treat articles and books on the paradox of the plenty as data points. Data were collected between February 10th and February 17th, using search engines in two digital libraries (JSTOR and Web of Knowledge) and Google Scholar. To ensure papers relevant to the resource curse literature were included, at least one of the keywords in the search in digital libraries needed to be present in the title of the paper.\(^3\)

Once the search was finalized, additional criteria were used to obtain the sample for the meta-analyses. In general, we consider articles that have been published in peer-reviewed journals and working papers by the National Bureau of Economics Research, the International Monetary Fund, and the World Bank. All the estimated effects in the articles from models where the outcome variable is relevant to the question at hand are recorded except for those in Appendix or web Appendix tables. Finally, because of the importance of standard errors in the random effects meta-analysis model, studies that did not report this estimate (or t-values to derive the standard error) are excluded.

Since comparisons between covariate measurements as distinct as the ones described in the previous section are impossible, for the analysis that follows the more than

\(^3\)The terms used in the searches and the full list of books and articles obtained by this comprehensive search is available in the Appendix.
20 measurements are classified into six broad categories. The first three can be thought of as measures of natural resource dependence. The first category, *exports*, comprises measures of oil wealth defined as natural resource exports as a proportion of total exports, or the share of natural resource exports in a given country’s economic activity. In the second group, we include measures of natural resource *production* in monetary terms or as a proportion of a country’s economic activity. The third group is composed by measures of natural resource *rents*, most commonly defined as the share of resource rents in total rents.

The remaining categories are not measures of natural resources vis-a-vis the size of an economy. Rather, they attempt to measure natural resource abundance more explicitly—in a way that is independent of the country’s economic structure. Thus, the fourth category includes *binary* indicators such as “oil exporter” or “oil producer”. Measurements in the fifth group are natural resource production, export, or reserve levels, divided by a country’s population. We call this the *per capita* group. The final classification includes *non-monetary* measurements of resources.

For the political resource curse, we will leave aside studies concerned with the determinants of government survival and transitions to democracy. These works concern a question that is inherently different from studies of the level or quality of a democracy, the most common definition of the political resource curse. The Democracy All Set is a sample of twenty-nine studies and 327 estimated effects of natural resources on economic growth. Within this set, however, there is variation in the outcome variable. Twenty studies (224 estimates) operationalize the level of democracy in a country-year as its Polity score (Marshall and Jaggers, 2002). Nine studies (52 estimates) define the level of democracy according to the Civil Liberties and Political Rights
indexes of Freedom House (Freedom House, 2001). Five studies (22 estimates) use the Democracy-Dictatorship (DD) Data by Przeworski et al (2000). Finally, Alexeev and Conrad (2009) use a measure of rule of law in the World Bank Governance indicators (2005) as an outcome variable. Since this is the only article in the sample with such a measure, it is not possible to create a separate group for it. However, it is one of the most highly cited works in the political resource curse literature. As a compromise, we include it in the Democracy All Set, but exclude it from all other subsets. Table 2.1 describes some of the characteristics of the articles in the sample.

Table 2.1: Political resource curse: descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>All Set</th>
<th>Polity</th>
<th>Freedom House</th>
<th>Democracy-Dictatorship</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effect</td>
<td>-0.49</td>
<td>-0.06</td>
<td>0.00</td>
<td>0.15*</td>
</tr>
<tr>
<td>sd</td>
<td>2.60</td>
<td>3.13</td>
<td>0.41</td>
<td>5.11</td>
</tr>
<tr>
<td>Countries</td>
<td>96.15</td>
<td>93.17</td>
<td>110.60</td>
<td>93.08</td>
</tr>
<tr>
<td>sd</td>
<td>46.26</td>
<td>51.57</td>
<td>24.14</td>
<td>58.48</td>
</tr>
<tr>
<td>Observations</td>
<td>1218.00</td>
<td>1287.00</td>
<td>921.10</td>
<td>1709.00</td>
</tr>
<tr>
<td>sd</td>
<td>1588.47</td>
<td>1628.62</td>
<td>779.46</td>
<td>1983.47</td>
</tr>
<tr>
<td>Covariate is:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Production</td>
<td>135</td>
<td>96</td>
<td>21</td>
<td>0</td>
</tr>
<tr>
<td>%</td>
<td>45.45</td>
<td>48.73</td>
<td>43.75</td>
<td>0.00</td>
</tr>
<tr>
<td>Rents</td>
<td>46</td>
<td>33</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>%</td>
<td>15.54</td>
<td>16.75</td>
<td>4.17</td>
<td>9.09</td>
</tr>
<tr>
<td>Exports</td>
<td>84</td>
<td>63</td>
<td>21</td>
<td>4</td>
</tr>
<tr>
<td>%</td>
<td>28.28</td>
<td>31.98</td>
<td>43.75</td>
<td>18.18</td>
</tr>
<tr>
<td>Not monetary</td>
<td>8</td>
<td>4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>%</td>
<td>2.69</td>
<td>2.03</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Dichotomous</td>
<td>23</td>
<td>0</td>
<td>4</td>
<td>16</td>
</tr>
<tr>
<td>%</td>
<td>7.74</td>
<td>0.00</td>
<td>8.33</td>
<td>72.73</td>
</tr>
<tr>
<td>Studies</td>
<td>27</td>
<td>18</td>
<td>8</td>
<td>5</td>
</tr>
<tr>
<td>Estimates</td>
<td>296</td>
<td>197</td>
<td>48</td>
<td>22</td>
</tr>
</tbody>
</table>

* Odds Ratio

There are important nuances in the economic resource curse literature as well. Even though most of the research is concerned with the effect of natural resources on
economic growth, annual growth rate is the outcome variable of only three articles. Five articles measure growth as the rate of growth per year per economically active person (165 estimates) and the vast majority of articles (327 estimates) use annual growth rates per capita. To the extent that these measures tap at the same abstract concept, we refer to the Growth All Set as the group of twenty-nine studies and 555 estimates in the sample. This sample is then divided into subgroups according to the outcome measure. Descriptive statistics for this sample are presented in Table 2.2.

Table 2.2: Economic resource curse: descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>All Set</th>
<th>GDP Growth</th>
<th>GDP Growth/EAP</th>
<th>GDP Growth per capita</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effect</td>
<td>-0.051</td>
<td>-9.0656</td>
<td>-0.07</td>
<td>-1.35</td>
</tr>
<tr>
<td>sd</td>
<td>13.31</td>
<td>22.69</td>
<td>3.27</td>
<td>13.7</td>
</tr>
<tr>
<td>Observations</td>
<td>308</td>
<td>424.7</td>
<td>78.28</td>
<td>401.2</td>
</tr>
<tr>
<td>sd</td>
<td>658.56</td>
<td>304.13</td>
<td>10.08</td>
<td>825.43</td>
</tr>
<tr>
<td>Covariate is:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Production</td>
<td>79</td>
<td>0</td>
<td>28</td>
<td>51</td>
</tr>
<tr>
<td>%</td>
<td>14.23</td>
<td>0.00</td>
<td>16.97</td>
<td>15.6</td>
</tr>
<tr>
<td>Rents</td>
<td>39</td>
<td>39</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>%</td>
<td>7.03</td>
<td>61.9</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Exports</td>
<td>278</td>
<td>20</td>
<td>76</td>
<td>182</td>
</tr>
<tr>
<td>%</td>
<td>50.09</td>
<td>31.75</td>
<td>46.06</td>
<td>55.66</td>
</tr>
<tr>
<td>Not monetary</td>
<td>37</td>
<td>0</td>
<td>0</td>
<td>37</td>
</tr>
<tr>
<td>%</td>
<td>6.667</td>
<td>0.00</td>
<td>0.00</td>
<td>11.31</td>
</tr>
<tr>
<td>Per-capita</td>
<td>122</td>
<td>4</td>
<td>61</td>
<td>57</td>
</tr>
<tr>
<td>%</td>
<td>21.98</td>
<td>6.34</td>
<td>36.97</td>
<td>17.43</td>
</tr>
<tr>
<td>Studies</td>
<td>29</td>
<td>4</td>
<td>5</td>
<td>23</td>
</tr>
<tr>
<td>Estimates</td>
<td>555</td>
<td>63</td>
<td>165</td>
<td>327</td>
</tr>
</tbody>
</table>

Tables 2.1 and 2.2 provide interesting insights on the different approaches in the political and economic resource curse literatures. Political resource curse hypotheses tend to be tested on much larger samples than economic resource curse models. With respect to the debate on whether the curse is caused by wealth or dependence on natural resources, political resource curse literature favors production measures over exports, the preferred measure in the Growth All Set.
Admittedly, information is lost from broad summaries. However, it is important to remark that in the top rows of Tables 2.2 and 2.1 the average estimated effects are very near zero, with very large standard deviations. The funnel plots in Figure 2.1 provide another view of the state of the literature. Panel (a) shows the estimated effects from the Democracy All Set on the vertical axis. The effects are ordered by the number of observations used to estimate them. Studies appear to converge toward the “no effect line”, and although the funnel is asymmetric and skewed in favor of the resource curse (i.e., most observations appear under the line), several results suggesting natural resources can be positively associated with democratic regimes are apparent. Panel (b) in Figure 2.1 shows the recorded coefficients from the Growth All Set. Results also seem to favor the existence of a resource curse, but the small-N region of the plot shows substantial evidence that natural resources may be a blessing. With so much

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4 Three outlier coefficients were excluded so as to depict the majority of the reported results more efficiently

5 Again, I exclude outlier coefficients were excluded to depict the majority of the reported results more clearly
variation in sample size and so many estimates, a firm conclusion cannot be drawn based on these descriptions.

2.3 Meta-Regression: A method for quantitative literature reviews

In this chapter, we are interested in assessing the effect of natural resource wealth on countries’ quality of democracy and growth rates. As we have shown above, research is abundant and qualitative evaluations have stated that results are inconclusive. In this section we propose to analyze the resource curse from a quantitative perspective. In a nutshell, the aim of meta-analysis is to use the estimated effects from a corpus of research to calculate a mean effect and the uncertainty around it. This section will explain the evolution of the meta-analysis and meta-regression framework, estimation methods for it, and interpretations of the results.

To meta-analyze a literature, we begin with the null hypothesis that there is no effect of the covariate of interest on the outcome (Gelman, 2004, 147), and use existing studies to calculate a test statistic and estimate uncertainty around it. Frequentist and Bayesian methods are commonly used in meta-analytic studies. The first frequentist approach, fixed effects meta-analysis, assumes that the differences in results across studies are due to sampling error and differences in research procedures, but there is ultimately a unique effect that all studies aim to estimate (Doucouliagos and Ulubasoglu, 2008, 66). This assumption is quite strong and untenable, especially when the effects are estimated using observational data.
The second approach, *random effects* meta-analysis, assumes that the estimated effects are not estimates of a common parameter. We then account for sources of variability in the studies in addition to the errors that fixed effects analysis assumes (Lipsey and Wilson, 2000; Thompson and Sharp, 1999). These sources may be randomly distributed if we assume that they are different and unrelated across studies (Higgins, Thompson and Spiegelhalter, 2009). A related procedure is to model the random differences between studies and use additional variables to account for systematic differences between the studies (Doucouliagos and Ulubasoglu, 2008). This approach is also known as *mixed effects* meta-analysis (Higgins, Thompson and Spiegelhalter, 2009).

The *Bayesian meta-analysis* generalizes the random-effects approach in the sense that it explicitly models the governing parameters of the random-effects distribution. In other words, the Bayesian approach models the underlying cause for heterogeneity in the studies. To fix ideas, suppose a linear model $Y = \beta_0 + \beta_1 X + \epsilon$, where $Y$ is an observed outcome and $X$ is the covariate of interest. This model—or a version of it—is estimated in $i$ models of $J$ studies. We call the effect of interest is $\beta_1$ and think of meta-analysis as a hierarchical model. For convenience, we refer to $\beta_1$ as $\beta$. In the first level, the estimated effect $\hat{\beta}_i$ in each model $i$ is an observation. These estimates are essentially draws from distributions (assumed Gaussian) of possible effects.

\[
\hat{\beta}_i \sim N(\beta_i, \sigma_i^2); \\
\beta_i \sim N(\beta, \tau^2) \\
\Rightarrow \hat{\beta}_i \sim N(\beta, \sigma_i^2 + \tau^2)
\]
\( \beta_i \) represent the possible “true” treatment effects and \( \sigma_i^2 \) are the “true” sampling variances of each study. These parameters are themselves assumed to be random deviates of a distribution, and they are modeled in the second level of the hierarchy through a prior distribution. For \( \sigma_i^2 \) it is generally assumed that the estimated sampling variances (i.e. squared standard errors) can be used in place of the true sampling variances (Higgins, Thompson and Spiegelhalter, 2009). This obviates the need for a prior distribution for \( \sigma_i^2 \). Applying Bayes’ theorem, the posterior density of interest is

\[
p(\beta|\hat{\beta}, \sigma^2) \propto \prod_i \{p(\hat{\beta}_i|\beta_i, \sigma_i^2, \tau^2)\} \pi(\beta_i|\beta, \tau^2) \pi(\beta, \tau^2)
\]

\[
\propto \prod_i \{N(\beta_i, 1/\sigma_i^2)\}N(b, 1/\tau^2)\pi(\tau^2)
\]

where \( b \) and \( \tau \) are unmodeled parameters.

This approach is advantageous for several reasons. First, a specific distribution for the random effects becomes possible and effects can more easily be predicted (Higgins, Thompson and Spiegelhalter, 2009) thanks to the posterior predictive distribution. In addition, Bayesian meta-analysis has an innate ability to incorporate existing knowledge on the subject at hand to the current investigation (Gill, 2004) through prior distributions, although Higgins, Thompson and Spiegelhalter (2009) warn that when few studies are available, Bayesian models rely heavily on the distributional assumptions made for the random effects.

Exchangeability is also an important advantage of the Bayesian meta-analysis model. It is a common practice in the social sciences to estimate several model specifications to test a single hypothesis, generating several estimated effects from slightly different
model specifications. Under these circumstances it is difficult to defend the idea that estimated effects within the same study are independent, because they will tend to come from similar research designs. Exchangeability requires that the joint distribution of a group of observations be “invariant to permutations” (Greenberg, 2007, 50). More specifically, in a Bayesian meta-analysis the treatment effects may ultimately be different in each study, but we cannot identify their magnitude (Higgins, Thompson and Spiegelhalter, 2009). This is tantamount to assuming that “there are no important covariates that might form the basis of a more complex model” (Gelman, 2004, 148), and if “particular covariates are believed to be important then an exchangeability assumption would not be appropriate” (Higgins, Thompson and Spiegelhalter, 2009, 144).

Meta-regression analysis takes a further step in exploring the causes of variation across studies (see Sutton and Higgins, 2008; Sutton and Abrams, 2001) by incorporating information about the studies’ research design as covariates to model the mean effect (Doucouliagos and Ulubasoglu, 2008; Harbord and Higgins, 2008). Specifically, we model

$$\hat{\beta}_i = \gamma_0 + \gamma'_Z Z_i + \delta D_i + \nu_i$$

where $\nu \sim (0, \sigma^2_i)$. Z and D represent specification and data differences, respectively. Additional study-level variables can easily be incorporated (see Doucouliagos and Ulubasoglu, 2008, 66). A Bayesian estimation of this random-effects regression makes it possible to assess the uncertainty around these estimates better, and to retain accuracy despite small samples of estimates. For convenience at the estimation stage, the prior probability distribution for $(\hat{\beta}, \tau^2)$ is assumed Normal-Inverse
Gamma, although truncated Gaussian, Cauchy, and Jeffrey’s distributions have also been suggested as priors in meta-regression literature (Sutton and Abrams, 2001).

Before presenting the results, it is important to emphasize the interpretation of the coefficient posterior means. In particular, the outcome of the meta-regressions is the estimated effect of the key covariate (e.g., natural resource wealth) and not natural resource wealth itself. In the same way, the covariates in the meta-regression are study-level measurements of each model, and not levels of those covariates themselves. The meta-regression coefficients are thus the average estimated change in the estimated effect for a one-unit change in the study-level characteristic. To be sure, a meta-regression coefficient indistinguishable from zero would mean that the presence of this variable in the original regression model is orthogonal to the estimated result.

For the special case of binary indicators of model specification differences, the coefficients obtained in the meta-regression are useful to explore the possibility of a mediating effect. In their seminal paper, Baron and Kenny defined mediation as the mechanism through which a covariate influences an outcome (Baron and Kenny, 1986, 1173). Investigating whether this type of relationship exists is key for our understanding of the outcome variable and its relation to the covariate we are interested in. Moreover, a statistical link between covariates is a violation of the no-multicollinearity assumption in ordinary least squares (OLS) estimation, a common method in the resource curse literature.

To understand why, suppose a linear model $Y = \beta_0 + \beta_1 X + \beta_2 M + \epsilon$, where $Y$ is an observed outcome, $X$ is the covariate of interest, and $M$ is a covariate which we suspect to be a mediator. The authors proposed a simple test for mediation using a
system of equations:

\begin{align*}
M &= \beta_0m + \beta_1mX + \epsilon_m \\
Y &= \beta_01 + \beta_11X + \epsilon_1 \\
Y &= \beta_02 + \beta_12X + \beta_22M + \epsilon_2
\end{align*} 

Mediation exists if the following conditions hold (Baron and Kenny, 1986, 1177):

1. \( \beta_1m \) in Equation 1 must be statistically distinguishable from zero. We need to establish that \( M \) and \( X \) are not statistically independent.

2. \( \beta_{11} \) in Equation 2 must also be statistically distinguishable from zero to show that changes in \( X \) are indeed associated with changes in \( Y \)

3. A statistically significant \( \beta_{22} \) in Equation 3 shows that the suspected mediator also affects the outcome.

If mediation exists, then the effect of \( X \) on \( Y \) should be reduced or nullified once \( M \) is included in the model. Now suppose some models are estimated in \( J \) studies and will be analyzed using meta-regression. Some studies fit Model 1

\[ Y = \beta_0 + \beta_1X + \beta_2M + \epsilon \]

while others fit Model 2

\[ Y = \beta_0 + \beta_1X + \epsilon \]
The meta regression model is

\[
\hat{\beta}_{1j} = \gamma_0 + \gamma_1 1(M)_j + v_j
\]  

(2.4)

where \(1(\cdot)\) is the indicator function, equal to one if \(M\) is present in study \(j\) and zero otherwise. \(\gamma_1\) in this case represents the average difference in \(\hat{\beta}_1\) between Models 1 and 2, which is equivalent to comparing Equations 2 and 3 above. When, for example, \(\gamma_0\) and \(\gamma_1\) have opposite signs, the meta-regression suggests that all else equal, the relationship between \(Y\) and \(X\) is on average weakened by the inclusion of \(M\). Of course, the statistical significance of \(\gamma_1\) is a necessary but not a sufficient condition for a mediation effect. Since it relies on published results, the meta-regression analysis cannot confirm the presence of mediation because it is impossible in this context to estimate Equation 2.1. Rather, \(\gamma_1\) should be taken as a canary in the coal mine of mediation in the literature under examination.

Baron and Kenny define moderation as a mechanism where the size and/or direction of a covariate’s impact on the outcome variable is contingent on a third variable. Moderator effects are most commonly thought of as interactions between two variables, where the marginal effect of the covariate of interest changes in sign or in size given changing levels of the moderator:

\[
Y = \beta_0 + \beta_1 X + \beta_2 M + \beta_3 XM + \epsilon
\]  

(2.5)

One may be tempted to interpret \(\gamma_1\) in Equation 2.4 as a conditioning effect of \(M\) on \(X\), suggesting \(M\) is a moderator of the relationship between \(X\) and \(Y\). In other words, at first glance one may be inclined to interpret \(\gamma_1\) in Equation 2.4 as equivalent to \(\beta_3\).
in Equation 2.5. This may be especially alluring when \( M \) itself is a binary indicator, because we are likely to observe \( 1(M) = M \). This interpretation is incorrect. Meta-regression cannot help us inspect the presence of moderation. In terms of a regression model, a moderator \( M \) “is a variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable” (Baron and Kenny, 1986, 1174).

To see why, we consider Models 1 and 2 again. Suppose \( M \) is a binary variable, and we estimate the meta-regression of Equation 2.4. Assuming that in Equation 2.4 \( E(\beta_1) = \gamma_0 + \gamma_1 1(M) \) and in Model \( E(\beta_{01}) = E(\beta_{02}) = \beta_0 \), it is true that from Model 1 and Equation 2.4:

\[
Y = \beta_0 + (\gamma_0 + \gamma_1 1(M))X + \beta_2 M
\]

when \( 1(M) = M = 0 \):

\[
Y = \beta_0 + \gamma_1 X
\]

when \( 1(M) = M = 1 \):

\[
Y = \beta_0 + \gamma_0 X + \gamma_1 X + \beta_2
\]

This exercise would yield similar results if we substituted the values of \( M \) in the interaction model in Equation 2.5, suggesting \( \gamma_c \) is a moderator coefficient. However,
when $1(M) = 1$ and $M = 0$:

\[
Y = \beta_0 + \gamma_0 X + \gamma_1 * X \\
= \beta_0 + (\gamma_0 + \gamma_1)X
\]

which is an impossible configuration in interaction models like Equation 2.5.

In conclusion, Bayesian meta-analysis is a useful tool to summarize the results of a voluminous literature because in this framework it is possible to incorporate prior knowledge about the literature into the analysis and this approach allows more options in terms of distributional assumptions made for the estimated effects and their variability. By including information on the differences in research design across studies, meta-regression analysis attempts to explain the heterogeneity in estimated effects. Finally, by including information on model specification, meta-regression makes it possible to explore mediator relationships.

With these considerations in mind, we will build a Bayesian random-effects linear model for the effect of natural resources on levels of democracy and growth rates. The model will be implemented using the R2jags library in R. Three parallel chains were run for 50,000 iterations each and the first half were discarded as burn-in. Convergence was monitored using the superdiag library.
2.4 Results

Is there a resource curse? To assess the overall state of the literature in this topic, we use a Bayesian random-effects meta-analysis based on the model by Higgins, Thompson and Spiegelhalter (2009) to calculate the average overall estimated effect of natural resource wealth on economic growth and the levels of democracy. We use the Democracy All Set and the Growth All Set for these estimates with vague prior distributions centered at zero.⁶

The results of this analysis are presented in Figure 2.2. In both panels, the main results of the most highly cited studies in the economic and political resource curse literatures are shown. In panel (a), except for the seminal work of Haber and Menaldo (2010), estimating that natural resources will be associated with more autocratic regimes. Turning to the economic resource curse, Figure 2.2, panel (b) plots the estimated effects in the ten most cited articles in the sample. For example, while Sachs and Warner (1995) operationalize resource dependence as the share of primary exports in the GDP, Stijns (2005) uses billions of barrels of oil reserves per capita. Nevertheless, most studies in panel (a) agree with panel (b) that natural resource wealth has adverse consequences for institutional quality and economic growth.

Although a majority of studies suggest a negative effect, the variation in magnitude of the estimated effects cannot be ignored. In addition, measurement differences in the covariate of interest make the assumption that the estimates come from the same probability distribution—the main assumption made by fixed effects meta-analysis models—

⁶Specifically, the prior hyperparameters are m=0 and precision 0.001. As robustness checks, these models were re-estimated using “resource blessing” (centered at 1 with precision 0.1) priors and “resource curse” (centered at at –1 with precision 0.1). Results remained unchanged.
Figure 2.2: Forest plots of estimated effects and meta-analysis results

Studies in alphabetical order. Estimated effects and 90% confidence intervals are plotted. For the meta-analysis results, posterior random-effects mean and means of the posterior predictive distribution with 90% credible intervals are displayed. In panel (b), the horizontal axis has been cropped to display the meta-analysis results more clearly.

Untenable. For these reasons, Figure 2.2 also includes the posterior mean of the estimated overall effect, obtained from a random-effects Bayesian meta-analysis (Higgins, Thompson and Spiegelhalter, 2009) using the Democracy All Set and Growth All Set. In both cases, the posterior densities suggest that until now, literature leans toward the conclusion that there is indeed a curse. More specifically, the Democracy All Set suggests that on average, increases in resource wealth decrease the level of democracy by 0.1396 points. The overall effect in the Growth All Set can be interpreted as a suggestion that an increase in resource wealth leads to a 0.89% smaller growth rate.

The means of the posterior predictive distributions tell us the estimated effect in a new article is expected to be negative in both the democracy and growth literatures. Its standard deviation is larger than the mean overall effect because the distribution’s
uncertainty stems from the estimated standard errors in addition to the variation between these estimates. For this reason the 90% credible intervals include zero, casting doubt upon the robustness of the resource curse evidence. For the political resource curse, the probability that a newly published article finds a resource blessing rather than a curse is 0.313. For the economic resource curse, this probability is 0.325.

We turn to investigating the degree to which differences in each article’s research design can explain the heterogeneity in the estimates. As mentioned above, meta-regression analysis models the estimated coefficients as a function of other characteristics of the study they come from. To perform this analysis, information was gathered from each article regarding their data, specification, and measurement of natural resource wealth. We choose the variables for which the most data is available across studies.

Data characteristics refer to differences in sample size, country sample, and time period. We measure these characteristics by including the number of observations in the model, decade indicators for the sample period, and binary variables by region. Specification differences refer to the types of control variables included in the sample. For the political resource curse, these include country income level (GDP) and a dummy variable equal to one if the study included a dummy variable for Islam. For the economic resource curse, we record whether or not the studies controlled for other factors that are known to influence growth, such as investment, human capital, investment and institutional quality. Due to the importance of measuring natural resource wealth in our literature, we think of measurement differences as an additional category, although they could be thought of as specification differences as well.
Table 2.3 presents the results of the Bayesian random effects meta-regression for the effect of natural resource wealth on levels of democracy. Diffuse normal prior distributions were used for the coefficients, although informed priors in favor or against a curse did not change the results. It is readily apparent that a dichotomous approach to democracy does not yield much information, given the width of the credible intervals for the odds ratios. The first three models, however, offer important insights.

First, across all models, the meta-regression suggests that studies including data from the 1980s is associated with a positive effect of natural resource wealth on levels of democracy, especially in the Polity model. In contrast, studies including data from the 1990s found, overall, a more negative estimated effect. Andersen and Ross (2014) argue that the relationship between natural resources and democracy has not been constant over time. Specifically, changes in the global oil market led to nationalizations and changes in the influence that governments in oil-producing countries had over their economies. The authors find that while natural resources may have been a blessing in the past, this changes from the 1980s on. Table 2.3 speaks to this hypothesis. The coefficients for 1980s and 1990s suggest a possible shift in the role of natural resource wealth on political institutions. Substantively, these results suggest that the conclusions in Andersen and Ross (2014) may have been driven by the 1990s data. In terms of this dissertation, these results suggest the change-point in oil prices and world trade found in Chapter 3 may also be related to levels of democracy.

The meta-regression results also suggest that regional fixed effects are an important determinant of the coefficients. Specifically, studies that included a dichotomous
Table 2.3: Natural resource wealth and level of democracy

<table>
<thead>
<tr>
<th></th>
<th>All Set</th>
<th>Polity</th>
<th>Freedom House</th>
<th>Democracy-Dictatorship</th>
<th>90% credible intervals, All Set model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.0826</td>
<td>-0.5664</td>
<td>-2.4410</td>
<td>0.1537</td>
<td></td>
</tr>
<tr>
<td>(0.0800)</td>
<td>(0.2137)</td>
<td>(0.9056)</td>
<td>(0.482E+16)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. Obs.</td>
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<td>0.0000</td>
<td>0.0000</td>
<td>0.9993</td>
<td></td>
</tr>
<tr>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.99, 1.00)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1970s</td>
<td>0.0144</td>
<td>0.0107</td>
<td>1.3233</td>
<td>15.4752</td>
<td></td>
</tr>
<tr>
<td>(0.0848)</td>
<td>(0.0833)</td>
<td>(25.4515)</td>
<td>(0, 1.76 E+18)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1980s</td>
<td>0.4117</td>
<td>0.3177</td>
<td>0.8624</td>
<td>6.3343</td>
<td></td>
</tr>
<tr>
<td>(0.1184)</td>
<td>(0.1350)</td>
<td>(25.5842)</td>
<td>(0, 6.81 E+17)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1990s</td>
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<td>-0.0827</td>
<td>0.2814</td>
<td>0.2471</td>
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</tr>
<tr>
<td>(0.1007)</td>
<td>(0.1322)</td>
<td>(25.4793)</td>
<td>(0, 5.07 E+13)</td>
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<td></td>
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<tr>
<td>2000s</td>
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<td>0.2351</td>
<td>2.4670</td>
<td>2.9367</td>
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</tr>
<tr>
<td>(0.0443)</td>
<td>(0.0577)</td>
<td>(0.9047)</td>
<td>(0.68, 12.69)</td>
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<td></td>
</tr>
<tr>
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<td>0.4129</td>
<td>0.2755</td>
<td>2.5505</td>
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<td></td>
</tr>
<tr>
<td>(0.1471)</td>
<td>(0.1610)</td>
<td>(0.458 E+17)</td>
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</tr>
<tr>
<td>Asia</td>
<td>2.1582</td>
<td>0.1847</td>
<td>5.0155</td>
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<td></td>
</tr>
<tr>
<td>(0.5295)</td>
<td>(31.3973)</td>
<td>(0.02, 1.42 E+03)</td>
<td></td>
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</tr>
<tr>
<td>Latin America</td>
<td>-2.9667</td>
<td>-2.7666</td>
<td>2.1107</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.5363)</td>
<td>(0.5595)</td>
<td>(0.422 E+14)</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Middle East</td>
<td>0.1825</td>
<td>0.0921</td>
<td>1.4738</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.1155)</td>
<td>(0.1193)</td>
<td>(0.100 E+18)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income</td>
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<td>-0.1069</td>
<td>0.1099</td>
<td></td>
</tr>
<tr>
<td>(0.0479)</td>
<td>(0.1971)</td>
<td>(0.0335)</td>
<td>(0.390 E+16)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Islam</td>
<td>0.0021</td>
<td>0.1299</td>
<td>0.0733</td>
<td>0.5645</td>
<td></td>
</tr>
<tr>
<td>(0.0370)</td>
<td>(0.0482)</td>
<td>(0.0378)</td>
<td>(0.16, 1.98)</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>-0.1103</td>
<td>-1.2025</td>
<td>1.3507</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.0914)</td>
<td>(0.2851)</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Binary</td>
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<td>1.3507</td>
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<td></td>
</tr>
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<td>(0.0937)</td>
<td>(0.0727)</td>
<td>(0.361 E+12)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rents</td>
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<td>-0.0502</td>
<td>-0.6443</td>
<td>6.6689</td>
<td></td>
</tr>
<tr>
<td>(0.0467)</td>
<td>(0.0511)</td>
<td>(0.1113)</td>
<td>(0, 1.74 E+13)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Production</td>
<td>-0.2021</td>
<td>-0.2433</td>
<td>-2.4798</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.0424)</td>
<td>(0.0487)</td>
<td>(0.9035)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\tau)</td>
<td>0.1661</td>
<td>0.1584</td>
<td>0.0600</td>
<td>1.3467</td>
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</tr>
<tr>
<td>(0.0128)</td>
<td>(0.0129)</td>
<td>(0.0130)</td>
<td>(0.99, 1.82)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DIC</td>
<td>-745.5</td>
<td>-645.4</td>
<td>-222.2</td>
<td>42.6</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>296</td>
<td>197</td>
<td>48</td>
<td>22</td>
<td></td>
</tr>
</tbody>
</table>

Posterior means and standard deviations in parenthesis.
\(\tau\) is the between-studies standard deviation.
For the Democracy-Dictatorship model, odds ratios and 90% credible intervals are reported.

indicator for Latin American countries were more likely to obtain a more negative coefficient, that is, stronger evidence in favor of the resource curse than those who didn’t. The opposite is true for articles who included a varying intercept for Asian
countries. Studies concerned with the Middle East as a potential driver of the resource curse found positive, albeit not statistically significant, results than those which pooled these countries together with others. This result holds for the economic resource curse in Table 2.4 as well. In the mediation framework discussed above, if the estimated effect of natural resource wealth on economic growth and the level of democracy was negative, including a dummy variable in the models to identify the observations from the Middle East drew this estimate closer to zero, weakening the evidence of a resource curse. More research must be conducted to understand what idiosyncrasies of this region mediate the relationship between natural resources, institutions, and growth.

A similar relationship is found for the religion indicator. We recorded whether or not each model included a measurement of Muslim population or an indicator for Muslim majority. In the meta-regression, the Islam indicator is positive in all models and indistinguishable from zero in the All Set and DD Set. In the Polity and Freedom House columns, there is evidence of a mediating effect of Islam on natural resource wealth: models that controlled for this religion were significantly more likely to find a less negative effect of natural resource wealth on levels of democracy. The theoretical explanation of this result may be related to the challenge of separating Islam and resource wealth from each other in Middle Eastern states (Ross, 2001, 331). While Islam is frequently branded as an anti-democratic religion, authors like Rowley and Smith (2009) have pointed out that Islam may proxy for natural resource wealth.

Finally, we explore how the choice of measurement of resource abundance affects the estimated effect on levels of democracy. In Table 2.3, we use the “exports” category of measurements as the baseline and include dichotomous indicators for the measure
used in a given model. The most important result is that production-based measures are significantly more likely to find more negative effects than the baseline category. Previously we had claimed that the share of natural resource exports in total income made the strong assumption that exports and production were always directly related. For the political resource curse, the posterior mean for this coefficient reveals that the bias introduced by using the exports measure works against the resource curse hypothesis.

Table 2.4 shows the meta-regression posterior means and standard deviations for the economic resource curse models. In contrast to the political resource curse meta-regression, the results in Table 2.4 suggest the choice of measurement for natural resource wealth is crucial. There is no significant difference in the estimated effect using rents-based measures vis-a-vis exports measures, but the posterior means for the rest of the resource wealth measurements are all statistically and substantively relevant. Models with production-based measurements obtained weaker evidence of a resource curse in all three models. Also in the three models, Per Capita indicator is positive and significant. In terms of the debate over whether natural resource abundance or dependence defines natural resource wealth, the meta-regression reveals that models of natural resource abundance were significantly less likely to find a resource curse than exports-based measures (such as the share of primary exports in total income measure by Sachs and Warner).

In terms of data, results are similar to the political resource curse in the sense that when the model included data from the 1980s, the impact of natural resource wealth on economic growth was on average less negative. As in the case of the resource
Table 2.4: Natural resource wealth and economic growth

<table>
<thead>
<tr>
<th></th>
<th>All Set</th>
<th>GDP Growth per EAP</th>
<th>PC per capita</th>
<th>90% credible intervals, All Set model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-2.0680</td>
<td>-7.8169</td>
<td>-4.0334</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.6148)</td>
<td>(1.3927)</td>
<td>(1.5882)</td>
<td></td>
</tr>
<tr>
<td>No. Obs.</td>
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<td>0.1114</td>
<td>-0.0001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0183)</td>
<td>(0.0002)</td>
<td></td>
</tr>
<tr>
<td>1970s</td>
<td>0.0377</td>
<td>-1.6551</td>
<td>-0.7946</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.3296)</td>
<td>(1.6557)</td>
<td>(0.3615)</td>
<td></td>
</tr>
<tr>
<td>1980s</td>
<td>0.8575</td>
<td>-0.1044</td>
<td>1.2913</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.6450)</td>
<td>(1.5804)</td>
<td>(1.1957)</td>
<td></td>
</tr>
<tr>
<td>1990s</td>
<td>0.2822</td>
<td>-1.7380</td>
<td>1.0167</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2280)</td>
<td>(0.4586)</td>
<td>(0.4306)</td>
<td></td>
</tr>
<tr>
<td>2000s</td>
<td>0.3604</td>
<td>0.8351</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2489)</td>
<td>(0.3906)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Africa</td>
<td>0.9793</td>
<td>0.8778</td>
<td>1.6281</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.2723)</td>
<td>(25.7496)</td>
<td>(1.2165)</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>-0.6304</td>
<td>0.5264</td>
<td>-2.0004</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.4674)</td>
<td>(25.9400)</td>
<td>(0.8219)</td>
<td></td>
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<tr>
<td>Latin America</td>
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<td>0.2441</td>
<td>-0.2364</td>
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</tr>
<tr>
<td></td>
<td>(1.2925)</td>
<td>(25.3064)</td>
<td>(1.2201)</td>
<td></td>
</tr>
<tr>
<td>Middle East</td>
<td>0.6261</td>
<td>0.3663</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.4209)</td>
<td>(0.7224)</td>
<td></td>
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<tr>
<td>Income</td>
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<td>-0.0955</td>
<td>0.7836</td>
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<tr>
<td></td>
<td>(0.2676)</td>
<td>(0.3263)</td>
<td>(1.1594)</td>
<td></td>
</tr>
<tr>
<td>Investment</td>
<td>-0.9557</td>
<td>-0.1773</td>
<td>-1.9742</td>
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</tr>
<tr>
<td></td>
<td>(0.2114)</td>
<td>(0.2931)</td>
<td>(0.4906)</td>
<td></td>
</tr>
<tr>
<td>Human Capital</td>
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<td>0.0201</td>
<td>2.6381</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2551)</td>
<td>(0.4113)</td>
<td>(0.4466)</td>
<td></td>
</tr>
<tr>
<td>Openness</td>
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<td>-0.7062</td>
<td>-0.4772</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2113)</td>
<td>(0.3273)</td>
<td>(0.3671)</td>
<td></td>
</tr>
<tr>
<td>Institutions</td>
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<td>-0.9063</td>
<td>0.3241</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.1751)</td>
<td>(0.2690)</td>
<td>(0.2673)</td>
<td></td>
</tr>
<tr>
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<td>1.4584</td>
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</tr>
<tr>
<td></td>
<td>(0.6255)</td>
<td>(1.0132)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Per capita</td>
<td>1.8669</td>
<td>1.0983</td>
<td>1.9877</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2299)</td>
<td>(0.3131)</td>
<td>(0.3743)</td>
<td></td>
</tr>
<tr>
<td>Rents</td>
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<tr>
<td></td>
<td>(1.3202)</td>
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<td>2.3331</td>
<td>1.0857</td>
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</tr>
<tr>
<td></td>
<td>(0.2650)</td>
<td>(0.4542)</td>
<td>(0.3655)</td>
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</tr>
<tr>
<td>τ</td>
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<td>1.0580</td>
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</tr>
<tr>
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<td>(0.1040)</td>
<td>(0.1561)</td>
<td>(0.1189)</td>
<td></td>
</tr>
<tr>
<td>DIC</td>
<td>1873.6</td>
<td>-19.3</td>
<td>1158.7</td>
<td>-2 -1 0 1 2</td>
</tr>
<tr>
<td>N</td>
<td>555</td>
<td>165</td>
<td>327</td>
<td></td>
</tr>
</tbody>
</table>

Posterior means and standard deviations in parenthesis.
τ is the between-studies standard deviation.
curse, including a dummy variable for Latin America resulted in more negative results. Investment, human capital and trade openness are three of the most important contributors to economic growth in economics literature and are thus included in most models exploring alternative explanations for economic growth. Here, the meta-regression suggests that human capital plays a mediating role in the relationship between natural resource wealth and economic growth.

This finding is obtained in the All Set and Per Capita growth models: all else equal, models that included a measure of human capital obtained significantly less negative estimated effects of natural resource wealth on economic growth than those that did not include this measure. Gylfason (2001) identifies education as a channel by which natural resources stymie economic growth. Resource-rich countries are known to have lower enrollment rates and spend lower shares of their income on education than other countries. While human capital accumulation is crucial for economic growth and political stability around the world (Barro, 1999), it is not a priority for resource-rich countries because incentives to invest in high-skilled labor are weak. Gylfason explains:

“[...] insofar as high-skill labor and high-quality capital are less common in primary production than elsewhere, this may help explain why natural resource abundance and the associated preponderance of primary production and primary exports tend to impede learning by doing, technological advance, and economic growth.” (Gylfason, 2001, 856)

Economic resource curse literature is also concerned with the endogenous role of institutions in economic development. Auty (2007); Boschini, Pettersson and Roine (2007); Isham et al. (2005); and Mehlum, Moene and Ragnar (2006) acknowledge that
some countries have escaped the Dutch disease. They argue that with the proper institutional framework, natural resources may be a blessing. For instance, they can prevent resource rents from being captured by small groups. In addition, democratic political institutions, low levels of corruption, or higher rule of law scores can ensure the investment of resource rents into productive economic activities and stymie rent-seeking behavior. In Table 2.4, we include a binary indicator equal to one if institutional controls such as polity scores, corruption or rule of law measures are included in the model. The model finds a significant, albeit small, contribution of institutions. However, their negative sign indicates that including political institutions in the model would contribute to a resource curse finding rather than weaken it.

An important limitation of the meta-analysis so far is its inability to study moderation effects. While moderation effects are not commonly proposed in the political resource curse literature, they are very frequently included in economic resource curse models. Specifically, meta-analysis can record a single estimated effect for each model, but if a model takes the form of Equation 2.5 above, the marginal effect of X has two additive components. Meta-analysis forces us to set the moderator variable to zero, which may not make substantive sense. This is especially limiting given recent contributions to especially resource curse literature suggesting a conditional effect of natural resource wealth on economic development and political stability. Furthermore, meta-analysis depends on published data, and the covariance of X and M, while crucial for the standard error of the marginal effect, is not usually published.

Fortunately, Bayesian prior distributions can allow us to model the uncertainty over the standard errors of the interaction term. In addition, for many of the studies the proposed moderator variable is a measure of institutional quality such as polity scores
or rule of law indexes: discrete variables with a well-known range. As an attempt to assess the moderation effects, we perform a random-effects meta-analysis on the marginal effect of natural resource wealth for fixed values of the institutional quality measure.

Four studies containing 68 models (Boschini, Pettersson and Roine, 2007, 2013; Brunnschweiler, 2008; Mehlum, Moene and Ragnar, 2006) proposed institutional quality as a possible moderator for natural resource wealth and economic growth. The four studies measure institutional quality through a rule of law index. In Brunnschweiler (2008), the rule of law measurement is taken from Kaufmann, Kraay and Mastruzzi (2005) and measures “the quality of contract enforcement, the police, and the courts, as well as the likelihood of crime and violence” (Kaufmann, Kraay and Mastruzzi, 2005, 4), and varies from –2.5 to +2.5. In Brunnschweiler (2008) this index varies from 0 to 5. The rest of the studies in this subsample use the rule of law measure by Knack and Keefer, an index based on measures of expropriation risk, corruption in government, quality of the bureaucracy, and a rule of law index where “higher scores indicate sound political institutions, a strong court system, and provisions for an orderly succession of power” (Knack and
Keefer, 1995, 225). The raw index ranges from 0 to 50, but is scaled to vary between 0 and 1 in all the studies in this subset.

For the meta-analysis, we adjust the estimated effects in Brunnschweiler (2008) so they would apply to a re-scaled rule of law index between 0 and 1. We estimate the marginal effect of natural resource wealth with seven different levels of rule of law. The results of this exercise are displayed in Figure 2.3. The meta-analysis would confirm that institutional quality moderates the economic resource curse: the estimated effect of natural resource wealth on economic growth is less negative as the rule of law index grows. However, the net estimated marginal effect remains negative, even though natural resources appear to turn into a blessing for the highest possible values of rule of law. In conclusion, better institutions help economic growth in resource-rich countries, but only the best of them can reverse the curse.

Finally, to understand the implications of the meta-regression results for the overall effect, we plot the posterior predictive distributions of the regression model in Figure 2.4. The conclusions are similar to those that we drew earlier from Figure 2.2, although it is worth noting that in this case, the estimated overall effect for the All Set is slightly less negative for the political resource curse now than before. The opposite is true for the economic resource curse in the bottom panel of Figure 2.4: the posterior mean is now further away from zero than the one reported in Figure 2.2.

In terms of the political resource curse, the overall effect remains negative. That is, conditioned on differences in research design and sample characteristics, it remains true that extant literature has found evidence that natural resource wealth harms the level of democracy. However, this finding is significantly weaker when the political rights and civil liberties Freedom House indicators are taken as the dependent variable,
and the posterior mode is slightly above zero. The All Set results seem to be driven mostly by the Polity Set data. This is understandable given that Polity Scores are the outcome variable in nearly 70% of the models in the sample.

In the bottom panel of Figure 2.4, it is clear that measurement differences in the economic resource curse literature are not as crucial as in the political resource curse, since the posterior predictive distributions for all three models overlap almost entirely. The modes of the three models are approximately negative one: on average, future studies may find that a one-unit increase in natural resource wealth is associated with a one-percent decrease in economic growth.

2.5 Concluding Remarks

This chapter has addressed two of the most important links in resource curse research: how natural resource wealth affects a country’s political stability and economic development. We first reviewed the general hypotheses put forth in the resource curse literature qualitatively and quantitatively, using a large sample of published studies in political science and economics. Then, after explaining the meta-regression methodology and model, we discussed the most important differences across studies.

The first objective of the chapter was to summarize existing knowledge and evidence on the resource curse, and we used Bayesian random-effects meta-analysis to do so. We find that research thus far has found an overall negative effect of resource wealth on institutional quality and economic growth, but we would expect future research to find evidence to the contrary. This result remained true after conditioning on research
For DD Set in panel (a), we plot the posterior predictive distribution of the odds ratio. Since most of the density is located below 1, it is safe to conclude that overall the effect of resource wealth remains negative.

design differences in the meta-regression portion of the analysis. The second objective of this chapter was to understand the sources of this debate. We applied Bayesian meta-regression methods to explore how differences in research design, measurements, and samples contributed to differences in estimated effects.
There are several important conclusions to be drawn from this exercise. Overall, natural resource abundance *per se* is not a curse. The effect of natural resource dependence on economic growth and political systems is less straightforward. In the economic resource curse research, institutions have long been recognized as moderators of the curse. Political resource curse literature has also explored the role of institutional design in moderating the impact of natural resource windfalls. These conditional relationships are difficult to test in the meta-regression context, and extensions of the meta-regression analysis should seek to leverage the information in the estimated effects of other variables in the same model to improve our insights on the effect we are interested in.

There is evidence in the meta-regressions of a mediating effect of human capital on the economic resource curse. This link is currently understudied.

Second, we must acknowledge the importance of measuring natural resource abundance and natural resource dependence consistently and accurately. As discussed in the literature review, in several studies little attention is paid to the choice of measure. Especially in the economic resource curse literature, the meta-regression reveals that this choice impacts the estimated effect significantly. For example, studies that explicitly attempt to measure natural resource abundance instead of dependence estimated significantly less negative results than those who did not. What’s more, even though the share of natural resource production in a country’s income may be proportional to the share of natural resource exports in a country’s income or total exports, the meta-analysis reveals that models using the former measure were much less likely to find evidence of a resource curse than those using the latter.
Finally, the consequences of an increasingly volatile oil market are apparent in the meta-regressions: the estimated effect of natural resource wealth is significantly different in studies that included data from the 1980s and 1990s. In fact, in the economic resource curse analysis it appears that natural resource wealth was less of a burden during this time. Future research should delve into the political consequences of commodity price volatility during that period, as the following chapters in this dissertation will explore.
Chapter 3

Do Oil Prices Help Globalization?

A Bayesian Change-Point Analysis

Amidst a steady climb in the price of crude oil around the world, IMF Deputy Director Agustin Carstens called upon countries to “resist protectionisms in both trade and foreign direct investment” and continue efforts to conclude the Doha Round by the end of 2006 (United Nations News & Media Division, 2006). That same year, government officials from countries like Thailand and India appeased worries about high oil prices by pointing to recent trade agreements, export promotion measures, and the resulting improvement in their trade balance (Khan, 2006; The Nation (Thailand), 2006). More recently, in 2011, the Nigerian Export Promotion Council announced a plan to encourage investment in non-oil industries. In order to increase domestic stability motivated by the fluctuation in prices that characterizes crude oil in recent years, the Nigerian government has held a conference to promote non-oil industries.
for its oil-producing states. Specifically, the Nigerian government announced its intention to attract funding for the private sector and negotiate bilateral, regional, and multilateral trade agreements.

There are many similar stories over the years in multiple countries. When oil prices are high, political actors are quick to recognize that the national economy is threatened. However, unlike other threats to the economy, nowadays there is rarely ever a call for a coordinated international solution to return oil prices to their previous stable level. Instead, leaders seem to call for unilateral policy changes in areas other than oil, such as environmental, monetary, and trade policy. In fact, cooperation in the oil market is a classic example of rational individual behavior that leads to sub-optimal collective results. Given the importance of oil in any country’s energy needs and the increasing volatility of oil prices in the past two decades, it should not be surprising that oil price changes force economic actors to compete with each other for this scarce resource, leading to an even more volatile market. The international oil market thus resembles a Prisoner’s Dilemma, where the payoff to defection — obtaining crude oil supplies before prices rise more — is quite large.

Yet even if we accept that widespread international cooperation is highly unlikely, oil-importing and oil-exporting countries alike still face adverse macroeconomic consequences of oil price volatility. Furthermore, as volatile episodes become more frequent, so do the shocks to the national economy. How do countries adapt to a difficult international policy issue area? In this chapter I argue that countries have relied on economic interdependence to cope with the consequences of non-cooperation in the distribution of crude oil around the world. Specifically, countries turn to cooperation
in successful areas, such as trade and investment, to compensate for the variations in oil income and expenditure due to a volatile fossil fuels market.

The most straightforward way to understand this mechanism is to observe the impact of oil price levels on a national economy’s trade balance. Trade surpluses—most simply, selling more abroad than the country buys from abroad—stimulate demand and create capital inflows. In contrast, trade deficits imply that a country is paying the rest of the world for goods and services more than it obtains from it: capital becomes scarce in the domestic economy, decreasing national investment and consumption. By focusing on crude oil as a traded commodity, it is clear that increases in its price may bring or increase a trade deficit for oil-importing countries. Conversely, decreases in crude oil prices would bring or increase a trade deficit in oil-exporting countries. As these changes become larger and more frequent, there is a need for national economies to create mechanisms to eliminate this deficit. Although direct international cooperation in this area is unlikely, current economic interdependence gives way to opportunities to address this issue indirectly through trade and investment.

Exploring these claims is important because they suggest that cooperation across issues in the international arena extends beyond normal “vote trading” in international organizations. Indeed, interdependence may be more complex than we have usually thought. Additionally, in this chapter a new Bayesian approach to dynamic relationships will be presented. Specifically, the bivariate change point models presented here will allow us to assess changes in relationships between variables and changes in the variables themselves simultaneously. In addition, this chapter brings attention to the
advantages of the Bivariate Poisson distribution as a tool to model count variables that are abundant in our discipline.

The following section will explore existing literature on international cooperation in times of global distress, and continue on to explore current research on the challenges of oil price volatility. This section will also develop the two hypotheses to be tested in this chapter. The first one focuses on oil-importing countries and economic interdependence when oil prices are high. The second hypothesis pertains to oil-exporting countries when oil prices are low. The third section presents the empirical strategy to test the hypotheses, where a new multidimensional Poisson change point model is introduced and tested. Finally, the model is applied to trade, investment and commodity price data from 1980-2010.

3.1 The Political Economy of Oil Prices

In many international regimes, notably those of trade and investment, modern institutions have been put in place to foster sustained cooperation. Obviously, cooperation is not obstacle-free. Some of the challenges of cooperation in trade, for example, include domestic pressures for protection, and uncertainty about future economic conditions. Because of this, it is difficult for national governments to make credible commitments to liberalization and avoid defection from trade agreements. Yet these obstacles have been overcome through several institutional arrangements and mechanisms. At the national level, research has shown that democracies are more likely to participate and comply with international agreements (Mansfield, Milner and Rosendorff, 2002; Milner and Kubota, 2005). In the international arena, Rosendorff and Milner (2001)
and Koremenos (2005) have argued that treaties with built-in mechanisms for “acceptable defection” such as escape clauses and limited duration reduce uncertainty about cooperation for countries, making the commitments in these treaties credible. The conclusion is that even though cooperation in trade is a Prisoner’s Dilemma-type interaction (Axelrod and Keohane, 1985), many mechanisms have been put in place to alter the incentives to defect and make it easier for countries to remain compliant to these agreements. These mechanisms have been successful, and as a consequence trade in goods and services is one of the most prominent international interactions nowadays.

The distribution of oil around the world contrasts starkly with the trade regime. Attempts at cooperation in the oil market were widely unsuccessful from the early twentieth century on. The oil crisis that began in 1973 is a quintessential example of how cooperation is less likely in hard times. When oil prices were pushed upward because of Arab producers’ decision to reduce oil production, the “consuming countries were unable to solve the dilemma of collective action: in trying individually to save themselves, they contributed to the quadrupling of official prices” (Keohane, 1984, 222). Even after the International Energy Agency (IEA) had been created to facilitate communication between oil consuming countries, cooperation in case of oil shortages, and inform about oil prices, countries competed for oil supplies when Iranian oil exports ceased in 1979. Their competition led to sky-rocketing prices (Keohane, 1984, 226-227), very possibly higher prices for a longer time than what would have occurred if countries would have continued to cooperate through the IEA.

One of the main obstacles to cooperation is the strategic importance of the commodity at hand. Energy policy is undoubtedly a pillar of any economy. Because of the
importance of fossil fuels in all industrialized and industrializing countries’ energy
demands, it is difficult to simultaneously accept that countries are rational actors in
the international arena and that they are able to credibly commit to an international
regime where they do not compete for this high-demand, non-renewable resource.
Even if such a commitment were made in times of stable oil prices and supplies, any
change in this environment would increase uncertainty for countries, rendering the
cooperative regime obsolete (Axelrod and Keohane, 1985). Thus, in a volatile oil
price environment, countries will have strong incentives to abandon the cooperative
behavior in favor of their individual best interest (Kindleberger, 1986).

Of course, this behavior implies a sub-optimal equilibrium for countries with very
high costs to pay, that is, the outcome for countries is worse when they do not
cooperate than the outcome if they would have done so. Energy security is only one
of the aspects of countries’ oil needs. High oil prices affect the productive sectors
of the economy in many more ways: industries are affected through transportation
costs and raw materials derived from petroleum by secondary effects. Thus, poorly
negotiated oil acquisitions leave each country with a high bill to pay. In times like
these, many countries are not capable of efficiently absorbing this additional cost
on their own. However, since direct international cooperation is unlikely, alternative
instruments become necessary.

Admittedly, national governments are not the sole consumers or purchasers of crude
oil in the world. It is quite possible they are not the largest either. Why, then, would
they feel a need to react to these shocks? I argue that national leaders face domestic
political pressures to do so. The literature that links economic conditions to electoral
outcomes states that voters will punish incumbents for their "poor performance"
when elections occur in a bad economic environment. In the case at hand, several studies (Backus and Crucini, 1998; Blanchard and Gali, 2009; Mankiw, 2006; Mork, 1989; Park and Ratti, 2008) have found an important connection between oil prices and economic outcomes, and so it is plausible to expect oil prices to be related to macroeconomic conditions. However, unlike other macroeconomic outcomes, national governments have little control over these prices.

Expecting citizens not to hold leaders accountable for economic shocks requires an important assumption: that voters are able to correctly identify the culprit of the economic circumstance. Nevertheless, there is reason to believe this is not the case with oil and gas. As Chapter 4 of this dissertation will argue, citizens tend to blame leaders for oil price fluctuations instead of private actors and financial markets. Citizens confuse oil and gas prices as a sign of poor economic performance of the government. They are less inclined to re-elect an incumbent, and more inclined to disapprove of the government (Lewis-Beck and Paldam, 2000). From this perspective, domestic political leaders initiate calls for policy changes in other areas during times of high oil prices because a) they are unable to directly influence oil prices and b) their political survival is at risk.

To observe the impact of oil prices on national economies, we focus on oil as a commodity which is traded across countries, like many other raw materials, and we assume most countries are price-takers. Suppose an upward oil price fluctuation occurs, and consider the effect on oil-importing countries. The countries that produce oil will consume some and export the remaining amount to the rest of the world. The countries without oil resources are obviously comparatively disadvantaged in oil production and will import oil from the rest of the world. More expensive imported oil implies a shift
in the national trade balance, as total imports are now more expensive. Therefore the
total trade deficit in this country grows. To counteract this condition, countries may
enact policies such as increasing debt by borrowing capital from abroad; changing
the trade balance in their favor by reducing imports other than oil; or changing the
trade balance in their favor by increasing exports (al Khail, 1979; Balassa, 1985).

Increasing national debt is a difficult strategy for some countries, because only some
nations in the international system have access to the necessary amounts of credit.
Furthermore, previous financial crises have shown that excessive indebtedness can
have devastating consequences for a country. Reducing imports, that is, erecting
trade barriers, is a counterproductive measure for two main reasons. First, trade
barriers will make other imports more expensive, increasing the trade deficit even
more. Second, al Khail (1979) explains that other countries may opt to retaliate,
thus increasing the short and medium term difficulty to effectively sell more goods
and services around the globe.

al Khail (1979) posits that altering the trade balance is not an option either, because
for one country to increase exports other countries must necessarily increase their
imports. al Khail concludes that though some countries will be better off, the inter-
national economic environment will remain adverse. It is true that in global terms,
world trade is a zero sum game: the world trade balance must be (nearly) equal to
zero by definition. However, at a more disaggregated level, trade can be viewed as
a positive-sum game. Specifically, given countries’ factor endowments, the produc-
tion of certain goods will be relatively less costly than other goods. Assuming that
countries have comparative advantages in different goods, standard macroeconomic
theory would conclude that opportunities for mutually beneficial arrangements arise.
Like financial crises, oil price fluctuations have a dramatic and simultaneous impact on many countries. How is cooperation affected by an unfavorable financial global situation? Common knowledge in the international political economy literature points to political leaders’ domestic incentives to insulate their economies from the international arena. Kindleberger (1986) explains the adverse consequences for a country of cooperating in times of financial duress when others in the international system do not. In the case of trade, this translates into the erection of trade barriers and barriers to capital movement. As explained above, an uncertain oil price environment should also deter cooperation among countries in this issue area. However, this should not preclude continued cooperation in other issues in the international arena. In fact, trade may be a viable defense against an oil-induced trade deficit. Balassa (1985) studies 43 developing countries from 1973, one of the most important oil crisis years in history, until 1978. The author compares growth rates in these countries after the crisis, and finds a positive association between export promotion and growth rates in a “hostile” oil environment.

To sum up, all net oil-importing countries face the problem of a growing trade deficit at the same time. Further, even though the world’s total imports should match the world’s total exports, at the industry or product-level between countries, each country produces different mixes of export goods. Thus, at this time net oil-importing countries’ incentives should be aligned toward export promotion provided they can find mutually advantageous export arrangements. Preferential Trade Agreements (PTAs) and Regional Trade Agreements (RTAs) are the institutions by which countries achieve precisely this goal and gain market access to the rest of the world. Like oil, trade liberalization also poses a dilemma for countries: all countries would benefit from removing tariffs, but individually they would benefit most if others lowered their trade
barriers while they maintained them. Unlike oil, this dilemma has been overcome and credible commitments to lower trade barriers have been made. RTAs and PTAs align the interests of all countries involved in liberalization, through mechanisms like reciprocity and dispute settlement mechanisms.

In times of oil price shocks, then, an additional incentive is added to trade negotiations: oil-importing countries should have more incentives, rather than less, to seek out trade agreements as a tool to finance the increased price of oil imports. This is expressed in the following hypothesis:

**Hypothesis 1**: Oil-importing countries will be more likely to sign trade agreements when oil prices are high.

A few important annotations should be made to this hypothesis. First, it is clear that trade policies in any countries are developed with strategic interests in other areas of the economy than the oil market. Second, oil prices may outlive negotiations. It is important to note that the claim made here is that countries have incentives to finalize pre-existing negotiations, not to initialize them. That is, rather than oil prices altering country commercial strategies, I argue that they affect the timing within which these strategies are executed. One would expect this to be the case especially in net oil-importing developing countries,
as they may have less access to foreign credit and less domestic mechanisms to cope with expensive oil.

Figure 3.1 shows some evidence of a relationship: the last twenty years seem to be marked by a sharp increase in trade agreements and crude oil, whereas in the previous two decades both of these indicators had relatively more stable behavior. A similar trend in both oil prices and the number of PTAs each year. More new trade agreements have been reported to the World Trade Organization (WTO) in years when oil prices have been high.

Obviously, oil-exporting countries benefit from high oil prices, and thus have no incentive to change their pattern of international cooperation. However, a downward oil price fluctuation will diminish oil-exporting countries’ income from oil exports. In this case, countries face the challenge of replacing the income they would have received if the price of oil had not shifted downward. A first alternative is to impose barriers to capital mobility, to prevent additional income from leaving the country. However, it has been argued (Jensen and Johnston, 2011) that this may deter foreign actors from investing in this country in the future. A second option for countries is to borrow from abroad (al Khail, 1979), but it is not certain that all countries can obtain the necessary amount of credit. Finally, they may attempt to attract capital inflows. Bilateral Investment Treaties (BITs) are agreements between countries designed to promote investment. Voeten and Ross (2011) have found that oil-exporting countries are more likely to participate in international agreements when oil prices are low.

Though oil-exporting countries are politically and economically diverse and geographically dispersed, they share some characteristics. Recent research in international political economy (IPE) has explored the less cooperative members of the international
arena. Authoritarian regimes, Least Developed Countries (LDCs), and resource-rich countries are among the “international misfits” that are more likely to be involved in armed conflicts (Bannon and Collier, 2003) and also lag behind in international cooperation. Jensen and Johnston (2011) find that resource-rich authoritarian regimes are most likely to discount the cost of reneging on investment contracts. The authors argue that their natural resource endowment gives them leverage over international investors. In contrast, Voeten and Ross (2011) develop a theory of unbalanced globalization where they contend that even though resource-abundant countries are politically uncooperative, they tend to be highly economically integrated to the rest of the world.

In summary, there is ample evidence that natural resource-abundant countries are less vulnerable and less dependent on international cooperation for prosperity. However, this claim is set on the important assumption that resource income is relatively stable for these countries. In other words, natural resource-abundant countries must be relatively certain that the costs of disengagement are small as well as stable. To the extent that oil price volatility increases uncertainty about these costs, we can expect that oil-exporting countries incentives will change at that time. This leads to the second hypothesis:

**Hypothesis 2:** Oil-exporting countries will be more likely to sign BITs when oil prices are low.

Figure 3.2 shows that the number of bilateral investment treaties signed each year has varied significantly more than oil prices in the past 30 years. Supporting Hypothesis 2, the plot suggests that oil-exporting countries sought bilateral investment treaties
with oil importing countries more often during low oil price years than during high oil price years, when the number of BITs signed is drastically lower. It remains to be studied whether this pattern holds beyond BITs with only one oil-exporting participant. For example, it is plausible that low oil prices lead to a global capital scarcity, such that oil-importing countries attempt to attract investment during this time as well. As with Hypothesis 1, this should be especially the case for developing oil-exporting countries.

An important implication of these hypotheses is that larger shocks should increase political leaders’ incentives to search for more mechanisms to prevent the adverse consequences of future shocks: structural changes in the oil market could potentially lead to a regime shift in world trade. The change point approach, as will be shown below, posits that variations in one variable contribute to structural changes in another variable. The choice of this type of analysis over other approaches, involves a subtle, yet important, distinction about the relationship shown by each.

Figure 3.2: New BITs and Oil Prices: A First Glance
3.2 A Multidimensional Poisson Bayesian Change-Point Model

To show the connection between the new era of volatile oil prices and heightened trade and investment, it is necessary to study the relationship between these two issue areas regarding their behavior over time, and not only their day-to-day relationship. This analysis can be achieved through a new approach to change point modeling. Change point models are a useful tool for a variety of political science research questions, as they provide a quantitative method to find paradigm shifts in behaviors, values and relationships. In what follows, I will show that by finding joint change points across variables, a better grasp of dynamic relationships can be assessed.

Literature developing and applying change point models is abundant in fields as diverse as sports, environmental studies and hydrology. This method is particularly helpful for testing hypotheses where more precise knowledge about an intuitive idea of structural change is needed. In Bayesian statistics, change point models are one of the most straightforward illustrations of the properties of the Gibbs sampler (Carlin, Gelfand and Smith, 1992; Casella and George, 1992; Chib, 1998; Gill, 2002; Tierney, 1994). A classic change-point problem involves finding the point in a sequence beyond which the distribution of the sequence is different than the distribution before this critical point. Although the model is theoretically open to an entirely different probability distribution before and after the change point, analyses in social sciences
focus on changes in the governing parameters of a fixed distribution.

\[ y_i \sim f_1(y) \text{ for } i = 1, \ldots, k \]
\[ y_i \sim f_2(y) \text{ for } i = k + 1, \ldots, n \]

Where the governing parameters of \( f_1 \) and \( f_2(y) \), as well as \( k \), are unknown. A Bayesian change point model is nearly always hierarchical, assigning prior distributions to the parameters of interest and the change point.

Change point models have recently gained importance in political science and international relations as a tool for identifying paradigm shifts and structural changes in several types of international and domestic regimes. Bayesian change point models have allowed political scientists to approach time series with multiple and often unknown change points through Hidden Markov models (Chib, 1998). In his seminal paper, Green (1995) suggests a Reversible Jump MCMC algorithm for multidimensional change point models.

In addition, while this model is useful for locating the shift in behavior, our interest as social scientists is commonly to explore the factors behind it, specifically which factors make the change more likely. One of the most useful approaches for this has been the change point regression model, developed and implemented by Carlin, Gelfand and Smith (1992). The hierarchical change point regression model implies that the structural change is solely characterized by a change in the relationship between \( Y \) and \( X, \beta \), under the assumptions that \( X \) is exogenous to the structural change and has no marginal structural changes itself. Change point regression models with continuous (Carlin, Gelfand and Smith, 1992) and limited outcome variables (Park,
have become a useful tool in political science. The latter models, however, rely on the assumption that structural change occurs in only one variable at a time, or in the relationship between two variables. Although this assumption is both useful and many times plausible, it limits our ability to assess how structural changes in one variable affect structural changes in another.

The importance of this type of model lies in its ability to relax the assumption of a fixed relationship between variables, in favor of a more flexible—and often times more plausible—dynamic link. In political science, this type of relationship has very seldom been addressed through quantitative methods, although models for dynamic and endogenous relationships between variables have been implemented. Dyadic models and Vector Autoregression (VAR) models are examples of tools to address contemporaneous feedback. Brandt and Sandler (2012) have recently joined Poisson models with the Bayesian VAR model. King (1989) proposed a bivariate Poisson distribution for a seemingly unrelated regression model, but no other work in political science to our knowledge has made use of this distribution.

Univariate Poisson change point models have been used more frequently, especially (but not exclusively) in international relations and international political economy (Beck, King and Zeng, 2000; Brandt and Sandler, 2010; Friedman et al., 2012; Park, 2010; Spirling, 2007). Continuous variables with structural changes are also abundant, but have been more rarely studied in political science. Bringing the two approaches, endogenous and bivariate models on the one hand, and change point modeling on the other, is an important innovation for our discipline with several advantages. First, count variables are abundant in political science. In addition, if both a change point and an association between variables are found, acausal claims are strengthened in
two ways. First, the day-to-day relationship between these variables can be studied through the covariance structures in multivariate distributions. Second, incorporating information from change points in other variables in addition to information about their correlation could provide a more efficient estimate of where in the sequence the structural change occurred.

Especially when studying macroeconomic and international phenomena, omitted variables in a model can have strong repercussions in its results, because of the interdependence between many different aspects of international cooperation nowadays. In the context of change point modeling, this has previously been addressed by change point regression. However, an important limitation of this type of model is the assumption that only one variable, the outcome variable, has a change point, while the covariates are governed by the same probability distribution for the entire period under study. Furthermore, in a change point regression, we can only study changes in the relationship between outcome and covariates (the $\beta$ coefficients), but little can be said about idiosyncratic changes in the data’s behavior (the regression intercept, the covariate means). The goal of this section is to develop a model to address this limitation.

Hypothesis 1 is an example of how multidimensional change point models can provide more insight into international phenomena. It is uncontroversial to state that there has been a regime shift in trade in the twentieth century toward a highly open and cooperative international system. It is also uncontroversial to state that the international oil market has changed to a more volatile and expensive environment. Are these structural changes related? If so, how? These questions can be addressed by
modeling the sequences jointly. The multivariate joint distribution is tractable in the Bayesian framework.

In the unidimensional change point approach, Granger causality may be the only alternative to compare regime shifts. The Granger causality approach would compare the probability of two change points in time: if a regime shift in variable $X$ is more likely before one in $Y$, and the opposite is not true, then one would be inclined to conclude that the change point in $X$ is likely to cause a change point in $Y$. However, to the extent that univariate change point models cannot incorporate information about other change points, this result may well be coincidental. A new approach is needed to allow us to confidently assess whether the change points are related to each other.

In the Bayesian framework, the classic change point model can easily be extended to multivariate probability distributions. I begin by considering the case of count variables, using the bivariate Poisson distribution. This distribution describes the joint behavior of two observed count variables $X$ and $Y$. To model them jointly, we suppose that the observed counts are made up of an “idiosyncratic component” and a “common component” which is unobserved (we name it $U$): $X = X^* + U; Y = Y^* + U$. Further, assume that $X^* \sim \text{Poisson}(\lambda_1), Y^* \sim \text{Poisson}(\lambda_2)$, and $U \sim \text{Poisson}(\xi)$. The probability mass function of their joint distribution is:

$$f(x, y | \lambda_1, \lambda_2, \xi) = \exp \left( - (\lambda_1 + \lambda_2 + \xi) \right) \frac{\lambda_1^x \lambda_2^y}{x! y!} \sum_{i=0}^{\min(x, y)} \left( \begin{array}{c} x \\ i \end{array} \right) \left( \begin{array}{c} y \\ i \end{array} \right) i! \left( \frac{\xi}{\lambda_1 \lambda_2} \right)^i$$  (3.1)
Since the sum of two Poisson variables is a Poisson variable itself, with a rate equal to the sum of the rates of the individual variables, we know the marginal distributions of the observed counts will be Poisson with $E(X) = \lambda_1 + \xi$ and $E(Y) = \lambda_2 + \xi$. Further, as $\xi$ is closer to zero, the “common component” of the observed counts is smaller, indicating a smaller relationship between the two variables. In this sense, $\xi = \text{cov}(X,Y)$. By definition, the correlation coefficient $\rho$ is obtained by the formula $\rho = \frac{\xi}{\sqrt{(\lambda_1+\xi)(\lambda_2+\xi)}}$ Finally, it should be clear that if $X$ and $Y$ are in fact independent, the bivariate Poisson distribution reduces to the product of two Poisson distributions with rates $\lambda_1$ and $\lambda_2$ (King, 1989).

### 3.2.1 Model Specification

Let $\theta_1 = \lambda_1, \lambda_2, \xi_1$ and $\theta_2 = \phi_1, \phi_2, \xi_2$. The change point problem is formulated as follows:

$$(x_j, y_j) \sim f(\theta_1) \text{ for } j = 1, \ldots, k$$

$$(x_j, y_j) \sim f(\theta_2) \text{ for } j = k + 1, \ldots, n$$

Where $\theta_1, \theta_2$ and $k$ are unknown. We are therefore interested in the posterior density:

$$\pi(k, \theta_1, \theta_2 | x, y) \propto \pi(\theta_1 | \alpha, \beta), \pi(\theta_2 | \gamma, \delta), \pi(k) L(\theta_1 | x, y) L(\theta_2 | x, y)$$

We assume that all intensity parameters ($\lambda$, $\phi$, and $\xi$) are independent. As with the univariate Poisson distribution, the Gamma distribution is the corresponding conjugate prior. The prior distribution for the change point is assumed discrete
uniform.

\[
\pi(\lambda_i | \alpha_i, \beta_i) = \frac{\beta_i^{\alpha_i}}{\Gamma(\alpha_i)} \lambda_i^{\alpha_i-1} \exp(-\beta_i \lambda_i) \text{ for } i = 1, 2
\]

\[
\pi(\phi_i | \gamma_i, \delta_i) = \frac{\delta_i^{\gamma_i}}{\Gamma(\gamma_i)} \phi_i^{\gamma_i-1} \exp(-\delta_i \phi_i) \text{ for } i = 1, 2
\]

\[
\pi(\xi_i | \upsilon_i, \kappa_i) = \frac{\kappa_i^{\upsilon_i}}{\Gamma(\upsilon_i)} \xi_i^{\upsilon_i-1} \exp(-\kappa_i \xi_i) \text{ for } i = 1, 2
\]

\[
\pi(k) = \frac{1}{n} \text{ Where } n \text{ is the number of time periods in the series.}
\]

To express the likelihood function clearly, some rearrangement of (1) is necessary. Following Holgate’s (1964) formulation of the bivariate Poisson distribution:

\[
f(x, y | \lambda_1, \lambda_2, \xi) = \exp \left[-(\lambda_1 + \lambda_2 + \xi) \frac{x^y}{x! \ y!} \sum_{i=0}^{\min(x,y)} \binom{x}{i} \binom{y}{i} i! \left( \frac{\xi}{\lambda_1 \lambda_2} \right)^i \right]
\]

\[
= \exp \left[-(\lambda_1 + \lambda_2 + \xi) \sum_{i=0}^{\min(x,y)} \frac{x^y}{x! \ y!} \binom{x}{i} \binom{y}{i} i! \left( \frac{\xi}{\lambda_1 \lambda_2} \right)^i \right]
\]

\[
= \exp \left[-(\lambda_1 + \lambda_2 + \xi) \sum_{i=0}^{\min(x,y)} \frac{x^y}{x! \ y! (x-i)! (y-i)!} i! \left( \frac{\xi}{\lambda_1 \lambda_2} \right)^i \right]
\]

Assuming the observations are i.i.d. within the regime, the bivariate Poisson is simply the product of the probability mass function (PMF) for the observations before the change point multiplied by the product of the PMF of the observations after the
change point. Using equation (2):

\[ L(x, y | \lambda_1, \lambda_2, \xi_1, \phi_1, \phi_2, \xi_2) = \prod_{j=1}^{k} f(x_j, y_j | \lambda_1, \lambda_2, \xi_1) \prod_{j=k+1}^{n} f(x_j, y_j | \phi_1, \phi_2, \xi_2) \]

\[ = \exp \left[ -n(\lambda_1 + \lambda_2 + \xi_1) \right] \exp \left[ -(n - k)(\phi_1 + \phi_2 + \xi_2) \right] \]

\[ \times \prod_{j=1}^{k} \sum_{i=0}^{\min(x_j, y_j)} \lambda_1^{x_j} \lambda_2^{y_j} \frac{(\xi_1)^i}{i!} \frac{1}{\lambda_1 \lambda_2} \]

\[ \times \prod_{j=k+1}^{n} \sum_{i=0}^{\min(x_j, y_j)} \phi_1^{x_j} \phi_2^{y_j} \frac{(\xi_2)^i}{i!} \frac{1}{\phi_1 \phi_2} \]

In conclusion, the posterior density of interest is:

\[ \pi(\lambda_1, \lambda_2, \phi_1, \phi_2, \xi_1, \xi_2, k | x, y) \propto \lambda_1^{\alpha_1-1} \lambda_2^{\alpha_2-1} \phi_1^{\gamma_1-1} \phi_2^{\gamma_2-1} \xi_1^{\upsilon_1-1} \xi_2^{\upsilon_2-1} \exp[-(\beta_1 + n)\lambda_1]
\]

\[ - (\beta_2 + n)\lambda_2 - (n - \kappa_1)\xi_1 - (n - k + d_1)\phi_1 - (n - k + d_2)\phi_2
\]

\[ - (n - k - \kappa_2)\xi_2 \prod_{j=1}^{k} \sum_{i=0}^{\min(x_j, y_j)} \lambda_1^{x_j} \lambda_2^{y_j} \frac{(\xi_1)^i}{i!} \frac{1}{\lambda_1 \lambda_2} \]

\[ \times \prod_{j=k+1}^{n} \sum_{i=0}^{\min(x_j, y_j)} \phi_1^{x_j} \phi_2^{y_j} \frac{(\xi_2)^i}{i!} \frac{1}{\phi_1 \phi_2} \]

\[ (3.3) \]

### 3.2.2 Implementation: Gibbs sampling with data augmentation

Due to the non-standard form of (3), we can only approximate this distribution using Markov chain Monte Carlo simulation methods. In this section, I develop a Gibbs sampling algorithm to this end. This MCMC algorithm allows us to sample from high-dimension posterior probability distributions. By Markov chain theory, “after
an initial transient or burn-in stage, [draws from the chain] can be taken as approximate correlated draws from the posterior distribution” (Chib and Winkelmann, 2001, 429). It is also widely known that the Gibbs sampler is a special case of the Metropolis-Hastings method, and differs from it in that no proposal distribution is needed. Rather, the sampler relies on the full conditional distributions of each parameter, or even a group of parameters, and samples sequentially from them. Current Gibbs sampling programs like WinBUGS and JAGS do not support the multivariate Poisson distribution, and thus the Gibbs sampler needs to be programmed in R.

Despite its intuitive simplicity, the multivariate Poisson distribution was not considered easy to solve or sample from. Techniques to obtain maximum likelihood estimates include recurrence relations (find citation) and expectation maximization algorithms (Karlis, 2003). Alternatively, Tsionas (1999) proposes a data augmentation method, an approach that can be easily combined with extant Bayesian change-point models. In what follows, I present his model.

From equation 2, we can further rearrange the bivariate Poisson PMF by recalling the construction of the observed counts $X = X^* + U$ and $Y = Y^* + U$ and that the latent variables each follow a Poisson distribution with rate parameters $\lambda_1, \lambda_2$, and $\xi$. Then:

$$ f(x, y | \lambda_1, \lambda_2, \xi) = \exp \left[ - (\lambda_1 + \lambda_2 + \xi) \right] \sum_{u=0}^{\min(x, y)} \frac{\lambda_1^{(x-u)} \lambda_2^{(y-u)} \xi^u}{(x-u)! (y-u)! u!} \times$$

$$= \sum_{u=0}^{\min(x, y)} \exp(-\lambda_1) \frac{\lambda_1^{(x-u)}}{(x-u)!} \exp(-\lambda_2) \frac{\lambda_2^{(y-u)}}{(y-u)!} \exp(-\xi) \frac{\xi^u}{u!} \times$$

$$= \sum_{u=0}^{\min(x, y)} f_u(u | \lambda_1, \lambda_2, \xi) f_{x^*}(x - u | \lambda_1, \lambda_2, \xi) f_{y^*}(y - u | \lambda_1, \lambda_2, \xi) $$
The posterior can be restated:

\[
\pi(\lambda_1, \lambda_2, \xi|x, y) \propto \pi(\lambda_1, \lambda_2, \xi) \prod_{j=1}^{n} \sum_{u=0}^{\min(x_j, y_j)} f_u(u_j|\lambda_1, \lambda_2, \xi) f_{x*}(x_j - u_j|\lambda_1, \lambda_2, \xi) f_{y*}(y_j - u_j|\lambda_1, \lambda_2, \xi)
\]

To evaluate this likelihood, Tsionas (1999) suggests data augmentation as an alternative to using recurrence relations, which can become inefficient and cumbersome in high dimensions. Specifically, the unobserved \(U_j\) can be treated as an additional parameter in the model:

\[
\pi(\lambda_1, \lambda_2, \xi, \{U_j\}|x, y) \propto \pi(\lambda_1, \lambda_2, \xi) \prod_{j=1}^{n} f_{x*}(x_j - u_j|\lambda_1, \lambda_2, \xi) f_{y*}(y_j - u_j|\lambda_1, \lambda_2, \xi) f_u(u_j|\lambda_1, \lambda_2, \xi) f_u(u_j; \lambda_1, \lambda_2, \xi) I(u_j)
\]

Where \(1(\cdot)\) is an indicator function that takes a value of 1 if \(0 \leq u_j \leq \min(x_j, y_j)\).

Tanner and Wong (1987) suggested data augmentation could be applied when such an augmentation made analysis easy in comparison to the non-augmented model, and generation of the augmented data is straightforward given the existing parameters (Tanner and Wong, 1987, 528). This formulation highlights the characteristics that make data augmentation an attractive way to evaluate the multivariate Poisson likelihood function: first, the distribution of \(U\) is known to be Poisson with parameter \(\xi\). Second, if the latent variable \(U\) were known, then the likelihood is simply a composition of univariate Poisson distributions, which is easy to analyze with Gibbs
sampling. Finally, Tsionas (1999) proves that the marginal distribution of the parameters in this formulation, that is, integrating the posterior distribution above with respect to \(\{U_j\}\) returns the multivariate Poisson P.M.F.

Applying this procedure for the change point model is straightforward. Together with the conjugate prior specifications, the full conditional distributions of the rate and covariance parameters are:

\[
\begin{align*}
\lambda_1|k, \lambda_2, \xi_1 & \sim \text{Gamma}\left(\sum_{j=1}^{k} x_j + a_1, n + b_1\right) \\
\phi_1|k, \phi_2, \xi_2 & \sim \text{Gamma}\left(\sum_{j=k+1}^{n} x_j + a_1, n + b_1\right) \\
\lambda_2|k, \lambda_1, \xi_1 & \sim \text{Gamma}\left(\sum_{j=1}^{k} y_j + a_2, n + b_2\right) \\
\phi_2|k, \phi_1, \xi_2 & \sim \text{Gamma}\left(\sum_{j=k+1}^{n} y_j + a_2, n + b_2\right) \\
\xi_1|k, \{u\} & \sim \text{Gamma}\left(\sum_{j=1}^{k} u_{1j} + a_3, n + b_3\right) \\
\xi_2|k, \{u\} & \sim \text{Gamma}\left(\sum_{j=k+1}^{n} u_{1j} + a_3, n + b_3\right)
\end{align*}
\]

The augmented vector, \(\{U\}\) is drawn from:

\[
\begin{align*}
u_{1j}|k, \lambda_1, \lambda_2, \xi_1 & \sim \text{Poisson}(\xi_1); 0 \leq u_{1j} \leq \min(x_j, y_j) \\
u_{2j}|k, \phi_1, \phi_2, \xi_2 & \sim \text{Poisson}(\xi_2); 0 \leq u_{2j} \leq \min(x_j, y_j)
\end{align*}
\]

I derive a full conditional distribution for the change point, \(k\), using Bayes’ law and the law of total probability (Carlin, Gelfand and Smith, 1992; Gill, 2002):

\[
k|x, y, \{u\}, \ldots = \frac{L(x, y|k, \{u\}, \phi_1, \phi_2, \xi_1, \xi_2, \lambda_1, \lambda_2)\pi(k)}{\sum_{z=1}^{n} L(x, y|k_z, \{u\}, \phi_1, \phi_2, \xi_1, \xi_2, \lambda_1, \lambda_2)\pi(k_z)}
\]

These distributions will make it possible to sample from the joint posterior density of the intensity parameters before and after the change point. The day-to-day relationship between the variables, before and after the regime shift, will be assessed
by examining the covariance parameters. The sampler will also provide a posterior
distribution for the location of the joint structural change, \( k \). I leverage on the likeli-
hood information that is already available in the MCMC algorithm (Gill, 2002, 260)
to calculate the Deviance Information Criterion (DIC) developed by Spiegelhalter
et al. (2002) to assess model fit. Posterior predictive checks are an alternative way
to do this, and they are perhaps more useful when comparing similar models tested
on different datasets. The next section will show results from simulated data. The \texttt{R}
algorithm will produce \texttt{mcmc} objects that can be analyzed using standard diagnostic
tools for MCMC methods (Plummer et al., 2006; Tsai and Gill, 2012).

### 3.2.3 Synthetic Data Examples

It remains to be answered whether multivariate change point models provide an im-
provement over their univariate analogues. In this section, I conduct tests on sets of
simulated data to illustrate the bivariate Poisson change point model’s advantages.
Most importantly, the simulations below show that failing to account for underlying
common variation between count variables will lead to biased estimates of the rate
parameters of their Poisson distributions. In addition, incorporating information from
other sequences into a change point model estimation can significantly improve accu-
curacy in the estimated change point, especially in cases where the rate shifts subtly, in
absolute terms. Finally, the covariance parameter in itself is useful, as it allows us to
describe the common elements in the sequences independently of the series’ intrinsic
counts.
Table 3.1: Synthetic data–generating parameters

<table>
<thead>
<tr>
<th>Before</th>
<th>After</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change-Point</td>
<td>Change Point</td>
</tr>
<tr>
<td>( \lambda_1 )</td>
<td>( \lambda_2 )</td>
</tr>
<tr>
<td>Simulation 1</td>
<td>7</td>
</tr>
<tr>
<td>Simulation 2</td>
<td>4</td>
</tr>
<tr>
<td>Simulation 3</td>
<td>7</td>
</tr>
<tr>
<td>Simulation 4</td>
<td>8</td>
</tr>
</tbody>
</table>

For each simulation, a sequence of 40 observations was drawn from a bivariate Poisson distribution with the parameters in Table 3.1. To estimate the parameters three chains were run for 5000 iterations, each beginning at randomly generated values. The burn-in period was set to 2000 iterations.

First, I conduct a baseline simulation, designed to compare the model’s performance to existing univariate models when no change point is present. In Figure 3.3, the bivariate model obtains the same posterior mode of the change point at time 1. In other words, there is consensus across models that there is no change point in the sequence. It is worth noting that the plots suggest the bivariate model estimates a
considerably larger posterior mean than the univariate models. We do not consider this damning, as the posterior mode and median, the standard quantity of interest in Bayesian change point models, are still the same across all models. Table 3.2 makes

Table 3.2: Simulation 1 results

<table>
<thead>
<tr>
<th></th>
<th>Bivariate</th>
<th>Univariate on X</th>
<th>Univariate on Y</th>
<th>Posterior medians and 80% credible intervals</th>
</tr>
</thead>
<tbody>
<tr>
<td>k</td>
<td>11.224</td>
<td>1.629</td>
<td>3.864</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(14.062)</td>
<td>(3.491)</td>
<td>(9.107)</td>
<td></td>
</tr>
<tr>
<td>λ₁</td>
<td>5.047</td>
<td>4.421</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.766)</td>
<td>(1.275)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>λ₂</td>
<td>3.471</td>
<td></td>
<td>3.739</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.184)</td>
<td>(1.391)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ξ₁</td>
<td>2.741</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.787)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>φ₁</td>
<td>7.130</td>
<td>10.472</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.004)</td>
<td>(0.495)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>φ₂</td>
<td>3.932</td>
<td></td>
<td>7.239</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.721)</td>
<td>(0.586)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ξ₂</td>
<td>3.335</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.627)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MV PSRF</td>
<td>1.02</td>
<td>1.01</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>DIC</td>
<td>666.07</td>
<td>239.25</td>
<td>218.52</td>
<td></td>
</tr>
<tr>
<td>Iterations</td>
<td>3000</td>
<td>3000</td>
<td>3000</td>
<td></td>
</tr>
</tbody>
</table>

Means and posterior standard deviations in parenthesis.
MVPSRF: Multi-Variate Potential Scale Reduction Factor (analogous to Gelman-Rubin statistic)

a case in favor of the bivariate model. The rate of the marginal distributions of X and Y are the same across models: By modeling covariance and rate parameters separately with a bivariate Poisson likelihood, their posterior estimates become more precise and closer to the true values used in the data-generating process.

An important advantage of this multidimensional model should be its ability to pool information across dimensions to improve estimates. In the second simulation, the series were designed so that a joint change point existed at time 24. However, in this simulation the rates for Y shifted only slightly, whereas the rates of X before and after the break were clearly distinguishable. The results are reported below.
Because of the clear shift in the rate of $X$, the univariate model of $X$ manages to locate the “true” change point. In contrast, the change point is greatly underestimated in the univariate model for $Y$. Specifically, the histogram of the posterior mass of $k$, the change point parameter (see Figure 3.5) appears at point 10, when the true change occurred at point 24. These results imply that a univariate model of $Y$ would make biased predictions of the counts between time 10 and time 24. Finally, the bivariate model presents similar results to the univariate model of $X$. Although trivial in simulated data, this result should constitute an important motivation to model counts jointly: by pooling information from both series, the model gains accuracy in non-evident shifts that would have otherwise been miscalculated or declared nonexistent.

The third synthetic dataset is designed to test the model’s ability to distinguish changes in the relationship between the two dimensions from changes in their independent rate parameters. The simulated data therefore contains only a change in the covariance parameter, while the others remain fixed.
Table 3.3: Simulation 2 results

<table>
<thead>
<tr>
<th></th>
<th>Bivariate</th>
<th>Univariate on X</th>
<th>Univariate on Y</th>
<th>Posterior medians and 80% credible intervals</th>
</tr>
</thead>
<tbody>
<tr>
<td>k</td>
<td>25.695</td>
<td>25.383</td>
<td>17.382</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.313)</td>
<td>(1.909)</td>
<td>(11.643)</td>
<td></td>
</tr>
<tr>
<td>λ₁</td>
<td>2.57</td>
<td>4.218</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.363)</td>
<td>(0.398)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>λ₂</td>
<td>2.028</td>
<td></td>
<td>3.285</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.329)</td>
<td></td>
<td>(0.581)</td>
<td></td>
</tr>
<tr>
<td>ξ₁</td>
<td>1.957</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.323)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>φ₁</td>
<td>6.172</td>
<td></td>
<td>7.533</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.637)</td>
<td></td>
<td>(0.616)</td>
<td></td>
</tr>
<tr>
<td>φ₂</td>
<td>2.961</td>
<td></td>
<td>4.314</td>
<td></td>
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<td></td>
<td>(0.512)</td>
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<td>(0.482)</td>
<td></td>
</tr>
<tr>
<td>ξ₂</td>
<td>1.597</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.445)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Means and posterior standard deviations in parenthesis.

MVPSRF: Multi-Variate Potential Scale Reduction Factor (analogous to Gelman-Rubin statistic)

Figure 3.5: Posterior mass histograms of estimated change point, Simulation 3

(a) Bivariate estimate  (b) Univariate CP estimate for X  (c) Univariate CP estimate for Y

The results in Table 3.4 show that the use of a multidimensional model can reduce uncertainty about the parameter: the credible intervals in the bivariate model are entirely contained in the univariate model credible intervals. It is also worth noting that the bivariate model’s posterior medians are significantly closer to the true parameter values than the univariate models. Before the change point, the univariate models
Table 3.4: Simulation 3 results

<table>
<thead>
<tr>
<th></th>
<th>Bivariate</th>
<th>Univariate on X</th>
<th>Univariate on Y</th>
<th>Posterior medians and 80% credible intervals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Univariate X</td>
<td>Univariate Y</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>True Value</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$k$</td>
<td>24.696</td>
<td>19.565</td>
<td>22.595</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(9.772)</td>
<td>(5.475)</td>
<td>(0.809)</td>
<td></td>
</tr>
<tr>
<td>$\lambda_1$</td>
<td>6.251</td>
<td>8.145</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.323)</td>
<td>(0.853)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\lambda_2$</td>
<td>5.067</td>
<td></td>
<td>7.194</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.147)</td>
<td></td>
<td>(0.534)</td>
<td></td>
</tr>
<tr>
<td>$\xi_1$</td>
<td>2.999</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.673)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_1$</td>
<td>7.188</td>
<td></td>
<td>13.164</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.725)</td>
<td></td>
<td>(0.897)</td>
<td></td>
</tr>
<tr>
<td>$\phi_2$</td>
<td>6.644</td>
<td></td>
<td>12.615</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.231)</td>
<td></td>
<td>(0.724)</td>
<td></td>
</tr>
<tr>
<td>$\xi_2$</td>
<td>5.388</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.135)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Means and posterior standard deviations in parenthesis.

MVPSRF: Multi-Variate Potential Scale Reduction Factor (analogous to Gelman-Rubin statistic)

slightly over-estimate the rate parameters for X and Y, while the bivariate model manages to separate the common count component from the independent count component relatively accurately. However, after the change point, when the covariance parameter is twice as large as the covariance parameter before the change point, the univariate models yield highly uncertain values for their parameters, with a posterior median nearly three times as large as the true value.

The final set of simulations aimed to assess the consequences of modeling sequences with non-concurrent change points jointly. For this exercise, four synthetic datasets are created. I begin with two non-independent count variables with a concurrent change point in the first dataset. In the subsequent datasets, the change point in each sequence is spread apart in two year increases. I run the model on each dataset and study the posterior mass of the change point for each data set.
Figure 3.6: Posterior mass histograms of estimated change point, Simulation 4

(a) Concurrent CP  
(b) CP 2 units apart  
(c) CP 4 units apart  
(d) CP 8 units apart

Clearly, uncertainty about the joint change point location increases as the true change point locations diverge in each dimension. This is made evident in Figure 3.6. The width of the credible intervals in Table 3.5 reflects the model’s ill fit as the change points in each dimension are further apart. Nevertheless, the posterior means and medians correspond to the values used in the synthetic data DGP.
Table 3.5: Simulation 4 results

<table>
<thead>
<tr>
<th></th>
<th>Same year</th>
<th>2-unit sep</th>
<th>4-unit sep</th>
<th>8-unit sep</th>
<th>Posterior medians and 80% credible intervals</th>
</tr>
</thead>
<tbody>
<tr>
<td>k</td>
<td>23.921</td>
<td>24.994</td>
<td>23.918</td>
<td>22.618</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.625)</td>
<td>(1.637)</td>
<td>(2.397)</td>
<td>(3.731)</td>
<td></td>
</tr>
<tr>
<td>( \lambda_1 )</td>
<td>5.087</td>
<td>5.062</td>
<td>4.991</td>
<td>4.897</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.844)</td>
<td>(0.807)</td>
<td>(0.819)</td>
<td>(0.843)</td>
<td></td>
</tr>
<tr>
<td>( \lambda_2 )</td>
<td>6.871</td>
<td>7.026</td>
<td>7.108</td>
<td>7.116</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.886)</td>
<td>(0.847)</td>
<td>(0.860)</td>
<td>(0.907)</td>
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<td>( \xi_1 )</td>
<td>2.647</td>
<td>2.521</td>
<td>2.419</td>
<td>2.386</td>
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<tr>
<td></td>
<td>(0.764)</td>
<td>(0.738)</td>
<td>(0.731)</td>
<td>(0.751)</td>
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<tr>
<td>( \phi_1 )</td>
<td>1.915</td>
<td>1.912</td>
<td>1.914</td>
<td>1.915</td>
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<tr>
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<td>(0.461)</td>
<td>(0.472)</td>
<td>(0.456)</td>
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<tr>
<td>( \phi_2 )</td>
<td>3.597</td>
<td>3.819</td>
<td>4.066</td>
<td>4.798</td>
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<td></td>
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<td>(0.620)</td>
<td>(0.707)</td>
<td>(0.919)</td>
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<tr>
<td>( \xi_2 )</td>
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<td>(0.425)</td>
<td>(0.415)</td>
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<td>1.01</td>
<td>1.02</td>
<td>1.01</td>
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</table>

Means and posterior standard deviations in parenthesis.
MVPSRF: Multi-Variate Potential Scale Reduction Factor (analogous to Gelman-Rubin statistic)

3.3 Oil Price Fluctuations in a Globalized World

This section implements the bivariate Poisson change point model to test the hypotheses set forth in this article. Data for this project spans from 1980 to 2010 for trade agreements. For investment, data was obtained for the years 1980 through 2007. All information was collected from primary sources. The United Nations Energy Database 2009 provides information on production, consumption, exports and imports of crude oil (used here) and oil derivatives from 1950 to 2009. We use this database to classify countries oil importers or exporters as accurately as possible. Information for 2010 was obtained from the World Factbook. Oil importing countries in this chapter are countries in which oil imports exceed oil exports in a given year. Where export data was unavailable, oil importing countries were those whose oil production was less than the reported oil imports.

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Finally, yearly and monthly crude oil prices were obtained from the World Bank Commodity Price Data (Pink Sheet). Models presented here are expressed in constant US dollars per barrel. A discrete proxy for this variable is developed by counting the months in a year in which oil prices were one standard deviation higher than their three-month moving average. This criterion is developed to capture high oil prices relative to the circumstances in that year, discount seasonal effects, and to allow continuity over the entire series. The number of months where oil prices suddenly drop are counted as the months in a year in which oil prices were one standard deviation lower than their three-month moving average.

RTA information was obtained from the WTO Regional Trade Agreements Database and complemented by the World Bank Global Preferential Trade Agreement Database. Data on Bilateral Investment Treaties was obtained from the World Bank’s International Center for the Settlement of Investment Disputes. In both cases, we count the number of agreements or treaties signed in a given year. In addition, for RTAs we exclude the treaties signed exclusively by oil-exporting countries. For BITs, we exclude the treaties signed by oil-importing countries only. Treaties signed by former USSR and the nations created following its collapse are also omitted from the dataset.

I now use the model to test Hypothesis 1, that high oil price months stimulate international cooperation in trade. The left panel of Figure 3.7 describes the time series to be used: the number of months with unusually high oil prices and the number of RTAs and PTAs that signed by oil importing countries and in that year. It suggests two regime transitions, the first —as we would expect— in the early 1970's and the second in the early to mid 1990’s, as suggested by the figure. The right panel of Figure 3.7 suggests the same trend.
One of the most useful approaches for this has been the change point regression model, developed and implemented by Carlin, Gelfand and Smith (1992). The hierarchical change point regression model implies that the structural change is solely characterized by a change in the relationship between $Y$ and $X$, $\beta$, under the assumptions that $X$ is exogenous to the structural change and has no marginal structural changes itself.

Although change-point regression analysis is appealing, there are theoretical and empirical reasons against this type of model to test the hypothesis at hand. In addition, while this model is useful for locating the shift, our interest as social scientists is commonly to explore the factors behind it, specifically which factors make the change
more likely. Substantively, the use of oil futures as financial instruments became widespread in the late twentieth century. A surge in international cooperation around the same years was also observed. A regression approach would make it necessary to ignore one of these change points. Statistically, it is important to remember that under a regression design the computed distribution is a conditional one: the regime of the outcome variable given the covariate.

The bivariate Poisson change point model will address both these concerns. First, we can find a joint change point if it exists. The model will also provide evidence of a non-concurrent change point. Either way, we can do away with the assumption that one of the dimensions has a fixed regime. Second, by estimating the parameters of the joint distribution, assumptions about conditionality or causality are not made. A final advantage of this model is that we will obtain a description of the “common counts” between the two variables, thanks to the data-augmentation vector. At the same time, we will be able to distinguish these counts from those that occur regardless of the other variable.

Regional Trade Agreement negotiations are obviously driven by strategic economic interests. It is reasonable to believe that oil prices do not override these interests. Because of this, the argument made here is that countries will sign treaties, rather than initiate negotiations or execute them. As an attempt to capture countries’ pre-existing interests in the trade agreements, in the first model I count the total treaties signed each year. In Model 2, the treaty dimension is measured as the number of treaties signed in a year where both oil-exporting countries and oil-importing countries are signatories. This measure attempts to test the idea that oil-importing countries would seek to sign agreements with economically stable partners. In times of high oil
prices, oil-exporters could experience a growth in demand for goods and services and therefore also be interested in signing agreements. The final model takes the most strict treaty count, since it counts trade agreements signed where all parties were oil-importing countries. The results are shown in Table 3.6.

Figure 3.8: Estimated regime shift, RTAs and Oil Price Surges

(a) Model 1     (b) Model 2     (c) Model 3

All models agree the change occurred at the 11th year, 1990, although some uncertainty around this estimate can be observed in the second model. This may be evidence of a gap in the change point years for each dimension. The parameter posterior densities agree with theoretical expectations. There is evidence across the models that after the joint change point, we have entered in a joint regime of both increased economic cooperation and high oil price volatility. For example, in Model 1, the world experienced on average 1.5 months of high oil prices before 1990 and nearly 3 after that year. Since the rate parameter in a Poisson distribution is both the random variable’s mean and variance, we can interpret this rate shift as a sign not only of a mean shift, but an increase in variability as well: whereas years with many months of high oil prices were rare before, the model suggests there are now contrasting trends regarding oil prices across the years.
Table 3.6: Bivariate Poisson model: RTAs and Oil Price Surges

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>Mixed</th>
<th>Importers Only</th>
<th>Posterior medians and 80% credible intervals</th>
</tr>
</thead>
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<td>11.000</td>
<td>12.000</td>
<td>10.847</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.494)</td>
<td></td>
</tr>
<tr>
<td><strong>Before CP</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treaties</td>
<td>0.585</td>
<td>0.274</td>
<td>0.752</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.216)</td>
<td>(0.142)</td>
<td>(0.245)</td>
<td></td>
</tr>
<tr>
<td>Oil Price Surges</td>
<td>0.892</td>
<td>1.277</td>
<td>1.056</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.264)</td>
<td>(0.303)</td>
<td>(0.313)</td>
<td></td>
</tr>
<tr>
<td>ξ₁</td>
<td>0.723</td>
<td>0.227</td>
<td>0.528</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.238)</td>
<td>(0.129)</td>
<td>(0.212)</td>
<td></td>
</tr>
<tr>
<td><strong>After CP</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treaties</td>
<td>14.644</td>
<td>9.705</td>
<td>5.031</td>
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<tr>
<td></td>
<td>(0.830)</td>
<td>(0.703)</td>
<td>(0.502)</td>
<td></td>
</tr>
<tr>
<td>Oil Price Surges</td>
<td>1.914</td>
<td>1.984</td>
<td>1.709</td>
<td></td>
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<tr>
<td></td>
<td>(0.330)</td>
<td>(0.349)</td>
<td>(0.309)</td>
<td></td>
</tr>
<tr>
<td>ξ₂</td>
<td>0.356</td>
<td>0.392</td>
<td>0.574</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.198)</td>
<td>(0.213)</td>
<td>(0.207)</td>
<td></td>
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<tr>
<td>MV PSRF</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Mean Deviance</td>
<td>310.31</td>
<td>272.12</td>
<td>317.51</td>
<td></td>
</tr>
<tr>
<td>DIC</td>
<td>438.61</td>
<td>395.59</td>
<td>364.73</td>
<td></td>
</tr>
<tr>
<td>Iterations</td>
<td>15000</td>
<td>15000</td>
<td>15000</td>
<td></td>
</tr>
</tbody>
</table>

Means and posterior standard deviations in parenthesis.
MVPSRF: Multi-Variate Potential Scale Reduction Factor (analogous to Gelman-Rubin statistic)

To assess the relationship between the dimensions, I will focus on the covariance parameters, ξ₁ and ξ₂. It is worth noting this parameter decreases before and after the change point for Models 1 and 3. This suggests that a lesser proportion of the treaties signed per year can be counted as contemporary to a year of unstable oil prices in the post-1990 international trade system. However, in Model 2 the parameter is larger. Nevertheless, none of these rates are statistically significantly different from each other.

By recalling that the marginal distributions in bivariate Poisson processes are the sum of the rates and covariance parameters, Model 1 tells us that before 1990, nearly twice as many treaties signed amongst oil-importing countries occurred jointly with years of high oil prices. The covariance parameter is nearly the same size as the
rate of oil price volatility, suggesting that on average, half of the observed volatility in a year occurred jointly with new trade agreements. After 1990, the covariance’s contribution to the marginal distribution of trade agreement signatures is minute, but it accounts for about 15% of the marginal count of oil price surges per year.

Perhaps the most important result to take away here is the large increase in treaties between oil-importing countries and oil exporters. In Figure 3.9, I use the estimated median rates from Model 2 to simulate the distributions of high oil price months and free trade agreements. It is easy to see how after 1990, we expect a higher average number of treaties that included at least one oil exporting country per year. With respect to oil price volatility, The probabilities of observing three to six months of high oil prices each year is significantly higher than the estimate before 1990.

Figure 3.9: Model 2 Expected Counts

(a) RTAs
(b) Oil Price Surges

To test Hypothesis 2, I estimate three models of investment patterns and oil prices. The three models presented in Table 3.7 below differ in their estimated regime shift year: For Model 1 it occurs around 1987, whereas in Model 2 the posterior median
occurs in 1990. A surprising result is that the estimated rate of oil price drops per year remains nearly identical in Models 1 and 3. In Model 2, the estimate is actually larger before the regime shift than after. Substantively, this is evidence that even though we have observed more sudden increases in oil prices each year, the opposite has not happened: oil prices do not drop as quickly as they rise.

Model 1 counts all bilateral investment treaties signed and the number of months in a year where the price of crude oil dropped. After 1989, countries signed a dramatically larger number of bilateral investment treaties, averaging 48 per year. However, these results also suggest this shift in BIT signings may not be related to oil price drops: before 1989, the correlation between the two variables is 0.899 whereas after that year it is 0.302. We can conclude, then, that countries do not seek more BITs when oil prices drop. This aligns with the logic in Hypothesis 1: oil-importing countries do not have incentives to sign agreements during times of relatively stable oil prices. It is worth exploring whether they attract capital when oil prices increase dramatically.

In Model 2, the BIT dimension included counts of BITs only one of the parties is an oil exporter. The regime shift is estimated to have occurred in 1991, although the center
panel of Figure 3.10 suggests this change may not have occurred simultaneously in both dimensions: oil-rich nations may have begun to cooperate amongst each other before months of low oil prices became more frequent. As in the case of RTAs, there is an important increase in the number of mixed treaties—treaties between exporters and importers—nearly five times as many after the change point than before. How much can we attribute to the regime shift? The covariance between the variables is drastically reduced, at 0.737 and 0.333 before and after the change point. Using the empirical means and standard deviations of the covariance parameters, I simulate draws from their posterior distribution. The relatively low overlap suggests we can agree on an increased number of signed agreements that coincides with years of many oil price drops. Nevertheless, this growth in the common component of the marginal distributions is substantially smaller than the growth in their idiosyncratic components.

Finally, Model 3 counts the number of BITs signed where both parties are oil exporters. The results are encouraging evidence in favor of Hypothesis 2, since the average number of treaties shifts from 0.662 before 1989 to 3.094 after this year. Nevertheless, the estimated covariance also decreases, suggesting an even milder relationship between drops and investment treaties between these countries. Under Hypothesis 2, this result makes intuitive sense as during oil price drops, other oil-exporting countries may not be credible investment partners. This issue may be related to measurement: although the number of high oil price jumps has increased dramatically, oil prices seem to drop more slowly than they increase. In fact, all the models estimate a lower number of oil price drops per year after the change point. Since Bilateral Investment Treaties may also be a politically attractive strategy for national leaders in oil importing countries to counteract the impact of an oil price
Table 3.7: Bivariate Poisson Model: BITs and Oil Price Drops

<table>
<thead>
<tr>
<th></th>
<th>Importers Only</th>
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<th>Exporters Only</th>
<th>Posterior medians and 80% credible intervals</th>
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<tr>
<td><strong>Before CP</strong></td>
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<tr>
<td>Treaties</td>
<td>9.02 (0.204)</td>
<td>9.986 (0.115)</td>
<td>11.07 (1.513)</td>
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<tr>
<td>Oil Price Drops</td>
<td>2.092 (0.556)</td>
<td>2.013 (0.501)</td>
<td>2.379 (0.443)</td>
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<tr>
<td>$\xi_1$</td>
<td>0.899 (0.445)</td>
<td>0.737 (0.382)</td>
<td>0.456 (0.214)</td>
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</tr>
<tr>
<td><strong>After CP</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treaties</td>
<td>47.731 (1.528)</td>
<td>24.603 (1.114)</td>
<td>3.094 (0.503)</td>
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<td>Oil Price Drops</td>
<td>1.511 (0.168)</td>
<td>1.567 (0.183)</td>
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<td>$\xi_2$</td>
<td>0.302 (0.180)</td>
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<td>0.275 (0.172)</td>
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<td><strong>MV PSRF</strong></td>
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<td>1.00</td>
<td>1.00</td>
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</table>

Means and posterior standard deviations in parenthesis.

MVPSRF: Multi-Variate Potential Scale Reduction Factor (analogous to Gelman-Rubin statistic)

Surge, the final set of models studies this possibility. As in the previous table, Model 1 in Table 3.8 estimates the joint change point between oil price surges and total BITs signed in that year. The second model here counts the number of treaties signed where only one party is an oil importer. The results suggest that the dramatic increase in BITs signed amongst oil importing countries is unrelated to oil price volatility: even though the number of treaties nearly quadruples in size, the covariance parameters before and after the change, estimated to have occurred between 1988 and 1989, remain unchanged. We learn from the second model that BITs between importers and exporters have also quadrupled, and the covariance parameter nearly doubles in size. Finally, by comparing the covariance parameters between these two models in the high oil price regime, we can see that twice as many treaties between importers and
exporters are expected to occur jointly with an oil price surge than between importers only. In the final model, only oil-exporting countries are taken into account.

Table 3.8: Bilateral Investment Treaties and Oil Price Surges

<table>
<thead>
<tr>
<th></th>
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<th>Mixed</th>
<th>Exporters Only</th>
<th>Posterior medians and 80% credible intervals</th>
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</tr>
<tr>
<td>Treaties</td>
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<td>5.399</td>
<td>0.834</td>
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<td>Oil Price Surges</td>
<td>0.809</td>
<td>0.735</td>
<td>0.951</td>
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</tr>
<tr>
<td>$\xi_1$</td>
<td>0.386</td>
<td>0.665</td>
<td>0.444</td>
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<tr>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treaties</td>
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<td>24.508</td>
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<td>Oil Price Surges</td>
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<td>2.005</td>
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</tr>
<tr>
<td>$\xi_2$</td>
<td>0.398</td>
<td>0.397</td>
<td>0.399</td>
<td></td>
</tr>
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</table>

Means and posterior standard deviations in parenthesis.
MVPSRF: Multi-Variate Potential Scale Reduction Factor (analogous to Gelman-Rubin statistic)

Perhaps a more intuitive way to assess model fit than deviance is to use posterior predictive checks. The idea behind these checks is to compare the distribution of observed data to the distribution of data that would be predicted, or replicated, given the posterior density that has been estimated. A well-fitting model would predict distributions of data which are similar to the observed data, whereas differences between these two are taken as a sign that the model performs poorly (Lynch and Western, 2004). I take 100 random draws from the posterior distributions of the parameters of Model 1 in Table 3.6, Model 3 in Table 3.7 and Model 2 in Table 3.8, and use them to generate 100 predicted datasets for each model. These datasets form the posterior
predictive distribution of the data given the models. The final step in this check is to plot the observed data against the predicted data, as shown in Figures 3.11 to 3.13.

Figure 3.11 shows the results of this exercise for the first model. The squares in the background are a scatter-plot of the predicted values. Darker points indicate a more frequently drawn value. The estimated model finds it more likely that the number of RTAs signed in a year around the world will be in the darker region of points, while the lighter points are unlikely to occur. The bold line in each plot are the observed number of treaties and oil price surges or drops, depending on the model. Notice how most of the data series occurs in the dark areas of the scatterplot, while the unusually high or low treaty signing years appear in the lighter areas of the predicted values.

Most importantly, these plots provide a clearer picture of what the model’s results imply: There is very strong evidence of a new era of regional trade cooperation. In terms of oil prices, the evidence is more subtle in terms of a change in the expected count months with oil price jumps, but we do observe larger variability after the change point than before. It is important to recall that in the Poisson distribution, the rate parameters are both the mean and the variance of the distribution. In this sense, the model perhaps predicts more uncertainty in the sense that currently, we observe either years with many months of high oil prices (1999, 2007) or years with nearly no high oil price months (1998, 2009).

Figure 3.12 repeats the exercise for the model that used the BITs signed per year between oil exporting countries only and the observed months with oil price drops. After 1991, the average number of treaties signed per year is higher than before, indicating more economic cooperation between oil exporters. At the same time, we observe more uncertainty in the predicted number of treaties to be signed after the
change point in 1991. This could be explained by the sudden drop in new treaties after 2005. With respect to the number of oil price drops, the model correctly acknowledges a slightly lower count of low oil price months per year after 1991.

The left panels in Figure 3.11 and Figure 3.12 highlight the collective action dilemma in the global oil market. As mentioned before, in Figure 3.11 the observed count
of months with high oil prices is a measure constructed by counting the number of
months in which the average price of crude oil was a standard deviation higher than
a three-month moving average. The observed and estimated counts after the change
point are higher than before indicating that prices now tend to change abruptly from
month to month, and that these types of changes happen more frequently in a year. In
other words, it is more common nowadays to see market actors engage in competitive
acquisitions of oil that drive prices up suddenly. In Figure 3.12, we see that months
where the price of oil drops precipitously have become less frequent after the change
point in 1989. Interpreting the two plots together, can conclude oil prices tend to rise
more quickly because of market actors’ self-fulfilled expectations of higher prices, and
they decrease slowly because of the difficulty for each country to regain confidence in
the market.

The final set of plots, Figure 3.13, uses the estimates and data for the model of mixed
BITs and oil price increases. The models suggested a dramatic surge in treaty signing
between oil importers and oil exporters during oil price fluctuations. The observed
data confirms this: there was an exponential increase –followed by an exponential
drop– in the number of treaties. This can be theoretically explained by considering
that during times of high oil prices, oil importers may seek to promote trade links
with oil exporters because they would seem economically stronger in this environment
and vice-versa. An important observation on the limitations of the model is made
explicit in the left-hand plot. The model offers a poor fit to the data after the change
point in 1990: The model predicts a stable “cloud” of observations around 25 treaties
per year, but the observed data lies outside of the predicted values for many years.
Clearly, the observations in this series are not exchangeable, as there appears to be
an important trend in treaty signing. Because the model ignores this trend, it fails
to adjust to the full range of observed data and merely calculates the global average for the series.
3.4 Concluding Remarks

As the primary energy source for most countries in the world, crude oil is an especially strategic good in the global economy. Its very importance for national economies has hindered credible and open mechanisms to ensure stable oil supply and demand, and as a consequence, stable prices. However, while fuel and energy sources are a
sensitive topic among countries, trade in goods and services is the embodiment of a globalized world, where agreements are obtainable and commitments to cooperate are credible. This article has argued that governments use trade as a strategy to palliate the adverse economic shocks that originate from unstable oil prices. If we set aside the strategic, non-renewable characteristics of crude oil and treat it as a traded good, we can incorporate oil into the list of traded goods, and analyze countries’ trade policies given their situation in the world oil market.

The results of the empirical analysis give encouraging evidence of a relationship between oil prices and international economic cooperation. The analysis points to different mechanisms operating in oil-rich countries and oil-importing countries: while the former have dramatically increased their participation in globalization, there is little evidence that this is correlated with oil price volatility. As for oil importers, signing RTAs with other countries like themselves is a strategic interest where oil prices are a weak contributor, but concluding treaties with oil exporters has remained as important before and after the oil price regime shift. The hypotheses advanced here –that countries turn to successful international cooperative regimes to compensate for non-cooperation in the energy market – find strongest support in the fact that BITs are signed more frequently between importers and exporters when oil prices are unstable.

There are alternative important moments in treaty negotiation that could be timed strategically depending on the impact these treaties could have on the national economy, and they should be explored in the context of adverse international circumstances. Finally, alternative measures of oil price volatility could improve our understanding of its political consequences. In fact, the results pointed to a regime shift
in upward oil price movements and not in downward shifts. Specifically, the months where oil prices increase abruptly are, on average, twice as frequent after 1990 than before this year, but we have observed sudden oil price drops just as frequently before and after this year. In any case, further research should seek to understand how oil exporting countries cope with the consequences of a volatile crude oil market they cannot control.

Methodologically, this chapter makes two important contributions. First, we incorporate a new, powerful probability distribution that can have many applications for political science data analysis, as well as a straightforward algorithm to estimate this type of model. Count variables are abundant in many subfields of political science beyond international relations. The number of terrorism incidents and international conflict, or district magnitudes and the number of parties, financial crises and bailouts or bankruptcies. Regarding the change point model, studies in Judicial Politics have used change-point models to study jurisprudential regimes (Friedman et al., 2012; Lax and Rader, 2010; Richards and Kritzer, 2002). A multidimensional change point model could allow for the study of the interaction and of regime shifts across issue areas.

Second, this chapter has shown that univariate change point analysis can be misleading about the location of a change point and inefficient about the estimates for the parameters of interest. Specifically in the case of the Poisson change point model, failure to model joint change points where they exist will result in biased estimates of the rate parameter. In sum, this article has shown that additional information can and should be incorporated into change point models, and it is possible to do so outside of the regression framework. Incorporating covariates into the model could make
estimation of the rate and covariance parameters more efficient and accurate. This is computationally challenging because non-conjugate distributions and an even larger number of parameters would need to be estimated using (usually) limited sequences. Although the Poisson bivariate change point model specifically is unable to model negative relationships between variables, multidimensional change point models using other probability distributions have been developed (Perreault et al., 2000).
Chapter 4

Fueling the Fire: Public Reactions to Changes in Gasoline Prices

In the second presidential debate for the 2012 election in the US, candidates were asked whether they agreed or not that lowering gas prices should be a priority for the Energy Department, and how their own views on energy would affect gas prices (Crowley, Obama and Romney, 2012). Rather than committing to a specific gas price, they were keen to point out how each other’s policies would increase gas prices. The candidates’ responses about their own policies focused on the impact that energy policy has on jobs and the environment. This strategy is understandable given their very limited control over gas prices. François Hollande was the Socialist Party candidate for the 2012 presidential election in France. Unlike Mr. Obama and Mr. Romney, he proposed to freeze gasoline prices and make the fuel tax more flexible, so that the government would not contribute to even higher prices during gas price shocks (Bourmaud, 2012). Once in power, Mr. Hollande was reminded of his campaign promise
after a fuel price increase in August of 2012. The government committed to a three euro cent reduction of the fuel tax for three months and eventually announced the reinstatement of the tax after this period (Bourmaud, 2012). By the end of the tax reduction period, he had “broken the record as the most unpopular French president at the six-month mark of a mandate” (Chrisafis, 2012).

Oil and gasoline prices are a sensitive issue in elections around the world. Politicians blame adversaries for high fuel prices and assure audiences they could be lower. In truth, leaders’ ability to affect gasoline prices in the immediate or short term is limited, so we should not expect fuel prices to factor into citizens’ appraisals of national leaders. Figure 4.1 suggests the opposite: over time, the periods with highest fuel prices occur together with the president’s highest approval ratings.

Studies in political science and economics have focused on macroeconomic indicators such as unemployment, growth and inflation, and find that they track closely with leadership popularity and electoral turnover. In fact, research in political science has produced the theory of economic voting, where macroeconomic phenomena have been shown to relate to government survival. This paper will contribute to understanding on the micro-mechanism behind economic voting theory. Despite its popularity in political campaigns and mass media, the link between gasoline prices and politics has rarely been studied in political science research. This oversight is in part explained by the theory itself. The expectation that voters can hold governments accountable for what they perceive as poor macroeconomic performance carries an assumption that they they are able to discern the results of macroeconomic policy from other exogenous economic shocks. In this logic, the apparent link between fuel prices and
Figure 4.1: US Presidential Approval and Fuel Prices

(a) George W. Bush

(b) Barack Obama

Sources: Energy Information Administration (national average price per gallon of regular unleaded gasoline), Gallup (monthly presidential job approval)

presidential approval should be spurious, because rational voters would understand the president’s limited role in the world oil market.
The rest of the chapter proceeds as follows. In the following section, we engage the debate in economic voting literature about how voters formulate their opinions about politics and the economy. Through his discussion, we derive hypotheses about fuel prices as proxies for the state of the economy. Even though citizens are regularly exposed to fuel prices, they are not exposed to clear and accurate information about national leaders’ role in them. As a consequence, politicians may be held accountable for high fuel prices despite their negligible role in them. We test these hypotheses using Bayesian multilevel models and use data from the American National Election Panel Survey from 2008-2009 to test the hypotheses from the second section. The final section summarizes the empirical findings and opens new avenues for research.

4.1 Fuel Prices and Political Accountability

Fossil fuels are undeniably connected to a country’s economic activity. Studies in economics have found that oil and gas prices –especially sudden price increases (Mory, 1993) –affect aggregate demand and production patterns (Hamilton, 1996; Kilian, 2008; Mork, 1989). At the same time, the relationship between the state of the economy and electoral outcomes, vote choice, or government approval has been extensively studied over numerous elections and countries. As one of the most direct tests of the democratic principle, understanding this link is central to political science. As Anderson (2007) and Lewis-Beck and Stegmaier (2000) summarize, many attributes have been added to this broad claim, but overall there is support for the idea that “the voter observes the economy, judges its economic performance, and alters his or her
vote accordingly” (Lewis-Beck and Paldam, 2000, 119), thus holding politicians accountable for economic policy. Although fossil fuel prices have rarely been mentioned in it, this literature provides a theoretical foundation for the relationship we are interested in. We begin by summarizing the state of the literature and then derive our hypotheses and expectations about the impact of gasoline prices on assessments of national leaders’ performances.

Economic voting scholarship can be decomposed into two branches (Lewis-Beck and Paldam, 2000). Research in the first branch has focused on the link between voter’s judgments of incumbents and electoral outcomes. An important part of this research involves understanding the “structural features of polities [that] can hinder voters’ access to necessary information about representatives’ activities” (Anderson, 2007, 281). Perhaps the most important contribution here is the notion of clarity of responsibility, first introduced by the seminal work of Powell Jr and Whitten (1993). The authors introduce political context as a conditioning variable in the economy-elections relation, arguing that voters would hold leaders accountable only in cases where they could correctly identify the actors in government responsible for the economic outcomes they observe. Ideology (Evans and Andersen, 2006), the party system and party control (Anderson, 2000; Erikson, 1990; Powell Jr and Whitten, 1993), and electoral institutions (Lewis-Beck and Stegmaier, 2000), are some of the strongest institutional determinants of the strength of the association between economic performance and electoral results.

A second branch of research concerns whether and how citizens process the information around them to shape their judgments of politicians’ competence. Research about how citizens form their political opinions is often discordant, because although
there is ample aggregate-level evidence of a link between economic performance and electoral outcomes, empirical support for this idea at the micro-level varies greatly across studies (Powell Jr and Whitten, 1993). Scholars recommended interpreting polls “as revealing a balance of considerations rather than as counts of people’s ‘true attitudes’” (Zaller and Feldman, 1992, 612), but the jury is still out on whether this balance is necessarily rational and unbiased (Bartels, 1996; Duch, Palmer and Anderson, 2000; Lupia and McCubbins, 1998). Lewis-Beck (2006) makes the sharp observation that interpreting the aggregate evidence as a sign that voters observe and interpret the state of the economy accurately is an ecological fallacy. In other words, there are still many challenges to proving that political accountability is behind this macroeconomic pattern.

The democratic principle of accountability is by no means limited to economic outcomes, but it is believed to be “more straightforward for average citizens than judging other areas of government performance, such as biotechnology or air traffic control” (Anderson, 2007, 277). Still, embedded in economic voting theory is an idealistic view of voters. The micro-mechanism inferred from the aggregate trends necessitates a certain level of rationality and sophistication. This contrasts with research on public opinion and survey design, which has cast doubt on this assumption and suggested that citizens are not only poorly informed, but also uninterested in policies and politics. Popkin (1991) defends that because of this, citizens are more likely to obtain information from readily available sources, instead of assuming the costs of becoming an informed voter. Zaller (1992) further proposes that citizens build their opinions “on the fly” rather than fixing their position beforehand, and that they “make greatest use of ideas that are, for one reason or another, most immediately salient to them –at the ‘top of the head’” (Zaller, 1992, 1). Hence, evaluations of the economy are
not purely objective, but instead have a strong relationship with voters’ immediate environment (Duch, Palmer and Anderson, 2000).

Concerns about individuals’ objectivity and awareness of growth, inflation or unemployment levels put the use of objective economic measurements as explanatory variables for electoral outcomes and popularity levels into question. First, it spurred the emergence of models using voters’ perceptions of the economy to explain these outcomes. This measure addressed the issue at first glance, but ultimately raised more questions because voters may rely on partisanship to formulate their opinions about topics and policies (Bartels, 2000). More specifically, “individuals with stronger attachments to the incumbent (president’s) party may perceive the national economy more positively” (Duch, Palmer and Anderson, 2000, 638). This suggests that the causal arrow may also point from vote choice and approval to evaluations of the state of the economy (Evans and Andersen, 2006), giving strong theoretical reasons to suspect an endogenous relationship.

With financial crises being an unmistakably bad state of the economy, a parallel literature addressed the objectivity issue by studying how economic shocks affect political survival (Bernhard and Leblang, 2008; Martin, 2000; Rosas, 2009; Sattler and Walter, 2010). The assumption that individuals are informed about the state of the economy was more plausible here, because of financial crises’ clear macroeconomic effects and high media coverage. Although there was empirical evidence in favor of economic voting, this research design is also afflicted by endogeneity: just as crises have been shown to affect political survival, there is evidence that elections can also trigger financial hardship. Kayser (2005); Walter (2009) show that governments are
strategic about timing elections before adverse economic environments and argue that this is done to maximize the possibility of remaining in power.

Gasoline and oil prices can shed light on this problem in two ways. First, except for a few oil-producing countries, political instability in an oil-importing country has yet to cause a spike in oil prices: it is a reliably exogenous intervention on the economy. Second, these objective measures are arguably more connected to voters’ immediate environments than other macroeconomic indicators like growth, unemployment, or exchange rates. Further, citizens are regularly exposed to information about gasoline prices. If it is true that “[i]ndividuals generally learn about national economic conditions as a byproduct of activities engaged in for other purposes” (Duch, Palmer and Anderson, 2000, 638), it shouldn’t be surprising that fuels come to mind when thinking about their economic environment. In addition, oil derivatives serve as raw materials for several industries, and gasoline is the main transportation fuel for most countries around the world. As long as fossil fuels are the dominant fuel source for power and transportation, changes in crude oil and gasoline prices will deeply affect world economies. The ubiquity of information about fuel prices and its clear relationship to the economy could be used by individuals as an economic signal independent of their partisan views. This leads to our first hypothesis:

**Hypothesis 1**: High gas prices will have a negative impact on citizens’ evaluations of the economy.

How does this connect to political accountability? In principle, it should not connect at all. Studies on the consequences of globalization for domestic politics can shed light on this question. Globalization, or the degree to which a national economy
interacts with the rest of the world, is also closely linked to the overall health of most economies. Research on the consequences of globalization for domestic politics has argued that national governments in open economies face a constrained set of economic policy choices, and this limits their ability to mitigate the adverse effects of openness among the most challenged groups (Rodrik, 1997). It ultimately diminishes governments’ control over a country’s economic performance and constrains governments’ policy options. Because of this, globalization should dampen voters’ ability to hold incumbents accountable for the countries’ economic performance (Hellwig, 2001; Kayser, 2007). If anything, globalization may contribute to a more informed electorate. Hellwig and Samuels (2007), Leigh (2009), and Duch and Stevenson (2010) explain that globalization makes information from other economies available to citizens, and they can use this information as a benchmark of their own government’s performance.

To sum up, we would expect that even if Hypothesis 1 were confirmed, extant research would predict that fuel prices do not affect voters’ approval of the government. To be sure, research on political accountability in open economies posits that voters would not hold politicians accountable for their limited ability to respond to shocks originated in the international arena. As discussed in the previous chapter, most countries in the world are price-takers when it comes to oil. Although in the long run, the growth of alternative energy sources may change the energy market, national governments have limited power to influence short-term fuel price fluctuations. This means that only a fraction of the prices seen at the pump is determined by government policies, and the larger portion of the price is determined in the global energy market.
Empirical support for this theory is mixed. On the one hand, Hellwig (2001) showed that the poor performance of leaders in countries open to international trade was less relevant for their survival. Similarly, Duch and Stevenson (2010) found that “voters appear to understand the extent to which their economies are subject to shocks from the international economy; and voters who perceive that the variation in the national economy differs from variation in the global economy seem more inclined to exercise an economic vote” (Duch and Stevenson, 2010, 122). Finally, Hellwig and Coffey (2011) study the consequences of the recent British financial crisis and find that the government was not seen as a culprit.

In contrast, Achen and Bartels (2006) famously find that incumbents were more likely to be ousted amidst poor economic conditions but also amidst natural disasters and other local tragedies outside of their control. Leigh (2009) shows that Australian voters tend to punish state governments for poor economic conditions at the national level. Similarly, Wolfers (2006) finds evidence that voters in the US re-elect governors during national economic booms, regardless of their limited involvement in the process. At the national level, exogenous shocks like global economic booms have also been shown to have an important impact on national leaders’ political survival (Crespo-Tenorio, Jensen and Rosas, 2014; Leigh, 2009). This evidence would favor the conclusion that voters are in fact naïve and tend to punish incumbents for poor outcomes, whether these are product of their policies or not.

Perhaps these mixed signals can be explained by an endogeneity issue. Many of these studies treat globalization’s contributions to the domestic economy—such as foreign direct investment and trade—as beyond the government’s hands, when in fact they are controlled by the government through the decision to participate in globalization
in the first place. For example, the growing share of trade in GDP is the product of past decisions to commit to trade openness. Fuel prices are thus a highly visible and decidedly exogenous economic shock, because a country’s demand for fossil fuels is not determined by governmental policy at any point.

Fluctuations in fuel prices thus open a new opportunity to test whether citizens hold governments in oil-importing countries responsible for poor economic conditions that originate in the international sphere. We believe that even though citizens are usually aware of fuel price levels, they are not aware of national leaders’ role in them. Furthermore, they receive mixed information about this by political adversaries and mass media. The second hypothesis is:

**Hypothesis 2:** Voters are more likely to disapprove of the government’s performance when fuel prices are high.

From a methodological standpoint, testing hypotheses of economic voting is challenging. The first two issues have been mentioned above, but are worth discussing further. The first is the potentially endogenous relationship between vote choice or evaluations of the government and perceptions of the economy. One of the most recent empirical attempts to address the issue was put forth by Dicle and Dicle (2011), who uses Granger causality tests to fully test the causal direction between economic and financial indicators and presidential job approval. Evans and Andersen (2006) introduce lagged party identification variables to account for the endogeneity. At the aggregate level, there is potential for endogeneity from economic markets’ reactions to electoral outcomes. Sattler, Freeman and Brandt (2008) study popular support and policy changes using Bayesian Structural VAR models, and show that there is
in fact feedback. However, the policy changes turned out not to affect inflation and growth. The second issue is the mediating effect of partisanship: individuals may choose to follow their party’s position on all issues instead of gathering their own information. In this case, voters’ perceptions and evaluations are all tainted by their party identification. Lewis-Beck (2006) says “researchers should strive to make partisan measures, such as party identification, as exogenous as possible” (Lewis-Beck, 2006, 211).

The final challenge pertains broadly to the way in which the key variables are operationalized. Hellwig (2001) points out that a debate has been posed between egocentric and sociotropic behavior: are individuals’ views influenced most by their personal economic circumstance, by their community’s situation, regardless of theirs relative to the community, or both? While personal circumstances can be measured –through survey instruments– in the same way as personal opinions, capturing the effect of individuals’ environments is not as simple as one would think. Specifically, the data sources for the individuals are usually different than those for their environments, and at a different level of aggregation. Dicle and Dicle (2011) point out the mismatch between the frequency at which economic data is reported and that at which approval ratings are measured. On the other hand, individuals’ low levels of information on the economy make their estimates “on the spot” highly unreliable (Caplan, 2001) and incomparable across individuals.

Studies of economic voting are frequently afflicted with at least one of these issues. It is not uncommon for studies on economic voting to ignore the issue and incorporate objective measures of the economy as explanatory variables with individual-level evaluations of the government as the outcome. Few have directly addressed the role
of partisanship. The following section will implement a non-nested multilevel model to test Hypotheses 1 and 2. It will be shown that a multilevel model addresses these methodological challenges simultaneously.

4.2 A Bayesian multilevel model of public opinion

In this section we test the hypotheses laid out above using a sample of respondents from the American National Election (ANES) Panel Study 2008–2009. First, we use questions in the survey to assess respondents’ levels of information about the economy in general and fuel prices in particular. The second part of the section implements a Bayesian multilevel model for respondents’ opinions on the economy and the president’s performance. The final portion of this section discusses the empirical findings from these models.

Before analyzing the dynamics of the president’s approval rating and fuel prices, it is important to assess whether respondents of the survey were informed about fuel prices. Previous studies had suggested that individuals are not aware of how the domestic and international energy markets work. In the Survey of Americans and Economists on the Economy, respondents were asked whether they believed fuel prices were too high, too low, or about right. More than half of the respondents believed it was too high or about right, while more than half of the economists surveyed believed the opposite (Caplan, 2001, 402). They were also asked which was more responsible for the recent increase in gasoline prices: oil companies or the law of supply and demand. While 90% of the economists believed it was the latter, 73% of the surveyed Americans thought it was the former (Caplan, 2001, 402). As would be expected,
respondents with a lower education level were more likely to have different views that economists (Caplan, 2001, 406). However, these results do not necessarily imply that individuals are uninformed about fuel prices or that they are not a salient political topic for them. I turn to the American National Election Survey to test these basic questions.

Results of this survey suggest that voters are just as informed about candidates’ energy promises as they are about other social and economic issues. In October 2008, ANES participants were asked a few questions about the two presidential candidates’ (John McCain and Barack Obama) positions on a variety of issues. Table 4.1 below shows very similar rates of correct responses across issues, with a remarkable proportion of correct responses about Mr. Obama’s position on increasing fuel efficiency standards for automakers. A simple test for the difference in sample proportions shows that the proportion of respondents informed about Obama’s stance on fuel efficiency requirements for car manufacturers was significantly larger than the proportion for any other topic. The proportion of respondents informed about McCain’s position regarding a raise in the federal gasoline and diesel tax was significantly larger than the proportion of respondents informed about his views on immigration policy.

The ANES also asked respondents what the price of regular unleaded gasoline was at the time of the interview, in November 2009. I construct a five-level categorical variable based on how far respondents’ guesses are from the national average at the time the interviews were conducted. The variable ranges from 0 for those who were within 25 cents of the correct price to 4 for those who were one dollar or further away from the national average price of regular unleaded gasoline per gallon. There is no evidence of an association between education and awareness of fuel prices. To sum up,
Table 4.1: Fact or Fiction: Public perceptions of Presidential Candidates’ policy positions

<table>
<thead>
<tr>
<th>Issue</th>
<th>John McCain</th>
<th>Barack Obama</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raise Taxes for Income &lt; $200K</td>
<td>Opposes 68.85%</td>
<td>Opposes 60.41%</td>
</tr>
<tr>
<td>Govt. Payment for Healthcare</td>
<td>Opposes 53.16%</td>
<td>Favors 69.22%</td>
</tr>
<tr>
<td>Illegal Immigrants- Work permit</td>
<td>Favors 41.88%</td>
<td>Favors 34.83%</td>
</tr>
<tr>
<td>Illegal Immigrants- Citizenship</td>
<td>Favors 66.22%</td>
<td>Favors 38.76%</td>
</tr>
<tr>
<td>Increase Fuel Efficiency Req</td>
<td>Opposes 85.75%</td>
<td>Favors 16.88%</td>
</tr>
<tr>
<td>Increase Fed. Gas Tax</td>
<td>Opposes 36.22%</td>
<td>Favors 46.08%</td>
</tr>
</tbody>
</table>

Candidates’ policy positions are written in italics and the percentage of survey respondents who answered the question “Does Barack Obama/John McCain favor or oppose...” correctly is written below.

Preliminary data analysis from the National Election Survey would suggest that for better or worse, individuals are just as informed about fossil fuels as they are about issues that have traditionally been considered more relevant to political campaigns. Further, there is evidence that acknowledgment of information about fuel prices is unbiased across education levels. This evidence should justify the use of fuel prices as a piece of information that a) citizens are uniformly aware of and b) is as relevant to the general population of voters as more conventional campaign topics. In what follows, this section explores whether individuals’ exposure to fuel prices is used in formulating their opinion on policy and government performance.
Table 4.2: Distribution of fuel price estimates by education level

<table>
<thead>
<tr>
<th>Education</th>
<th>( \leq 0.25 )</th>
<th>0.25-0.5</th>
<th>0.5-0.75</th>
<th>0.75-1</th>
<th>( \geq 1 )</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Some High School</td>
<td>3</td>
<td>30</td>
<td>26</td>
<td>7</td>
<td>7</td>
<td>73</td>
</tr>
<tr>
<td>High School</td>
<td>17</td>
<td>176</td>
<td>138</td>
<td>20</td>
<td>17</td>
<td>368</td>
</tr>
<tr>
<td>Some College</td>
<td>41</td>
<td>401</td>
<td>356</td>
<td>50</td>
<td>35</td>
<td>883</td>
</tr>
<tr>
<td>Bachelor’s Degree</td>
<td>18</td>
<td>269</td>
<td>234</td>
<td>40</td>
<td>27</td>
<td>588</td>
</tr>
<tr>
<td>Graduate Degree</td>
<td>9</td>
<td>204</td>
<td>201</td>
<td>34</td>
<td>11</td>
<td>459</td>
</tr>
<tr>
<td>Total</td>
<td>88</td>
<td>1080</td>
<td>955</td>
<td>151</td>
<td>97</td>
<td>2371</td>
</tr>
</tbody>
</table>

\[ \chi^2_{16} = 23.38008, \ p-value=0.1039 \]

Turning to the hypotheses tests, we use a sample of three waves from the ANES Panel Study. Although originally the study included 19 waves, the questions that constitute our outcome variables were not asked in every wave.\(^7\) Most respondents answered Wave 1 in January and February of 2008. The middle wave for which the outcome variables were collected was answered in November and December of 2008. Participants of the survey answered the final Wave in July and August of 2009. To measure voters’ economic environment around the time when they cast their opinion, a second dataset was gathered.

Unfortunately, data availability forces a trade-off between sample size, geographic accuracy, and time specificity. If sample size is prioritary, then the most specific available fuel price data is at the state-month level. However, these prices may be too aggregated and removed from the respondent’s experience to yield meaningful results. If geographic accuracy is most important, the most specific location information provided by ANES is the respondent’s congressional district. Weekly and monthly data are available for ten cities from the EIA, but congressional districts may not match metropolitan areas exactly. In addition, this sample would not represent neither fuel

\(^7\)See Appendix A for the original question wordings for the most relevant questions in this study.
prices across the US nor the average respondent. Finally, weekly data may reflect the prices that voters observed at the time of the interview more accurately in terms of time, but is only available for ten states. Forced to bite the bullet, we choose temporal accuracy over sample size, and gather weekly economic data from the US Energy Information Agency and the Bureau of Labor Statistics. Our data, then, is comprised of 560 individuals in nine states in the US. Economic information is matched to the week in which respondents participated in each survey wave. Data for this level was obtained from the US Energy Information Agency and the Bureau of Labor Statistics.

Viewed as a Time-Series Cross-Section (TSCS), the data in the sample begins at the response level $y_{ijt}$ where we have repetitions $t = 1, ..., T_{ij}$ nested within respondents $i = 1, ..., n_j$ which are nested within states $j = 1, ..., J$ (Congdon, 2010, 380). Although Maximum Likelihood (ML) approaches exist for TSCS data, Bayesian Multilevel Models are the best alternative for "more complicated TSCS setups, where subunits (such as congressional districts or individuals) are nested in larger units (like states or countries), and both levels have observations across time" (Shor et al., 2007, 169). For one thing, they have better model fit than ML approaches, especially because they can incorporate the uncertainty in estimation that comes from having smaller samples in each cluster of the hierarchy. For another, thinking of TSCS data as a multilevel model dismisses the need for a "balanced" or "rectangular" structure that becomes problematic when issues such as attrition and irregular measurement intervals occur. Finally, Bayesian models provide flexibility to model parameters, which is useful particularly with complicated error structures (Shor et al., 2007).
In this case, the time-serial component of the gathered data is an additional challenge in terms of multilevel modeling. More concretely, respondents’ individual characteristics are time-invariant, but their responses are recorded at varying intervals. Participants were given up to three months to respond the internet-based survey (DeBell, Krosnick and Lupia, 2010, 30). Finally, some state level information does not vary by wave, such as the incumbent governor’s party, while the key explanatory variable, retail fuel prices, theoretically varies daily and at the gas-station level. Since fuel prices per week vary within and across states and respondents’ choice of week to answer the question is independent of the state they live in, we reduce the model to two levels: responses nested in individuals, with the explanatory variable at the response level and demographic data at the individual level.\footnote{Extensive robustness checks were performed, including a re-estimation as three-level models by wave, with the key explanatory variable at a state level, demographics in a second level, and responses at the first level. There was no evidence of state-level effects in this and a variety of other model specifications. When covariates were included in this level, their coefficients straddled zero while evidence of state-level effects remained null.}

The model follows the latent variable formulation for the ordered logistic regression model of Gelman and Hill (2007) and the link function specification by Gill and Waterman (2004) and Gill and Casella (2009). For every individual $i$ in state $j$, the model for a given month is specified:
For Hypothesis 1, the outcome variable $y$ is a respondent’s evaluation of the state of the economy. Two measurements of this outcome are available, and relate to the well-documented debate over whether voters use prospective or retrospective evaluations of the economic situation when evaluating incumbents (Fiorina, 1978; Lewis-Beck and Paldam, 2000; Palmer and Whitten, 1999; Radcliff, 1988). In the survey, respondents were asked how the current economic situation compared to that twelve months before the interview and how they believed it would compare to the situation twelve months into the future. Since the study was conducted around an election time, we believe the anticipation of elections may alter voters’ expectations of the future of the economy, and thus use only the retrospective evaluation as an outcome variable for Hypothesis 1. The measure is a five-point scale where 1 means the economy is much worse at the time of the survey than twelve months earlier, and 5 means the economy is much better.

For Hypothesis 2, the outcome is a respondent’s evaluation of the president’s performance. The ANES panel study contains two measurements of this outcome. First, respondents were asked to evaluate the president’s overall performance, and then they were asked to evaluate the president’s handling of the economy. Both variables can
be built into a five-point scale. However, preliminary tests revealed little evidence of a difference between categories 1 and 2 on the one hand and 4 and 5 on the other, so the presidential approval variable was recoded into three categories. In this case, we assign the value 1 for disapproving, 2 for neither disapproving nor approving, and 3 for approving.

The core model specifications for Hypotheses 1 and 2 are similar. At the response level, we include the economic variables at the time of the response as covariates. In the model above, $X_{it}$ includes fuel prices, the main explanatory variable, and unemployment rates. To match the frequency of fuel price updates, weekly unemployment rates are measured as insured unemployment rates—the number of unemployment insurance claims per week divided by the total number of insured workers in the state.\(^9\) Party identification was asked of respondents at each wave, and so it is included at the response level. This variable is operationalized as “distance from the president”: respondents who identified as “strongly republican” are closest to the republican president in 2008, but furthest away from the democratic president in 2009. This variable is based on the assumption that an individual who identifies as “strongly republican” or “strongly democrat” would be biased in favor of the leaders of their party and biased against leaders from the opposition. We expect that as party distance increases, respondents will evaluate the economy more negatively and disapprove more of the president’s performance.

\(^9\)This data were obtained at the state level from the Department of Labor Statistics. Insured unemployment does not correlate perfectly with total unemployment, but we suspect this measure causes an attenuation bias. Specifically, jobs with unemployment insurance are usually part of more inelastic job markets, so that insured unemployment rates would always be lower and vary less than total unemployment.
At the second level, $Z_i$ is a vector of demographic variables: education, income, and employment status. To reduce multicollinearity, we center the former two variables at their sample means. We expect that unemployed respondents and respondents of low-income levels to evaluate the economy more pessimistically. The variables are centered at their means to control correlation between them. A five-point education scale is included, although from the preliminary analysis above we expect it not to have an important impact on voters’ evaluations of the president and the economy.

The Bayesian model is estimated using MCMC methods. $\beta$ and $g$ are assigned Gaussian prior distributions centered at zero, while precision parameters are assigned diffuse Gamma priors ($\alpha = 2, \beta = 4$). Three chains were run using JAGS for 85,000 iterations each, discarding the first half as burn-in period. Convergence diagnostics—Gelman-Rubin statistics below 1.02, absolute values of the Geweke statistics less than 1.64—were run using the superdiag library in R (Tsai and Gill, 2012).

The results of the basic models for Hypothesis 1 are in Table 4.3. The first model tests this hypothesis directly. Models 2 and 3 test the robustness of the results in Model 1 by including a well-known correlate of public perceptions of the economy: unemployment rates. Unsurprisingly, the signs for education and party identification (measured here as “distance from the president”) have the expected negative sign. Specifically, more educated respondents were more likely to believe the economy at the time of the interviews—the aftermath of the financial crisis of 2007-2008—was worse than a year before. Moreover, respondents who identified themselves as belonging to a different party than the president were more likely to judge the economy in a
negative light. Finally, in terms of model fit, Model 1 emerges as the best, with the lowest DIC and 56% responses correctly predicted.\textsuperscript{10}

Table 4.3: Fuel prices and retrospective assessments of the economy

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Response level</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fuel Price</td>
<td>1.2806</td>
<td>1.5057</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.1400)</td>
<td>(0.1573)</td>
<td></td>
</tr>
<tr>
<td>Unemp</td>
<td>0.4712</td>
<td>0.5421</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0473)</td>
<td>(0.0565)</td>
<td></td>
</tr>
<tr>
<td>Party ID</td>
<td>-0.2696</td>
<td>-0.2023</td>
<td>-0.2887</td>
</tr>
<tr>
<td></td>
<td>(0.0246)</td>
<td>(0.0247)</td>
<td>(0.0264)</td>
</tr>
<tr>
<td><strong>Respondent level</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>-0.0231</td>
<td>-0.0041</td>
<td>-0.0392</td>
</tr>
<tr>
<td></td>
<td>(0.0606)</td>
<td>(0.0649)</td>
<td>(0.0712)</td>
</tr>
<tr>
<td>Income</td>
<td>-0.0089</td>
<td>-0.0061</td>
<td>-0.0080</td>
</tr>
<tr>
<td></td>
<td>(0.0158)</td>
<td>(0.0166)</td>
<td>(0.0186)</td>
</tr>
<tr>
<td>Unemployed</td>
<td>-0.0865</td>
<td>0.4480</td>
<td>0.4360</td>
</tr>
<tr>
<td></td>
<td>(22.4633)</td>
<td>(22.3176)</td>
<td>(21.9422)</td>
</tr>
<tr>
<td>Retired</td>
<td>0.4401</td>
<td>-0.2463</td>
<td>-0.4222</td>
</tr>
<tr>
<td></td>
<td>(22.4536)</td>
<td>(22.3171)</td>
<td>(21.9382)</td>
</tr>
<tr>
<td><strong>Cutpoints</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\kappa_1)</td>
<td>2.5339</td>
<td>0.5774</td>
<td>4.6660</td>
</tr>
<tr>
<td></td>
<td>(0.4296)</td>
<td>(0.2827)</td>
<td>(0.5385)</td>
</tr>
<tr>
<td>(\kappa_2)</td>
<td>4.0507</td>
<td>2.1183</td>
<td>6.3521</td>
</tr>
<tr>
<td></td>
<td>(0.4419)</td>
<td>(0.2904)</td>
<td>(0.5600)</td>
</tr>
<tr>
<td>(\kappa_3)</td>
<td>6.0738</td>
<td>4.2253</td>
<td>8.5492</td>
</tr>
<tr>
<td></td>
<td>(0.4592)</td>
<td>(0.3196)</td>
<td>(0.5917)</td>
</tr>
<tr>
<td>(\kappa_4)</td>
<td>8.3642</td>
<td>6.5595</td>
<td>10.8983</td>
</tr>
<tr>
<td></td>
<td>(0.5695)</td>
<td>(0.4655)</td>
<td>(0.6879)</td>
</tr>
<tr>
<td>Respondents</td>
<td>554</td>
<td>554</td>
<td>554</td>
</tr>
<tr>
<td>N</td>
<td>1587</td>
<td>1587</td>
<td>1587</td>
</tr>
<tr>
<td>DIC</td>
<td>3728</td>
<td>3834</td>
<td>3992</td>
</tr>
</tbody>
</table>

Posterior means; standard deviations in parenthesis.

Note that at the response level, “Unemp” refers to the observed unemployment rate at the time that the survey took place. At the respondent level, “Unemployed” refers to the respondent’s employment status at the start of the study.

Regarding the main explanatory variables, in Table 4.3, the estimated effect of fuel prices and unemployment rates on respondents’ evaluation of the economy are puzzling. The posterior densities of these estimates are quite precise. A 95% credible

\textsuperscript{10}Predictions for each response were obtained at each iteration of the MCMC algorithm. We compare the observed responses to the posterior medians of each prediction.
interval for them would not include zero suggesting there is an effect. However, the posterior means have the opposite sign than what was expected. They suggest that a one-dollar increase in fuel prices per gallon and a one-percent rise in unemployment rates improve the odds of believing the economy is somewhat or much better.

To understand these results more clearly, we estimate the marginal effects of unemployment and fuel prices in Figure 4.2. Panel (b) makes it clear that *ceteris paribus*, the probability of responding that the economy is “neither better nor worse” ($P(Y=3)$) or “somewhat better” ($P(Y=4)$) increases as unemployment increases. Nevertheless, the “somewhat worse” category has the highest predicted probability for all unemployment rates this increase is never enough to induce a change in the predicted category. In plain terms, even if the probability that the average respondent evaluates the economy as better now than last year increases as unemployment rates increase, for any unemployment rates she is most likely to evaluate the economy as “somewhat worse”. In contrast, panel (a) in Figure 4.2 suggests that for the highest fuel prices, an average respondent may be most likely to believe the economy is neither better nor worse. Thus, we can conclude that the evidence that fuel prices affect perceptions of the economy in this model is weak. In fact, this model suggests that fuel prices tend to pool together rather than polarize public opinion on the state of the economy.

What conditions could drive the relationship between fuel and evaluations of the economy? To refine the results from Table 4.3, we re-estimate Model 3 allowing the response-level slopes to vary by wave. This model correctly predicts 61.2% of the observed outcomes. The estimated slopes are plotted in Figure 4.3. During Wave 2, a respondent had 20% lower odds of believing the economy was “somewhat or much
At the respondent level, education and income are set at their median levels; we set the respondent as “employed”. All other variables held at their means. Predicted probabilities are estimated based on the posterior means for all coefficients.

better” than last year when compared to a respondent who was exposed to a fifty-cent lower fuel price. This result stands out because it contrasts with the results of Waves 1 and 3, where the odds ratios are reversed. Further, it occurs when average national fuel prices were at their lowest point in the period. Assuming that low fuel prices are “good” for respondents, there would not be a reason to expect animosity over fuel prices when they are, on average, very low. Since the Wave 2 survey took place in November of 2008, just after the presidential election, it is possible that partisan messages about energy policy and fuel around election time can influence the meaning that voters attach to the fuel prices they observe.

To inspect this possibility, we illustrate the marginal effect of fuel prices for Waves 1 and 2 by plotting the cumulative probability of each category in Figure 4.4. During
Wave 1, the probability mass moves from the “much worse” category for the lowest fuel prices to the “somewhat worse” and “neither better nor worse” categories. All in all, the probability of observing either of these two responses is more or less even, since for any plausible fuel price level, the total probability of observing any of these three categories is 0.3. In contrast, during Wave 2 it is clear that there is a very high probability of believing the economy is “somewhat worse” or “much worse” regardless of fuel prices, although they do contribute to increasing this probability even more.

Figure 4.3: Varying slopes by survey wave

In the boxplots above, the whiskers mark the 90% Credible Intervals of the posterior densities for the slope coefficients. The unemployment rates and fuel prices reported correspond to January 2008, November 2008, and July 2009, when most respondents answered each survey wave.

Finally, the right hand panel of Figure 4.3 shows the campaign effect of Wave 2 is an implausible explanation for the effect of unemployment rates on voters’ retrospective assessments of the economy. The posterior densities of the slope coefficient here become more positive over time. National average unemployment rates follow a similar trend: the unemployment rate in Wave 3 was twice as large than that of
Wave 1. Along similar lines as the pooled model, panel (b) of Figure 4.3 suggests that unemployment rates were not significant contributors to people’s perceptions of the economy. In fact, the effect of unemployment is centered at zero during the presidential election.

Figure 4.4: Marginal effects of fuel prices by survey wave

At the respondent level, education and income are set at their median levels; we set the respondent as “employed”. All other variables held at their means. Predicted probabilities are estimated based on the posterior means for all coefficients.

Party identification is an important determinant of the weight that fuel prices will have on respondents’ assessment of the economy. In panel (a) of Figure 4.5, it is clear that Democrats attach the least weight to fuel prices, as the estimated odds in the “Strong Democrat” category are the smallest. For this partisan group, the weight of a one-percent increase in unemployment on their assessment of the economy (panel (b)) is nearly five times as large as the impact of a one dollar increase in fuel prices (panel (a)). In line with expectations for a right-wing political party, Republicans give little weight to unemployment rates in their decision.
Figure 4.5: Varying slopes by party identification – opinion on the economy

(a) Fuel Price

(b) Unemployment Rate

The boxplot whiskers mark the 90% Credible Intervals of the posterior densities for the slope coefficients.

To interpret these results more intuitively, we calculate the cumulative predicted probabilities by fuel price, for strong Republican respondents and strong Democrat respondents in Figure 4.6. The gentle rate at which probabilities change in panel (a) of this figure show that even when fuel prices are extreme, Democrats are not very likely to change their opinion on the economy. In contrast, Republicans’ opinion of the economy becomes better as fuel prices increase.

To sum up, the empirical evidence suggests that the effect of fuel prices on respondents’ impression of the economy is highly influenced by political parties and political campaigns. We draw this conclusion from the evidence in favor of Hypothesis 1 found in the slope coefficient of fuel prices for survey Wave 2. Furthermore, in models where slopes vary according to political party, we see that Republican voters attach much more weight on fuel prices in their evaluation of the economy than Democrats. Nevertheless, the direction of this effect is opposite to what was expected. We now turn to testing whether voters hold the president accountable for changes in fuel prices.
Figure 4.6: Marginal effects of fuel prices by party ID

(a) Strong Democrats

(b) Strong Republicans

The “average respondent” is defined as an employed person, with annual income between $50,000 and $59,999, and “Some college” education level. All other variables are held to their mean values.

If this were true, then we expect fuel prices to behave similarly when we substitute presidential approval as the outcome variable.

The results for the Bayesian multilevel models that test Hypothesis 2 are presented in Table 4.4. The outcome variable in this case is a three-point ordered categorical measure of respondents’ approval of the president’s handling of the economy, and a similar scale for respondents’ overall approval of the president’s performance. The respondent-level coefficients mimic those of Table 4.3: respondents with higher levels of education have lower odds of approving of the president overall as well as lower odds of favoring the president’s handling of the economy. As before, employment status and income level are not statistically significantly distinguishable from zero. However, in Table 4.4 it is not the case that Model 1 is preferred: for both outcome variables,
the models that include unemployment rates fit the data considerably better than those which exclude this variable, using the DIC as a criterion.

Table 4.4: Fuel prices and Presidential approval

<table>
<thead>
<tr>
<th></th>
<th>Economic Policy Approval</th>
<th>Overall Approval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
</tr>
<tr>
<td>Response level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fuel Price</td>
<td>–0.0874</td>
<td>–0.0585</td>
</tr>
<tr>
<td></td>
<td>(0.1350)</td>
<td>(0.1382)</td>
</tr>
<tr>
<td>Unemp</td>
<td>–0.2766</td>
<td>–0.2752</td>
</tr>
<tr>
<td></td>
<td>(0.0489)</td>
<td>(0.0493)</td>
</tr>
<tr>
<td>Party ID</td>
<td>0.2161</td>
<td>0.2160</td>
</tr>
<tr>
<td></td>
<td>(0.0256)</td>
<td>(0.0257)</td>
</tr>
<tr>
<td>Respondent level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>–0.2614</td>
<td>–0.2623</td>
</tr>
<tr>
<td></td>
<td>(0.0662)</td>
<td>(0.0690)</td>
</tr>
<tr>
<td>Income</td>
<td>0.0132</td>
<td>0.0144</td>
</tr>
<tr>
<td></td>
<td>(0.0173)</td>
<td>(0.0179)</td>
</tr>
<tr>
<td>Unemployed</td>
<td>0.5274</td>
<td>0.1347</td>
</tr>
<tr>
<td></td>
<td>(22.6006)</td>
<td>(22.4494)</td>
</tr>
<tr>
<td>Retired</td>
<td>–0.3967</td>
<td>0.1244</td>
</tr>
<tr>
<td></td>
<td>(22.5871)</td>
<td>(22.4613)</td>
</tr>
<tr>
<td>Cutpoints</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\kappa_1$</td>
<td>–1.9786</td>
<td>–2.6328</td>
</tr>
<tr>
<td></td>
<td>(0.4337)</td>
<td>(0.3094)</td>
</tr>
<tr>
<td>$\kappa_2$</td>
<td>1.0883</td>
<td>0.5072</td>
</tr>
<tr>
<td></td>
<td>(0.4302)</td>
<td>(0.2954)</td>
</tr>
<tr>
<td>Respondents</td>
<td>562</td>
<td>562</td>
</tr>
<tr>
<td>N</td>
<td>1597</td>
<td>1597</td>
</tr>
<tr>
<td>DIC</td>
<td>3522</td>
<td>3489</td>
</tr>
</tbody>
</table>

Posterior means; standard deviations in parenthesis.
Note that at the response level, “Unemp” refers to the observed unemployment rate at the time of the response. At the respondent level, “Unemployed” refers to the respondent’s employment status at the start of the survey.

In terms of explanatory power, Model 3 correctly predicts 62.6% of the observed economic policy approval responses, and 68.7% of the observed overall approval responses. In comparison, Model 1 predicts only 58% of the former and 49.7% of the
latter responses. In the overall approval set of models, unemployment plays a stronger role than in economic policy approval models. Still, the posterior mean effect of unemployment is several times larger than that of fuel prices. All this, together with the fact that the posterior density of the fuel price coefficient straddles zero in all models, is discouraging evidence for Hypothesis 2.

Figure 4.7: Marginal effects of fuel prices and unemployment rates on presidential approval

At the respondent level, education and income are set at their median levels; we set the respondent as “employed”. All other variables held at their means. Predicted probabilities are estimated based on the posterior means for all coefficients.

To check the robustness of these results, the models are re-estimated, allowing the slope coefficients to vary by party identification and by wave and display the estimated slopes in Figure 4.8. It is readily apparent that partisanship again plays a key role on the effect of fuel prices on government approval. Respondents who identified as strong Republicans had lower odds of approving of the president’s economic policy and his performance overall, while the opposite is true for strong Democrats. Moreover, in
Table 4.4: The effect of unemployment was decidedly negative, but the varying-slopes by party in the bottom row of Figure 4.8 reveal that the coefficient changes sign for respondents who identified as Republican.

Figure 4.8: Varying slopes by party identification—presidential approval

The plots on the top row show the estimated slopes for the effect of fuel prices on approval rates. The bottom-row plots show the estimated slopes for the effect of unemployment rates. Both left-hand rows are coefficients based on models where the outcome variable was approval of the president’s economic policy, while both right-hand rows are coefficients based on models where the outcome variable was overall approval of the president. The boxplot whiskers mark the 90% Credible Intervals of the posterior densities for the slope coefficients.

That the fuel-price coefficient for Democrat respondents is positive does not necessarily imply that they favor increases in fuel prices. To further explore this dynamic, in Figure 4.9 we plot the cumulative probabilities of each economic policy approval for respondents who identified as strong Democrats and strong Republicans, as a function of fuel prices. For the most extreme fuel prices, strong democrats are equally likely to approve or evaluate the president’s economic policy neutrally. For realistic, yet high fuel prices, Democrat respondents are most likely to neither approve nor disapprove...
of the president’s economic policy. Therefore, rather than implying a preference for high fuel prices, the estimated fuel price coefficient for strong Democrats should be interpreted as a lack of association between fuel prices and Democrats’ evaluation of the president’s performance.

Strong Republicans, on the other hand, are certainly more likely to react to increases in fuel prices. Panel (b) in Figure 4.9 and Figure 4.9 show that the probability of disapproving of the president’s economic policy increases precipitously after the $3.00 / gallon threshold. In other words, Republicans are more likely than Democrats to hold the president accountable for them.

Figure 4.9: Predicted probabilities of economic policy approval

To sum up, this section tested the hypotheses that fuel prices are linked to voters’ perceptions of the economy and their evaluations of the president’s performance using data from ANES respondents in ten states. The Bayesian multilevel models for
ordered categorical outcomes revealed that fuel prices are most likely to affect voters’ perception of the state of the economy during the weeks prior and immediately following an election. Although at first glance, the evidence in favor of Hypothesis 2 is weak, a closer inspection reveals that the connection between fuel prices and government approval is not equal across the board. Rather, party identification plays a key role.

4.3 Concluding Remarks

This chapter has explored the connection between fuel prices and public opinion in nine states of an oil-importing country, the United States. The chapter first reviewed extant scholarly work on the idea that the state of the economy is the measure by which we can judge governments’ performance. The economic voting hypothesis is
common knowledge in political science research and outside of the academic world: voters across countries consider the economy to be among the top concerns regarding voting. Yet the degree to which this determines leader survival or electoral outcomes varies between countries (Anderson, 2007; Kayser, 2007; Lewis-Beck, 2006; Lewis-Beck and Stegmaier, 2000; Powell Jr and Whitten, 1993). In addition, there is controversy over which specific indicators of the state of the economy are used by voters to formulate their opinions.

This chapter proposed fuel prices as a new test for economic voting. Fuel prices are constants in political campaigns and mass media around election times, even though political leaders have little to do with them. After reviewing economic voting literature, this chapter argues that fuel prices are “information shortcuts” for voters: data that they are regularly exposed to and associate with their broader economic environment. If this were true, we would expect fuel prices to be correlated with public opinion on the state of the economy. Further, we argue that when making evaluations about politicians’ performance, voters may use this information more often than other macroeconomic indicators such as unemployment or growth rates because they are more straightforward to interpret. However, we find only weak evidence that fuel prices are linked to government approval ratings, as Figure 4.1 suggested.

The results in this chapter offer several opportunities for new research. First, the weakness of the empirical evidence in this chapter may be related to a loss of information involved with using state-level data and individual-level responses. Further research should take steps to improve the match between voters’ measurable economic environment and their political opinions. More specifically, survey experiments are a
promising avenue where economic environments could be manipulated or closely monitored. Second, the evidence presented here supports the idea that political parties have an important influence on the information that their constituents use to form their political opinion. Furthermore, the message often delivered in political campaigns—that fuel prices are the result of poor economic policy—is indeed effective. Survey respondents were not likely to evaluate the economy poorly due to changes in fuel prices except in the survey immediately following the election. This research can be extended and linked to existing knowledge about the role of partisan cues and issue framing in public opinion.
Appendix A

Bivariate Poisson distribution and Change-Point Model

Drawing random deviates from the Bivariate Poisson distribution

This function generates samples from the Bivariate Poisson distribution using rejection sampling and the bivariate normal density as the envelope distribution.

```
rbipois<-function(n, target.params, envelope.params=list(mean=c(3,3), var=5*matrix(c(2,1,1,2), ncol=2), k=1){
    #SET UP
    mean=envelope.params[[1]]; vcov=envelope.params[[2]]
    if (require(mvtnorm, quietly=TRUE)==FALSE) {
        stop("This function needs the mvtnorm package to run. Please install it and try again")
    }

    #STORAGE
    the.sample=matrix(NA, ncol=2, nrow=n)

    #FUNCTION TO EVALUATE THE BIVARIATE POISSON PMF:
    dbipois<-function(variables,params){
        #SETUP
```
\[
x = \text{variables}[1] \quad \text{y} = \text{variables}[2] \\
\lambda_1 = \text{params}[1] \quad \lambda_2 = \text{params}[2] \\
\xi = \text{params}[3]
\]

# PLUG IN VALUES

density_1 = \exp(- (\lambda_1 + \lambda_2 + \xi))

summation = 0

for (z in 0:min(x, y)) {
    summation = summation + (\(\frac{\lambda_1^x}{\text{factorial}(x-z)}\) \(\frac{\lambda_2^y}{\text{factorial}(y-z)}\) \(\frac{1}{\text{factorial}(z)}\) \(\frac{\xi}{\lambda_1 \lambda_2}\)^z)
}

density = density_1 \times \text{summation}

return(density)

# SAMPLING

for (j in 1:n) {
    calc = 1000
    U = calc \times k
    while (calc <= k \times U) {
        X = c(-1, -1)
        while (X[1] < 0 \text{ or} X[2] < 0) {
            X = \text{rmvnorm}(1, \text{mean=mean, sigma=vcov})
        }
        X = \text{floor}(X)
        \text{print(paste("X is", X))}
        U = \text{runif}(1)
        fofx = \text{dbipois}(X, \text{target.params})
        \text{print(paste("fofx is", fofx))}
        gofx = \text{dmvnorm}(X, \text{mean=mean, sigma=vcov})
        \text{print(paste("gofx is", gofx))}
        calc = fofx / gofx
    }
    the.sample[j,] = X
}

\text{return(the.sample)\}
Gibbs sampling algorithm for the bivariate Poisson change-point model

```r
bivpois.cp<-function(my.data,inits,a1,a2,a3,b1,b2,b3,c1,c2,c3,d1,d2,d3,M) {
  lambda1=inits[1]; lambda2=inits[2]; xi1=inits[3]
  phi1=inits[4]; phi2=inits[5]; xi2=inits[6]
  k=inits[7]
  results=matrix(NA,ncol=7,nrow=M)
  n=length(my.data[,1])
  k.prob=rep(0,n)

  ###BEGINNING MCMC ITERATIONS###
  for (i in 1:M){
    if (i%%1000==0) print(i)

    ###DATA SETUP###
    data.pre=matrix(data=my.data[1:k,],nrow=k,ncol=2,byrow=FALSE)
    u1=rep(1,k)
    if(k<n){
      data.post=matrix(data=my.data[(k+1):n,],nrow=(n-k),ncol=2,byrow=FALSE)
      u2=rep(1,(n-k))
    }

    ###PRE-K WORK###
    #SIMULATE A NEW U1 VECTOR
    for (j in 1:k){
      draw=max(data.pre[j,1],data.pre[j,2])
      this.min=min(data.pre[j,1],data.pre[j,2])
      while ( draw > this.min ) {
        draw=rpois(1,lambda=xi1)
      }
      u1[j]=draw
    }

    #DRAW LAMBDA'S AND XI
    lambda1=rgamma(1,shape=sum(data.pre[,1]-u1)+a1,rate=k+b1)
    lambda2=rgamma(1,shape=sum(data.pre[,2]-u1)+a2,rate=k+b2)
    xi1=rgamma(1,shape=sum(u1)+a3,rate=k+b3)

    ###POST-K WORK###
    if (k < n) {
      #DRAW LAMBDA'S AND XI
      lambda1=rgamma(1,shape=sum(data.pre[,1]-u1)+a1,rate=k+b1)
      lambda2=rgamma(1,shape=sum(data.pre[,2]-u1)+a2,rate=k+b2)
      xi1=rgamma(1,shape=sum(u1)+a3,rate=k+b3)
    }

    results[i,]=c(lambda1,lambda2,xi1,phi1,phi2,xi2,k)
  }

  #POST-HIERARCHICAL INFERENCE
  m=matrix(result[,1:6],nrow=M,ncol=6)
  k=matrix(result[,6],nrow=M)
  for (i in 1:M){
    k.prob[i]=length(m[,i]<1)/n
  }

  return(list(results,m,k,k.prob))
}
```

```r
gibbs.cp<-function(my.data,inits,a1,a2,a3,b1,b2,b3,c1,c2,c3,d1,d2,d3,M){
  lambda1=inits[1]; lambda2=inits[2]; xi1=inits[3]
  phi1=inits[4]; phi2=inits[5]; xi2=inits[6]
  k=inits[7]
  results=matrix(NA,ncol=7,nrow=M)
  n=length(my.data[,1])
  k.prob=rep(0,n)

  ###BEGINNING MCMC ITERATIONS###
  for (i in 1:M){
    if (i%%1000==0) print(i)

    ###DATA SETUP###
    data.pre=matrix(data=my.data[1:k,],nrow=k,ncol=2,byrow=FALSE)
    u1=rep(1,k)
    if(k<n){
      data.post=matrix(data=my.data[(k+1):n,],nrow=(n-k),ncol=2,byrow=FALSE)
      u2=rep(1,(n-k))
    }

    ###PRE-K WORK###
    #SIMULATE A NEW U1 VECTOR
    for (j in 1:k){
      draw=max(data.pre[j,1],data.pre[j,2])
      this.min=min(data.pre[j,1],data.pre[j,2])
      while ( draw > this.min ) {
        draw=rpois(1,lambda=xi1)
      }
      u1[j]=draw
    }

    #DRAW LAMBDA'S AND XI
    lambda1=rgamma(1,shape=sum(data.pre[,1]-u1)+a1,rate=k+b1)
    lambda2=rgamma(1,shape=sum(data.pre[,2]-u1)+a2,rate=k+b2)
    xi1=rgamma(1,shape=sum(u1)+a3,rate=k+b3)

    ###POST-K WORK###
    if (k < n) {
      #DRAW LAMBDA'S AND XI
      lambda1=rgamma(1,shape=sum(data.pre[,1]-u1)+a1,rate=k+b1)
      lambda2=rgamma(1,shape=sum(data.pre[,2]-u1)+a2,rate=k+b2)
      xi1=rgamma(1,shape=sum(u1)+a3,rate=k+b3)
    }

    results[i,]=c(lambda1,lambda2,xi1,phi1,phi2,xi2,k)
  }

  #POST-HIERARCHICAL INFERENCE
  m=matrix(result[,1:6],nrow=M,ncol=6)
  k=matrix(result[,6],nrow=M)
  for (i in 1:M){
    k.prob[i]=length(m[,i]<1)/n
  }

  return(list(results,m,k,k.prob))
}
```
#SIMULATE A NEW U2 VECTOR
for (j in 1:(n-k)) {
    draw = max(data.post[j,1], data.post[j,2])
    this.min = min(data.post[j,1], data.post[j,2])
    while (draw > this.min) {
        draw = rpois(1, lambda=xi2)
    }
    u2[j] = draw
}

#DRAW LAMBdas AND XI
phi1 = rgamma(1, shape=sum(data.post[,1]-u2)+c1, rate=(n-k)+d1)
phi2 = rgamma(1, shape=sum(data.post[,2]-u2)+c2, rate=(n-k)+d2)
xi2 = rgamma(1, shape=sum(u2)+c3, rate=(n-k)+d3)
}

###DRAW K###
u = c(u1, u2)
for (j in 1:n) {
multiplicand1 = rep(1, n)
    for (w in 1:j) {
        summation = 0
        for (z in 1:min(my.data[w,1], my.data[w,2])) {
            part1 = (xi1^z / factorial(z)) * exp(-xi1)
            part2 = (lambda1^(my.data[w,1]-u[w]) / factorial(my.data[w,1]-u[w])) * exp(-lambda1)
            part3 = (phi1^(my.data[w,1]-u[w]) / factorial(my.data[w,1]-u[w])) * exp(-phi1)
            summation = summation + (part1 * part2 * part3)
        }
        multiplicand1[w] = summation
    }
multiplicand2 = rep(1, n)
if (k < n-1) {
    if (j < n) {
        for (w in (j+1):n) {
            summation = 0
            for (z in 1:min(my.data[w,1], my.data[w,2])) {
                part1 = (xi2^z / factorial(z)) * exp(-xi2)
                part2 = (phi1^(my.data[w,1]-u[w]) / factorial(my.data[w,1]-u[w])) * exp(-phi1)
                part3 = (phi2^(my.data[w,2]-u[w]) / factorial(my.data[w,2]-u[w])) * exp(-phi2)
                summation = summation + (part1 * part2 * part3)
            }
        }
    }
}

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multiplicand2[w]=summation
}
}

#assembling likelihood
k.prob[j]=prod(multiplicand1)*prod(multiplicand2)
}
k=sample(1:n,size=1,prob=k.prob[1:n])
results[i,] <- c(k,lambda1,lambda2,xi1,phi1,phi2,xi2)
}
colnames(results)<- c("k","lambda1","lambda2","xi1","phi1","phi2","xi2")
return(as.mcmc(results))
}
#end function
Appendix B

Compilation of Resource Curse Articles and Books

Table B.1: List of Keywords Used in Searches

<table>
<thead>
<tr>
<th>oil</th>
<th>democracy</th>
<th>growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>natural resources</td>
<td>political regime</td>
<td>economic growth</td>
</tr>
<tr>
<td>resource abundance</td>
<td>level of democracy</td>
<td>development</td>
</tr>
<tr>
<td>resource curse</td>
<td>authoritarian regime</td>
<td>dutch disease</td>
</tr>
<tr>
<td>resource wealth</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The following tables list articles and books on the subject of the resource curse. Articles used in the meta-analysis and meta-regression are identified with an asterisk.

Table B.2: Selected studies: Oil and Democracy

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Aslaksen (2010)*</td>
<td>Gundlach and Paldam (2009)*</td>
<td>Ross (2004)*</td>
</tr>
<tr>
<td>Bearce and Laks Hutnick (2011)*</td>
<td>Haber and Menaldo (2010)*</td>
<td>Rowley and Smith (2009)*</td>
</tr>
<tr>
<td>Collier and Hoeffler (2005)*</td>
<td>Oskarsson and Ottosen (2010)*</td>
<td>Williams (2011)*</td>
</tr>
</tbody>
</table>
Table B.3: Selected studies: Oil and Economic Growth.

<table>
<thead>
<tr>
<th>Study 1</th>
<th>Study 2</th>
<th>Study 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Collier and Hoeffler (2005)*</td>
<td>Mehlum, Moene and Ragnar (2006)*</td>
<td></td>
</tr>
<tr>
<td>Cerny and Filer (2007)*</td>
<td>Mushedi and Sorino (2011)*</td>
<td></td>
</tr>
</tbody>
</table>
Appendix C

ANES Panel Study 2008-2009
Question Wordings

Figure C.1: Field dates of interview waves and U.S. National Average Regular Gasoline Price
C.0.1 Outcome variables

Economic Performance

To test the robustness of the models regarding prospective and retrospective economic evaluations, a three-point scale based only on questions 1 and 2 was considered as well as a five-point scale derived from the questions and their follow-up questions.

1. Now thinking about the economy in the country as a whole, would you say that as compared to one year ago, the nation’s economy is now better, about the same, or worse?
   a) Better
   b) About the same
   c) Worse

   1.a Much better or somewhat better?
      a) Much better
      b) Somewhat better

   1.b Much worse or somewhat worse?
      a) Much worse
      b) Somewhat worse

2. What about 12 months from now? Do you think the economy, in the country as a whole, will be better, about the same, or worse in 12 months?
   a) Better
   b) About the same
   c) Worse

   2.a Much better or somewhat better?
      a) Much better
      b) Somewhat better

   2.b Much worse or somewhat worse?
      a) Much worse
      b) Somewhat worse
Presidential Approval

To test the robustness of the models regarding presidential approval, a three-point scale based only on questions 1 and 2 was considered as well as a seven-point scale derived from the questions and their follow-up questions.

1. Do you approve, disapprove, or neither approve nor disapprove of the way [George W. Bush/ Barack Obama] is handling his job as president?
   a) Approve
   b) Disapprove
   c) Neither approve nor disapprove

1.a Do you [approve/disapprove] extremely strongly, moderately strongly, or slightly strongly?
   a) Extremely strongly
   b) Moderately strongly
   c) Slightly strongly

2. Do you approve, disapprove, or neither approve nor disapprove of the way [George W. Bush/ Barack Obama] is handling the economy?
   a) Approve
   b) Disapprove
   c) Neither approve nor disapprove

2.a Do you [approve/disapprove] extremely strongly, moderately strongly, or slightly strongly?
   a) Extremely strongly
   b) Moderately strongly
   c) Slightly strongly

Presidential candidates’ position on policy issues

As part of the Panel Study, ANES asked respondents to recall the Presidential candidates’ position on a selection of policy issues that were discussed in the campaign. For the questions below, the answer options were:
1. Does [Barack Obama/John McCain] favor, oppose, or neither favor nor oppose raising federal income taxes for people who make less than $200,000 per year?

2. Does [Barack Obama/John McCain] favor, oppose, or neither favor nor oppose the U.S. government paying for all necessary medical care for all Americans?

3. Does [Barack Obama/John McCain] favor, oppose, or neither favor nor oppose allowing illegal immigrants to work in the United States for up to three years, after which they would have to go back to their home country?

4. Does [Barack Obama/John McCain] favor, oppose, or neither favor nor oppose the U.S. government making it possible for illegal immigrants to become U.S. citizens?

5. Does [Barack Obama/John McCain] favor, oppose, or neither favor nor oppose the federal government requiring automakers to build cars that use less gasoline?

6. Does [Barack Obama/John McCain] favor, oppose, or neither favor nor oppose increasing taxes on gasoline so people either drive less or buy cars that use less gas?
References


Cesari, A. 2011. “Oil and Democracy.”


Khan, M.Y. 2006. “Indian exports yet to go places.”


Ross, M. 2009. “Oil and Democracy Revisited.”


The Nation (Thailand). 2006. “Ministry sees repeat 15% growth: FTAs, return of GSP both give a boost.”.


United Nations News & Media Division. 2006. “Secretary-General Calls for Elimination of Trade-Distorting Subsidies for Agriculture at High-Level ECOSOC Meeting.”


