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# Utilizing Natural and Man-made Resources for Economic Development: What Are the Mechanisms and Why?

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# UTILIZING NATURAL AND MAN-MADE RESOURCES FOR ECONOMIC DEVELOPMENT: WHAT ARE THE MECHANISMS AND WHY?

by

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ABSTRACT

UTILIZING NATURAL AND MAN-MADE RESOURCES
FOR ECONOMIC GROWTH: WHAT ARE THE MECHANISMS AND WHY?

by

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This dissertation studies the roles of natural resources in determining economic outcomes such as innovation, investment, profitability and economic growth.

The first chapter studies the ease of substitution between energy and other production inputs over time and across countries. Improvements in energy efficiency over the past decades have substantially decreased the amount of energy used per unit of capital. Yet, previous literature often assumes a constant elasticity of substitution between capital and energy. In this chapter, we develop a Solow growth model with a variable elasticity of substitution (VES) between production inputs and show that the long-run growth rate directly depends on the behavior of this VES over time. Next, using country-level data from 108 countries between 1971 and 2011, we provide the first empirical evidence for a capital-energy VES. Specifically, the elasticity of substitution between capital and energy positively relates to a country's level of economic development and environmental protection efforts. Our results imply that growth-enhancing policies can ease the substitution between capital and energy, which in turn can foster long-run economic growth.

In the second chapter, I study the risk and return behavior of green bonds, a new financial instrument that supports green projects around the world. Since its inception in 2007, the green bond market has experienced a compound growth rate of 50% annually. In 2014, green bond issuance totaled USD 36.6 billion, more than threefold its previous year's level of USD 11 billion. This paper is the first to analyze the volatility behavior of the green bond market using data on

daily closing prices of the S&P green bond indices between April 2010 and April 2015. Building on a multivariate GARCH framework, I find that compared to the "labeled" segment of the green bond market, the "unlabeled" segment experiences smaller volatility clustering. I also found a time-varying spillover effect between the green bond market and the overall conventional bond market. These results are meaningful insights into this new, yet very promising market, therefore, have important implications for asset pricing, portfolio management and risk management.

The third chapter evaluates the role of a fossil fuel tax and research subsidy in directing innovation from fossil fuel toward renewable energy technologies in the electricity sector. Using a global firm-level electricity patent database from 1978 to 2011, we find that the impact of fossil fuel taxes on renewable energy innovation varies with the type of fossil fuel. Specifically, a tax on coal reduces innovation in both fossil fuel and renewable energy technologies while a tax on natural gas has no statistically significant impact on renewable energy innovation. The reason is that easily dispatchable energy sources (e.g., coal-fired power) need to complement renewable energy technologies (e.g., wind or solar) in the grid because renewables generate electricity intermittently. Our results suggest that a tax on natural gas, combined with research subsidies for renewable energy, may effectively shift innovation in the electricity sector towards renewable energy. In contrast, coal taxation or a carbon tax that increases coal prices has unintended negative consequences for renewable energy innovation.

Finally, the last chapter of my dissertation takes a closer look at the efficiency of firms in developing countries. The private sector is the primary source of employment and local development in developing countries. Previous research in developing countries has documented a number of factors contributing to firm-level efficiency. However, which of these factors are the most important drivers of efficiency? This paper ranks the relative importance of the firm-level efficiency determinants in a transitional economy, using a comprehensive firm-level panel data set in Vietnam between

2005 and 2013. The empirical results show that firm-specific production and labor characteristics are the most significant determinants of efficiency. In contrast, legal factors such as formalization and government financial support play a modest role, due to the crowding-out effect of corruption. Thus, firms actively seeking to improve their own production process and labor force can be well-rewarded. Moreover, government technical supports and human resource training programs, combined with anti-corruption efforts, are beneficial for firm-level efficiency, thereby improving the living standards in developing economies.

For my family

# TABLE OF CONTENTS


**1 Can capital-energy substitution foster economic growth? 1**
1.1 Introduction . . . 1
1.2 A Solow growth model with VES . . . 5
1.2.1 The VES production function . . . 6
1.2.2 The VES production function and the Solow model . . . 9
1.3 Data . . . 12
1.4 Identification Strategy and Testable Hypotheses . . . 16
1.5 Empirical Results . . . 18
1.5.1 Capital-Energy VES and Economic Progress . . . 23
1.5.2 Capital-Energy VES and Environmental Performance . . . 25
1.6 Conclusions . . . 28

**2 Is it risky to go green? A volatility analysis of the green bond market 30**
2.1 Introduction . . . 30
2.2 Overview of the green bond market . . . 34
2.3 Modeling the green bond market volatility . . . 36
2.4 Data . . . 40
2.5 Results and Discussion . . . 48
2.5.1 Preliminary tests . . . 48
2.5.2 Univariate GARCH empirical results . . . 49
2.5.3 Multivariate GARCH empirical results . . . 56
2.6 Conclusion . . . 67

**3 Do Fossil fuel Taxes Promote Innovation in Renewable Electricity Generation? 70**
3.1 Introduction . . . 70
3.2 Theoretical background: energy taxes and innovation in the electricity sector . . . 75
3.3 Data . . . 79
3.4 Identification strategy . . . 90
3.5 Estimation results . . . 94
3.5.1 Are energy taxes successful at promoting innovation in renewable technologies? 94
3.5.2 How effective are research subsidies in shaping global innovation in the electricity sector? . . . 97
3.5.3 What other factors shift innovation in the electricity sector toward renewable technologies? . . . 99
3.6 Robustness analysis . . . 106
3.7 Policy recommendations and concluding remarks . . . 111

**4 What are the leading contributors to growth of private firms in transitional economies? 113**
4.1 Introduction . . . 113
4.2 Econometric framework . . . 117
4.3 Data and Identification Strategy . . . 122
4.3.1 Profit frontier variables . . . 126
4.3.2 Efficiency explanatory variables . . . 129
4.4 Main empirical results . . . 134

4.4.1 How efficient are private firms in Vietnam? . . . . . 134
4.4.2 What internal characteristics should an efficient firm possess? . . . . . 135
4.4.3 How does the external environment affect the firm-level efficiency? . . . . . 137
4.4.4 Summary of key findings and policy implications . . . . . 140
4.5 Robustness checks . . . . . 140
4.6 Conclusion . . . . . 148

**References** **163**

**Appendices** **164**
Appendix A: Appendix to Chapter 1 . . . . . 164
A-1 Variable elasticity of substitution between energy and capital . . . . . 164
A-2 The shares of capital, energy and labor in a three-input VES production function . . . . . 165
A-3 Pre-bootstrapping estimations . . . . . 167
A-4 Classifications of countries . . . . . 171
A-5 Estimations of full specifications without restrictions on $b_1$ . . . . . 174
Appendix B: Appendix to Chapter 2 . . . . . 176
B-1 Testing for asymmetric leverage effects . . . . . 176
Appendix C: Appendix to Chapter 3 . . . . . 177
C-1 A directed technological change model of the electricity sector . . . . . 177
C-2 Data appendix . . . . . 181
C-3 Robustness analysis . . . . . 193
Appendix D: Appendix to Chapter 4 . . . . . 209
D-1 Geographical distribution of the Vietnam SME survey . . . . . 209
D-2 Robustness checks: Detailed estimation results . . . . . 209

**Curriculum Vitae** **219**

# LIST OF FIGURES


1.1 Global total final energy consumption, 1971-2011. . . . . 16
1.2 Regional final energy consumption, 1971-2011. . . . . 16

2.1 Green bond index daily returns, 2010-2015 . . . . . 41
2.2 Green project bond index daily returns, 2010-2015 . . . . . 43
2.3 U.S. aggregate bond index daily returns, 2010-2015 . . . . . 44
2.4 Autocorrelations of Returns, Returnsˆ2 and Absolute Values of Returns, 2010-2015 . 46
2.5 Rolling covariance and correlation between GB and AB indices, 2010-2015 . . . . . 47
2.6 Rolling covariance and correlation between GPB and AB indices, 2010-2015 . . . . . 47
2.7 Univariate GARCH results: Conditional standard deviation between GB, GPB and AB . . . . . 52
2.8 Comparison of daily returns with and without outliers, 2010-2015 . . . . . 53
2.9 Univariate GARCH results: Conditional standard deviation between GB, GPB and AB without outliers . . . . . 55
2.10 Bivariate DCC M-GARCH results: Conditional standard deviation and conditional correlation between GB and AB . . . . . 61
2.11 Bivariate DCC M-GARCH results: Conditional standard deviation and conditional correlation between GPB and AB . . . . . 62
2.12 Bivariate DCC M-GARCH results: Conditional standard deviation and conditional correlation between GB and AB without outliers . . . . . 64
2.13 Bivariate DCC M-GARCH results: Conditional standard deviation and conditional correlation between GPB and AB without outliers . . . . . 65
2.14 Hedge ratio computed from the bivariate GARCH model with outliers . . . . . 67
2.15 Hedge ratio computed from the bivariate GARCH model without outliers . . . . . 67

3.1 Annual aggregate patent count, 1978-2011. . . . . 84
3.2 The price of coal and natural gas in the most innovative regions, 1978-2009. . . . . 85
3.3 Electricity retail price (USD per MWh) in the most innovative regions, 1978-2009. . 86
3.4 Renewable innovation and energy prices. . . . . 87
3.5 Base-load fossil fuel innovation and energy prices. . . . . 88
3.6 Peak-load fossil fuel innovation and energy prices. . . . . 89
3.7 Global RD&D subsidies in million USD in renewable, general fossil fuel and efficiency-improving technologies, 1978-2009. . . . . 90

C-1 Innovating firms by country. . . . . 191
D-1 Geographical coverage of the Vietnam SME survey . . . . . 209

# LIST OF TABLES

1.1 Properties of the VES production function. . . . . 7
1.2 List of variables and sources of data. . . . . 13
1.3 Summary statistics by development level, 1971-2011: means with standard deviations in parenthesis. . . . . 14
1.4 GDP growth rates 1971-2011, by development level. . . . . 14
1.5 Marginal effects of capital-labor VES and income levels. . . . . 20
1.6 Marginal effects of capital-energy VES and income levels. . . . . 23
1.7 Marginal effects of capital-energy VES and environmental performance. . . . . 26

2.1 Unit root tests . . . . . 43
2.2 Descriptive statistics . . . . . 45
2.3 Box-Ljung Test of Squared Returns . . . . . 48
2.4 Univariate Volatility Modelling - GARCH(1,1) . . . . . 51
2.5 Univariate Volatility Modelling - GARCH(1,1) with outlier-free data . . . . . 54
2.6 Bivariate volatility modeling - DCC M-GARCH(1,1) . . . . . 60
2.7 Bivariate volatility modeling - DCC M-GARCH(1,1) with outlier-free data . . . . . 63
2.8 Summary of the estimated hedge ratios . . . . . 66

3.1 Electricity production by source and region in 2013. . . . . . 77
3.2 Baseline: Fixed-effect Poisson estimates of the determinants of firm-level innovation in renewable and fossil fuel technologies using global data from 1978 to 2009. . . . . 102
3.3 Fixed-effect Poisson estimates of fossil fuel price effect in renewable and fossil fuel technologies. . . . . 103
3.4 Fixed-effect Poisson estimates of fossil fuel price effect in renewable, base- and peak-load technologies. . . . . 104
3.5 Fixed-effect Poisson estimates of innovation in general and efficiency-improving non-renewable technologies using global data from 1978 to 2009. . . . . 105

4.1 Distribution of firms across ownership types and industries. . . . . 125
4.2 Summary statistics of profit frontier variables by industry and by ownership status . 128
4.3 Summary of efficiency explanatory variables. . . . . 132
4.4 Summary statistics of efficiency explanatory variables. . . . . 133
4.5 Maximum likelihood estimation of the profit frontier and determinants of profit efficiency between 2005 and 2013 . . . . . 136
4.6 Marginal effects on profit efficiency ($\frac{\Delta E[\ln \pi^a_{it}]}{\Delta \mathbf{z}_{it}}$), alternative sub-samples . . . . . 144
4.7 Marginal effects on profit efficiency ($\frac{\Delta E[\ln \pi^a_{it}]}{\Delta \mathbf{z}_{it}}$), alternative specifications of the profit frontier model . . . . . 145
4.8 Profit efficiency for firms that face competition . . . . . 146
4.9 Profit efficiency using non-normalized data . . . . . 147
A-1 Marginal effects of capital-labor VES and income levels – pre-bootstrapping results. 168
A-2 Marginal effects of capital-energy VES and income levels – pre-bootstrapping results. 169
A-3 Marginal effects of capital-energy VES and environmental performance – pre-bootstrapping results. . . . . 170
A-4 Classification of countries, by income. . . . . 171
A-5 Classification of countries, by HDI level. . . . . 172

A-6 Kyoto Annex B countries. . . . 172
A-7 Classification of countries, by EPI. . . . 173
A-8 Full specification without restrictions on $b_1$. . . . 175
C-1 Variables and sources of data. . . . 181
C-2 List of countries. . . . 181
C-3 Patent classes for renewable electricity generation technologies. . . . 182
C-4 Patent classes for efficiency-improving electricity generation technologies. . . . 186
C-5 Patent classes for general fossil-fuel technologies. . . . 189
C-6 Patent classes for base load electricity generation technologies. . . . 190
C-7 Patent classes for peak load electricity generation technologies. . . . 190
C-8 Total number of patents in each renewable and fossil fuel technology. . . . 192
C-9 Cross-correlation table of energy prices in the most innovative regions. . . . 192
C-10 Zero-inflated Poisson estimates of the determinants of firm-level innovation in renewable and non-renewable technologies using global data from 1978 to 2011. . . . 194
C-11 Negative binomial estimates of the determinants of firm-level innovation in renewable, base load and peak load technologies in the five most innovative countries. . . . 195
C-12 Fossil fuel price effect in base load and peak load technologies using global data from 1978 to 2009 (firms with more than 10 patents – top 22% innovators). . . . 196
C-13 Estimates with second lags of explanatory variables. . . . 197
C-14 Estimates with third lags of explanatory variables. . . . 198
C-15 Alternative definition of regional spillovers: five regions. . . . 199
C-16 Baseline estimates with additional macroeconomic indicators (population density). . . . 200
C-17 Five most innovative countries: France, Germany, Japan, United Kingdom, United States. . . . 201
C-18 Baseline estimates with large and small firms. . . . 202
C-19 Baseline estimates with specialized and mixed firms. . . . 203
C-20 FE Poisson estimates for top five innovating countries excluding hydro, geothermal, and biomass from renewable technologies. . . . 204
C-21 All patents separated between base load and peak load technologies. . . . 205
C-22 Baseline estimates without pre-sample patenting activity. . . . 206
C-23 Fossil fuel price effect in renewable, base and peak load technologies. . . . 207
C-24 Country and year fixed effects in the five most innovative countries. . . . 208
D-1 Profit efficiency among incumbent firms . . . . 211
D-2 Profit efficiency among household businesses . . . . 212
D-3 Profit efficiency among non-household businesses . . . . 213
D-4 Profit efficiency of the full sample under alternative measures of human capital . . . 214
D-5 Profit efficiency of the full sample under alternative measures of production upgrading activities . . . . 215
D-6 Profit efficiency of the full sample under alternative measures of access to credit . . . 216
D-7 Profit efficiency of the full sample under alternative measures of location . . . . 217
D-8 Profit efficiency of the full sample with interactive variables . . . . 218

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# Chapter 1

# Can capital-energy substitution foster economic growth?

## 1.1 Introduction

The substitution of energy with other production inputs is fundamental to evade the impact of energy crises and to meet fossil fuel reduction targets while maintaining economic growth. Yet, the ease of substitution between energy and other production inputs is often assumed constant in economic growth theory. However, in light of the rapid innovations in energy-efficient technologies in recent decades,[1] a constant elasticity of substitution between energy and other production inputs seems unlikely. Instead, the relationship between energy and other inputs could be better described by a general production function that allows for a non-constant elasticity of substitution between production inputs. In this paper, we explore how the ease at which capital substitutes energy varies over time and its implications for economic growth.

Empirical studies provide diverse evidence of the capital-energy relationship across both time and geography. While in some sectors and regions, capital and energy are complements, in others, the two inputs are easily substitutable.[2] One reason for this heterogenous empirical evidence could be that the ease of substitution between capital and energy increases with technological advancements. Unfortunately, previous studies mainly focus on estimating a single constant elasticity of

[1] Between 1971 and 2011, energy intensity, defined as the amount of energy needed to operate one unit of capital, has declined by 57% which implies a steady decline at an average annual rate of 8%.

[2] For example, capital can easily substitute energy in North America and even among major coal consumers in China(Koetse et al., 2008; Smyth et al., 2011; Zha and Ding, 2014). In the manufacturing sectors in the OECD countries, however, substitutability depends on the energy type; capital and fuel tend to be complements whereas capital and electricity are substitutes (Kim and Heo, 2013). Finally, Apostolakis (1990) finds capital and energy to be substitutes in the long run while complements in the short run.

substitution between production inputs. To the best of our knowledge, our paper is the first to study a non-constant capital-energy elasticity of substitution over time.

In this context, we ask two questions. Does the ease of substitution between capital and energy increase over time? And, what are the implications of a variable capital-energy elasticity on economic growth? We address these questions by first building a simple growth model with energy where a general production function allows for a non-constant elasticity of substitution. Then, we empirically test this variable elasticity of substitution (VES) hypothesis using aggregate country-level data for 108 countries from 1971 to 2011.

Our theoretical model builds on a Solow growth model where we introduce two distinct characteristics. Firstly, we account for energy in the production of goods, and secondly, the production function exhibits a non-constant elasticity of substitution. Within this framework, we identify that the speed at which capital and energy become more substitutable can directly foster long-run economic growth. While the standard assumption of a constant elasticity of substitution (CES) has allowed traditional theories to successfully explain the impact of the input mix on economic growth, unfortunately, they have been unable to capture that changes in the elasticity of substitution can speed up or slow down economic growth.[3] Departing from the traditional CES assumption, we are the first at identifying that the rate of change in the capital-energy substitutability can foster economic growth.

To empirically test this VES hypothesis, we estimate a general production function using aggregate country-level data on GDP, capital and energy consumption from 108 countries between 1971 and 2011. This production function features a non-linear relationship between production inputs and can exhibit either a constant or variable elasticity of substitution.

Our empirical analysis provides evidence for a variable capital-energy elasticity of substitution

[3] See, for example, Solow (1974), Aghion and Howitt (1998), Di Maria and Valente (2008), or Acemoglu et al. (2012).

at the aggregate level. These results are consistent using both the global and regional data. In addition, we find that capital and energy tend to substitute each other, and more interestingly, the substitutability between capital and energy is positively correlated with a country's income level. Specifically, we find that a one-unit increase in energy efficiency increases the capital-energy elasticity of substitution in high-income countries by more than 0.05 units, thereby increasing the speed of substitution between capital and energy. In contrast, a one-unit increase in energy efficiency will reduce the capital-energy elasticity of substitution in low income country by 0.08 units, thereby strengthening the capital-energy complementarity. These results validate our theoretical predictions which imply that a country's effort toward enhancing its income level or improving its energy efficiency can also indirectly foster long-run economic growth through the responses of the capital-energy elasticity of substitution to such policies.

Our paper relates to three main strands of literature. First, our paper is in line with the early macroeconomic literature investigating the ease at which production inputs can be substituted (Revankar, 1971; Sato and Hoffman, 1968; Karagiannis et al., 2005). From this literature, our paper is most related to Karagiannis et al. (2005) who first examine Revankar's VES hypothesis between capital and labor. Our paper builds on their framework but differs from this study in that our focus is on the substitution between energy and other inputs while Karagiannis et al. (2005) focus on capital and labor. By accounting for energy, we are able to identify the growth impact of the capital-energy substitution relationship as well as the long-run benefits of environmental policies directed at improving the energy intensity. Another feature that differentiates our paper from Karagiannis et al. (2005) is that in addition to using global data, we account for economic development levels. This allows us to not only capture the heterogeneous characteristics of countries at different stages of development, but to also highlight how the availability of energy relative to capital might disproportionately contribute to economic growth in different regions at the aggregate level. Our empirical analysis suggests that capital and energy are substitutes in highly developed countries while they are complements in less developed countries.

Our paper also relates to the extensive literature that empirically studies the ease of substitution between capital and energy. The earliest work by Berndt and Wood (1975) finds that energy and capital were complements in the U.S. manufacturing sector between 1947 and 1971, while Griffin and Gregory (1976) reversed this finding and conclude that energy and capital were substitutes.[4] More recent work still provides discrepant estimates of the capital-energy substitution relationship (see, for example, Thompson, 2006; Arnberg and Bjørner, 2007; Koetse et al., 2008; Ma et al., 2008). These and other studies estimate a constant capital-energy elasticity of substitution, while we focus on estimating a non-constant elasticity of substitution.

Finally, our paper contributes to the literature studying nonbalanced economic growth (e.g., Baumol, 1967; Acemoglu and Guerrieri, 2008). In the context of energy and natural resources, Pittel and Bretschger (2010) study the long-run implications of heterogenous resource intensity in different sectors, while Bretschger and Smulders (2012) point out the challenges highly innovative sectors impose on sustainability when natural resources are complements in production. These and other papers focus on nonbalanced growth due to uneven sectoral technological progress. We take a simpler approach by presenting a case in which a general aggregate production function leads to unbalanced growth. By doing so, we provide a complementary explanation to the understanding of the role of the capital-energy substitution on long-run economic growth.

The remainder of the paper unfolds as follows. Section 3.2 presents our theoretical model, while section 3.3 describes the data used to test our theoretical predictions. Section 1.4 presents the identification strategy and section 3.5 discusses the estimation results. Finally, section 4.4 concludes.

[4] Berndt and Wood (1979) suggests that these differences are due to omitted variables while Field and Grebenstein (1980) points out that both studies treated capital differently.

## 1.2 A Solow growth model with VES

In this section, we analyze a simple growth model where the production function exhibits a variable elasticity of substitution (VES) in production inputs. This production function, first introduced by Revankar (1971), is a general version of the well-known constant elasticity of substitution (CES) specification, which allows the elasticity of substitution between production inputs to vary over time. Karagiannis et al. (2005) used Revankar's production function in a Solow growth model to study the capital-labor substitution. We follow the same approach but we focus instead on the capital-energy substitution.

The CES assumption is the norm in economic growth models perhaps because it contributes to the existence of a balanced growth path (BGP) equilibrium. Even though the empirical evidence is not supportive of the stability of the factor shares of income,[5] growth models with a CES production function seem to be the norm. In the case of energy, large improvements in energy intensity in recent decades imply that the ease at which capital substitutes energy at the aggregate level may not be well-explained by a single constant elasticity of substitution. Therefore, in this paper, we depart from the standard CES assumption to study the change in the ease at which capital and energy are substituted. Our main interest, however, is not to quantify the capital-energy elasticity of substitution. Instead, we are interested in analyzing how the capital-energy substitution evolves over time with the energy-capital ratio and its role in explaining long-run economic growth.

Our framework builds on a Solow growth model without population growth and technological progress. While the Solow growth model is often criticized because exogenous decisions drive economic growth, in our setting, that simplicity is useful for the study of a general VES production function. The production function is $Y_t = F\left(A_t, K_t, L_t, E_t\right)$ where $Y_t$, $A_t$, $K_t$, $L_t$ and $E_t$ are

[5] See, for example, recent estimates by Karabarbounis and Neiman (2014).

aggregate output, total factor productivity, physical capital, labor and energy. Energy is a vector containing renewable and non-renewable sources; for example, $E_t = H(R_t, NR_t)$ where $R_t$ and $NR_t$ denote renewable and non-renewable resources. We first describe the characteristics of the general VES production function before we turn to its long-run growth implications.

### 1.2.1 The VES production function

We consider a VES production function that uses capital, energy and labor as production inputs:

$$Y_t = A_t P_t^{a_1 v_1} \left(L_t + b_1 a_1 P_t\right)^{(1-a_1)v_1}, \tag{1.1}$$

where $t$ is the time subscript; $Y_t$, $A_t$, $P_t$, $L_t$, stand for aggregate final output, total factor productivity, physical inputs and labor. $a_1$ captures the role that physical inputs play in the production process, $v_1$ is the returns to scale parameter and $b_1$ establishes the variability of the elasticity of substitution between labor and physical inputs. We assume that the production of physical inputs requires capital and energy according to the following VES technology:

$$P_t = K_t^{a_2 v_2} \left(E_t + b_2 a_2 K_t\right)^{(1-a_2)v_2}, \tag{1.2}$$

where $K_t$ is physical capital and $E_t$ is energy. As before, $a_2$ reflects the importance of physical capital relative to energy in the production of physical inputs, $v_2$ is the returns to scale parameter while $b_2$ establishes the variability of the elasticity of substitution between capital and energy. Thus, we can rewrite the general function (1.1) as:

$$Y = A \left(K^{a_2 v_2} \left(E + b_2 a_2 K\right)^{(1-a_2)v_2}\right)^{a_1 v_1} \left(L + b_1 a_1 K^{a_2 v_2} \left(E + b_2 a_2 K\right)^{(1-a_2)v_2}\right)^{(1-a_1)v_1}. \tag{1.3}$$

Parameters $b_1$ and $b_2$ characterize the new feature of our production function compared to the standard CES production functions. When $b_1 = 0$, the ease at which we substitute physical inputs and labor is constant over time while it is variable when $b_1 \neq 0$. Likewise, $b_2 = 0$ implies a constant elasticity of substitution between capital and energy while it is variable when $b_2 \neq 0$. Thus, in our setting, parameter $b_1$ captures the variability of the elasticity of substitution *between* physical inputs and labor, while parameter $b_2$ captures the variability of the elasticity of substitution of the elements *across* physical inputs.

Table 1.1: Properties of the VES production function.

| Parameter constraints | Production function properties |
|---|---|
| $v_1 = v_2 = 1$ | Constant returns to scale |
| $b_1 = 0$; $b_2 = 0$ | CES Cobb-Douglas production function (capital, labor and energy) |
| $a_2 = 1$ | VES production function (capital and labor) |
| $a_2 = 1$; $b_1 = 0$ | CES Cobb-Douglas production function (capital and labor) |
| $a_1 = 1$; $a_2 = 1$ | AK production function |

The main advantage of the VES production function described in equation (1.3) is that its flexibility facilitates the empirical test of multiple specifications of the production function. Table 1.1 summarizes how our production function can be reduced to other already well-known production functions. When $v_1 = 1$ and $v_2 = 1$, there are constant returns to scale in production. Parameters $b_1 \neq 0$ and $b_2 \neq 0$ differentiate production function (1.3) from the standard production function with CES. Note that when $b_1 = 0$ and $b_2 = 0$, the production function reduces to a Cobb-Douglas form with CES. Moreover, when $a_2 = 1$, this production function reduces to a standard two-input production function with capital and labor in absence of energy. Finally, the production function follows an AK structure when $a_1 = 1$ and $a_2 = 1$. We use the most general production function in equation (1.3) as the basis for our empirical analysis in Section 3.5.

For the remainder of the theory section, we simplify our theoretical model by assuming $b_1 = 0$ in equation (1.1) because our main goal is to study the capital-energy substitution.[6] In other words,

[6]This assumption is supported by our empirical finding of a constant elasticity of substitution between physical

we assume the elasticity of substitution between physical inputs and labor is constant. We also set $v_1 = v_2 = 1$ in equation (1.1), which implies constant returns to scale in production. These simplifying assumptions increase the tractability of the model, thus allowing us to identify the role of a variable capital-energy elasticity of substitution on long-run economic growth. We return to the validity of these two assumptions in the empirical section.

Imposing the aforementioned simplifying assumptions, the production function in equation (1.3) simplifies to:

$$Y_t = A_t \left( K_t^{a_2} \left( E_t + b_2 a_2 K_t \right)^{(1-a_2)} \right)^{a_1} L_t^{(1-a_1)}. \tag{1.4}$$

And the corresponding marginal products of capital and energy are:

$$\begin{aligned} MP_K &= \frac{\partial Y_t}{\partial P_t}\frac{\partial P_t}{\partial K_t} = \frac{\partial Y_t}{\partial P_t} a_2 K_t^{a_2-1}(E_t + b_2 a_2 K_t)^{-a_2}(E_t + b_2 K_t), & (1.5)\\ MP_E &= \frac{\partial Y_t}{\partial P_t}\frac{\partial P_t}{\partial E_t} = \frac{\partial Y_t}{\partial P_t}(1-a_2) K_t^{a_2}(E_t + b_2 a_2 K_t)^{-a_2}. & (1.6) \end{aligned}$$

The production function satisfies standard properties; that is, $Y_t > 0$, $MP_K > 0$, $MP_E > 0$ and diminishing marginal returns if $A_t > 0$, $0 < a_1, a_2 \leq 1$, $b_2 > -1$, $1/K_t \geq b_2$. We show in Appendix A-1 that the elasticity of substitution between energy and capital is:

$$\sigma\left(E_t, K_t\right) = 1 + b_2 \left( \frac{E_t}{K_t} \right), \tag{1.7}$$

where $\sigma\left(E_t, K_t\right)$ is the elasticity of substitution between energy and capital and $\left(\frac{E_t}{K_t}\right)$ is the energy-capital ratio. The key feature that differentiates our paper from others is that the ease at which capital can substitute energy varies with the energy-capital ratio. Therefore, energy-efficiency-improving technologies can influence aggregate production both directly through total factor pro-

inputs and labor. It is also in line with the Kaldor's fact of constant labor and capital shares in production (Kaldor, 1961).

ductivity ($A_t$) and indirectly through the variable elasticity of substitution ($\sigma(E_t, K_t)$). Moreover, parameter $b_2$ determines the speed at which the energy-capital ratio affects the substitutability between energy and capital. When $b_2 > 0$, energy and capital are substitutes in production, while $b_2 < 0$ implies a complementarity between them.

In addition to capturing the variable elasticity of substitution between different production inputs, $b_2$ also plays a role in determining the shares of capital and energy in final output. The shares of labor, capital and energy reduce to:[7]

$$\begin{aligned} s_{L_t} &= 1 - a_1, \\ s_{K_t} &= \frac{a_1\left(a_2 + b_2 a_2 \frac{K_t}{E_t}\right)}{1 + b_2 a_2 \frac{K_t}{E_t}}, \\ s_{E_t} &= \frac{a_1(1-a_2)}{1 + b_2 a_2 \frac{K_t}{E_t}}, \end{aligned}$$

where $s_{K_t}$, $s_{E_t}$, $s_{L_t}$ denote the shares of capital, energy and labor in final output production.

Next, we turn to analyzing how the more flexible VES production function affects long-run growth. To do so, we incorporate this production function into a Solow growth model. Subsequently, in section 3.5, we empirically test the non-constant elasticity of substitution hypothesis.

### 1.2.2 The VES production function and the Solow model

In this section, we study long-run economic growth in a standard Solow model (Solow, 1956) with no population growth and technological progress. We introduce two new features to the standard Solow growth model. First, we account for the role of energy in production. Second, our general production function in section 1.2.1 allows the elasticity of substitution between capital and energy

[7] In the most general case with $b_1 \neq 0$, we show in Appendix A-2 that the shares of labor, capital and energy are: $s_{K_t} = \frac{a_1 + b_1 a_1 p_t}{1 + b_1 a_1 p_t} * \frac{a_2 + b_2 a_2 \frac{K_t}{E_t}}{1 + b_2 a_2 \frac{K_t}{E_t}}$, $s_{E_t} = \frac{a_1 + b_1 a_1 p_t}{1 + b_1 a_1 p_t} * \frac{1 - a_2}{1 + b_2 a_2 \frac{K_t}{E_t}}$, and $s_{L_t} = \frac{1 - a_1}{1 + b_1 a_1 p_t}$, where $s_{K_t}$, $s_{E_t}$, $s_{L_t}$ denote the shares of capital, energy and labor in final output production.

to vary with the energy-capital ratio, which implies that it varies over time.

We start by describing the evolution of energy resources in the economy. We let $Z_t$ denote the aggregate energy stock at the beginning of each period $t$. Two opposing factors affect the growth or decay speed of $Z_t$ during period $t$. First, the use of energy in the production of goods reduces the energy resource stock by $E_t$. At the same time, $Z_t$ increases through its own regeneration process and the discovery of new resource stocks. Thus the law of motion for $Z_t$ is given by $Z_{t+1} = (1 + r_t^z)Z_t - E_t$, where $r_t^z$ is the exogenous increase in resources through regeneration and new discoveries. We assume a constant fraction $s^z$ of the stock $Z_t$ is extracted at no cost for production purposes in each period $t$. This implies that the amount of energy used in production during period $t$ is: $E_t = s^z Z_t$. Therefore:

$$Z_{t+1} - Z_t = (r_t^z - s^z)Z_t. \tag{1.8}$$

Our assumption that both the increase in the resource stock and the extraction of resources are exogenous implies that the aggregate energy stock in (1.8) is exogenous and independent of the capital-energy substitution. Next, we describe the law of motion for physical capital $K_t$ to see in which direction the variable elasticity of substitution will affect capital accumulation, which describes economic growth in this model.[8] For analytical simplicity, we assume that there is no depreciation and a constant exogenous fraction $s$ of final output $Y_t$ is saved toward capital accumulation. Thus, using the production function in (1.4), the capital accumulation equation is:

$$K_{t+1} - K_t = sA_t K_t^{a_1 a_2} \left(E_t + b_2 a_2 K_t\right)^{a_1(1-a_2)} L_t^{(1-a_1)}. \tag{1.9}$$

[8]In this paper, we are primarily interested in specifying the direction of the impact of the VES assumption on economic growth, therefore, we analyze the law of motion for capital. An analysis of the system of equations would be necessary to study the exact magnitude of the impact.

One distinguishing feature of our model is that capital accumulation depends on $b_2$, the speed at which the energy-capital ratio increases or decreases the substitutability between capital and energy (cf. equation (1.7)). Since we depart from the CES assumption, the characterization of the long-run growth rate is complex and we can no longer assume a balanced growth path. Instead, we analyze how the elasticity of substitution affects capital accumulation. Differentiating (1.9) with respect to $b_2$ and simple manipulations, we analyze how the energy-capital ratio affects capital accumulation.

$$\frac{\partial(K_{t+1} - K_t)}{\partial b_2} = sAK_t^{1+a_1a_2} L_t^{(1-a_1)} a_1a_2(1-a_2)E_t^{a_1(1-a_2)-1}\left(1 + b_2a_2\frac{1}{E_t/K_t}\right)^{a_1(1-a_2)-1}. \quad (1.10)$$

where $\frac{1}{E_t/K_t}$ is the inverse of the energy-capital ratio. When capital and energy are substitutes ($b_2 > 0$), improvements in energy efficiency lead to faster capital accumulation as seen by a positive (1.10). This means that growth can be sustained in the long run when it is easy to substitute manmade capital for energy. However, when capital and energy are complements ($b_2 < 0$), equation (1.10) can be negative if $b_2$ is significantly negative and the energy-capital ratio is significantly low. This implies that when the availability of energy for production is limited relative to the amount of capital available (for example, an energy crisis), then *ceteris paribus*, a high level of complementarity between capital and energy can slow down the rate of capital accumulation, thereby dwindling long-run economic growth.

In a Solow growth model with a CES assumption, Klump and de La Grandville (2000) show that the economy with the higher elasticity of substitution between capital and labor also exhibits a higher level of per capita income.[9] Departing from a CES assumption, we also find that a higher elasticity of substitution leads to a higher level of capital accumulation.

[9] Technological progress and the elasticity of substitution are the primary determinants of long-run economic growth (Stern, 2010). Our proposed generalized production function, which can exhibit a constant or a variable elasticity of substitution, has the advantage that it allows the elasticity of substitution to interact with capital accumulation.

To summarize, a general production function that accounts for changes in the substitutability between capital and energy over time helps us build a simple framework to explain the interdependent role between the input mix and long-run economic growth. In our simple framework, we show that a change in the substitutability between energy and capital influences capital accumulation, thus determining the growth rate of the current period. In turn, present economic growth influences the energy-capital ratio, which feeds back into their substitution. Depending on its sign and magnitude, the elasticity of substitution can further foster or dampen capital accumulation in the next period, thereby changing future economic growth.

Is this a theoretical curiosity? Or, is there empirical evidence for a variable elasticity of substitution between production inputs? In light of the recent improvements in energy efficiency, we expect to find empirical evidence for a capital-energy elasticity of substitution that changes over time. We turn to this analysis next by estimating the general production function (1.3) above using a panel data from 108 countries between 1971 and 2011. We start out by describing the dataset in section 3.3 and turn to the empirical analysis in sections 1.4 and 3.5.

## 1.3 Data

The estimation of the production function in equation (1.3) requires aggregate country-level data on output, total factor productivity (TFP), capital, labor, human capital and energy. Our dataset, which spans 41 years (1971-2011) and 108 countries, comes primarily from two sources: the Penn World Table (Feenstra et al., 2013) and the United Nation Environment Programme (UNEP) database (United Nation Environmental Programme, 2013). Specifically, data for output, total factor productivity, capital, labor and human capital are drawn from the Penn World Table and energy data are drawn from the UNEP database.[10] Table C-1 summarizes the source of data for

[10]Our empirical analysis does not include former Soviet Union and Yugoslavian countries, since their data are not available before 1991.

each variable, while Table 1.3 presents the overall descriptive statistics of the data.

Table 1.2: List of variables and sources of data.

| Variable | Unit of measure | Source |
|---|---|---|
| Real GDP | Constant 2005 national prices (in millions of 2005 U.S. $ ) | Penn World Table |
| Real total factor productivity | Constant 2005 national prices (TFP for 2005 = 1) | Penn World Table |
| Real capital stock | Constant 2005 national prices (in millions of 2005 USD) | Penn World Table |
| Population | Millions of people | Penn World Table |
| Human capital index | Larger than 1 | Penn World Table |
| Energy consumption | Thousand tonnes of oil equivalent (KTOE) | United Nation Environment Programme (UNEP) |

Note: The human capital index is in terms of the average years of schooling and the return to education per person.

Aggregate output ($Y$) is measured by the annual level of real GDP at constant 2005 national prices for each country. We classify the countries into five income groups to account for the vast income differences across countries. We adopt this classification from the World Bank database, listed in Table A-4, which assigns each of the world's countries into the following five groups: high-income (OECD), high-income (non-OECD), upper middle income, lower middle income, and low income. Column (1) of Table 1.3 lists the average real GDP for each income group during the period of 1971-2011. High-income OECD countries experienced little change in their income distribution between 1971 and 2011, while for other income groups, the improvement in real GDP has been quite significant. This reflects the fact that the average growth rate of real GDP was the lowest for high-income OECD countries during this time period, as shown in Table 1.4. On average, real GDP grows faster in high-income non-OECD and upper-middle-income countries between 1971-2011. This is consistent with the fact that these two income groups include many of the well-known rapidly-growing countries such as Singapore, China, Malaysia, Botswana, to name a few.

Table 1.3: Summary statistics by development level, 1971-2011: means with standard deviations in parenthesis.

| Income-group | (1) Log real GDP | (2) Log real TFP | (3) Log real capital | (4) Log population | (5) Log energy | (6) Human capital index |
|---|---|---|---|---|---|---|
| High income: OECD | 12.497 | -0.083 | 13.534 | 2.472 | 10.402 | 2.841 |
| | (1.561) | (0.120) | (1.596) | (1.516) | (1.455) | (0.365) |
| High income: non-OECD | 10.190 | -0.024 | 11.174 | 0.066 | 7.882 | 2.319 |
| | (1.356) | (0.363) | (1.345) | (1.222) | (1.639) | (0.368) |
| Upper middle income | 11.278 | 0.006 | 12.361 | 2.601 | 9.178 | 2.222 |
| | (1.592) | (0.194) | (1.630) | (1.590) | (1.632) | (0.381) |
| Lower middle income | 10.484 | 0.018 | 11.494 | 2.879 | 8.733 | 1.915 |
| | (1.499) | (0.221) | (1.415) | (1.462) | (1.474) | (0.439) |
| Low income | 9.718 | 0.045 | 10.446 | 2.853 | 8.648 | 1.607 |
| | (1.069) | (0.303) | (1.094) | (1.022) | (1.226) | (0.349) |
| Global | 11.156 | -0.022 | 12.163 | 2.398 | 9.126 | 2.283 |
| | (1.773) | (0.217) | (1.807) | (1.662) | (1.776) | (0.566) |

Table 1.4: GDP growth rates 1971-2011, by development level.

| Income group | Mean GDP growth rate | Standard deviation |
|---|---|---|
| High income: OECD | 2.647% | 2.881% |
| High income: non-OECD | 4.804% | 7.996% |
| Upper middle income | 4.230% | 6.893% |
| Lower middle income | 4.217% | 6.292% |
| Low income | 3.828% | 4.835% |
| Global | 3.805% | 5.872% |

Our energy data are drawn from the United Nation Environment Programme (UNEP). Specifically, we use total final energy consumption as a proxy for the variable $E$ in our theoretical model, where total final energy consumption is defined as the sum of consumption by the different end-use sectors. Total final energy consumption is measured in thousand tonnes of oil equivalent (KTOE).

Figure 1.1 shows the global final energy consumption between 1971 and 2011 while Figure 1.2 decomposes global final energy consumption between 1971 and 2011 into six different regions: Africa, Asia and Pacific, Europe, Latin America and Caribbean, North America, West Asia. Overall, global consumption energy is increasing during the period of 1971 to 2011. However, this period also experienced vast heterogeneity in regional energy consumption. Specifically, total final energy consumption grows the fastest in the Asia and Pacific region. This region, together with Europe and North America, constitutes most of the world's energy consumption between 1971-2011. Moreover, these regions also experienced a more volatile trend in energy consumption, compared to the other regions of the world. The United States, China, and India are the largest consumers of energy.

In addition to a global analysis using aggregate country-level data, we estimate our general production function at the regional level. We construct income development levels following two classifications of countries. The first classification follows the World Bank's income development levels: high income (OECD), high income (non-OECD), upper middle income, lower middle income, and low income. The second classification follows the United Nations Development Programme's Human Development Index (HDI). Tables A-4 and A-5 in Appendix A-4 detail the list of the countries in each classification and group.

Finally, we consider a country's effort to reduce energy consumption following two measures. First, we separate countries in the Kyoto Protocol Annex B from the rest. These countries voluntarily choose to reduce carbon emission, and therefore, they may have stronger incentives to reduce their energy use. Our second measure of environmental performance builds on the Yale University's Environmental Performance Index (EPI) where environmentally friendly countries obtain a higher score. Table A-6 in Appendix A-4 lists the Annex B countries of the Kyoto Protocol while Table A-7 classifies countries according to their EPI scores.

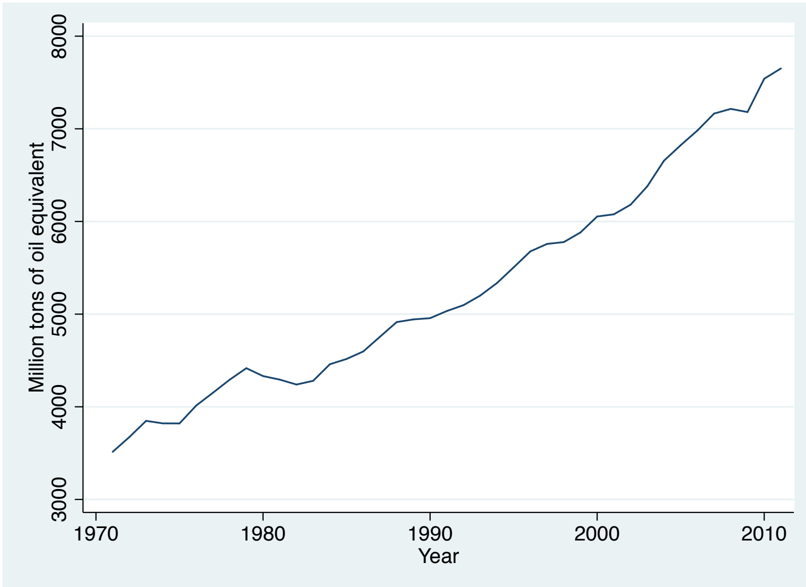



Figure 1.1: Global total final energy consumption, 1971-2011.

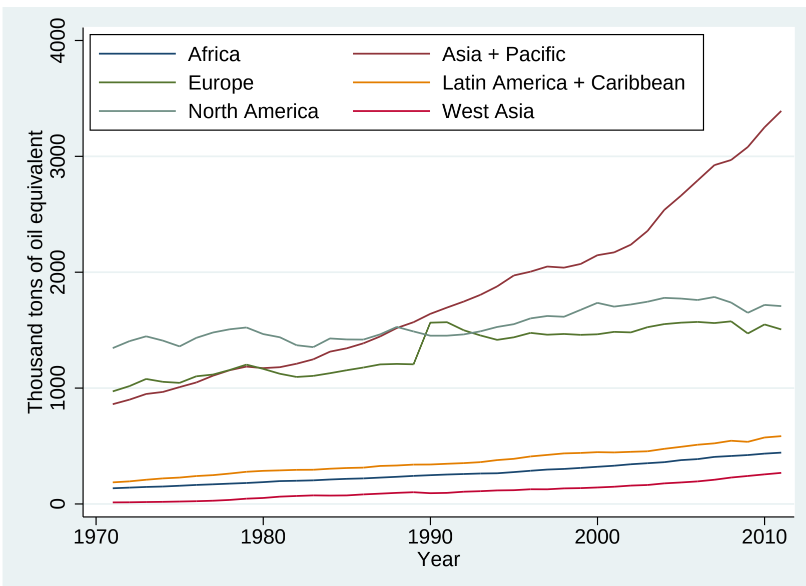



Figure 1.2: Regional final energy consumption, 1971-2011.

## 1.4 Identification Strategy and Testable Hypotheses

The dataset described above allows us to empirically test which specification of the production function, CES or VES, best fits the data. From the theoretical model in section 3.2, log-linearizing the production function (1.3) gives the baseline estimation equation:

$$\ln Y_{it} = \ln A_{it} + a_1 v_1 a_2 v_2 \ln K_{it} + a_1(1-a_2)v_1 v_2 \ln(E_{it} + (b_2 + \sum_{j=1}^{J} b_{2j} D_j) a_2 K_{it})$$

$$+ (1-a_1)v_1 \ln[L_{it} + (b_1 + \sum_{j=1}^{J} b_{1j} D_j) a_1 K_{it}^{a_2 v_2} (E_{it} + (b_2 + \sum_{j=1}^{J} b_{2j} D_j) a_2 K_{it})^{(1-a_2)v_2}] + \delta_i + \delta_t + \epsilon_{it}. \tag{1.11}$$

where $i$, $j$ and $t$ denote country, region and year, respectively. $D_j$ are regional interactive dummies, $\delta_i$ and $\delta_t$ are country and time fixed effects and $\epsilon_{it}$ is the error term. From this baseline specification, we derive two main testable hypotheses: the elasticity of substitution between production inputs is variable ($b_1 \neq 0$ and $b_2 \neq 0$) and energy is a significant input in production ($a_2 \neq 1$).[11]

First and foremost, the parameters $b_1$ and $b_2$ capture the variability of the elasticity of substitution between production inputs. We test for the variability of the elasticity of substitution both at global and regional levels. In the global estimates, $b_1$ captures the variable elasticity of substitution between labor and physical inputs (a combination of energy and capital), while $b_2$ captures the variable elasticity of substitution between energy and capital (i.e., $b_2$ capture the variable elasticity of substitution *across* the elements of physical inputs). $b_h = 0$ $(h = 1, 2)$ supports a CES specification for the production function while $b_h \neq 0$ $(h = 1, 2)$ supports a VES specification. Moreover, from (1.7), $b_h > 0$ implies substitutability between production inputs, while $b_h < 0$ implies complementarity between production inputs. In the regional estimates, we derive the marginal effects $(b_h + b_{hj})$ to study the substitutability between production inputs in each region. To our knowl-

[11] Our focus is not to estimate the exact magnitude of the capital-energy elasticity of substitution. However, we are primarily interested in capturing the variables that improve the ease at which capital can substitute energy, and the implication on the long-run economic growth across countries and over time. To analyze how the elasticity of substitution changes with changes in energy efficiency across countries, we employ aggregate country-level data. While this aggregate dataset can provide meaningful inferences about the strength of the relationship between energy efficiency and the capital-energy substitution effect, it is inappropriate to estimate the exact measure of the capital-energy elasticity of substitution using this dataset. The estimation of the capital-energy elasticity of substitution is more appropriate with more disaggregated data at the industry level, however, this is infeasible, given the large scope of our study, which spans across 108 countries and 40 years (1971-2011).

edge, empirical evidence for VES between labor and capital has been studied by Karagiannis et al. (2005), while no previous work has analyzed the VES between capital and energy.

The second feature we are interested in studying is the role of energy in final production. Table 1.1 summarizes the properties of our general production function. Specifically, $a_2 = 1$ suggests that the role of energy is relatively negligible in the production of final output and the data fit well into a two-input production function with capital and labor. Moreover, $a_1 = a_2 = 1$ suggests a good fit for an AK production function. The magnitudes of $a_1$ and $a_2$ help us infer about the relative importance of production inputs. In a two-input production model with capital and labor, a larger $a_1$ means that capital plays a more important role in the production process. In the three-input production model we use here, with capital, labor and energy, a larger $a_1$ means that physical inputs, which is a combination of energy and capital, plays a larger role in production compared to that of labor. A larger $a_2$ implies that capital is more important in final output production than energy.

Let us finally discuss our estimation strategy. We estimate equation (1.11) using a non-linear least square (NLLS) regression model, where an OLS regression provides the initial parameter values for our NLLS estimations.[12]

## 1.5 Empirical Results

In this section, we present our main estimation results followed by multiple robustness checks that validate our results. We begin our empirical analysis by estimating a production function that excludes energy to compare our results with previous studies; $a_2 = 1$ in equation (1.11). Under this assumption, our production function reduces to the special case where labor and capital are the

[12] Due to the complexity of the estimation equation, other methods such as Generalized Methods of Moments (GMM) or Maximum Likelihood Estimation (MLE) are computationally infeasible even after we transform the estimation equation using first order Taylor series expansion.

only two inputs, which is in line with Karagiannis et al. (2005). Our baseline estimating equation in (1.11) reduces to:

$$\ln Y_{it} = \ln A_{it} + a_1 v_1 \ln K_{it} + (1 - a_1) v_1 \ln(L_{it} + (b_1 + \sum_{j=1}^{J} b_{1j} D_j) a_1 K_{it}) + \delta_i + \delta_t + \epsilon_{it}. \quad (1.12)$$

Table 1.5 reports the NLLS bootstrapped estimation results in (1.12) using a global panel dataset between 1971 and 2011.[13] The first specification does not include fixed effects while the second specification controls for regional and time fixed effects. Our regressions do not converge to a maximum likelihood if we also include country and year fixed effects. In addition, we are unable to control for country-by-year fixed effects. To deal with this, we estimate the model with a set of fixed effects for 17 subregions and four decades.[14]

Our global estimates in column (2) of Table 1.5 suggest that the VES parameter $b_1$ is negative and statistically significant. This suggests the existence of a non-constant elasticity of substitution and a complementarity between capital and labor in our global sample. This result differs from Karagiannis et al. (2005), who find $b_1$ to be positive and statistically significant. We offer two possible explanations. First, compared to Karagiannis et al. (2005), our sample includes a larger set of countries and spans over a longer time frame. Second, Karagiannis et al. (2005) assumes that total factor productivity grows at an exogenous rate, which is constant over time and across countries, and that all countries share the same initial total factor productivity. This assumption ignores the existing empirical evidence supporting cross-country differences in total factor productivity (see for example Easterly and Levine, 2001; Hall and Jones, 1999). In contrast, our empirical analysis

[13] Appendix A-3 discusses the estimations without bootstrapping. Post-estimation analysis suggests the residuals obtained from these analytical estimations are not white noise. The comparison between the bootstrapped and analytical estimates show a lower significance for bootstrapped estimates.

[14] The 17 subregions are: Arabian Peninsula, Australia & New Zealand, Caribbean, Central Africa, Central Europe, Eastern Africa, Mashriq, Meso America, North America, North East Asia, Northern Africa, South America, South Asia, South East Asia, Southern Africa, Western Africa, and Western Europe. Regarding time fixed effects, we examine several options including years, five-year periods and decades. Since five-year periods and decades provide similar results, we settle for decade fixed effects.

Table 1.5: Marginal effects of capital-labor VES and income levels.

| Dependent variable: GDP | | | | | | |
|---|---|---|---|---|---|---|
| | Global | | Income group | | HDI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $a_1$ | .8961*** | .8676*** | .8729*** | .8644*** | .8794*** | .8645*** |
| | (.00422) | (.00333) | (.00342) | (.00311) | (.00363) | (.00337) |
| $v_1$ | 1.005*** | 1.037*** | 1.026*** | 1.043*** | 1.021*** | 1.04*** |
| | (.00332) | (.00315) | (.00297) | (.00305) | (.00302) | (.00309) |
| $b_1$ (Global) | 2.9e-06 | -1.4e-06*** | – | – | – | – |
| | (1.8e-06) | (3.9e-07) | – | – | – | – |
| $b_1$ (High:OECD) | – | – | 2.1e-05*** | -4.3e-06*** | – | – |
| | – | – | (5.8e-06) | (4.9e-07) | – | – |
| $b_1$ (High: Non-OECD) | – | – | 1.9e-05*** | 9.5e-06** | – | – |
| | – | – | (7.3e-06) | (4.7e-06) | – | – |
| $b_1$ (Upper middle) | – | – | -1.7e-05*** | -1.7e-05*** | – | – |
| | – | – | (1.0e-07) | (1.3e-07) | – | – |
| $b_1$ (Lower middle) | – | – | -4.2e-05*** | -4.3e-05*** | – | – |
| | – | – | (2.0e-06) | (2.0e-06) | – | – |
| $b_1$ (Low) | – | – | -.00028*** | -.00028*** | – | – |
| | – | – | (2.1e-06) | (8.6e-06) | – | – |
| $b_1$ (Very high HDI) | – | – | – | – | 9.9e-06*** | -5.0e-07 |
| | | – | – | – | (3.2e-06) | (6.4e-07) |
| $b_1$ (High HDI) | – | – | – | – | -2.4e-05*** | -2.2e-05*** |
| | – | – | – | – | (8.4e-07) | (9.1e-07) |
| $b_1$ (Medium HDI) | – | – | – | – | -1.7e-05*** | -1.7e-05*** |
| | – | – | – | – | (8.5e-08) | (1.3e-07) |
| $b_1$ (Low HDI) | – | – | – | – | -.00015*** | -.00015*** |
| | – | – | – | – | (3.3e-06) | (3.3e-06) |
| Regional fixed effect | No | Yes | No | Yes | No | Yes |
| Time fixed effect | No | Yes | No | Yes | No | Yes |
| Number of observations | 3277 | 3277 | 3277 | 3277 | 3277 | 3277 |
| R-squared | 0.9989 | 0.9992 | 0.9990 | 0.9993 | 0.9990 | 0.9993 |

* p-value < 10%, ** p-value < 5%, *** p-value < 1%.
Numbers in parentheses are standard errors.

utilizes country-level data on total factor productivity (TFP) to account for the differences in TFP across time and countries and controls for regional and time fixed effects. Moreover, variations in the production process could result in variations in the substitutability of labor and capital across countries. It is then possible that capital and labor are substitutes in some countries while they are complements in other countries. The complementarity of capital and labor in one country can be offset by the substitutability of the two inputs in another country. To account for this, and also to study the relationship between economic progress and changes in the substitution between capital and labor over time, we estimate (1.12) using regional interactive dummies in columns (3)-(6) of Table 1.5.

At the regional level, columns (4) and (6) of Table 1.5 report marginal effects $b_1$ for each region. The parameter $b_1$ is negative and statistically significant in all regions except for high non-OECD region, which supports our VES hypothesis between capital and labor. A negative $b_1$ indicates that the elasticity of substitution between capital and labor is smaller than one, that is, capital and labor are complements in final output production. Note also that the parameter $b_1$ increases in its absolute value as we move from a higher income group to a lower income group. This suggests that the complementarity between capital and labor is negatively correlated with a country's level of development. Furthermore, even though $b_1$ is statistically significant, its magnitude is very close to zero at both the global and regional level. This implies a very small role of the capital-labor ratio in changing the capital-labor substitution relationship.

Next, we turn to the empirical study of a production function that includes energy in addition to capital and labor. We start with the most general estimation equation (1.11). We show in Appendix A-5 that these estimates provide supports for a production function with a constant elasticity of substitution between physical inputs and labor ($b_1 = 0$) and constant returns to scale ($v_1 = v_2 = 1$). Therefore, and as we did in the theory section 3.2, we impose these restrictions on the analysis presented later in the paper and derive the following estimation equation:

$$\ln Y_{it} = \ln A_{it} + a_1 a_2 \ln K_{it} + a_1(1-a_2)\ln(E_{it} + (b_2 + \sum_{j=1}^{J} b_{2j} D_j) a_2 K_{it})$$
$$+ (1-a_1)\ln[L_{it}] + \delta_i + \delta_t + D_t^{oil} + \epsilon_{it}. \quad (1.13)$$

In addition to the main variables described above, we include an additional variable $D_t^{oil}$ to control for the impact of an oil price shock on the capital-energy relationship. This dummy variable equals 1 in the years oil prices soared and 0 otherwise.

Columns (1) and (2) of Table 1.6 report the NLLS bootstrapped estimation results in eq. (1.13) using the global dataset. Column (1) does not control for any fixed effect while Column (2) controls for regional, time and oil-price-shock fixed effects. The coefficient estimate for the VES parameter $b_2$ is statistically significant at 99%, which support the existence of a non-constant elasticity of substitution between capital and energy. Moreover, since $b_2$ is positive both before and after controlling for the fixed effects, our results suggest that the data is best described by a production function that allows for a variable elasticity of substitution, where capital and energy are substitutes. Specifically, a one-unit improvement in the energy-capital ratio increases the capital-energy elasticity of substitution by 0.05 units. More interestingly, the substitution effect between capital and energy is stronger in the estimates that include fixed effects. Once we control for regional and time fixed effects, the impact of the improvement in the energy-capital ratio on the capital-energy elasticity of substitution almost doubles. These results suggest that any exogenous policy that improves energy efficiency, and therefore the substitution between capital and energy, plays an indirect role in shaping the patterns of long-run economic growth. Specifically, a substitutability between capital and energy at the global level implies that in the long run, growth can be sustained by substituting energy and manmade capital.

### 1.5.1 Capital-Energy VES and Economic Progress

Next, we study how the capital-energy substitution varies with economic progress. Columns (3)-(6) of Table 1.6 report marginal effects of our regional estimates for different income levels.

Table 1.6: Marginal effects of capital-energy VES and income levels.

| Dependent variable: GDP | | | | | | |
|---|---|---|---|---|---|---|
| | Global | | Income group | | HDI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $a_1$ | 1.062*** | 1.066*** | 1.042*** | 1.053*** | 1.051*** | 1.058*** |
| | (.00692) | (.0091) | (.00828) | (.00875) | (.00898) | (.00976) |
| $a_2$ | .4165*** | .3618*** | .547*** | .447*** | .4809*** | .3925*** |
| | (.03502) | (.06215) | (.03231) | (.04424) | (.04105) | (.0625) |
| $b_2$(Global) | .05401*** | .09723* | – | – | – | – |
| | (.01671) | (.05501) | – | – | – | – |
| $b_2$ (High income: OECD) | – | – | .00903* | .05022** | – | – |
| | – | – | (.00529) | (.01964) | – | – |
| $b_2$ (High income: Non-OECD) | – | – | .01584*** | .06112*** | – | – |
| | – | – | (.0058) | (.02038) | – | – |
| $b_2$ (Upper middle income) | – | – | -.00078 | .02898* | – | – |
| | – | – | (.00606) | (.01637) | – | – |
| $b_2$ (Lower middle income) | – | – | -.00397 | .02349 | – | – |
| | – | – | (.00802) | (.01804) | – | – |
| $b_2$ (Low income) | – | – | -.08541*** | -.08796*** | – | – |
| | | – | (.00196) | (.0037) | – | – |
| $b_2$ (Very high HDI) | – | – | – | – | .03351*** | .08641* |
| | – | – | – | – | (.01219) | (.0464) |
| $b_2$ (High HDI) | – | – | – | – | .02893** | .07205 |
| | – | – | – | – | (.01449) | (.04423) |
| $b_2$ (Medium HDI) | – | – | – | – | .01958 | .06589 |
| | – | – | – | – | (.01477) | (.04491) |
| $b_2$ (Low HDI) | – | – | – | – | -.00822 | .04542 |
| | | – | – | – | (.00953) | (.03382) |
| Regional fixed effect | No | Yes | No | Yes | No | Yes |
| Time fixed effect | No | Yes | No | Yes | No | Yes |
| Oil crisis dummy | No | Yes | No | Yes | No | Yes |
| Number of observations | 3277 | 3277 | 3277 | 3277 | 3277 | 3277 |
| R-squared | 0.9994 | 0.9995 | 0.994 | 0.995 | 0.994 | 0.995 |

* p-value $<$ 10%, ** p-value$<$ 5%, *** p-value$<$1%.
Numbers in parentheses are standard errors.

Our empirical results show that the VES parameter $b_2$ tends to be positive and higher in countries with high income or high level of HDI while it tends to be negative and lower in other countries. Hence, there is strong evidence for the substitutability between capital and energy in the most developed countries, while this substitution effect is weaker and less significant in less developed countries. Specifically, a one-unit improvement in the energy-capital ratio increases the capital-energy elasticity of substitution by about 0.09 and 0.016 units, respectively, in high income OECD and high income non-OECD countries. In contrast, for low-income countries, a one-unit improvement in the energy-capital ratio decreases the capital-energy elasticity of substitution by 0.08541 units. This means that at the aggregate level, it is relatively easy to substitute capital for energy in the most developed countries, whereas in less developed countries, these two inputs tend to be complements.

After controlling for the regional and time fixed effects, and the impact of oil prices, we found an increase in the coefficient estimates for the capital-energy substitutability. The estimate for parameter $b_2$ increases by more than fivefold in high income countries (both OECD and non-OECD) after controlling for these fixed effects. We also reach similar conclusions when we use the Human Development Index (HDI) as an economic progress indicator. Specifically, after controlling for the fixed effects, a one-unit improvement in the energy-capital ratio increases the capital-energy elasticity of substitution by more than 0.05 units in high income countries and by 0.09 units in countries with very high level of HDI. However, the estimates for the VES parameter $b_2$ in less advanced economies are almost unchanged after controlling for the fixed effects. One possible explanation is that the use of more advanced technology in high-income countries' production process accelerates the substitution speed between capital and energy.

In short, our empirical analysis suggests that the ease of substitution between capital and energy is higher in wealthier countries. Specifically, the variability of the capital-energy elasticity of substitution tends to increase with a country's income level. Moreover, a high level of income accelerates the speed at which we can substitute between capital and energy, where capital and energy are more likely to be substitutes in highly developed countries. In less developed countries, however, capital and energy are more likely to complement each other. As we have shown in the theoretical part, the substitutability between capital and energy has a positive effect on economic growth while the complementarity between capital and energy can have a negative effect. This implies that adverse events such as an oil crisis will have asymmetric effects on economic growth, where countries at early stages of development tend to suffer more than richer countries.[15] Moreover, our results also suggest that economic growth policies not only can influence economic growth directly through increasing income level but also indirectly through increasing the speed at which capital can substitute energy.

### 1.5.2 Capital-Energy VES and Environmental Performance

Finally, we study the impact of a country's environmental performance on the capital-energy elasticity of substitution. Our goal is to analyze whether the speed of substitution between capital and energy is faster in countries that make a bigger effort to protecting the environment. Countries that are more proactive in their environmental efforts also have a stronger incentive to reduce energy consumption, and therefore, their environmental performance might affect the capital-energy substitution. Thus our interactive dummy variable ($\sum_{j=1}^{J} b_{2j} D_j$) in estimating equation (1.13) separates the countries in our sample following the two measures of environmental performance described earlier instead of separating them by income levels.

Columns (3)-(6) of Table 1.7 report the NLLS bootstrapped estimates of the estimation equation (1.13). Specifically, we use the Kyoto Protocol as an environmental performance indicator to derive the marginal effects in Columns (3) and (4) and we use the Yale University's EPI as an environmental performance indicator for the estimated marginal effects in Columns (5) and (6).

[15] This is in line with Van der Ploeg and Poelhekke (2009) and Van der Ploeg (2011) who find evidence for a resource curse in the presence of price fluctuations.

Table 1.7: Marginal effects of capital-energy VES and environmental performance.

| Dependent variable: GDP | | | | | | |
|---|---|---|---|---|---|---|
| | Global estimates | | Kyoto Annex B | | EPI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $a_1$ | 1.062*** | 1.066*** | 1.06*** | 1.075*** | 1.046*** | 1.054*** |
| | (.00692) | (.0091) | (.00767) | (.00975) | (.00719) | (.00893) |
| $a_2$ | .4165*** | .3618*** | .4263*** | .3497*** | .498*** | .3874*** |
| | (.03502) | (.06215) | (.03763) | (.06257) | (.03041) | (.05975) |
| $b_2$ (Global) | .05401*** | .09723* | – | – | – | – |
| | (.01671) | (.05501) | – | – | – | – |
| $b_2$ (Kyoto Annex B) | – | – | .054*** | .08127 | – | – |
| | – | – | (.01603) | (.05036) | – | – |
| $b_2$ (No Kyoto Annex B) | – | – | .04908*** | .1085* | – | – |
| | – | – | (.01715) | (.05891) | – | – |
| $b_2$ (Very high EPI) | – | – | – | – | .03462*** | .1069** |
| | | – | – | – | (.00818) | (.05316) |
| $b_2$ (High EPI) | – | – | – | – | .03425*** | .08335* |
| | – | – | – | – | (.00929) | (.04763) |
| $b_2$ (Medium EPI) | – | – | – | – | .01445* | .06153 |
| | – | – | – | – | (.00869) | (.04247) |
| $b_2$ (Low EPI) | – | – | – | – | .00175 | .07651 |
| | – | – | – | – | (.0073) | (.04825) |
| $b_2$ (Very low EPI) | – | – | – | – | -.01395 | .06878 |
| | – | – | – | – | (.01032) | (.04877) |
| Regional fixed effect | No | Yes | No | Yes | No | Yes |
| Time fixed effect | No | Yes | No | Yes | No | Yes |
| Oil crisis dummy | No | Yes | No | Yes | No | Yes |
| Number of observations | 3277 | 3277 | 3277 | 3277 | 3277 | 3277 |
| R-squared | 0.9994 | 0.9995 | 0.9994 | 0.9995 | 0.9994 | 0.9995 |

* p-value < 10%, ** p-value< 5%, *** p-value<1%.
Numbers in parentheses are standard errors.

Our results suggest that a voluntary promise to reduce carbon emission plays an insignificant role in determining the speed of substitution between capital and energy. Even though we find the VES parameter $b_2$ to be positive in Kyoto Protocol Annex B countries, our post-estimation F-test suggests that the difference in the VES parameter between Kyoto Protocol Annex B countries and the rest of the sample is negligible. Specifically, a one-unit improvement in energy efficiency increases the capital-energy elasticity of substitution by 0.054 units in Kyoto Annex B countries, which is not statistically different from the estimate of 0.049 units for other countries outside of Annex B. Our explanation relies on the fact that even though the Kyoto Protocol was adopted in 1997, it only entered into force for a very short period of time in our sample (2005-2011). This means that countries which identify themselves in Annex B of the protocol may have started to make stronger carbon emission reduction efforts only recently, therefore, the impacts of their efforts have not been fully transferred into any significant change in the capital-energy relationship.

One drawback of using the Kyoto Protocol Annex B is that it only reveals the willingness to reduce carbon emissions rather than a country's actual environmental performance. Therefore, our analysis also employs an alternative indicator for environmental performance, the Yale University's EPI. The use of the EPI has clear advantages because the index is built based on a country's actual performance in two broad policy areas: protection of human health from environmental harm and protection of ecosystems. These two areas are further divided into many sub-areas, and a country's final score is based on how it performs in each of these sub-areas.[16] Using the EPI as an indicator for environmental performance, we divide our sample into the following groups according to their EPI scores: Very High EPI, High EPI, Medium EPI, Low EPI, Very Low EPI. In table A-7, we present the list of countries that are included in each group. Our empirical results in Columns (5) and (6) of Table 1.7 show that the VES parameter $b_2$ is positive and statistically significant in

[16]The subareas include: Climate and Energy, Health Impacts, Air Quality, Water and Sanitation, Water Resources, Agriculture, Forests, Fisheries, Biodiversity and Habitat.

countries with very high and high EPI scores. Specifically, a one-unit improvement in the energy-capital ratio increases the capital-energy elasticity of substitution by 0.107 units in Very High EPI countries and 0.083 units in High EPI countries. These provide strong evidence for the capital-energy variable elasticity of substitution in countries with very high and high EPI scores, where capital and energy tends to be more easily substitutable in these countries. This substitution effect increases in its magnitude once we control for the regional and time fixed effects and the impacts of oil prices. On the other hand, we observe little evidence of the same phenomenon in countries with lower EPI scores. One explanation is that highly environmentally friendly countries make greater efforts to reduce energy dependence, as a result, this will speed up the substitution of energy with other production inputs.

To summarize, our empirical results suggest that the elasticity of substitution between capital and energy varies with changes in the energy-capital ratio over time. The speed at which capital and energy can substitute each other increases with a country's level of income and its effort to protect the environment. This suggests that growth policies not only influence long-run economic growth through changes in income level but also indirectly through changes in the capital-energy substitution effect. Moreover, a country's effort at improving the environment also has a positive effect on long-run economic growth as it tends to accelerate the speed of substitution between capital and energy. This partially reverses the popular debate regarding the policy trade-off between environmental protection and faster economic growth.

## 1.6 Conclusions

As countries seek to reduce their carbon emissions, policies targeted at reducing the energy intensity in production plays an important role in reducing emissions while meeting global energy demand. The effectiveness of such policies depends largely on the ease at which energy can be substituted by other manmade production inputs such as capital. Whereas previous research studying this relationship often focuses on a constant elasticity of substitution between capital and energy, our paper takes a new approach and analyzes the capital-energy substitutability in a framework that allows for this substitution to vary over time. Building on a simple Solow growth model, we identify in our theoretical model that the variable elasticity of substitution, which explicitly depends on the energy-capital ratio, directly determines capital accumulation. Moreover, this elasticity that changes over time can either strengthen or dampen long-run growth depending on the sign and magnitude. Using global aggregate data between 1971 and 2011, we present evidence for this non-constant capital-energy elasticity of substitution, which is a novel contribution to the literature examining the capital-energy substitution.

Our results provide new insights into the policy debate looking for alternatives to reduce energy dependency while maintaining economic growth. As the potential costs and impacts of environmental policies are largely influenced by the value of the elasticity of substitution between energy and other production inputs (Nijkamp et al., 2005; Antimiani et al., 2013), understanding the behavior of the elasticity of substitution at each stage of economic development is crucial in modeling the optimal environmental policies. Specifically, our global estimates suggest that energy and capital tend to be substitutes, and this substitution relationship is positively related with a country's income level. Therefore, growth policies not only influence long-run economic growth directly through improving per capita income but also indirectly through increasing the speed of substitution between capital and energy. These results imply that in less developed countries, policy efforts towards increasing the substitutability between capital and energy can improve the speed at which their economies grow.

# Chapter 2

# Is it risky to go green? A volatility analysis of the green bond market

## 2.1 Introduction

Gandhi once said "Earth provides enough to satisfy every man's needs, but not every man's greed." Indeed, increasing amounts of greenhouse gas emissions from human activities[1] are not only a major contributor to climate change but also bring about various negative consequences on the human society.[2] The urging question of our time is how to prosper economically without impacting the ecological systems beyond irrevocable changes. In fact, in recent years, countries and multinational agencies across the world have made tremendous efforts to promote environmentally friendly investments. Yet, fundraising efforts to date have been inadequate to meet the immense amount of funding required to address climate change. According to the World Bank, climate change mitigation efforts in developing countries could cost about USD 275 billion annually over the next 20 years, which is more than double the current level development assistance of USD 100 billion per year (World Bank, 2015b). Therefore, new sources of financing for climate change must be considered. In the financial world, new financial instruments have been created to facilitate the increasing demand for green investing. One very promising financial instrument of that kind is green

[1] In 2012, greenhouse gas emissions from human activities were 47.6 metric tons of carbon dioxide equivalent, which was a 40% increase from 1990 (World Resource Institute, 2016).

[2] The adverse impacts of human activities on the natural environment have been documented by many environmental scientists (Stenseth et al., 2002; Oreskes, 2004). However, concerns over climate change are broader than just a negative environmental impact. For example, Stern et al. (2006) claims that climate change can dampen economic growth, while Portier et al. (2010) anticipates that climate change can lead to increasing risks of cancer, cardiovascular diseases, heat-related illness and many other health disorders.

bonds, which are debt instruments with a bonus environmental feature. Since its first appearance in 2007, the green bond market has expanded at more than 50% compounded annual growth rate, providing funding for environmental projects all over the world (Kochetygova and Jauhari, 2014; World Bank, 2015a).[3] Given the potential environmental and economic benefits of green bonds, it is crucial to understand the volatility behavior of this green financial instruments in comparison with other conventional investments as the market continues to expand. In this paper, my goal is to provide an insight into the volatility behavior of the green bond market and study the relationship between the green bond market volatility and the volatility of the conventional bond market.

The World Bank defines a green bond as "a debt security that is issued to raise capital specifically to support climate-related environmental projects" (World Bank, 2015b). A green bond could either be "labeled" or "unlabeled". Labeled green bonds are formally marketed as "green" by the issuers, where the issuers define the types of environmental projects they plan to support with the bond proceeds and report back to investors on a regular basis. On the other hand, unlabeled green bonds do not have a formal green tag, but are issued by firms whose businesses are naturally aligned with environmental causes, for example, bonds issued by wind or solar energy companies. The range of projects supported by green bonds is very diverse, with low-carbon transport and clean energy projects being the two largest beneficiaries (Shankleman, 2016). From a market pioneered by large development banks, in 2014, two-thirds of all new green bonds came from issuers that are not multilateral development banks, attracting a broad group of investors such as asset managers, pension funds, companies, foundations and religious organizations (Kochetygova and Jauhari, 2014; Damutz, 2016).

The fast growth of the green bond market gives rise to the need to address its risk and return characteristics so that to equip investors with informative insights into the market. Within this

[3]For example, green bonds are funding a wide variety of projects that improve agricultural productivity, energy efficiency, forest management, and transportation. See Mathews and Kidney (2012) and World Bank (2015a) for case studies and examples of projects funded by green bonds in various countries.

context, this paper is the first to answer the following research questions: How does the volatility of the green bond market behave in comparison with the conventional bond market? Are there any spillover effects between the green bond market and the conventional bond market? How much does a shock in the green bond market contribute to the volatility of the conventional bond market and vice versa? To answer this question, I first build a framework to model the volatility of a financial asset based on the multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework, a family of statistical models originally proposed by Bollerslev (1986) and Engle (2002) and have been widely used in the literature studying the relationship between different financial time series' volatilities (Bauwens et al., 2006). With this model, I am able to test not only the pattern of volatility in the green bond market but also how the volatility in the green bond market transmits to the broader conventional bond market.

Using time series data on daily closing prices of the S&P green bond indices between April 2010 and April 2015, the results from my analysis suggest that there is significant volatility clustering in the green bond market, where periods of high volatility are often followed by further periods of high volatility and periods of low volatility are followed by periods of low volatility. This volatility clustering effect is particularly stronger for the labeled green bond sector, as compared to its unlabeled counterpart and the broader conventional bond market, since most labeled green bonds are of similar credit ratings while the markets for unlabeled green bonds and conventional bonds consist of a more diverse sets of bonds. Moreover, the green bond market is also interdependent with the conventional bond market. My empirical results show that a shock in the green bond market tends to spill over to the conventional bond market and this spillover effect variable over time. Furthermore, the data also suggest that there has been an upward trend in the correlation of volatility in the labeled green bond segment with the conventional bond market. One explanation is that there exists convergence of returns between the green bond market and the broader bond market as the green bond market continues to attract a broader group of investors.[4] The results are robust after accounting for the presence of extreme observations in the data.

This paper is related to three main strands of the literature. First, this paper relates to the literature modeling volatility of the financial market. This paper follows the work of Bollerslev (1986) and Engle (2002), who propose an econometric framework to study volatility clustering and volatility spillover among different time series. While this framework has been applied to multiple markets in the financial work, this paper is the first to apply the GARCH modeling techniques to studying the volatility of the green bond market, a new investment option that can potentially meet the growing demands for sustainable and socially responsible investing.

Second, this paper is also in line with the literature studying the fixed-income financial market (for example, Harford and Uysal (2014); Das (1998); Beber et al. (2006)). While this line of literature spans over a long period of time and covers multiple areas of the bond market, none of them has addressed the role of the fixed-income market in promoting environmentally sound investment. This paper contributes to the literature by focusing on the green fixed income market and providing the first empirical evidence for the performance of this new, yet promising market segment.

This paper also relates to the literature studying the characteristics of environmentally friendly financial instruments. Ortas and Moneva (2013) study the risk and return performance of 21 Clean Techs equity indexes using a state-space approach and found that the Clean Techs equity indexes outperform the market portfolio in terms of returns and that their returns are highly volatile even in uprising markets. Many other studies document the volatility spillover between the green equity market and other sectors of the market such as the conventional equity market, the oil and carbon

[4]The first participants in the green bond market was large institutions like multinational development banks. Nowadays the green bond market has attracted a broad group of investors such as asset managers, pension funds, companies, foundations and religious organizations. Issuers and investors use green bonds as a way to communicate their commitment to sustainability and social responsibility to their stakeholders. (Kochetygova and Jauhari, 2014; OECD, 2015; Damutz, 2016)

market and find that there are significant interdependence between the green equity market and the broader financial market (for example Kumar et al. (2012); Sadorsky (2012)). Climent and Soriano (2011) and Chang et al. (2012) study the performance of green mutual funds and find that green mutual funds have underperformed on a risk-adjusted basis compared to conventional funds. On the other hand, Gil-bazo et al. (2010) find that company management plays an important role in the performance of socially responsible mutual funds. While the literature studying green financial instruments has been well-developed, most of the emphasis so far has been on analyzing the performance of the equity sector of the market. To the best of my knowledge, this paper is among the first attempts in characterizing the behavior of the green fixed-income market. Understanding the performance of the green bond market is important because together with the broader USD 100 trillion bond market, the green bond market can serve as a low-cost financing tool toward a green economy (Caldecott, 2010; Mathews et al., 2010; Mathews and Kidney, 2012). Moreover, for investors interested in environmentally beneficial investing, the fixed-income market is a good starting point as it is often considered as a lower-risk market than other green investment options.

The rest of the paper is organized as follows. Section 2.2 provides an overview of the green bond market while 2.3 specifies the framework for modeling volatility in the green bond market. Section 3.3 describes the data and Section 4.4 presents the empirical results and analysis. Finally, Section 4.6 provides a concluding remark.

## 2.2 Overview of the green bond market

According to a survey of high net worth investors in 2016 by Morgan Stanley, sustainable investing is becoming more popular among investors, where 55% of investors reported that they are interested in sustainable investing and 32% view sustainable investing as a good investment approach for the future (Morgan Stanley, 2016). Yet, regardless of the growing interest among investors about sustainable investing, there still exists a large funding gap for low-carbon projects, which cannot be supported by public sources alone (World Bank, 2015b). This emphasizes the role of private funding in the transition toward a low-carbon economy.

While sustainable investing has been popular in the equity market, the green bond concept is a relatively new development. The most fundamental distinction between green bonds and conventional bonds is that all the proceeds from green bonds are used to finance environmentally friendly projects. The identification and labeling of green bonds typically follow the Green Bond Principles (GBPs), a set of voluntary standards established by industry participants including major banks and non-profit organizations (International Capital Market Association, 2015). The GBPs consist of four elements. First, in order to be labeled “green”, a bond’s proceeds must be used for environmentally beneficial capital expenditures, such as investments in alternative energy, energy efficiency, pollution prevention and control, sustainable water and green buildings. Second, the green bonds’ documentation must include specific criteria and process for determining eligible projects or investment. Third, a formal process that regulates the use of net proceeds must be disclosed in the bond prospectus or supporting document. And fourth, issuers of green bonds should report at least annually on the specific investments made from the green bond proceeds and document the environmental impacts of the specific investments. Total “labeled” green bonds outstanding were USD 65.9 billion in June 2015. In 2014, the issuance of the “labeled” green bond totaled USD 36.6 billion, which was more than three times the previous year’s amount of USD 11 billion (Kochetygova and Jauhari, 2014; Damutz, 2016).

Besides bonds that follow the GBPs and are formally labeled as “green”, many bonds in the market have been issued without a green label but having clear environmental benefits such as financing wind farms or solar installations. According to Standard and Poor’s, this “unlabeled” segment is potentially several times larger in size than the “labeled” green bond market segment.

In 2015, "unlabeled" green bond outstanding totaled USD 531.8 billion, which is significantly larger than the total outstanding amount of USD 65.9 billion in the "labeled" green bond market. From a small market pioneered by large development banks and institutional investors, the green bond market has attracted many different types of issuers and investors such as corporations, mutual funds, asset managers, insurance companies, subnational and municipal government entities. In 2014, about two-thirds of all new green bonds came from issuers that are not multilateral development banks in more than 20 different currencies (Kochetygova and Jauhari, 2014).

The growth of the green bond market reflects the increasing interests of investors in low-carbon projects.[5] In fact, since its inception, the green bond market has attracted a diverse group of investors, such as asset managers, pension funds, companies, foundations and religious organizations (Kochetygova and Jauhari, 2014; Damutz, 2016).

## 2.3 Modeling the green bond market volatility

As the green bond market continues to grow, it is important to understand the volatility dynamics of this market segment in relation with other sectors in the financial market. A widely used technique to in the literature studying the volatility of financial time series is Generalized Autoregressive Conditional Heteroskedasticity or GARCH, which uses an autoregressive structure to model the conditional variance of a time series, thereby allowing volatility shocks to persist over time.[6] Under this framework, the volatility of an asset's returns is given in the following set of equations:

$$R_t = E_{t-1}[R_t] + \epsilon_t, \qquad \epsilon_t | I_{t-1} \sim iid(0, \sigma_t^2) \tag{2.1}$$

where ; $E_{t-1}[R_t]$ denotes the conditional mean of the asset returns at time $t$ given the infor-

[5] According to the Organization of Economic Co-operation and Development, between 2012 and 2014, sustainable investments increased by 61%, where half of the investments are allocated to bonds (OECD, 2015).

[6] See Bauwens et al. (2006); Teräsvirta (2009) for a literature survey.

mation set $I_{t-1}$; $\epsilon_t$ is the error term and $\sigma_t^2$ is the conditional variance of asset returns at time $t$..

The specifications of $E_{t-1}[R_t]$ and $\sigma_t^2$ are of the following form:

$$E_{t-1}[R_t] - \mu = \sum_{h=1}^{r} \phi_h (R_{t-h} - \mu) + \sum_{k=1}^{s} \psi_k \epsilon_{t-k} \tag{2.2}$$

$$\sigma_t^2 = a_0 + \sum_{i=1}^{p} a_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} b_j \sigma_{t-j}^2, \qquad a_0 > 0; \quad a_i > 0 \forall i \in [1,p]; \quad b_j > 0 \forall j \in [1,q] \tag{2.3}$$

where $\mu = E[R_t]$ denotes the unconditional mean of the asset returns. Altogether, parameters $a_i$ $(i = 1, ...p)$ and $b_j$ $(j = 1, ...q)$ determine the extent of volatility clustering in asset returns. A high and significant $a_i$ and $b_j$ $(i = 1, ...p;\ j = 1...q)$ indicate the existence of volatility clustering, where periods of high volatility are followed by periods of high volatility and vice versa. Finally, the lag lengths $p$, $q$, $r$, $s$ are determined using the Schwartz information criteria.

To compare the volatility of the green bond market with that of the conventional bond market, one approach is to estimate equations (2.1), (2.2) and (2.3) for each market separately. While this approach allows us to study the pattern of volatility of individual markets, it ignores the interactions between the green bond market and the broader conventional bond market. To capture the possible volatility spillovers between the green bond market and the broader conventional bond market, I also extend the above univariate model in equations (2.1)-(2.3) to a multivariate case where the volatility of an asset's returns not only depends on its past values but also on the volatility of other assets in the financial market. One feature of the multivariate GARCH model is that it allows time-varying conditional variances of asset returns as well as covariances between the returns of different assets. This allows the analysis of the volatility structure of individual assets as well as the interaction between various assets. In this paper, the specification of this multivariate model consist of two components. First, returns are modeled using a vector autoregression (VAR) framework. Then a multivariate GARCH model is used to model the time-varying variances and covariances. Specifically, let $R_{Gt}$ be the returns on the green bond market at time $t$ and $R_{Mt}$ be the returns on a benchmark conventional bond market at time $t$. Let $\mu_G$ and $\mu_M$ be the unconditional means of the returns on the green bond market and the benchmark market. The specification for $R_{Gt}$ and $R_{Mt}$ is of the following form:

$$\begin{aligned} R_{Gt} - \mu_G = {} & \phi_{11}^1(R_{Gt-1} - \mu_G) + \phi_{12}^1(R_{Mt-1} - \mu_M) + \\ & + \phi_{11}^2(R_{Gt-2} - \mu_G) + \phi_{12}^2(R_{Mt-2} - \mu_M) + \\ & + ... + \phi_{11}^{r_G}(R_{Gt-r_G} - \mu_G) + \phi_{12}^{r_G}(R_{Mt-r_G} - \mu_M) + \epsilon_{Gt} \end{aligned} \tag{2.4}$$

$$\begin{aligned} R_{Mt} - \mu_M = {} & \phi_{21}^1(R_{Gt-1} - \mu_G) + \phi_{22}^1(R_{Mt-1} - \mu_M) + \\ & + \phi_{21}^2(R_{Gt-2} - \mu_G) + \phi_{22}^2(R_{Mt-2} - \mu_M) + \\ & + ... + \phi_{21}^{r_M}(R_{Gt-r_M} - \mu_G) + \phi_{22}^{r_M}(R_{Mt-r_M} - \mu_M) + \epsilon_{Mt} \end{aligned} \tag{2.5}$$

with $\epsilon_{\mathbf{t}}|I_{t-1} = \begin{bmatrix} \epsilon_{Gt} \\ \epsilon_{Mt} \end{bmatrix} |I_{t-1} \sim WN(0, \Sigma_t)$, where $\Sigma_t = \begin{bmatrix} \sigma_{Gt}^2 & \sigma_{GMt} \\ \sigma_{MGt} & \sigma_{Mt}^2 \end{bmatrix}$ denotes the conditional variance-covariance matrix at time $t$. [7] The lag legths $r_G$ and $r_M$ are jointly determined using the Schwartz information criteria.

To model the time-varying volatility of the return series $\{R_{Gt}\}$ and $\{R_{Mt}\}$, I apply maximum

[7] $\sigma_{it}$ denotes the standard deviation of series $i$ while $\sigma_{ijt}$ denotes the covariance between series $i$ and series $j$; $i, j = G, M$; $i \neq j$.

likelihood estimation (MLE) techniques to Engle (2002)'s dynamic conditional correlation (DCC) model. Under this approach, the conditional covariance matrix $\Sigma_t$ is modeled based on the univariate GARCH modeling of the individual series $\{R_{Gt}\}$ and $\{R_{Mt}\}$. Compared to other approaches which model the conditional variance-covariance matrix $\Sigma_t$ directly, the DCC approach has clear computational advantages because its flexibility allows for the estimation of very large correlation matrices. [8] The estimation of the DCC model relies on the decomposition of the conditional covariance matrix $\Sigma_t$ into:

$$\Sigma_t = D_t Q_t D_t, \tag{2.6}$$

where $Q_t = \begin{bmatrix} 1 & \rho_{GMt} \\ \rho_{MGt} & 1 \end{bmatrix}$ is the correlation matrix and $D_t = \begin{bmatrix} \sigma_{Gt} & 0 \\ 0 & \sigma_{Mt} \end{bmatrix}$ is a diagonal matrix with the standard deviations of the two series on the diagonal.[9].

The estimation of the DCC model's parameters involves two steps. In the first step, the volatility measures of each individual series are estimated under the following univariate GARCH model [10]:

$$\sigma^2_{Gt} = a_{0G} + \sum_{i=1}^{p_G} a_{iG}\epsilon^2_{Gt-i} + \sum_{j=1}^{q_G} b_{jG}\sigma^2_{Gt-j} \tag{2.7}$$

$$\sigma^2_{Mt} = a_{0M} + \sum_{i=1}^{p_M} a_{iM}\epsilon^2_{Mt-i} + \sum_{j=1}^{q_M} b_{jM}\sigma^2_{Mt-j} \tag{2.8}$$

Then an estimates for the standardized residuals is calculated from the above GARCH models: $\hat{z}_{it} = \frac{\hat{\epsilon}_{it}}{\hat{\sigma}_{it}}$ $(i = G, M)$. In the second step, the conditional correlation between the standardized residuals is modeled using the following GARCH (1,1) framework:

[8]See Bauwens et al. (2006) for a survey of multivariate GARCH models.

[9]$\rho_{ijt} = \frac{\sigma_{ijt}}{\sigma_{it}\sigma_{jt}}; i, j = G, M$

[10]The lag lengths $p_G$, $p_M$, $q_G$, $q_M$ are determined using the Schwartz information criteria

$$
\begin{aligned}
\hat{q}_{ijt} &= Cov(\hat{z}_{it}, \hat{z}_{jt} | I_{t-1}) \\
&= \hat{E}[\hat{z}_{it}\hat{z}_{jt}](1-\alpha-\beta) + \alpha \hat{z}_{it-1}\hat{z}_{jt-1} + \beta \hat{q}_{ijt-1}, \qquad i,j = G, M
\end{aligned} \tag{2.9}
$$

Thus, the correlation estimator is: $\hat{\rho}_{ijt} = \frac{\hat{q}_{ijt}}{\sqrt{\hat{q}_{iit}\hat{q}_{jjt}}}$.

Finally, the univariate volatility estimates in the first step and the bivariate conditional correlation estimates in the second step are combined to estimate $\Sigma_t = D_t R_t D_t$. Altogether, the parameters $a_i$ and $b_j$ in equations (2.7) and (2.8) show the magnitude of the volatility clustering within the returns series while the parameters $\alpha$ and $\beta$ in equation (2.9) show the magnitude of volatility spillover from one time series to the other. Moreover, the value of each element in the estimated $\Sigma_t$ will reveal about the magnitude of volatility clustering in asset returns and volatility spillovers from one asset's returns to another's.

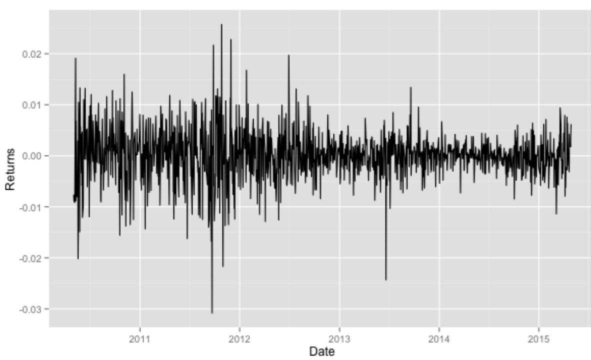
## 2.4 Data

To analyze the volatility behavior of the green bond market in relation to the overall conventional bond market, this study requires time series data on the market performances of green bonds and conventional bonds. Specifically, I use the daily closing prices of the S&P Green Bond Index (GB) and the S&P Green Project Bond Index (GPB) as indicators of the green bond market performance. The performance of the conventional bond market is approximated using the S&P U.S. Aggregate Bond Index (AB). The sample period for the data spans between April 30, 2010 and April 29, 2015

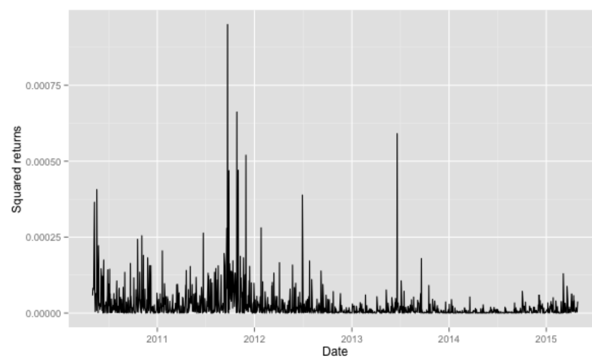
The S&P Green Bond Index (GB) and the S&P Green Project Bond Index (GPB) are complementary indices that serve as a tool to track the global green bond market. The Green Bond Index is constructed using bonds that have been independently verified to comply with the Green Bond

Principles. The goal of the index is to track the performance of the "labeled" green bond market. The majority of the bonds included in the Green Bond Index are of investment-grade, with 54% of the bonds are AAA rated by Standard and Poor as of August 2014 (Kochetygova and Jauhari, 2014). Figure 2.1 shows the daily returns on the Green Bond Index in the sampling period. It can be seen from the figure that the index is more volatile at the beginning of the sampling period. Moreover, the index seems to exhibit mean reverting behavior in returns, which suggests the data are stationary. In fact, results from a unit root test shows that returns on the S&P Green Bond Index is stationary, as can be seen on Table 2.1.

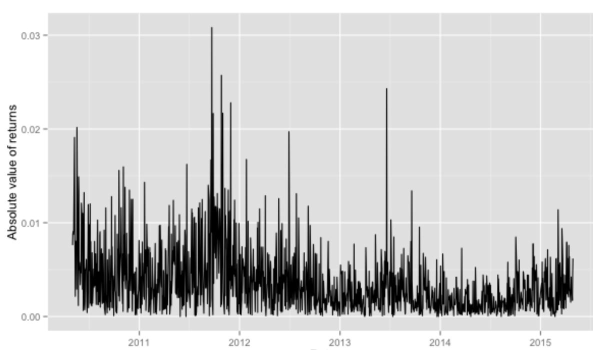
Figure 2.1: Green bond index daily returns, 4/30/2010 - 4/29/2015 *(Source: S&P)*




(a) Returns




(b) Squared returns




(c) Absolute value of returns

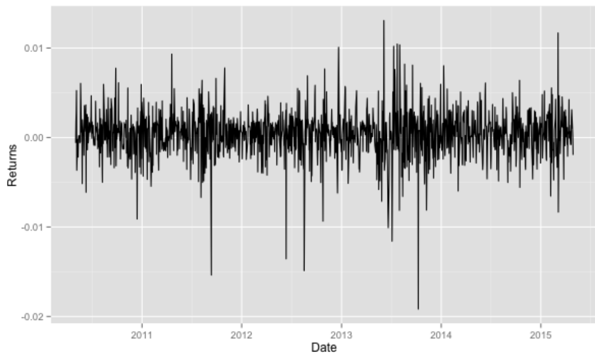
Sampling period: Daily 4/30/2010 - 4/29/2015

While the green-labeled bond market is growing, a significant part of the market consists of bond issues without a green label but having obvious environmental benefits such as financing wind farms or solar installations. The S&P Green Project Bond Index (GPB) is constructed to track the broader "unlabeled" green bond market. While bonds need not have a green label to be included in the Green Project Bond Index, they must fall into one of the following categories: bonds issued by special purpose entities to finance or refinanced a green project, asset-backed securities to securitize cash flows from pools of green assets and corporate bonds issued by companies whose revenues originate *only* from green activities. In contrast to the S&P Green Bond Index, which is dominated by bonds with high credit rating, the S&P Green Project Bond Index include both investment- and subinvestment-grade bonds. As of September 2014, 51% of the bonds in the Green Project Bond index are investment-graded while 42% of the bonds in the index are subinvestment graded, with B- being the lowest credit-rating. (Kochetygova et al., 2014). Figure 2.2 shows the daily returns on the Green Project Bond Index between April 2010 and April 2015. A unit root test of the index's daily returns shows that the series is stationary (Table 2.1).

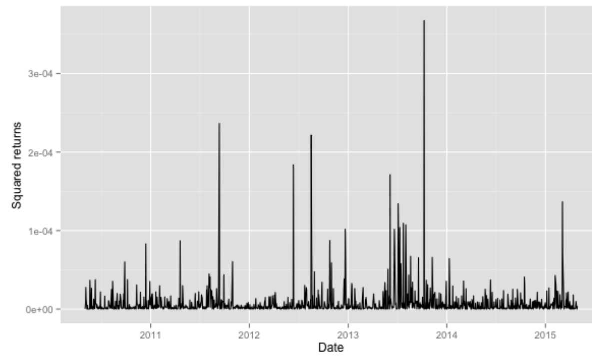
To compare the performance of the green bond indices with the broader conventional bond market, I use the S&P U.S. Aggregate Bond Index as a benchmark index for the analysis. The index provides an overview of the market for publicly-issued U.S. dollar denominated investment-grade bonds, where all bonds have a minimum credit rating of BBB- or equivalent. Similar indices that track the performance of publicly-issued U.S. dollar denominated investment-grade bonds have been used in previous studies as a benchmark for the overall bond market (for example, Daskalaki and Skiadopoulos (2011); Case et al. (2012)). Figure 2.3 shows the daily returns on the U.S. Aggregate Bond Index between April 2010 and April 2015. Again, a unit root test shows that the index's daily returns follow a stationary process (Table 2.1).

Table 2.2 summarizes the descriptive statistics of the indices' returns and Figure 2.4 plots the autocorrelation functions of the returns. The autocorrelation functions show that present returns have little correlation with their lagged values, which is consistent with the stylized fact

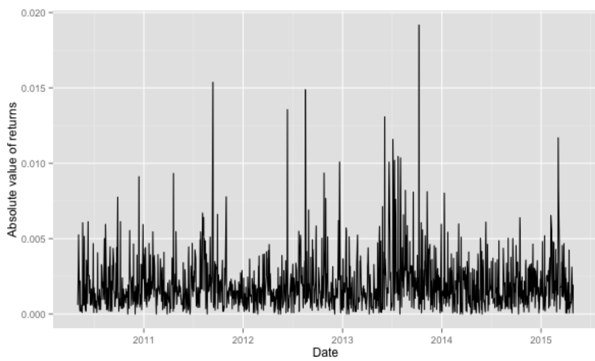
Figure 2.2: Green project bond index daily returns, 4/30/2010 - 4/29/2015 *(Source: S&P)*




(a) Returns




(b) Squared returns




(c) Absolute value of returns

Sampling period: Daily 4/30/2010 - 4/29/2015

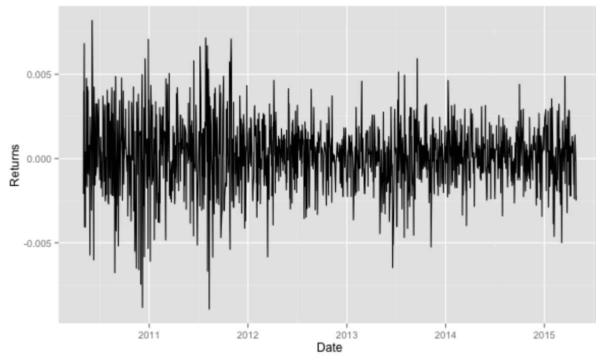
Table 2.1: Unit root tests

| | ADF test statistics |
|---|---|
| Returns on green bond index | -37.197*** |
| Returns on green project bond index | -37.559*** |
| Returns on aggregate U.S. bond index | -37.998*** |

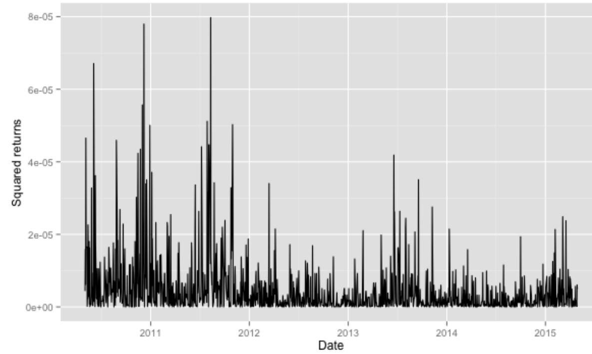
* p-value < 10%, ** p-value < 5%, *** p-value < 1%.

that financial market returns are more or less unpredictable. Among the three indices, the Green Project Bond Index has the highest average returns while the Green Bond Index has the highest standard deviation. The standard deviations in all three series are larger than their mean. The Green Bond Index has the highest Sharpe ratio. In other words, among the three indices, the Green Bond Index provide investors with the best returns given the same amount of risk or equivalently,

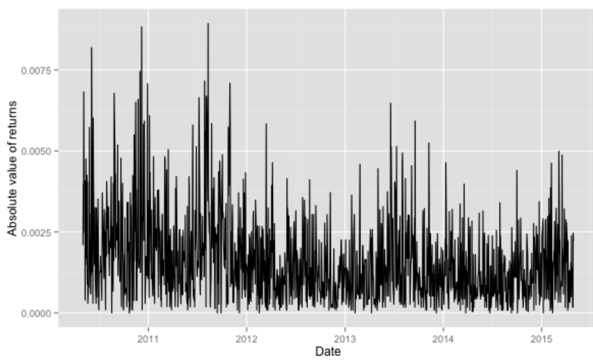
Figure 2.3: U.S. aggregate bond index daily returns, 4/30/2010 - 4/29/2015 *(Source: S&P)*




(a) Returns




(b) Squared returns




(c) Absolute value of returns

Sampling period: Daily 4/30/2010 - 4/29/2015

the lowest risk given the same amount of returns. Specifically, the Green Bond Index offers a 2.60% excess returns per unit of risk, which is much higher than that of the Green Project Bond Index and the U.S. Aggregate Bond Index (0.50% and 0.54% respectively). [11] [12] A closer look at the squared returns for each index (middle panels of Figures 2.1, 2.2, 2.3) indicates that all three series exhibit volatility clustering, where periods of high volatility tends to be followed by periods of high volatility and vice versa.

Figures 2.5 and 2.6 show the 20-day rolling covariances and correlations between the Green Bond Index, the Green Project Bond Index and the benchmark U.S. Aggregate Bond Index. There

[11] Sharpe ratio of an asset$=\frac{R_a - R_f}{\sigma_a}$, where $R_a$ and $\sigma_a$ denote the returns and standard deviation of the asset in consideration, and $R_f$ denotes the returns on a risk-free asset.

[12] I use 3-month yields on U.S. Treasury bill as a proxy for the risk-free asset returns. Data for U.S. Treasury bill yields are obtained from St. Louis FRED.

Table 2.2: Descriptive statistics

| | GB Returns | GPB Returns | AB Returns |
|---|---|---|---|
| Mean | 0.0001 | 0.0003 | 0.0001 |
| Min | -0.0308 | -0.0192 | -0.0089 |
| Max | 0.0257 | 0.0131 | 0.0082 |
| Std. Dev. | 0.0049 | 0.0027 | 0.0021 |
| Skewness | -0.1846 | -0.5710 | -0.1640 |
| Kurtosis | 3.5840 | 5.3900 | 1.1780 |
| Sharpe ratio | 0.0260 | 0.0050 | 0.0054 |
| Weighted average maturity | 6.83 years | 13.94 years | 6.60 years |
| Par weighted price | 103.53 | 104.1 | 106.21 |

GB=Green bond index

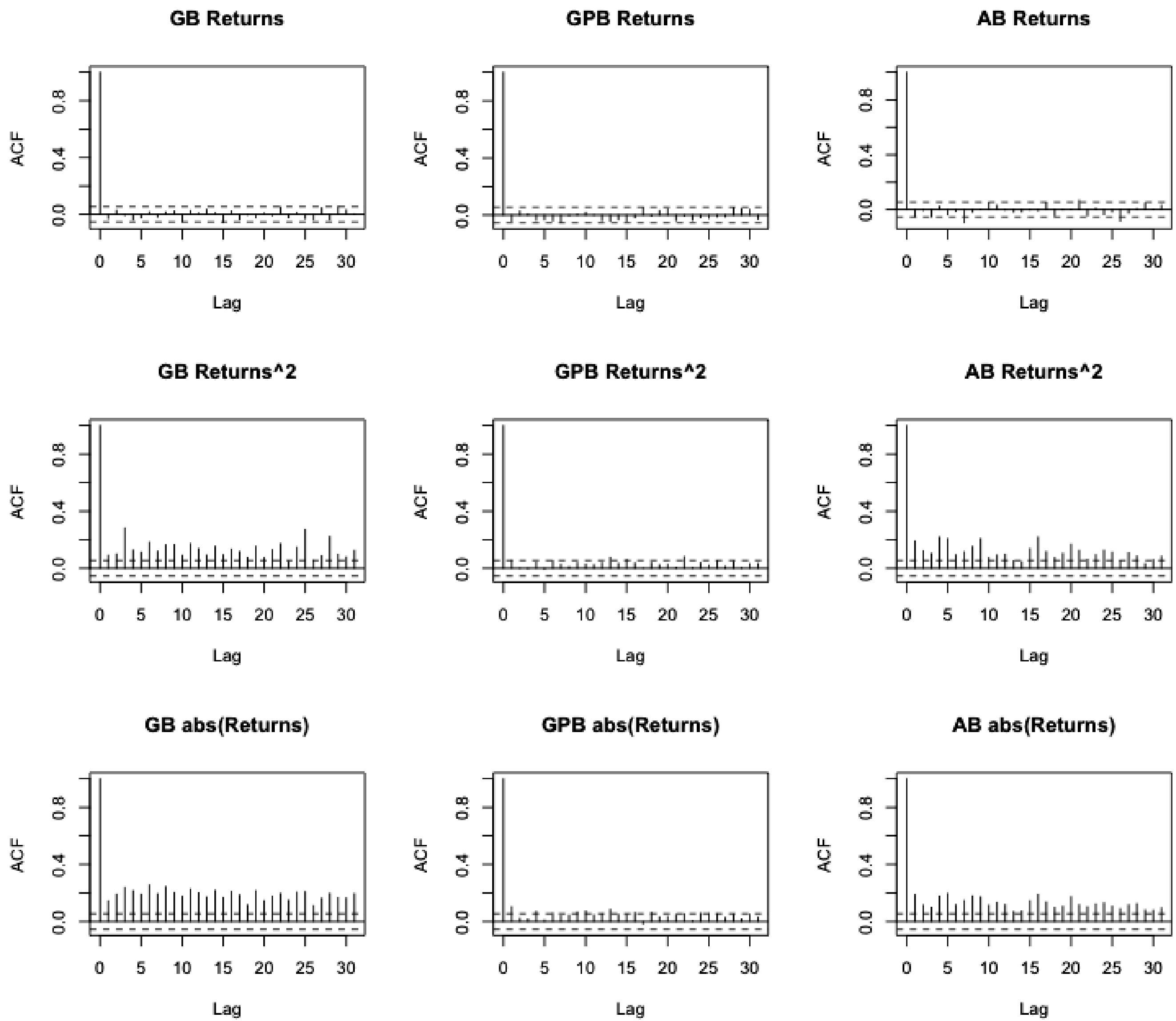
GPB=Green project bond index

AB=U.S. aggregate bond index

*Source: S&P.*

are considerable variations in the rolling covariances and correlations between the indices. The rolling covariances and correlations between the Green Bond Index and the U.S. Aggregate Bond Index (Figure 2.5) are mostly lower than their unconditional covariance and correlation for the first half of the sampling period and begin to rise above the unconditional measures for the second half of the sampling period. On the other hand, the rolling covariances and correlations between the Green Project Bond Index and the U.S. Aggregate Bond Index tends to stay above their unconditional counterparts during the sampling period.

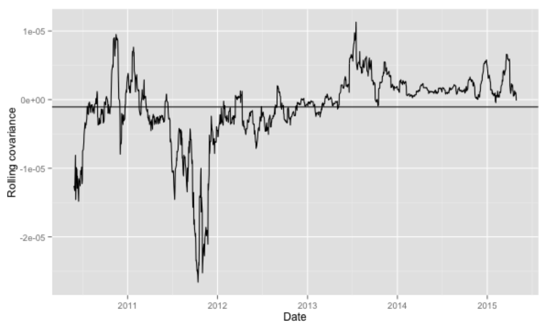
Figure 2.4: Autocorrelations of Returns, Returns^2 and Absolute Values of Returns *(Source: S&P)*.
Sampling period: Daily 4/30/2010 - 4/29/2015



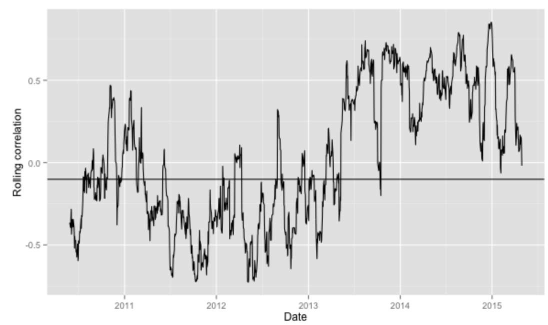

Returns^2= Squares of returns; abs(Returns)= Absolute values of returns.

GB=Green bond index; GPB=Green project bond index; AB=U.S. aggregate bond index.

Figure 2.5: Rolling covariance and rolling correlation between GB and AB indices, 4/30/2010 - 4/29/2015 *(Source: S&P)*



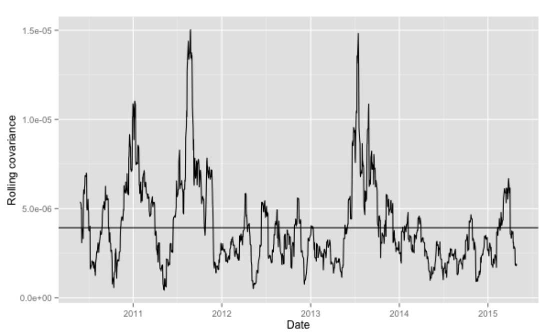

(a) Rolling covariance



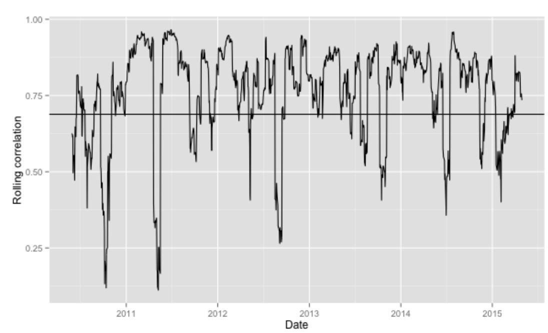

(b) Rolling correlation

GB=Green bond index; GPB=Green project bond index; AB=U.S. aggregate bond index.
The straight line is the unconditional covariance/ correlation between the two series.
Sampling period: Daily 4/30/2010 - 4/29/2015

Figure 2.6: Rolling covariance and rolling correlation between GPB and AB indices, 4/30/2010 - 4/29/2015 *(Source: S&P)*




(a) Rolling covariance




(b) Rolling correaltion

GB=Green bond index; GPB=Green project bond index; AB=U.S. aggregate bond index.
The straight line is the unconditional covariance/ correlation between the two series.
Sampling period: Daily 4/30/2010 - 4/29/2015

## 2.5 Results and Discussion

### 2.5.1 Preliminary tests

To test the validity of the GARCH models discussed in Section 2.3 given the available data, I first run a Box-Ljung test on the squared index returns. The Box-Ljung test is often used to test the independence of a given time series, where the null hypothesis is that there is no serial correlation within the series. Results from this test on squared index returns (Table 2.3) reject the null hypothesis of no serial correlation, thereby validating the existence of volatility clustering effect in the data where current volatility depends on the magnitudes of volatility in past periods. Moreover, I also found that positive and negative shocks have similar impacts on the volatility of the data, therefore, it is not necessary to incorporate a measure for the asymmetric leverage effects into the GARCH framework in Section 2.3. [13] Finally, the Schwartz information criteria suggests that the return equations (2.1), (2.4), (2.5) are best described by excluding all the lagged values (i.e. $r = r_M = r_G = s = 0$) and the volatility equations (2.3), (2.7), (2.8) are best described by a GARCH(1,1) process (i.e. $p = p_M = p_G = q = q_M = q_G = 1$).

Table 2.3: Box-Ljung Test of Squared Returns

| | GB Returns | GPB Returns | AB Returns |
|---|---|---|---|
| Q-statistic | 380*** | 17* | 350*** |

GB=Green bond index
GPB=Green project bond index
AB=U.S. aggregate bond index
* p-value < 10%, ** p-value < 5%, *** p-value < 1%.

[13] Appendix B-1 discusses the methodology used to test for asymmetric leverage effects of a time series.

### 2.5.2 Univariate GARCH empirical results

The preliminary test results suggest that we can reduce the univariate GARCH model in Section 2.3 to the following set of equations:

$$R_t = E_{t-1}[R_t] + \epsilon_t, \qquad \epsilon_t | I_{t-1} \sim iid(0, \sigma_t^2) \tag{2.10}$$

$$E_{t-1}[R_t] = \mu \tag{2.11}$$

$$\sigma_t^2 = a_0 + a_1\epsilon_{t-1}^2 + b_1\sigma_{t-1}^2, \qquad a_0 > 0; \quad a_1 > 0; \quad b_1 > 0 \tag{2.12}$$

Table 2.4 shows the estimated parameters of the univariate GARCH model for the two green bond return series (Green Bond Index (GB) and Green Project Bond Index (GPB)) as well as their market benchmark (U.S. Aggregate Bond Index (AB)). Figure 2.7 plots the conditional standard deviation of the three time series based on the univariate GARCH estimates.

Compared to the U.S. Aggregate Bond Index, the "labeled" segment of the green bond market, which is characterized by the Green Bond Index, tends to exhibit higher level of volatility clustering. The estimates for the ARCH/GARCH parameters $a_1$ and $b_1$ are higher for the Green Bond Index returns than for the U.S. Aggregate Bond Index. In fact, it takes 258.6 days for a shock to the Green Bond Index to reduce its impact by 50%. On the other hand, the half-life of a shock to the U.S. Aggregate Bond Index is only 68.3 days. Moreover, the conditional standard deviation for the Green Bond Index is higher and more volatile than the conditional standard deviation for the U.S. Aggregate Bond Index. As can be seen on figure 2.7, the conditional standard deviation of the Green Bond Index ranges between 0.00200 and 0.01120 over the sampling period, while the conditional standard deviation of the U.S. Aggregate Bond Index ranges between 0.00130 and 0.00390 over the same period.

The pattern of volatility clustering seems to lower significantly once we incorporate the "unlabeled" green bond market segment into the model, as illustrated by the empirical results for the Green Project Bond Index (Column (2) of Table 2.4). In fact, it only takes 34.41 days for a shock to the Green Project Bond Index to reduce its impacts by 50%, which is a significant decline compared to a half-life of 258.6 days for the Green Bond Index. Moreover, the conditional standard deviation of the Green Project Bond Index returns ranges between 0.00201 and 0.00457 (figure 2.7), which is much lower than that for the Green Bond Index. A possible explanation for the lower volatility clustering in the Green Project Bond Index return relies on the fact that there is more diversity in the bond portfolio used to calculate the Green Project Bond Index, which include both investment-grade- and subinvestment-grade- bonds (Kochetygova and Jauhari, 2014). As a result, there are lower correlations among the bonds within the Green Project Bond Index, thus reducing the magnitude of volatility clustering in the Green Project Bond Index compared to the Green Bond Index. Under this univariate GARCH framework, the unconditional average index return ($\mu$) is also the highest for the Green Project Bond Index, which is consistent with the descriptive statistics presented in Section 3.3.

In addition to the analysis using raw data on the bond indices' returns, I also exclude all outliers in the estimates to account for the potentially high sensitivity of volatility measures to extreme observations or outliers.[14] This will provide a more robust and stable estimation of the model parameters. Table 2.5 and figure 2.9, which summarize the results of the estimation with the outlier-free data, show that the main results still hold even after we exclude outliers from the analysis.

[14] I used the methodology specified in Khan et al. (2007) and Boudt et al. (2008) to clean the dataset from outliers. Under this approach, all observations are first ranked by their extremeness, which is measured by their squared Mahalanobis distance from the mean and variance. Then any observation with an estimated squared Mahalanobis distance greater than the 99.9% quantile will be identified as an outlier. Under this approach, the number of extreme values is 14 for both the Green Bond index and the Green Project Bond index, while the U.S. Aggregate Bond Index contains 9 extreme values. Figures 2.8 show the comparison between the raw data with outliers and the cleaned data that are outlier free.

Table 2.4: Univariate Volatility Modelling - GARCH(1,1)

| | (1) GB Returns | (2) GPB Returns | (3) AB Returns |
|---|---|---|---|
| $\mu$ | 0.00003 | 0.0004*** | 0.0001** |
| | (0.00010) | (0.0001) | (0.0000) |
| $a_0$ | 0.00000008*** | 0.00000015*** | 0.00000004** |
| | (0.00000004) | (0.0000000) | (0.000000002) |
| $a_1$ | 0.0510*** | 0.0328*** | 0.0483*** |
| | (0.0087) | (0.0080) | (0.0116) |
| $b_1$ | 0.9463*** | 0.9473*** | 0.9416*** |
| | (0.0084) | (0.0110) | (0.0144) |
| Unconditional mean in mean equation ($\mu$) | 0.00003 | 0.00035 | 0.00013 |
| Persistence ($a_1 + b_1$) | 0.9973 | 0.9801 | 0.9899 |
| Unconditional variance ($a_0/(a_1 + b_1)$) | 0.00000008 | 0.00000015 | 0.00000004 |
| Half-life (days) ($\ln(0.5)/\ln(a_1 + b_1)$) | 258.6 | 34.41 | 68.3 |

* p-value < 10%, ** p-value < 5%, *** p-value < 1%.

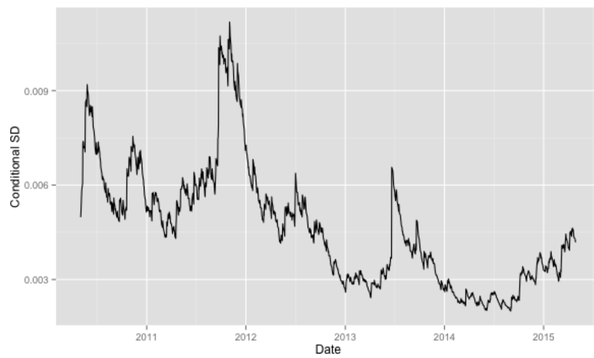
Numbers in parentheses are standard errors

GB=Green bond index

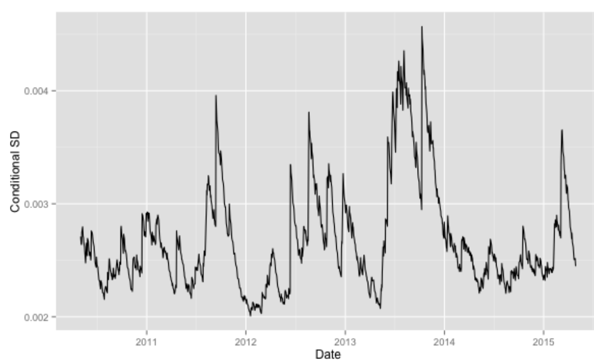
GPB=Green project bond index

AB=U.S. aggregate bond index

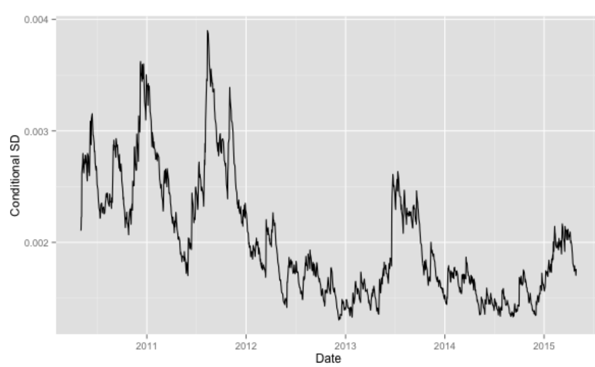
Figure 2.7: Conditional standard deviation ($\sigma_t$)
Model: Univariate GARCH (1,1)
Variables: GB, GPB and AB
Sampling period: Daily 4/30/2010 - 4/29/2015




(a) Green bond index (GB)

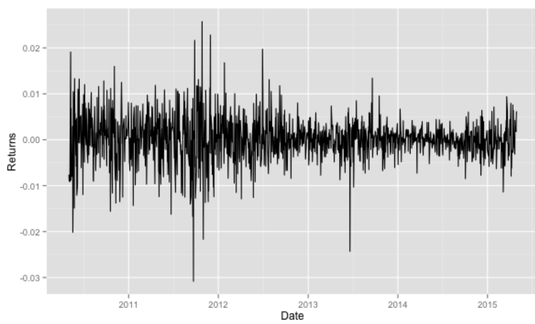



(b) Green project bond index (GPB)

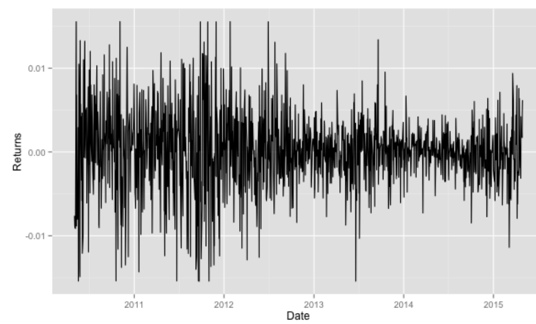



(c) U.S. aggregate bond index (AB)

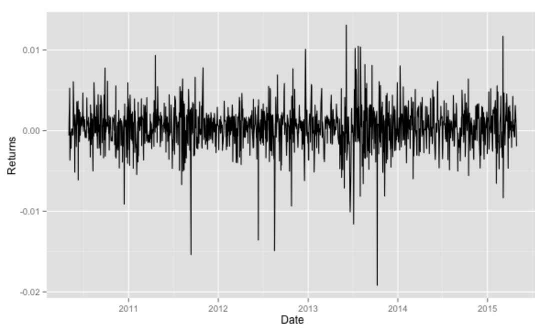
Figure 2.8: Comparison of daily returns with and without outliers, 4/30/2010 - 4/29/2015 *(Source: S&P)*



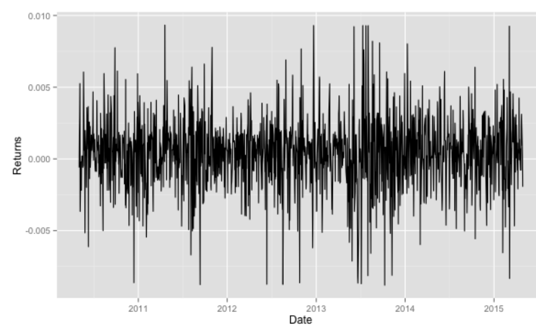

(a) GB index returns with outliers



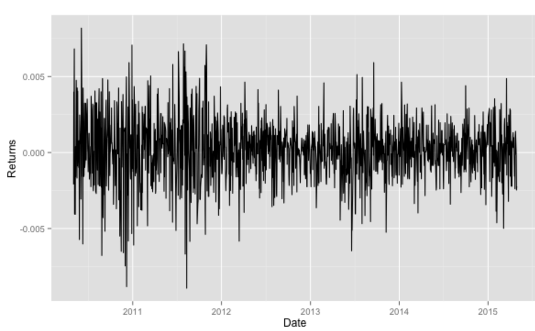

(b) GB index returns without outliers



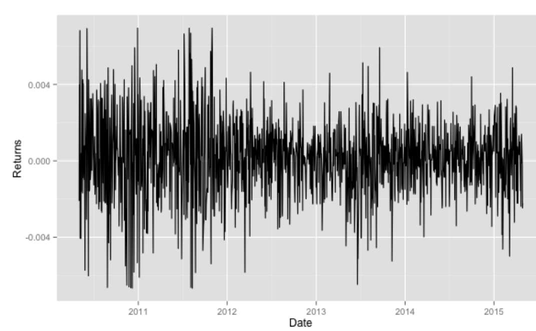

(c) GPB index returns with outliers




(d) GPB index returns without outliers




(e) AB index returns with outliers




(f) AB index returns without outliers

GB=Green Bond; GPB=Green Project Bond; AB=U.S. Aggregate Bond

Sampling period: Daily 4/30/2010 - 4/29/2015

Table 2.5: Univariate Volatility Modelling - GARCH(1,1) with outlier-free data

| | (1) GB Returns | (2) GPB Returns | (3) AB Returns |
|---|---|---|---|
| $\mu$ | 0.00003 | 0.00037*** | 0.00013*** |
| | (0.00009) | (0.00007) | (0.00005) |
| $a_0$ | 0.00000006** | 0.00000020*** | 0.00000004** |
| | (0.00000002) | (0.00000008) | (0.000000002)) |
| $a_1$ | 0.0423*** | 0.0463*** | 0.0453*** |
| | (0.0075) | (0.0129) | (0.0109) |
| $b_1$ | 0.9547*** | 0.9227*** | 0.9452*** |
| | (0.0074) | (0.0218) | (0.0137) |
| Unconditional mean in mean equation ($\mu$) | 0.00003 | 0.00037 | 0.00013 |
| Persistence ($a_1 + b_1$) | 0.9971 | 0.9691 | 0.9905 |
| Unconditional variance ($a_0/(a_1 + b_1)$) | 0.00000006 | 0.00000021 | 0.00000004 |
| Half-life (days) ($\ln(0.5)/\ln(a_1 + b_1)$) | 239.4 | 22.09 | 72.54 |

* p-value < 10%, ** p-value < 5%, *** p-value < 1%.

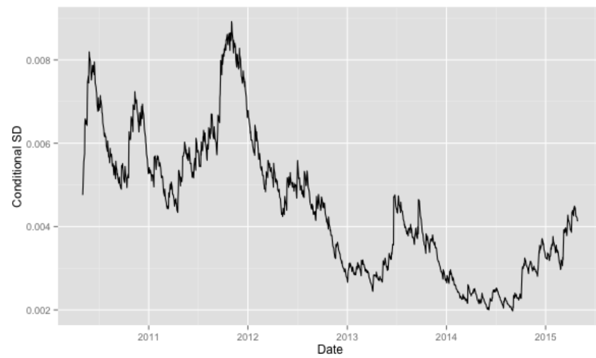
Numbers in parentheses are standard errors

GB=Green bond index

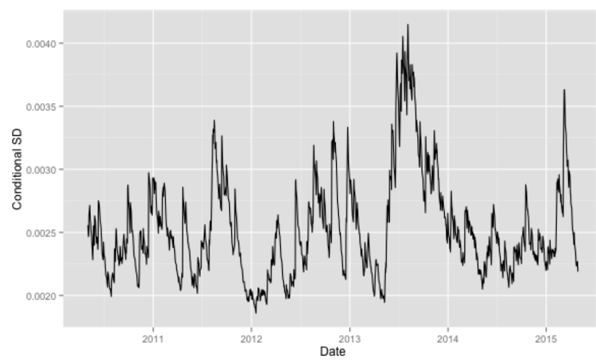
GPB=Green project bond index

AB=U.S. aggregate bond index

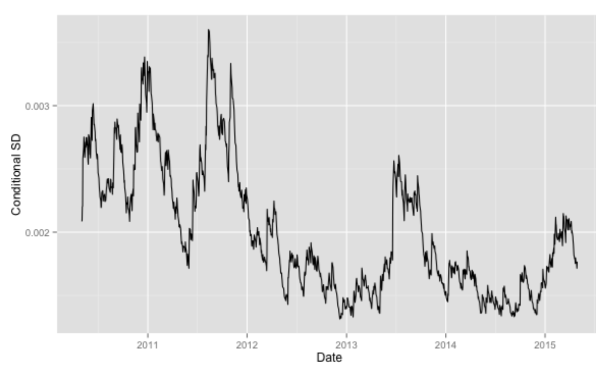
Figure 2.9: Conditional standard deviation ($\sigma_t$)
Model: Univariate GARCH (1,1)
Variables: GB, GPB and AB without outliers
Sampling period: Daily 4/30/2010 - 4/29/2015




(a) Green bond index (GB)




(b) Green project bond index (GPB)




(c) U.S. aggregate bond index (AB)

### 2.5.3 Multivariate GARCH empirical results

While the univariate GARCH framework above can capture the pattern of volatility clustering for a single time series, it fails to capture the potential volatility spillover from one time series to another. In fact, Figure 2.7 shows that there are comovements between the green bond market volatility (as characterized by the Green Bond and Green Project Bond Index) and the conventional bond market volatility (as characterized by the U.S. Aggregate Bond Index). Therefore, it is appropriate to analyze the volatility movement of the green bond market in relation with that of the conventional bond market in a multivariate setting. In this section, I present the empirical results of the bivariate GARCH model with two variables: a green bond market index and a conventional bond market index. In this setting, the index for the green bond market is either the Green Project Bond Index or the Green Project Bond Index while the benchmark market index is the U.S. Aggregate Bond Index. The conditional standard deviations for each individual series and the conditional correlations among the series are estimated using the Dynamic Conditional Correlation (DCC) model proposed by Engle (2002). Compared to other models, this model's flexibility in modeling time-varying conditional correlations has clear computational advantages as it allows for the estimation of very large correlation matrices.

According to the preliminary test results, we can reduce the bivariate GARCH model in Section 2.3 to the following set of equations:

$$R_{Gt} = \mu_G + \epsilon_{Gt} \tag{2.13}$$

$$R_{Mt} = \mu_M + \epsilon_{Mt} \tag{2.14}$$

$$\epsilon_t | I_{t-1} = \begin{bmatrix} \epsilon_{Gt} \\ \epsilon_{Mt} \end{bmatrix} | I_{t-1} \sim WN(0, \Sigma_t) \tag{2.15}$$

$$\Sigma_t = D_t R_t D_t; \quad R_t = \begin{bmatrix} 1 & \rho_{GMt} \\ \rho_{MGt} & 1 \end{bmatrix}; \quad D_t = \begin{bmatrix} \sigma_{Gt} & 0 \\ 0 & \sigma_{Mt} \end{bmatrix} \tag{2.16}$$

$$\sigma^2_{Gt} = a_{0G} + a_{1G}\epsilon^2_{Gt-1} + b_{1G}\sigma^2_{Gt-1} \tag{2.17}$$

$$\sigma^2_{Mt} = a_{0M} + a_{1M}\epsilon^2_{Mt-1} + b_{1M}\sigma^2_{Mt-1} \tag{2.18}$$

$$\hat{q}_{ijt} = Cov(\hat{z}_{it}, \hat{z}_{jt} | I_{t-1}) = \hat{E}[\hat{z}_{it}\hat{z}_{jt}](1 - \alpha - \beta) + \alpha\hat{z}_{it-1}\hat{z}_{jt-1} + \beta\hat{q}_{ijt-1}, \quad i, j = G, M \tag{2.19}$$

where $\hat{z}_{it} = \frac{\hat{\epsilon}_{it}}{\hat{\sigma}_{it}}$ $(i = G, M)$ is the standardized residuals is calculated from the GARCH models in equations (2.17) and (2.18).[15]

Table 2.6 summarizes the results of the bivariate GARCH modeling for the green bond market. Specifically, Column (1) of the table shows the results of a bivariate GARCH model for the returns of the labeled green bond market (as captured by the Green Bond Index) and the conventional bond market (as captured by the Green Project Bond Index). On the other hand, Column (2) of the table shows the results of the same model for the returns of the unlabeled green bond market

[15] As one reviewer pointed out, one concern with using the bivariate GARCH model is the amount of overlap in assets between the green bond indices and the U.S. Aggregate Bond Index. In this case, the overlap in assets between the Green Bond Index and the Green Project Bond Index will not affect the results, because the two indices are used in two separate estimates of the above bivariate GARCH model. The overlap of assets between the green bond indices and the U.S. Aggregate Bond Index doesn't affect the analysis of the bivariate GARCH model since the empirical results are consistent between the univariate and the bivariate GARCH models, as shown in the subsequent discussion of the results. Moreover, the amount of overlap in assets between the green bond indices and other bond indices that are not sustainability-themed is small, since the green bond indices are used to track a very specialized and small portion of the bond market. In 2015, total "labeled" and "unlabeled" green bond outstanding was USD 65.9 billion and USD 531.8 billion respectively, which represents less than 1% of the total value outstanding of the overall bond market (World Bank, 2015c).

(as captured by the Green Project Bond Index) and the conventional bond market. Overall, the labeled sector of the green bond market exhibit large volatility clustering compared to the unlabeled green bond sector and the conventional bond market. Figures 2.10a and 2.10b show the estimates of the conditional standard deviation of the Green Bond Index relative to the U.S. Aggregate Bond Index while Figures 2.11a and 2.11b show the estimates of the conditional standard deviation of the Green Project Bond Index relative to the U.S. Aggregate Bond Index. It can be seen from the figures that the conditional standard deviation of the Green Project Bond Index is lower than that of the conventional bond market while the conditional standard deviation of the Green Bond Index tends to be higher than that of the conventional bond market. This is consistent with the results obtained from the previous univariate GARCH model.

Moreover, the bivariate GARCH model also suggests that there exists volatility spillover between the green bond market and the overall fixed-income market since the parameters $\alpha$ and $\beta$ are both positive and statistically significant. This provides evidence for the existence of a non-constant interaction between the green bond indices and the market benchmark index with respect to conditional correlation. Figure 2.10c shows the conditional correlation between the Green Bond Index and the market benchmark index while Figure 2.11c shows the conditional correlation between the Green Project Bond Index and the market benchmark index. The figures show that there are increasing correlations between the Green Bond Index and the market benchmark over time while there is no clear pattern of correlations between the Green Project Bond Index and the market benchmark. However, on average, both the Green Bond Index and the Green Project Bond Index are positively correlated with the market benchmark (i.e. the U.S. Aggregate Bond Index). This is explained by the fact that besides the use of proceeds towards environmentally friendly projects, green bonds are no different from conventional bonds and are often priced very close to regular bonds (World Bank, 2015c).

To account for the potential impacts of extreme observations on the robustness of the results, I also repeat the above empirical analysis after cleaning the data from all outliers. Table 2.7 shows the estimation result of the multivariate GARCH model after accounting for outliers in the data and figures 2.12 and 2.13 show the conditional standard deviation and conditional correlation of the two green bond indices in comparison with the benchmark U.S. Aggregate Bond index. Overall, the main empirical results above still hold even after controlling for the impacts of outliers.

Table 2.6: Bivariate volatility modeling - DCC M-GARCH(1,1)

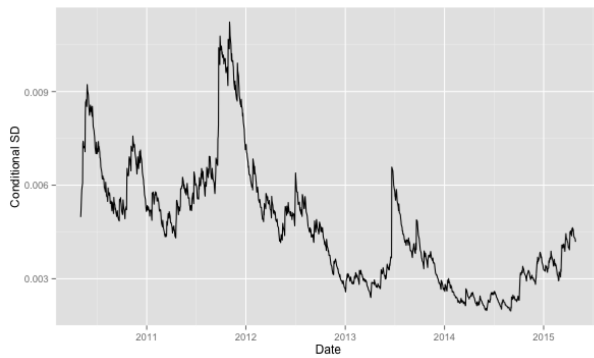
| | (1) Green bond index = GB | (2) Green bond index = GPB |
|---|---|---|
| Parameter estimates for the green bond market index: | | |
| $\mu_G$ | 0.000035 | 0.000367*** |
| | (0.000101) | (0.000073) |
| $a_{0G}$ | 0.000000 | 0.000000 |
| | (0.000003) | (0.000000) |
| $a_{1G}$ | 0.051400 | 0.028907*** |
| | (0.068685) | (0.008305 ) |
| $b_{1G}$ | 0.946498*** | 0.955050*** |
| | (0.064320) | (0.008399) |
| Parameter estimates for the benchmark conventional bond market (AB) | | |
| $\mu_M$ | 0.000139*** | 0.000139*** |
| | (0.000050) | (0.000051) |
| $a_M$ | 0.000000 | 0.000000 |
| | (0.000002) | (0.000002) |
| $a_{1M}$ | 0.044203 | 0.044203 |
| | (0.080317) | (0.080279) |
| $b_{1M}$ | 0.949094*** | 0.949094*** |
| | (0.077196 ) | (0.077158) |
| Estimates for the conditional correlation parameters | | |
| $\alpha$ | 0.022922*** | 0.000000 |
| | (0.005019) | (0.000006) |
| $\beta$ | 0.975484*** | 0.908743*** |
| | (0.005770) | (0.115694) |

* p-value < 10%, ** p-value < 5%, *** p-value < 1%.

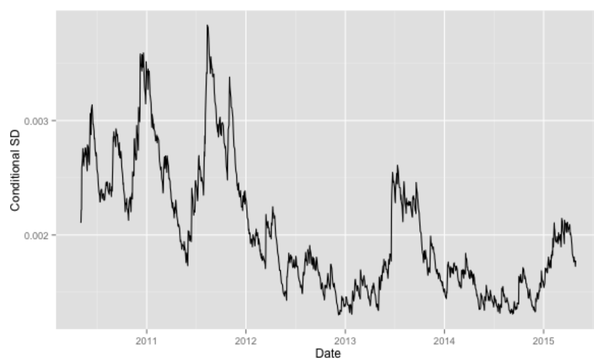
Numbers in parentheses are standard errors.

GB= Green bond index; GPB=Green Project Bond Index, AB=U.S. aggregate bond index.

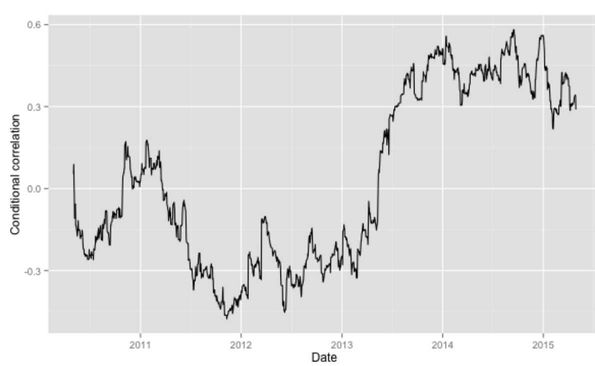
Figure 2.10: Conditional standard deviation and conditional correlation
Model: Bivariate DCC M-GARCH(1,1)
Variables: Green Bond Index (GB) and Aggregate Bond Index (AB)
Sampling period: Daily 4/30/2010 - 4/29/2015




(a) GB's conditional standard deviation

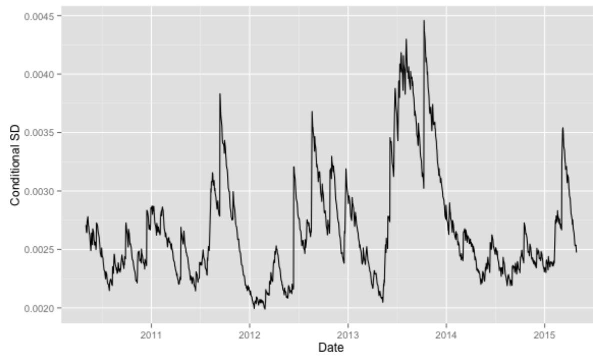



(b) AB's conditional standard deviation

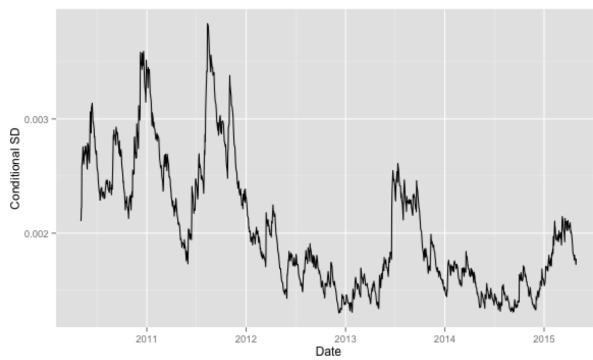



(c) GB-AB conditional correlation

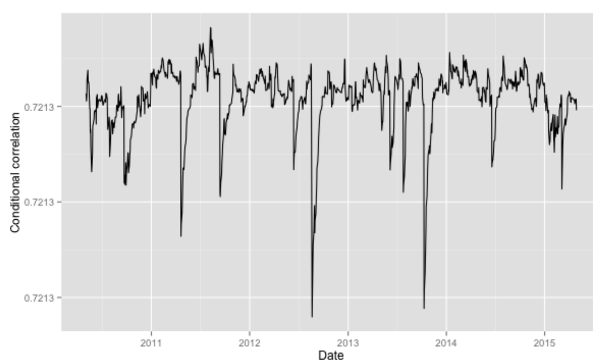
Figure 2.11: Conditional standard deviation and conditional correlation
Model: Bivariate DCC M-GARCH(1,1)
Variables: Green Project Bond Index (GPB) and Aggregate Bond Index (AB)
Sampling period: Daily 4/30/2010 - 4/29/2015




(a) GPB's conditional standard deviation




(b) AB's conditional standard deviation




(c) GPB-AB conditional correlation

Table 2.7: Bivariate volatility modeling - DCC M-GARCH(1,1) with outlier-free data

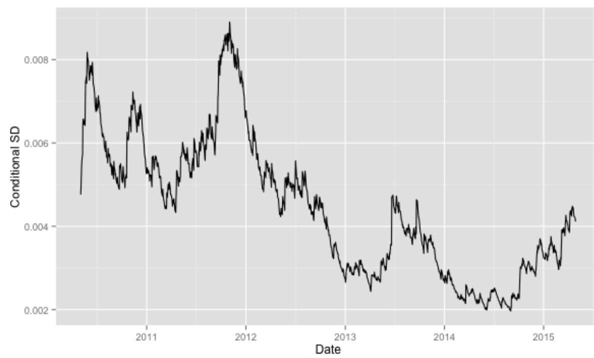
| | (1)<br>Green bond index = GB | (2)<br>Green bond index = GPB |
|---|---|---|
| Parameter estimates for the green bond market index: | | |
| $\mu_G$ | 0.000033 | 0.000367*** |
| | (0.000099) | (0.000073) |
| $a_{0G}$ | 0.000000 | 0.000000 |
| | (0.000001) | (0.000000) |
| $a_{1G}$ | 0.042206* | 0.028907*** |
| | (0.022859) | (0.008305 ) |
| $b_{1G}$ | 0.954773*** | 0.955050*** |
| | (0.021098) | (0.008399) |
| Parameter estimates for the benchmark conventional bond market (AB) | | |
| $\mu_M$ | 0.000128** | 0.000128** |
| | (0.000052) | (0.000052) |
| $a_{0M}$ | 0.000000 | 0.000000 |
| | (0.000007) | (0.000007) |
| $a_{1M}$ | 0.042728 | 0.042728 |
| | (0.210421) | (0.210348) |
| $b_{1M}$ | 0.950570*** | 0.950570*** |
| | ( 0.201990 ) | (0.201920) |
| Estimates for the conditional correlation parameters | | |
| $\alpha$ | 0.022333*** | 0.000000 |
| | (0.004981 ) | (0.000002) |
| $\beta$ | 0.975925*** | 0.908478*** |
| | (0.005722) | (0.117834) |

* p-value < 10%, ** p-value < 5%, *** p-value < 1%.

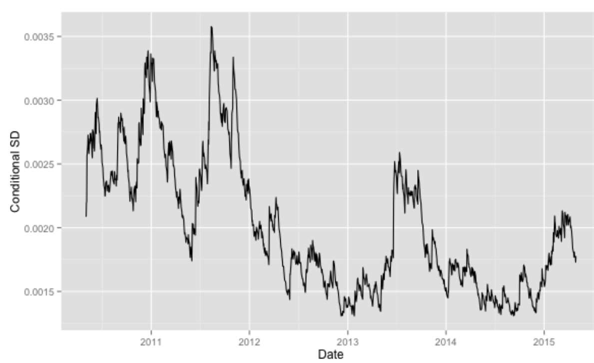
Numbers in parentheses are standard errors.

GB= Green bond index; GPB=Green Project Bond Index, AB=U.S. aggregate bond index.

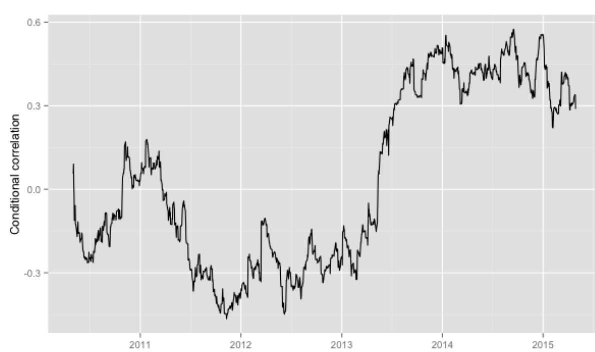
Figure 2.12: Conditional standard deviation and conditional correlation
Model: Bivariate DCC M-GARCH(1,1)
Variables: Green Bond Index (GB) and Aggregate Bond Index (AB) without outliers
Sampling period: Daily 4/30/2010 - 4/29/2015




(a) GB's conditional standard deviation

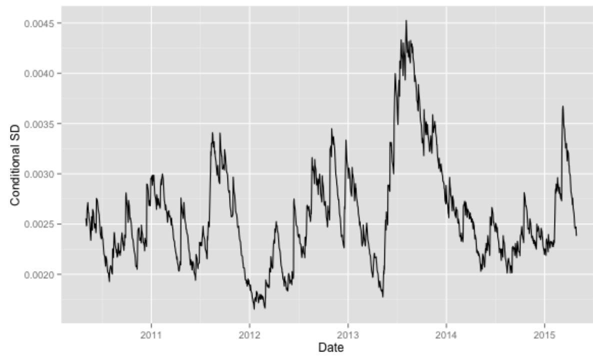



(b) AB's conditional standard deviation

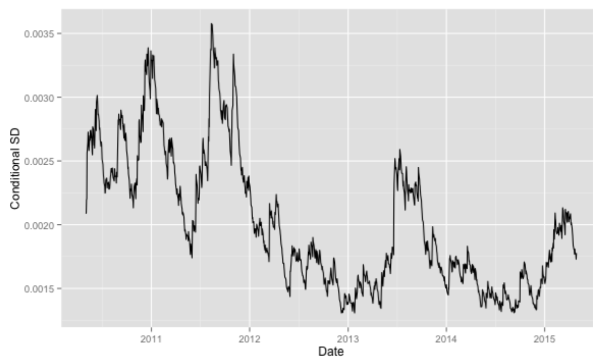



(c) GB-AB conditional correlation

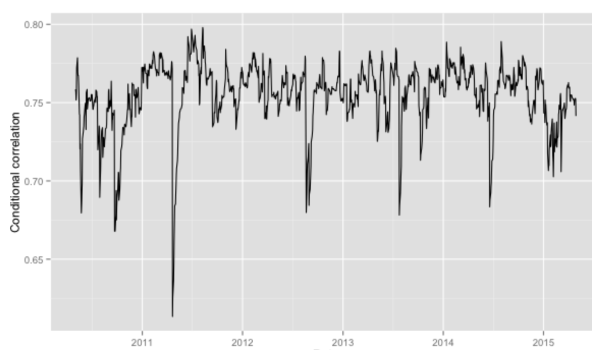
Figure 2.13: Conditional standard deviation and conditional correlation
Model: Bivariate DCC M-GARCH(1,1)
Variables: Green Project Bond Index (GPB) and Aggregate Bond Index (AB) without outliers
Sampling period: Daily 4/30/2010 - 4/29/2015




(a) GPB's conditional standard deviation




(b) AB's conditional standard deviation




(c) GPB-AB conditional correlation

**Using the MGARCH model to construct a hedge ratio between the green bond index and the market benchmark index**

The above estimates of the multivariate GARCH model can be used to construct hedge ratios. Following Kroner and Sultan (1993), the hedge ratio between the green bond index $G$ and the bond market benchmark index $M$ at time $t$ is:

$$\beta_{GMt} = \frac{\sigma_{GMt}}{\sigma^2_{Mt}} \tag{2.20}$$

where $\sigma_{GMt}$ denotes the covariance between the green bond index and the benchmark index at time $t$ and $\sigma^2_{Mt}$ denotes the variance of the benchmark index at time $t$. A positive hedge ratio $\beta_{GMt}$ shows the extent to which a long position in the green bond market can be hedged by a short position in the overall conventional bond market. On the other hand, a negative hedge ratio shows the extent to which a short position in the green bond market can hedge by a long position in the overall conventional bond market.

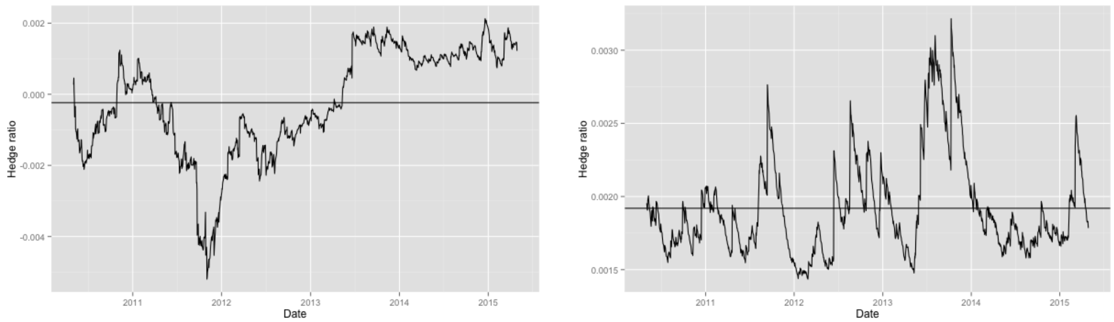
Figure 2.14 and 2.15 show the time-varying hedge ratio between the two green bond indices (the Green Bond Index and the Green Project Bond Index) and the U.S. Aggregate Bond Index while table 2.8 provides a summary of the hedge ratios. As can be seen on the figures and table, the estimated hedge ratios exhibit a lot of variability, which reflects the non-constant interaction of volatility between the green bond market and the overall broader bond market.

Table 2.8: Summary of the estimated hedge ratios

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| GB-AB (with outliers) | -0.00024 | 0.00152 | -0.00520 | 0.00212 |
| GPB-AB (with outliers) | 0.00192 | 0.00033 | 0.00144 | 0.00322 |
| GB-AB (without outliers) | -0.00019 | 0.00139 | -0.00398 | 0.00203 |
| GPB-AB (without outliers) | 0.00189 | 0.00031 | 0.00137 | 0.00309 |

GB=Green Bond Index; GPB=Green Project Bond Index; AB=U.S. Aggregate Bond Index.

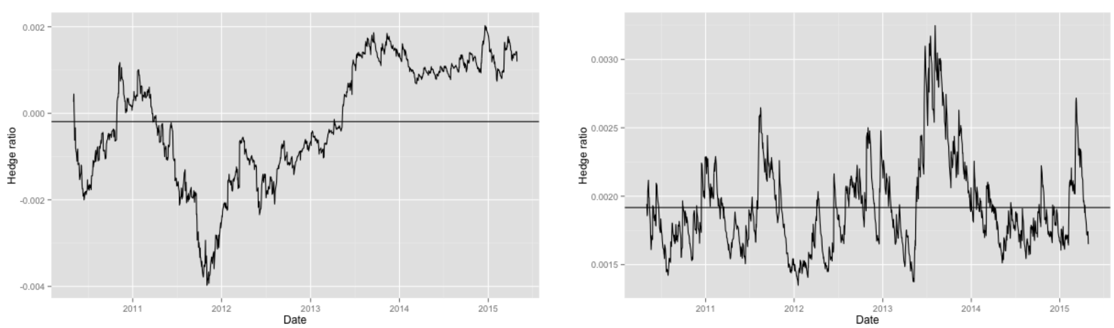
Figure 2.14: Hedge ratio computed from the bivariate GARCH model with outliers




(a) GB-AB (b) GPB-AB

GB=Green Bond Index; GPB=Green Project Bond Index; AB=U.S. Aggregate Bond Index.
The horizontal line in each graph indicates the average hedge ratio.
Sampling period: Daily 4/30/2010 - 4/29/2015

Figure 2.15: Hedge ratio computed from the bivariate GARCH model without outliers




(a) GB-AB (b) GPB-AB

GB=Green Bond Index; GPB=Green Project Bond Index; AB=U.S. Aggregate Bond Index.
The horizontal line in each graph indicates the average hedge ratio.
Sampling period: Daily 4/30/2010 - 4/29/2015

## 2.6 Conclusion

With the growing awareness of environmental issues among investors and the general public, the urge to mobilize the global debt market as a low-cost financing instrument for a green economy has been stronger than ever. The development of green bonds and other environmentally friendly investments offer a mechanism to promote investments that can both economically and environmentally sound. This paper is the first to study the volatility behavior of the green bond market in relation with the broader conventional bond market in the hope to provide investors with extra insight into this new, yet promising market. The paper utilizes data on the daily closing prices of the S&P Green Bond Index, Green Project Bond Index and U.S. Aggregate Bond Index between 4/30/2010 and 4/29/2015 and analyzes their volatility under both a univariate and multivariate GARCH framework. Overall, both the univariate and multivariate models suggest that there exists volatility clustering within each individual index and the multivariate model suggests that there are also evidence for time-varying volatility spillover between the green bond market and the conventional bond market, where both the “labeled” and “unlabeled” segments of the green bond market are positively correlated with the conventional bond market. These results are robust even after accounting for the impacts of extreme values in the data.

The paper has several implications for investors as well as policymakers. First, the estimation results can be used to construct the optimal risk-minimizing portfolio mix between green bonds and conventional bonds. However, the variability in the estimated hedge ratios between the green bond market and the conventional bond market indicates that the optimal portfolio mix requires frequent updating. Second, the results also show that there was an increase in the correlation between the “labeled” green bond market and the conventional bond market, indicating a convergence of returns between the the “labeled” green bond market and the conventional bond market. Therefore, as the green bond market continues to grow, it is important to introduce stronger differentiation strategies between green bonds and conventional bonds in order to attract a broader pool of investors. Finally, policies aimed at standardizing the certification process of green bonds and increasing investors’ awareness can allow the green bond market to reach a broader group of investors.

The analysis in this paper provides several suggestions for future research. First, the analysis could benefit from using a longer time series in the future to reflect the behavior of green bonds during a full business cycle. Second, it would be interesting to investigate the role of green bonds in mitigating climate or environmental risk and the relationship of green bonds with other financial markets, such as energy markets and equity markets. Third, depending on data availability, future research could study how the behavior of green bonds changes with changes in types and locations of issuers. Finally, a more complete understanding of the environmental impacts of the projects funded by green bonds would play an important role in fostering the growth of this new market.

# Chapter 3

# Do Fossil fuel Taxes Promote Innovation in Renewable Electricity Generation?

## 3.1 Introduction

The combustion of fossil fuels to generate electricity is the largest single emitter of carbon worldwide. In 2014, 70% of global electricity production came from fossil fuels such as coal, natural gas, and oil, making up 40% of global carbon emissions. In the U.S. only, electricity generation accounts for 37% of total carbon emissions and 31% of total greenhouse gas emissions (International Energy Agency, 2015b). With increasing concerns over climate change, many economists argue in favor of decarbonizing the electricity sector through higher use of less carbon-intensive technologies such as solar, wind, and other clean technologies.[1] For decades, an increasing number of private research firms have been competing for new technological breakthroughs to minimize the human carbon footprint. In addition, for at least three decades, governments throughout the world have implemented policies to promote the invention of both efficiency-improving fossil fuel technologies and technologies utilizing renewable energy.[2] In particular, there are two types of environmental policies that economists favor: subsidies to promote cleaner technologies and taxes to internalize

[1]While these technologies are commercially available, renewable energy still represents a modest share in global electricity production. According to the World Development Indicators, 21.5% of the world's total electricity generation comes from renewable sources, whereas only 5.4% comes from non-hydro renewable sources (see Table 3.1).

[2]According to the International Energy Agency (IEA), global subsidies for renewable energy totaled $112 billion in 2014 while fossil fuel subsidies totaled $493 billion (International Energy Agency, 2015e).

the environmental costs of burning fossil fuels.[3,4] While these efforts have resulted in a range of technological innovations, it is unclear whether there has been a shift in innovation efforts towards cleaner technologies. In this paper, we explore the role of environmental regulations, specifically fossil fuel taxes, in shifting innovation from fossil fuel to renewable energy.

In particular, we ask the following questions. First, are fossil fuel taxes successful at promoting innovation in renewable technologies in the electricity sector? Second, how effective are research subsidies in shaping global innovation in the electricity sector? Finally, what other factors shift innovation in the electricity sector towards renewable technologies? To answer these questions, we estimate a directed technological change model using global firm-level electricity patent data from 1978 to 2011. Past work has focused on the aggregate impact of all energy prices in fossil fuel and renewable technologies. In contrast, we take a different approach and distinguish fuels used in power generation (e.g., coal, natural gas, and oil) and technologies used for electricity generation (e.g., coal-fired plants, gas plants, solar power plants).[5] By doing so, we identify specific taxes that encourage and discourage renewable energy innovation.

The directed technological change (DTC) framework of Acemoglu et al. (2012, 2016) guides our empirical analysis. These and other DTC models predict that energy prices, taxes, subsidies and past innovation activity affect technological advancements, and that these effects depend on the elasticity of substitution between fossil fuels and renewable energy. Specifically, when fossil fuel and renewable energy technologies are substitutes, higher fossil fuel prices can shift innovation towards

[3] See for example Acemoglu et al. (2012); Bovenberg and Smulders (1995, 1996); Goulder and Schneider (1999) for a rigorous characterization of the role of these policies in decarbonizing the economy.

[4] In addition to these two policies, there are other policies like feed-in tariffs and cap and trade that promote innovation. Since only some countries have implemented these policies and for a relatively short period of time, we do not quantify their effect in this study. However, we do control for these policies in our empirical analysis.

[5] The distinction among electricity generating technologies is important because some plants are used in base-load electricity generation while others are used in peak-load electricity generation. Base-load electricity refers to electricity generated from power stations that operate continuously and are available 24 hours a day. In contrast, peak-load power plants run only when demand for electricity is high, such as during summer afternoons when air conditioning loads are high (International Energy Agency, 2015d). In 2013, coal (41.1%), hydro (16.1%), and nuclear (10.6%) generated most global base-load power. Table 3.1 presents electricity production by source and region in 2013.

more renewable energy technologies. However, when they are complements, a higher fossil fuel price discourages innovation in renewable technologies. Empirical studies have presented evidence for a substitute relationship between fossil fuel and renewable technologies in the electricity sector (see, for example, Papageorgiou et al., 2016). While this may be true for aggregate measures of fossil fuel technologies, the substitution between different fossil fuel and renewable technologies in electricity generation varies with time and location. To capture this idiosyncrasy of the electricity market, we disaggregate fossil fuel prices and technologies between coal, natural gas, and oil instead of employing an aggregate measure for fossil fuel technologies that summarizes them into one composite index.

In the electricity grid, renewable energy technologies are imperfect substitutes for fossil fuel-burning technologies because they supply electricity intermittently (see, for example, Joskow, 2011). The intermittency issue of many renewable energy sources, especially wind turbines and solar power plants, makes them an unstable energy source for base-load power plants that supply electricity continuously without any interruption.[6] This suggests that as long as wind and solar energy cannot be efficiently stored for later use, they cannot replace coal from base-load electricity generation and they present an imperfect substitute for fossil fuels.[7] Thus, the supply of electricity from renewable sources must be complemented with easily dispatchable fossil fuels like coal. Then, as predicted by the directed technological change models, we should expect a higher coal price to discourage innovation in renewable technologies as well as coal-burning technologies. The main goal of our paper is to empirically test this hypothesis.

[6]Hydropower technology is an exception. According to the International Energy Agency (2015b), 16% of the world's total electricity generation comes from hydroelectric power plants. The most common plants store water in a reservoir and release water to create energy when electricity is needed, depending on water availability. Thus, hydroelectric plants have been able to dispatch electricity since the late 19th century. Unfortunately, large hydroelectric plants are concentrated geographically and hydroelectric capacity expansion is limited.

[7]Many argue in favor of electricity storage as the solution to the intermittency issue of renewable sources, but the cost of large-scale electricity storage is the biggest roadblock for its success. See Lazkano et al. (2016) for an analysis of the role of electricity storage in the transition from fossil fuels to renewable sources in electricity generation.

To empirically evaluate the above hypothesis, we first construct a unique firm-level panel data set where we use electricity patent application data to measure innovation. To mitigate the problem that many patents have low values, our empirical analysis focuses on "triadic" patents, which are series of patents filed at all three of the world's most important patent offices: the European Patent Office (EPO), the U.S. Patent and Trademark Office (USPTO), and the Japan Patent Office (JPO). We classify these patents into the following three groups: renewable energy, base-load fossil fuel, and peak-load fossil fuel patents. By separating fossil fuel patents into base- and peak-load technologies, we can infer about the heterogeneity in the elasticity of substitution between renewable energy and different types of fossil fuels. In addition to the main patent data, we collect data on coal, natural gas, and oil prices, research subsidies, and economic indicators. Altogether, our data set includes 13,054 firms across 26 countries between 1978 and 2011, which covers 96.20% of all triadic electricity patents globally (OECD, 2009).

Our estimation results find evidence for a mixed effect of fossil fuel prices in renewable energy innovation. First, an increase in the price of coal discourages innovation in renewable energy. The reason is that renewables rely of coal-fired plants to complement their supply to the grid. Specifically, a 10% increase in the price of coal is associated with 3.4% decrease in renewable energy innovation. In contrast, we find an insignificant impact of an increase in the price of natural gas on the firm-level likelihood of innovation in renewable energy. These results imply that a tax on coal and a carbon tax that increases the price of coal may create unintended effects by discouraging the development of renewable electricity-generating technologies. In addition to energy prices, we also find that research subsidies play a significant role in shifting the direction of innovation in the electricity sector. Our results show that, to effectively direct innovation in the electricity sector towards more renewable energy, a combination of renewable energy research subsidies and natural gas taxation is desired. On the other hand, excessive reliance on a coal tax may negatively affect renewable energy innovation because the need of base-load fossil fuels to complement renewable energy.

Our paper contributes to recent empirical literature that studies incentives for innovation in the energy sector (for example, Buonanno et al. (2003); Popp (2002, 2005)).[8] While the empirical evidence from this literature is extensive, previous work has mainly focused on documenting the factors that affect clean innovations rather than focusing on whether these factors can steer innovations away from fossil fuel technologies (Newell et al., 1999; Lanzi et al., 2011). In addition, many of these papers rely on country-level data as the basis for their analysis, and have therefore ignored the responses of innovations to different environmental policy regimes at the firm level (Popp, 2002, 2010).

Methodologically, our paper closely relates to Aghion et al. (2016), who focuses on the direction of technological innovation in the auto industry. The paper also relates to Noailly and Smeets (2015) who look at innovation in the electricity sector by focusing on European firms. However, our paper also differs from these previous studies in several aspects. First, Aghion et al. (2016) and Noailly and Smeets (2015) focus on capturing the aggregate impact of all energy prices using a composite fossil fuel price index; therefore, they are unable to separate the impact of different types of energy prices on innovation. We take a different approach and distinguish between the impact of coal and natural gas prices on innovation. By doing so, we identify the relationship between renewables and different types of fossil fuels that previous empirical work overlooked. Our results show that the effectiveness of fossil fuel-price regulations in fostering renewable energy innovation varies largely with the type of fossil fuel targeted by these regulations. At the current technology level, taxing coal may be harmful for renewable innovation in the electricity sector. In contrast, taxing natural gas may steer innovation in the electricity sector towards more renewable energy by

[8] See also Calel and Dechezleprêtre (2012); Dechezleprêtre and Glachant (2014); Gans (2012); Hassler et al. (2012). In addition, Fischer and Newell (2008); Nesta et al. (2014); Sanyal and Ghosh (2013); Klemetsen et al. (2016) focus on the effectiveness of environmental policies to promote renewable energy technologies.

lowering the firm-level incentive to innovate in fossil fuel technology. Second, our paper is the first to explore the global pattern of innovation in the electricity sector. This is important because as shown in Table 3.1, electricity generation by source varies considerably across the most innovative regions and therefore a regional account of innovation cannot be extended to offer solutions to curb emissions from global electricity generation.[9] Finally, we are able to highlight the importance of government policies in shifting the direction of innovation in the electricity sector, alongside market forces like firm-level past knowledge stocks, energy prices, and other macroeconomic factors.

The paper is organized as follows. Section 3.2 summarizes our theoretical hypotheses, Section 3.3 describes the construction of our data, and Section 3.4 specifies our identification strategy. Section 3.5 presents our empirical results and discusses their robustness and policy implications. Finally, Section 4.6 presents our conclusion.

## 3.2 Theoretical background: energy taxes and innovation in the electricity sector

In this section, we present theoretical predictions and testable hypotheses about the direction of innovation in the electricity sector. These predictions are based on the directed technological change framework by Acemoglu et al. (2012). Building on Acemoglu (2002); Acemoglu et al. (2012, 2016), we apply a directed technological change model to the electricity sector. Because our theoretical predictions are in line with previous work, we present our model in Appendix C-1 and restrict this section to the discussion of the idiosyncrasies of the electricity sector, theoretical predictions, and testable hypotheses.

[9] For example, Noailly and Smeets (2015) study electricity innovation among European firms, which covers only 38.07% of all electricity patents and uses fossil fuels to generate 50.6% of electricity. In contrast, the U.S. applies for most electricity generating patents and uses fossil fuels to generate 61,7% of electricity. Our data set includes firms that claim residence worldwide and covers 96.2% of all electricity patents globally (OECD, 2009). Figure C-1 shows that most firms are located in the U.S. and Japan, followed by Germany, France, and the U.K. and as shown in Table 3.1, electricity generation by sources differs considerably in these countries.

One distinguishing feature of electricity is that it needs to be consumed as soon as it is produced; therefore, it is important to immediately adjust electricity supply to meet changes in electricity demand to avoid blackouts or other problems. System operators resolve this issue by producing a base electricity load available 24 hours a day in order to meet the minimum demand for electricity. During times of high demand, such as during summer afternoons when air conditioning loads are high, peak electricity loads are added to meet excess demand. Thus, we can separate electricity-generating technologies in two groups: base- and peak-load technologies. There are many sources used to generate electricity with these technologies. Generally, coal and nuclear are used to produce base-load electricity, while hydroelectric sources are used for both base-load and peak-load electricity because it is cheap to switch them on and off. Natural gas used to meet peak electricity load but since a new supply of natural gas from shale formations is available, natural gas is used in both base and peak-load electricity. Renewable resources can potentially meet base-load electricity demand since once they are installed, the marginal cost of using them is zero. These examples show that many energy sources can be used in electricity generation but their use depends on regional electricity markets. Table 3.1 summarizes the sources of electricity generation by region. At the global level, fossil fuels are used to generate 66.4% of total electricity, followed by hydropower (16.1%) and nuclear (10.6%). Renewable resources excluding hydro comprise a modest share of total electricity generation. Because the expansion of hydroelectric and nuclear capacity is limited, many argue in favor of increasing the share of other renewable sources in the energy mix as a solution to curb emissions from burning fossil fuels. The expansion of renewables in the electricity grid, however, presents several technological challenges.

One such challenge is that some electricity-generating sources such as fossil fuels are easily dispatched to the grid, while others, such as renewables, are difficult to dispatch (Joskow, 2011). For example, wind and solar technologies can only be used when the wind is blowing or the sun

Table 3.1: Electricity production by source and region in 2013.

| Region | Production | Sources of electricity production (%) | | | | | |
|---|---|---|---|---|---|---|---|
| | | Fossil fuel | | | Renewable | | Nuclear |
| | | Coal | Natural gas | Oil | Hydropower | Other Ren. | |
| East Asia and Pacific | 8,427.9 | 62.1 | 13.4 | 2.2 | 13.8 | 3.7 | 3.6 |
| Europe and Central Asia | 5,305.3 | 25.0 | 24.3 | 1.3 | 16.9 | 9.5 | 21.9 |
| Latin America and Caribbean | 1,546.0 | 6.4 | 25.6 | 10.9 | 47.1 | 5.3 | 2.1 |
| Middle East and North Africa | 1,323.2 | 3.4 | 64.7 | 21.6 | 3.1 | 0.3 | 0.4 |
| North America | 4,940.8 | 36.0 | 24.8 | 0.9 | 13.4 | 5.8 | 18.7 |
| South Asia | 1,372.6 | 63.5 | 9.8 | 5.0 | 13.4 | 4.4 | 2.8 |
| Sub-Saharan Africa | 454.3 | 53.7 | 7.9 | 3.4 | 20.5 | 0.9 | 3.1 |
| **World** | 23,354.4 | 41.1 | 21.7 | 3.6 | 16.1 | 5.4 | 10.6 |

*Note*: Electricity production is measured in kilowatt hours (billions).
Source: World Development Indicators.

is shining, and in absence of large-scale electricity storage solutions, these technologies can only supply electricity to the grid intermittently. The high variability in the supply of electricity from renewable energy make them an unstable input for base-load electricity power stations that must run continuously. This implies three things. First, renewable energy technologies are imperfect substitutes for fossil fuel-burning technologies. Second, renewable energy is as of today unable to replace coal from base-load power stations. Finally, renewable electricity relies on coal-fired plants as a complement to meet the electricity demand.

While these idiosyncrasies are well understood, previous work has concentrated on studying the incentives to innovate as if renewable and fossil fuels were substitutes. Thus, this previous work has concluded that higher energy prices and taxes promote innovation in renewable technologies with the underlying assumption that renewable energy and fossil fuels are substitutes. Indeed, the empirical literature has included all fossil fuels into one composite price index and all fossil fuel technologies into one group. While the assumption of a high elasticity of substitution is appropriate for other sectors,[10] this assumption is not applicable to the electricity sector. In contrast, our goal in this paper is to analyze firm-level incentives to innovate in the electricity sector while taking into account that some electricity-generating technologies complement each other.

[10]For example, Aghion et al. (2016) study innovation in the automobile sector under this assumption.

Our theoretical model is a general equilibrium model with two types of agents: (i) utility-maximizing consumers who consume electricity and an aggregate consumption good, and (ii) profit-maximizing firms who are either electricity generators or electricity retailers. There are two types of electricity generators: renewable and nonrenewable. Renewable generators use renewable energy to produce electricity, while nonrenewable generators use fossil fuels. At the beginning of each period, both renewable and nonrenewable generators engage in research to develop new electricity-generating technologies, which are later used to produce electricity. Each generator is eligible for a research subsidy that lowers the cost of innovation. At the end of the period, electricity retailers purchase electricity from renewable and nonrenewable generators and resell it to the end consumers. All electricity generators and retailers take prices, subsidies and initial technologies as given.

We solve the above general equilibrium model to derive the equilibrium innovation intensity for both renewable and nonrenewable technologies and we present the detailed solution of the model in Appendix C-1. In line with prior work, our model shows that the equilibrium innovation intensity depends on research subsidies, energy prices, and firms' research history. Moreover, the impact of energy prices on innovation depends on the elasticity of substitution between fossil fuel and renewable energy technologies. When this elasticity of substitution is sufficiently high (i.e., when fossil fuels and renewable energy are easily substitutable in electricity production), then an increase in fossil fuel prices and taxes promote innovation in renewable technologies. In contrast, when fossil fuels and renewable energy are complements, increasing fossil fuel prices and taxes discourage innovation in renewable technologies.

From these theoretical predictions, we derive the following hypotheses:

**Hypothesis 1.** *A higher coal price negatively affects the development of both renewable and fossil fuel based base-load technologies.*

**Hypothesis 2.** *A higher natural gas price negatively affects both fossil fuel based base-load and* *peak-load innovation.*

In addition, in line with previous work, we expect research subsidies to increase the likelihood of innovation in all technologies. Finally, the higher a firm's past innovation in a particular type of technology (knowledge stock), the more likely it is to innovate in that type of technology.

**Hypothesis 3.** *Research subsidies increase the likelihood of innovation in all technologies.*

**Hypothesis 4.** *The larger a firm's knowledge stock in a particular type of technology, the more likely it is to innovate in that type of technology.*

Next, we empirically test the above hypotheses using global firm-level panel data. We begin by describing the data set in Section 3.3 and turn to the empirical analysis in Sections 3.4 and 3.5.

## 3.3 Data

The estimation of the drivers of innovation requires firm-level data on research output, energy prices, taxes, research subsidies, and past innovation in addition to country-level economic data. Specifically, we measure research output and past innovation with patents, which are drawn from the OECD Patent Database (see OECD, 2009, for a description). Energy prices including taxes and research subsidies, are from the IEA, and economic data are from the Penn World Tables (International Energy Agency, 2015a,c; Feenstra et al., 2013). Altogether, our data set spans 34 years (1978-2011) across 26 countries and contains 96.2% of triadic electricity patents from all over the world. Table C-1 in Appendix C-2 summarizes the source of data for each variable, while Table C-2 lists countries. As follows, we describe the construction of this data set before presenting the overall descriptive statistics.

We use data on patent applications to measure innovation.[11] Each patent application contains

[11] Patents are a common measure of innovation in economic studies. (Popp, 2005) notes that other measures of

detailed information about the inventor(s), applicant(s), and the specific type of technology, which allows us to identify specific firms, while the International Patent Classification (IPC) codes assigned to each patent make it possible to identify technologies related to electricity generation.

Individual patents differ considerably in their worth, with many patents having low values (Aghion et al., 2016). We address this issue by only considering the most valuable patents from the OECD's Triadic Patent Database.[12] A patent belongs to this database when the same applicant or inventor files the same invention at the three most important patent offices: the EPO, the USPTO, and the JPO. Triadic patents then form a highly-valued patent family, which is a collection of patents that protect the same idea across different countries. Specifically, to qualify as a triadic patent family member, a particular patent must have equivalent applications at the EPO, the JPO, and the USPTO. Because triadic patents are applied for in three separate offices, they include only the most valued patents and allow for a common worldwide measure of innovation that avoids the heterogeneity of individual patent office administrations (Aghion et al., 2016).[13]

Once we have all patent information, we select patents related to electricity generation using IPC codes. We then categorize them into two broad groups: renewable energy and fossil fuel technologies. Renewable energy technologies are identified from the World Intellectual Property Office's (WIPO) IPC Green Inventory[14], while fossil fuel technologies are selected from the IPC codes used by Lanzi et al. (2011). Specifically, renewable energy patents are related to alternative

innovation, such as R&D expenditures, are generally only available at the industry level and for limited technology types. Thus, the detailed nature of patent data proves particularly useful when examining firm-specific incentives to innovate in selected technologies.

[12]One disadvantage of triadic patent families is the lag time associated with the USPTO. Legal delays for publishing applications are 18 months after the priority date and up to 5 years between the priority date and publication date (Dernis and Khan, 2004). As a consequence, U.S. patent grants may delay the completion of data on triadic patent families. To mitigate this limitation, the OECD utilizes forecasts called "nowcasting" in order to improve the timeliness of triadic patents (Dernis and Khan, 2004). Despite this difficulty, triadic patents still provide the most inclusive measure of high-value, firm-level, innovative performance.

[13]Furthermore, the OECD utilizes "extended families," which are designed to identify any possible links between patent documents (Martinez, 2010). This is advantageous, as it provides the most comprehensive method of consolidating patents into distinct families, allowing us to include an extensive number of patented ideas.

[14]The IPC codes listed in the IPC Green Inventory have been compiled by the IPC Committee of Experts in concordance with the United Nations Framework Convention on Climate Change (UNFCCC). For more information, see http://www.wipo.int/classifications/ipc/en/est/.

energy production, which includes fuel cells, pyrolysis, harnessing energy from manufactured waste, wind, solar, geothermal energy, other production or use of heat, using waste heat, and devices for producing mechanical power from muscle energy. Fossil fuel technologies combine both general and efficiency-improving technologies. Specific descriptions of the IPC codes used to identify electricity-generating patents are presented in Tables C-3-C-5 in Appendix C-2. Moreover, we separate fossil fuel technologies into those used to generate base- or peak-load electricity (Tables C-6-C-7 in Appendix C-2). We build on Voigt et al. (2009) and Lanzi et al. (2012) to identify base-load technologies, while we create a list of peak-load technologies by searching for specific patents on the EPO's Espacenet patent search website.

Next, we aggregate individual patent counts at the firm level. Using OECD's Harmonized Applicants Names (HAN) Database and REGPAT Database (OECD, 2009), we can match each patent applicant with a firm. Unfortunately, the HAN database does not contain firms' information for every patent application in our sample. Names that cannot be matched using the HAN database are synchronized using applicant information in the Triadic Patent Families Database. Although this allows us to match every patent to an applicant, it poses two difficulties. First, applicant names in the Triadic Patent Database contain a number of spelling, character, and name variations. For example, "General Electric" and "General Electric Inc" would be incorrectly treated as separate firms in the absence of name harmonization. Second, the Triadic Patent Families Database does not directly link patent applications to applicant names. Instead, applicant names are linked to family identifiers. Thus, if a given family contains more than one firm name, we are unable to determine which firm to associate with each patent. In order to minimize the complications that may result from these challenges, we harmonize the database in three steps. In the first step, we select all firms that contain full information from the HAN register. Second, we clean the firm-level information in the Triadic database. Third, we manually harmonize the Triadic and HAN databases. With these steps, we guarantee firm-level harmonization of the entire database. In addition, we account for multiple patent owners. Because some patents are owned by more than one firm, we allocate a patent to a firm weighted by the number of owners.

Following Aghion et al. (2016), we construct two variables that measure past innovation for each firm: internal and external knowledge. Internal knowledge measures past innovation by the cumulative count of all patents a firm has applied for in the past, while external knowledge measures the total number of patents other firms in the region have applied for. As listed in table C-2, we have patent data available for 73 countries and we use these to construct the regional external knowledge variables. We define five regions following the World Bank's income classification. These geographical regions are: Eastern Asia, Eastern Europe, Europe, Northern America, and Oceania. In our robustness analysis, we explore alternative definitions of spillover regions.

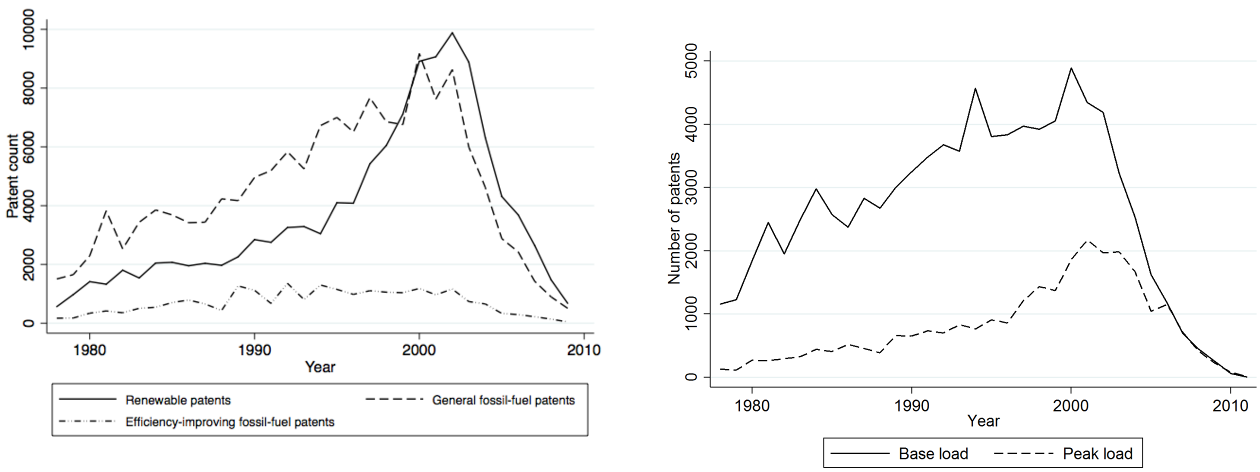
A distinguishing feature of innovation count data is that firms are widely heterogeneous in their success rate. While some firms make few innovations, others have a high innovation record. We create two variables to account for this permanent unobservable heterogeneity following Blundell et al. (1995). First, using patent data from 1963 to 1977, we construct a pre-sample research history variable that measures the average number of patents each firm applied for in a specific technology in the pre-sampling period. In addition, a dummy variable indicates whether a firm innovated in the pre-sample period. These variables are used to control for the size and propensity to patent of research firms.

Another feature of our data set is that only some firms exist during the entire sample period. We account for this by including each firm in the data set from the first until the last year they applied for a patent. Thus, only active firms are accounted for in our panel data set.

In addition to patent data, we include data on electricity input and output prices and taxes. Our energy price and tax data are drawn from the IEA Energy Prices & Taxes database and are measured in 2005 U.S. dollars (International Energy Agency, 2015a). Specifically, we use electricity retail prices to measure output and we proxy input with the prices of thermal coal and natural gas used in the production of electricity, which are those paid by power generation companies to purchase fuels for electricity production for sale. A limitation of these data is that net prices are rarely available. To address this, we use gross (tax-inclusive) fossil fuel prices. Although this implies that we are unable to separate net prices and taxes, we are able to infer the effect of taxes in our estimates. Another issue we account for is that international companies are affected by the regulations and taxes of several countries. Because we know the locations of international firms, we address this by constructing firm-level energy prices after calculating the average energy price across all locations for each firm.

The second environmental policy we study is public research and development subsidies for the energy sector. Data are drawn from the IEA Energy Technology RD&D Statistics and span 34 years (1978-2011) and 26 countries (International Energy Agency, 2015c). This gives us the total amount of subsidies to promote the development of renewable and different fossil fuel based technologies. While our research subsidy data set contains a smaller number of countries than our patent data set, firms in the 26 countries for which research subsidy data are available account for 96.2% of global electricity triadic patents. We convert R&D data to 2005 U.S. dollars and separate them by technology type: renewable technologies, efficiency-improving fossil fuel technologies, and general fossil fuel technologies. As with energy prices, we construct a firm-level subsidy variable by calculating the average subsidies a firm is exposed to across all locations. We think of this variable as a proxy that captures a firm's exposure to research subsidies because we are unable to determine if a given research firm received any subsidies. We exclude data on other environmental policies designed to promote renewable energy, such as feed-in tariffs, due to data availability. However, we control for country-level policies using country-level fixed effects and country-by-year dummies in our identification strategy.

Finally, we use economic data to measure the size and wealth of countries from the Penn World Table (Feenstra et al., 2013). We use real GDP to measure the size of a country and real GDP per capita to measure wealth. Both GDP and GDP per capita are at constant 2005 U.S. dollars. As before, we construct a firm-level exposure variable by calculating the average across all locations.

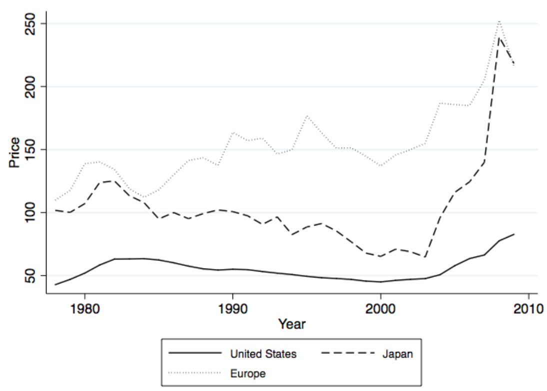



(a) Renewable, fossil fuel, and efficiency-improving patents.

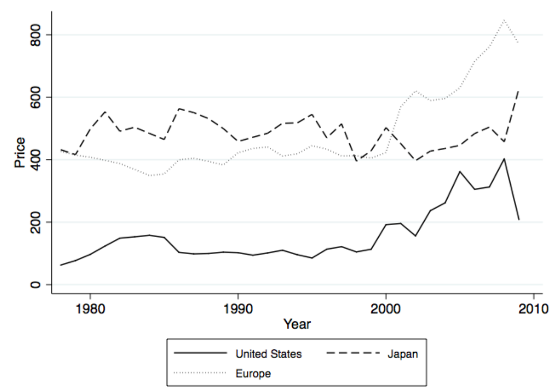
(b) Base- and peak-load fossil fuel patents.

Figure 3.1: Annual aggregate patent count, 1978-2011.

In total, we identify 236,605 unique triadic patent applications across 13,054 firms from 1978 to 2011. Of this total, 120,059 are designated as renewable technologies, while 116,546 are classified as fossil fuel technologies. Our baseline estimates combine efficiency-improving and fossil fuel technologies into one category, but once we separate these two types of technologies, we have 99,454 and 17,092 general and efficiency-improving fossil fuel technologies, respectively. In addition, we divide fossil fuel technologies into 89,425 base-load and 27,121 peak-load technologies. Fossil fuel base load technologies include both coal and natural gas based technologies while fossil fuel peak load technologies include diesel and natural gas. Table C-8 presents the number of patents by specific technology. The table shows that solar patents account for the largest share of all renewable patents, followed by fuel cells and waste patents. On the other hand, base-load fossil fuel patents account for 76.7% of all fossil fuel patents over the period 1978 to 2011. Figures 3.1a and 3.1b illustrate the OECD's trends in patent activity from 1978 to 2011. The number of renewable and general fossil fuel patents increased considerably until the mid-2000s, while the number of efficiency-improving fossil fuel patents enjoyed a modest increase. Our data also shows a downward trend in the number of patent applications between 2000 and 2009.[15] The reason for this downward trend is lag from the application date to the actual granting of the patent at the USPTO which lasts from 18 months to five years (Popp, 2005). We account for this by skipping the last 2 years of the data set to run our estimations.




(a) Thermal coal for electricity generation (USD per tonne).




(b) Natural gas for electricity generation (USD per MWh).

Figure 3.2: The price of coal and natural gas in the most innovative regions, 1978-2009.

Figures 3.2 and 3.3 illustrate the evolution of coal, natural gas and electricity prices in the most innovative countries: U.S., Japan, and OECD-Europe.[16] Coal price is measured in USD per tonne while natural gas and electricity prices are measured in USD per MWh. All inputs used in the production of electricity followed a similar trend. Coal was the cheapest input and most heavily used for electricity production in many countries. The price of coal stayed low and stable in the

[15]This trend is consistent with prior work. For example, Noailly and Smeets (2015) observe the same trend in European patents, even though they use non-triadic patent data, and Nesta et al. (2014) find a downward trend for German renewable patent families.

[16]Prices in Europe are represented by the average prices of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the U.K..

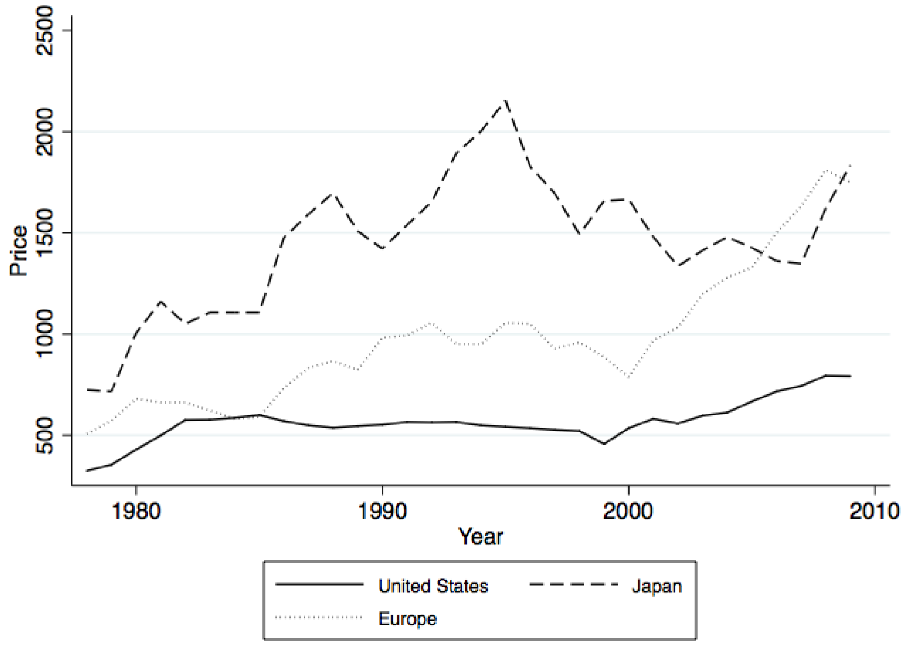



Figure 3.3: Electricity retail price (USD per MWh) in the most innovative regions, 1978-2009.

U.S., while it rose considerably in Japan and Europe after 2000, peaking in 2008. Because coal is heavily used for base-load electricity production in the U.S., it is no surprise that the price of electricity also hit its lowest price in 2000 and its highest price in 2008. In Japan, however, the price of electricity followed the price of natural gas, which presents a higher variation than in other regions. Finally, the average European price showed a rapid rise after 2000. Figures 3.4, 3.5, 3.6 show a scatter plot of energy prices and the total number of patents in each type of technology for the U.S., Japan, and OECD-Europe. The figures show a negative correlation between coal prices and innovation in both renewable and fossil fuel technologies. On the other hand, natural gas prices show a weaker correlation with innovation in all types of technologies.

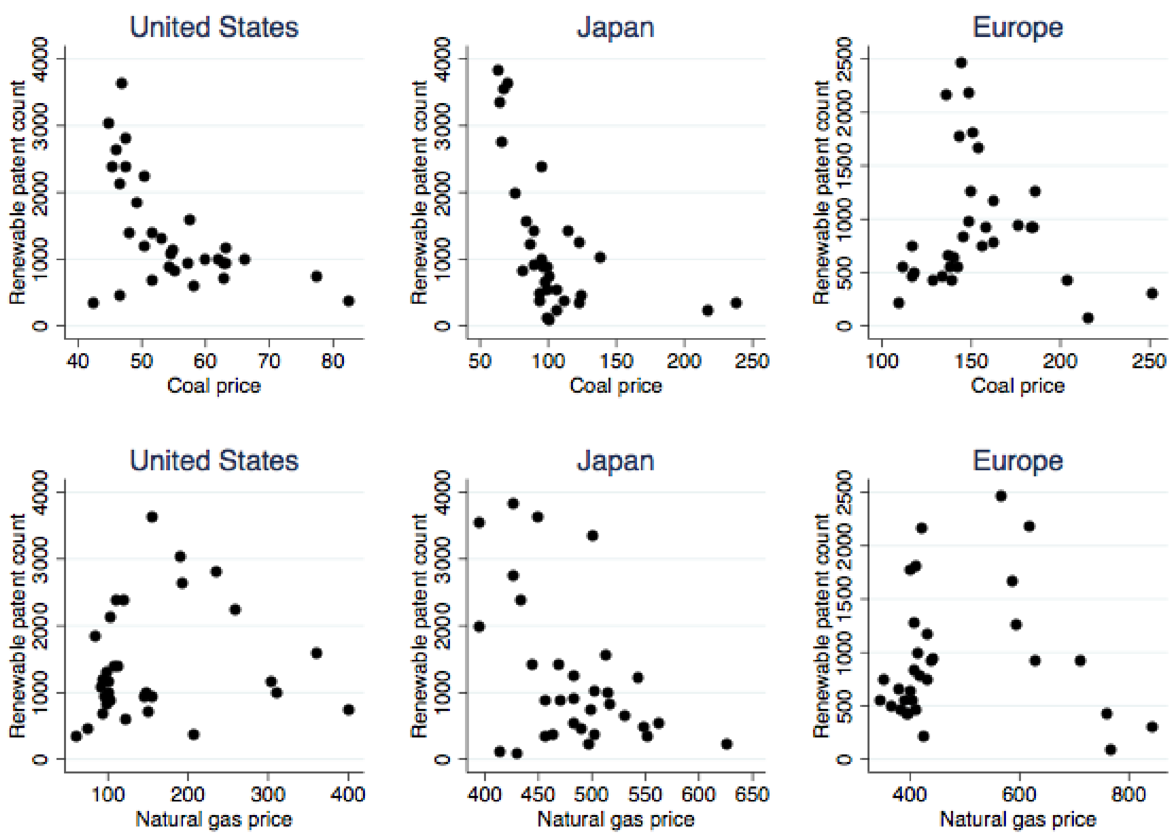



Figure 3.4: Renewable innovation and energy prices.

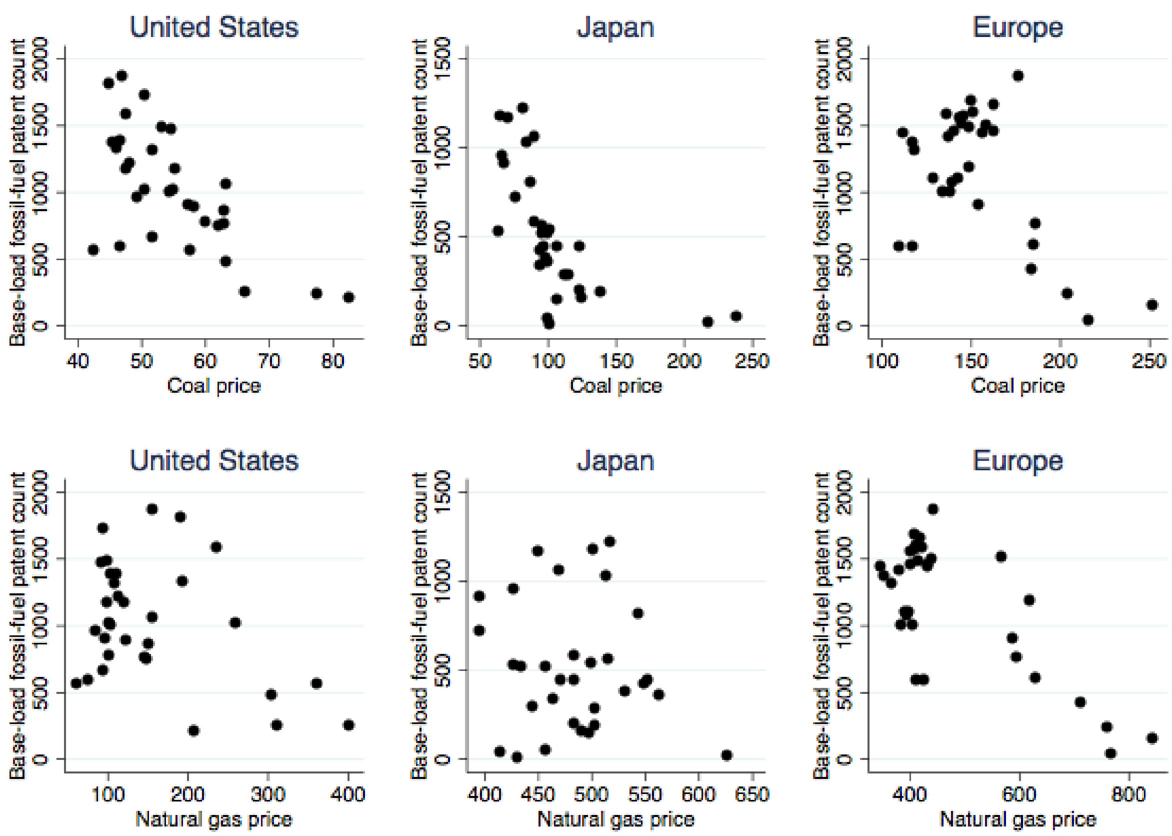



Figure 3.5: Base-load fossil fuel innovation and energy prices.

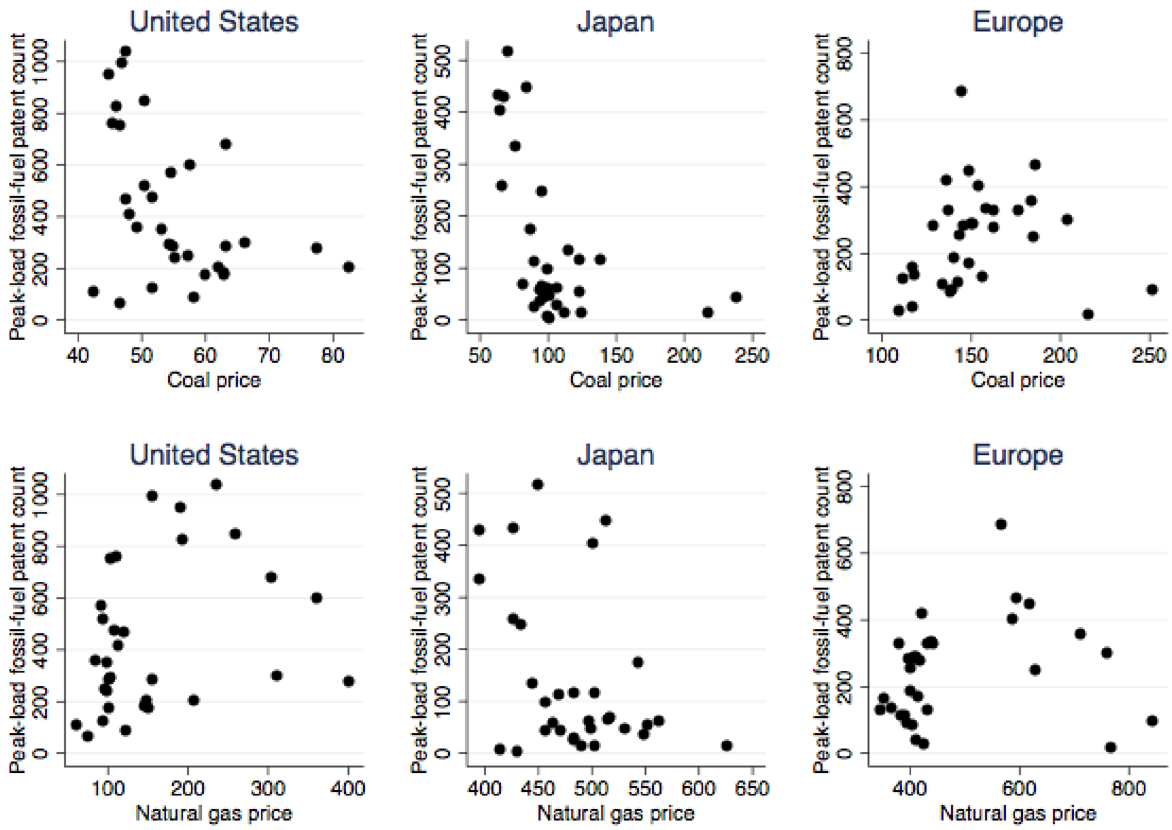



Figure 3.6: Peak-load fossil fuel innovation and energy prices.

Figure 3.7 illustrates global aggregate research subsidies. Most subsidies were directed towards general fossil fuel technologies until the early 1990s, when subsidies towards efficiency-improving fossil fuel technologies took off. Moreover, general fossil fuel subsidies decreased from 1980 to 2000, and after reaching their lowest point in 2000, they started increasing again. On the other hand, subsidies for renewable technologies peaked around the 1980s, and after a decade of relatively smaller subsidies, they started increasing again in the late 1990s.

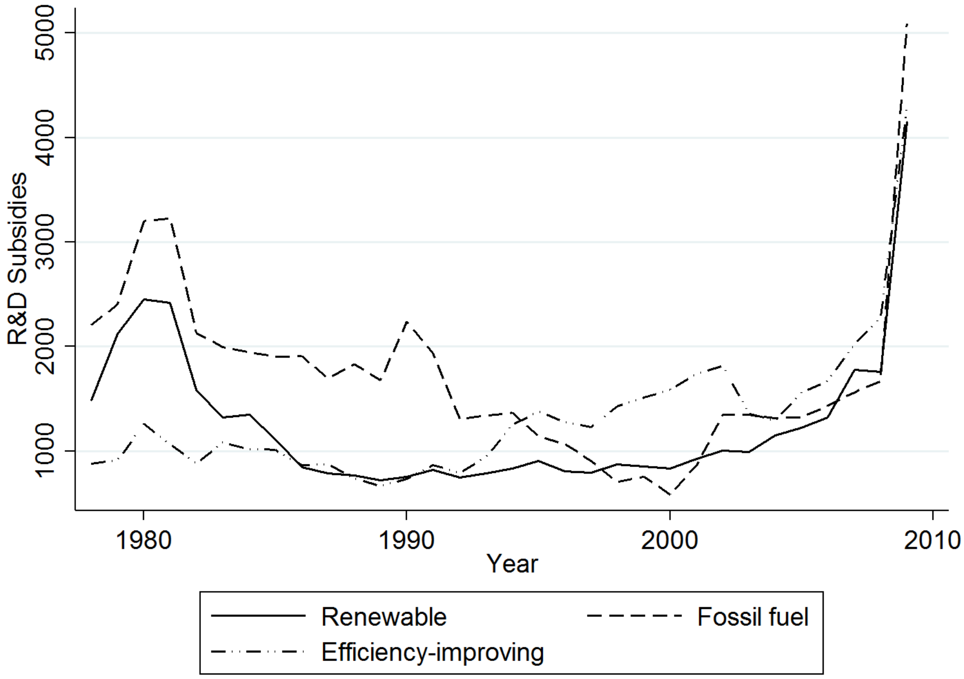



Figure 3.7: Global RD&D subsidies in million USD in renewable, general fossil fuel and efficiency-improving technologies, 1978-2009.

## 3.4 Identification strategy

This section describes the econometric approach we adopt to identify the firm-level determinants of innovation in the electricity sector. We estimate a dynamic innovation model with fixed effects. This model accounts for current patent applications $y_{j,it}$ that depend on past patent applications $y_{j,it-1}$ for firm $i$'s innovation in technology $j$ in year $t$ and it captures the feedback effects that result from innovations in different technologies affecting each other (Cameron and Trivedi, 2013). In particular, our baseline specification with one lag is:

$$\mathbb{E}[y_{j,it}|\mathbf{X_{j,it}}, \mathbf{Y_{j,it-1}}, \alpha_{j,i}] = \alpha_{j,i}\lambda_{j,i}, \tag{3.1}$$

where $\mathbf{X_{j,it}} = (\mathbf{x_{j,it}}, \mathbf{x_{j,it-1}}, \ldots, \mathbf{x_{j,i1}})$ are observable variables, $\mathbf{Y_{j,it-1}} = (y_{j,it-1}, \ldots, y_{j,i1})$ is a vector of past innovations, $\alpha_{j,i}$ captures individual technology-specific fixed effects, and $\lambda_{j,i}$ is the specified function of $y_{j,it-k}$, $\mathbf{x_{j,it}}$, and $\boldsymbol{\beta}$. We consider a linear feedback model to explain how $y_{j,it-1}$ enters $\lambda_{j,i}$ following Blundell et al. (2002). Specifically:

$$\mathbb{E}[y_{j,it}|\mathbf{X_{j,it}}, \mathbf{Y_{j,it-k}}, \alpha_{j,i}] = \rho y_{j,it-1} + \exp(\mathbf{x_{j,it}^{'}}\boldsymbol{\beta})\alpha_{j,i}, \tag{3.2}$$

where the lagged of past innovations enters linearly. The observable variables $\mathbf{x_{j,it}}$ are the determinants of innovation discussed in section 3.2. Thus, we estimate:

$$\begin{aligned} y_{j,it} =& \mathbf{A_{it-1}} + \exp(\ln \mathbf{P_{it-1}}\beta_{\mathbf{j,p}} + \ln \mathbf{S_{j,it-1}}\beta_{\mathbf{j,s}} + \ln \mathbf{EI_{it-1}}\beta_{\mathbf{j,e}} \\ &+ \gamma_1 \ln X_{j,it} + \gamma_2 ID_{it} + D_{nt})\alpha_{j,i} + \mu_{j,it}, \end{aligned} \tag{3.3}$$

where $j$ denotes the type of technology, while $i$, $n$ and $t$ represent firm, country and year. In the baseline specification, technology type $j$ is renewable ($r$) or fossil fuel ($f$). In addition, we consider efficiency-improving ($e$), base-load ($b$) and peak-load ($p$) fossil fuel technologies. $y_{j,it}$ is the number of patents in technology $j$ that firm $i$ applied for in year $t$.

One of the main determinants of current innovation is past innovation. $\mathbf{A_{it}}$ indicates the firm's existing stock of knowledge, which depends both on the firm's internal cumulative stock of past renewable and fossil fuel innovation, as well as aggregate knowledge spillovers from other firms. More specifically, following Aghion et al. (2016), a firm's total knowledge stock is given by internal and external knowledge stocks following $\mathbf{A_{it}} = \mathbf{K_{j,it}}\beta_{\mathbf{j,k}} + \mathbf{SPILL_{j,it}}\beta_{\mathbf{j,spill}}$. The internal knowledge stock $\mathbf{K_{j,it}}$ is a vector of firm $i$'s patent stock of the designated technology type $j$ in year $t$. The external knowledge stock $\mathbf{SPILL_{j,it}}$ is a vector of knowledge spillover from other firms for technology type $j$, calculated as the aggregate patent stocks of all other firms located in the same region as firm $i$. The baseline specification considers a 1-year lag in past innovations, but we consider other lag structures in the robustness section 3.6.

Another main determinant of innovation is given by energy prices and taxes. $\mathbf{P_{it}}$ is a vector that denotes a firm's exposure to energy prices including taxes in year $t$. We take the prices of both inputs and outputs in the electricity sector into account. Specifically, we use coal and natural gas prices as a proxy for input prices in electricity generation and electricity prices to proxy for output prices. We use alternative measures in our robustness analysis. Recall that we characterize governments' support for innovation, $\mathbf{S_{it}}$, using R&D subsidies in the energy sector. We use R&D subsidies in renewable energy as a measure of government's support for innovation in renewable technologies, while we use subsidies in efficiency-improving and pure fossil fuel technologies as a measure of government's support for innovation in fossil fuel technologies. We control for other country-level environmental policies, such as feed-in tariffs, with country-level fixed effects.

Our empirical model also accounts for other macroeconomic factors that may impact innovation, such as the economic environment of countries in which the firm is located. Specifically, $\mathbf{EI_{it}}$ is a vector that captures the firm-specific exposure to the economic environment, which we characterize by its size (proxied by GDP) and wealth (proxied by GDP per capita). Note that we calculate $\mathbf{EI_{it}}$ for each firm by taking the average of all the economic indicators across the countries in which the firm is located. This allows us to account for the fact that a multinational firm is exposed to the macroeconomic and policy conditions of all countries in which the firm operates, not just its home country. We consider other controls in the robustness section.

A challenge to estimate a linear feedback model with fixed effects is to get consistent estimates. We account for this by controlling for firm-level unobserved heterogeneity using patenting in the pre-sampling period following (Blundell et al., 1995, 1999). Specifically, we use information on firms' pre-sample history of successful innovation. Taking advantage of our extended patent data set, we include the average pre-sample patent count ($X_{j,it}$) for each firm and technology type. In addition, we use a dummy variable ($ID_{it}$) that equals 1 if the firm innovated in the pre-sample period (1963-1977).

We control for time-varying, firm- and country-specific differences using fixed effects. Specifically, we use a set of dummy variables ($D_{nt}$), which include year, country and country–year dummies to control for time-varying country-specific differences. Because all country-level variables, such as energy prices and research subsidies have been converted into firm-level variables, country and time dummies can be used to control for other unobserved variations in electricity markets and relevant policies such as feed-in tariffs across countries over time. Finally, $\alpha_{j,i}$ denotes a firm-level fixed effect, which captures other time-invariant unobservable firm-specific characteristics, such as differences in firm size, industry focus, and others.[17]

Finally, $\mu_{j,it}$ denotes the error term by technology type. We cluster standard errors at the firm level for each technology since our data are structured at the firm level. Since some of our firms are international and we calculate their average energy prices, subsidies and macroeconomic indicators taking into account all their locations, there are additional correlations in the data. Following Thompson (2011), we deal with this by using fixed effects in one dimension and clustering in the other dimension given that our data are not nested. Thus, dummies control for country fixed effects and the standard errors are clustered at the firm level.

We estimate the linear dynamic count data model in equation (3.3) using a fixed-effect Poisson estimator while controlling for pre-sample history (Blundell et al., 1995, 1999). The equation for each technology is estimated separately. We analyze alternative estimators in the robustness analysis in Section 3.6.

[17]The large number of fixed effects often presents another challenge to obtain consistent estimates of dynamic innovation models because of a potential incidental parameter problem. As Blundell et al. (1999) and Lancaster (2002) show, a linear Poisson maximum likelihood model has no incidental problem in parameters and therefore the maximum likelihood estimation of our model obtains consistent estimates.

This identification strategy shows that energy prices, research subsidies, and past innovation cause any differences in a firm's probability to apply for a patent in each technology type after controlling for pre-sample, macroeconomic, country and time-varying heterogeneity.

## 3.5 Estimation results

In this section, we present our main estimation results followed by multiple robustness tests to validate our results. Our main objectives are to identify whether increasing fossil fuels prices promotes innovation in renewable technologies and to quantify how research subsidies shape the direction of technological change in the electricity sector. To do this, we estimate the innovation equation given by equation (3.3) and we present our main results in Tables 3.2-3.5.

We use coal prices as a proxy for input prices in the electricity sector for our baseline estimation Table 3.2. To validate our results, we present multiple robustness checks in Section 3.6. Standard errors in all estimations are clustered at the firm level for each technology. Overall, our estimation results show that energy prices, R&D subsidies, and past innovation significantly influence innovation in the electricity sector. Therefore, policies targeting these factors can potentially direct innovation towards renewable energy. Let us first discuss how each of these factors determines the pattern of innovation in the electricity sector.

### 3.5.1 Are energy taxes successful at promoting innovation in renewable technologies?

The main estimation results in columns (1) and (2) of Table 3.2 suggest that energy prices and taxes have a significant impact on firm-level innovation. Specifically, a 10% increase in coal prices leads to a 3.8% decrease in the probability of applying for a renewable patent. This finding is in line with the theoretical directed technological change literature that shows a negative effect of fossil fuels on renewables when renewable and fossil fuel technologies are complements. However, our finding is in contrast to previous empirical work that concludes that fossil fuel prices promote innovation in renewable technologies. One explanation is that in the electricity sector, intermittent renewable sources are unable to supply electricity constantly and they rely on easily dispatchable technologies like coal-fired plants to meet the electricity demand. Cheap fossil fuels such as coal are typically used to generate base-load electricity that is easily dispatchable and available at all times. On the other hand, more expensive fossil fuels such as natural gas have been typically used in the generation of peak-load electricity that complements base-load electricity during peak hours (when the demand for electricity is high). While it may sound counterintuitive, it is thus reasonable to find that the number of renewable and base-load fossil fuel patents respond similarly to changes in coal prices. Columns (3)-(5) of Table 3.2 further explore this relationship by separating fossil fuel patents into base- and peak-load patents. We find that higher coal prices have a negative and statistically significant effect on innovations in renewable and base-load fossil fuel technologies, but no significant impact on peak-load fossil fuel innovations.

These results imply that making coal more expensive, for example, by increasing coal taxes or setting a carbon tax, is an ineffective tool to encourage innovation in renewable technologies. In absence of large-scale storage solutions, intermittent renewable sources such as wind and solar cannot fully replace coal in electricity generation; therefore, a tax on coal produces unintended negative effects on the development of renewable technologies.

Tables 3.3 and 3.4 further explore the relationship between coal and natural gas prices and innovation in renewable, base- and peak-load fossil fuel patents. Specifically, we analyze: (i) Coal and electricity prices, (ii) Coal prices only, (iii) Natural gas prices and electricity prices, and (iv) Coal and natural gas prices.[18] In the robustness analysis, we also consider the square term of

[18]We omit electricity prices in specifications (ii) and (iv) to address a potential endogeneity issue as electricity output prices are affected by the prices of inputs such as coal or natural gas. Tables 3.3 and 3.4 show that the impact

coal prices, oil prices and the gap between electricity and coal prices. Overall, we find evidence for a negative relationship between coal prices and innovation in renewable and base-load fossil fuel patents, thereby confirming the complementary relationship between renewable and base-load fossil fuel technologies in electricity generation. In contrast, increasing natural gas prices is only associated with a decrease in base-load fossil fuel innovation; it has no statistically significant impact on innovation in renewable energy. In addition, our estimates show that energy prices do not significantly affect the development of peak-load fossil fuel technologies (columns (5) in Table 3.2, columns (9)-(12) in Table 3.4). We explore additional specifications in the robustness section (3.6).

In addition to coal prices, firm-level innovation also depends on electricity prices; however, we only find a significant impact of electricity prices on fossil fuel innovation. Column (2) of Table 3.2 suggests that a 10% increase in electricity prices increases the probability of applying for a patent in fossil fuel by 4%. Moreover, the relationship between electricity prices and fossil fuel innovation is primarily driven by base-load innovations. As columns (4) and (5) of Table 3.2 show, increasing electricity prices has a positive and statistically significant impact on base-load innovations, where a 10% increase in electricity prices leads to a 3.7% increase in the number of base-load patents. On the other hand, the effect of electricity prices on peak-load innovations is much smaller and statistically nonsignificant. These effects are not surprising because coal, which is used in base-load electricity generation, contributes to 41.1% of global electricity generation (International Energy Agency, 2015b).

In addition to separating fossil fuel patents into base- and peak-load technologies, we also classify fossil fuel patents into general fossil fuel patents and efficiency-improving technologies.[19] Columns

of energy prices on innovation is robust to alternative specifications of energy prices.

[19]Tables C-4 and C-5 in Appendix C-2 detail the IPC codes for efficiency-improving and pure fossil fuel technologies. Ideally, we would like to further separate efficiency-improving and fossil fuel technologies into base- and peak-load technologies; however, the number of observations for each sub-group is too small to produce any significant result.

(3)-(5) of Table 3.5 report the estimation results for renewable, general fossil fuel, and efficiency-improving fossil fuel technologies. The coefficients on coal prices are negative and significant in all columns. Specifically, a 10% increase in coal prices decreases the number of patents in renewable, pure fossil fuel, and efficiency improving technologies by 3.5%, 3.3%, and 6.6% respectively.

To summarize, we find evidence that increasing coal prices discourages innovation not only in base-load electricity generation technologies, but also in renewable technologies. In addition, we find evidence of a negative impact of coal prices on efficiency-improving fossil fuel technologies. Therefore, our results suggest that policymakers looking for solutions to reduce the use of coal in electricity generation should be careful when taxing coal as it may have unintended consequences for innovation in renewables as well as efficiency-improving fossil fuel technologies. Taxing natural gas, however, does not significantly affect innovation in renewable and peak-load technologies, but it does discourage innovation in base-load technologies.

### 3.5.2 How effective are research subsidies in shaping global innovation in the electricity sector?

In addition to energy prices and taxes, government research subsidies play an important role in determining innovation in the electricity sector. The results from Table 3.2 show that innovation in renewable energy technologies is significantly increased by an increase of those technologies' research subsidies. In particular, a 10% increase in renewable research subsidies increases the number of patents in renewable energy by 1.4% (columns (1) and (3)). Our results also suggest that research subsidies play a role in the development of fossil fuel technologies. While subsidies for general fossil fuel technologies promote innovation in base-load technologies, efficiency-improving subsidies increase the probability of successfully innovating in peak-load technologies. Specifically, increasing subsidies for general fossil fuel technologies by 10% increases the number of base-load fossil fuel patents by 1.4%, while a 10% increase in subsidies for efficiency-improving fossil fuel technologies increases the number of peak-load fossil fuel patents by 3.3%. The results are robust to alternative specifications of energy prices (Tables 3.3 and 3.4).

In Table 3.5, we classify fossil fuel technologies into general fossil fuel and efficiency-improving technologies. After we separate these technologies, we find that general fossil fuel technologies promote the development of efficiency-improving technologies. Specifically, a 10% increase in general fossil fuel technologies increases the number of efficiency improving patents by 1.2%. Note, however, that we do not find any evidence that research subsidies improve the success rate of general fossil fuel research (column (2) in Table 3.2). One explanation for this small impact of research subsidies on fossil fuel innovation is that market forces have created strong incentives to develop fossil fuel technologies because the market share of fossil fuels in electricity generation has long been and remains very large (International Energy Agency, 2015b). We turn to studying these market forces in the next subsection.

In summary, the analysis in Sections 3.5.1 and 3.5.2 proves that environmental policies such as energy prices, taxes, and research subsidies are effective at shifting the direction of innovation in the electricity sector. Not surprisingly, our results in Tables 3.2 through 3.5 show that research subsidies play a role in promoting the development of all types of technologies in electricity generation. Note, however, that as seen in Figure 3.7, the amount of subsidies directed at fossil fuels is larger than that directed towards renewables. This implies that allocating more research subsidies to renewable innovators and cutting back on research subsidies to fossil fuel innovators can potentially shift innovation in the electricity sector towards more renewable energy. However, our results also suggest that, at the current technology level, renewable and fossil fuel technologies are complements in electricity production; therefore, energy price taxes may not have the expected effect on changing the direction of electricity-related innovations towards cleaner technologies. Our results are consistent with Acemoglu et al. (2012)'s theoretical conclusions that the optimal policy to promote clean innovation involves both taxes and research subsidies, and that excessive reliance on tax policies may have some negative impacts on innovation.

### 3.5.3 What other factors shift innovation in the electricity sector toward renewable technologies?

In addition to environmental policies, a firm's innovation is determined by its past innovation and macroeconomic indicators. Past innovation is a combination of the firm's internal cumulative stock of past innovation and the aggregate knowledge spillovers from other firms within the same region. Columns (1) and (2) of Table 3.2 indicate that a firm is more likely to innovate in fossil fuel technologies if it has a larger knowledge stock in fossil fuels. In addition, accumulated knowledge about peak-load technologies and/or general fossil fuel technologies plays a significant role in fostering fossil fuel innovation in the current period, as shown in columns (3)-(5) of Tables 3.2 and 3.5. On the other hand, firms that invested in more renewable innovations in the past are less likely to be involved in inventing renewable technologies in the current period. One possible explanation is that unlike fossil fuels, storable forms of renewable energy are not readily available to generate electricity at all times; therefore, the use of renewable energy in electricity production is intermittent. Unfortunately, many of the storage technologies are in their early development stages, and thus the lack of cheap and large-scale storage solutions may hinder further innovation in renewable technologies.

Moreover, we find that a firm's probability of successfully innovating in renewable research is affected by spillovers from other firms' innovation activities within the same region.[20] Specifically, a firm located in a region with a larger stock of fossil fuel innovations by other firms is less likely

[20] In our baseline results, we calculate regional knowledge spillovers using the World Bank income classification of countries. We define regional spillover variables instead of country-level spillover variables because we are interested in employing country-level fixed effects in our estimations.

to apply for a renewable patent (Table 3.2). In addition, Table 3.4 shows that a firm located in a region with an extensive knowledge stock of peak-load technologies is also less likely to innovate in renewable technologies. Finally, a firm located in a country with extensive renewable research is less likely to innovate in base-load fossil fuel technologies. Note that most coefficients on the spillover variables are not statistically significant in most cases, and even when they are, the coefficients are close to zero. One explanation for this phenomenon could be that regional innovation spillovers may have two opposite effects on firm-level decisions to conduct research. First, a firm is more willing to engage in research if it is located in a research-intense region because the firm can benefit from the existing knowledge created by other firms (i.e., standing on the shoulders of giants). At the same time, more intensive regional innovation activity also means tougher competition, which makes it more difficult to devise new patents. These two effects offset each other, leading to a small overall regional knowledge spillover effect on innovation.

In short, our estimation results suggest that a firm's past innovation is a strong determinant of future successful innovations. Specifically, firm-level innovation activity in renewables is negatively impacted by firms' internal knowledge stock, while fossil fuel innovation is positively affected by past innovation. On the other hand, it is not necessarily true that a firm is more likely to conduct research or to successfully create new innovations if it is exposed to a larger level of knowledge spillover from other firms within the same region. Our results are robust to alternative price measures, lag structures, pre-sample conditions, and to separating general fossil fuel technologies from efficiency-improving technologies.[21]

Finally, we consider other determinants of innovations such as country size (proxied by GDP) and wealth (proxied by GDP per capita). In our baseline estimates, we find that country size negatively affects innovation in all technology types, while wealth promotes innovation in base-load

[21] We find similar results when we exclude energy prices from our estimation.

technologies in the electricity sector. When we classify fossil fuel technologies into general fossil fuel patents and efficiency-improving technologies (Table 3.5), our results show that a 1% increase in GDP decreases a firm's incentive to conduct efficiency-improving research by 1.449%.

Table 3.2: Baseline: Fixed-effect Poisson estimates of the determinants of firm-level innovation in renewable and fossil fuel technologies using global data from 1978 to 2009.

| | **Dependent variable: firm-level number of patents** | | | | |
|---|---|---|---|---|---|
| | Renewable | Fossil fuel | Renewable | Fossil fuel base load | Fossil fuel peak load |
| | (1) | (2) | (3) | (4) | (5) |
| *Energy prices including taxes* | | | | | |
| L1.Coal price | -.3864** | -.2919 | -.4139** | -.4051** | -.5788 |
| | (.1801) | (.2197) | (.1666) | (.1695) | (.3614) |
| L1.Electricity price | .1745 | .2533 | .2475 | .3674 | -.02734 |
| | (.222) | (.2845) | (.1925) | (.2372) | (.37) |
| *Research subsidies* | | | | | |
| L1.Renewable | .1589** | .04735 | .1275* | -.02836 | .1749 |
| | (.07334) | (.1122) | (.07382) | (.08402) | (.2144) |
| L1.Fossil fuel | .00146 | .0569 | .02102 | .06796 | .06561 |
| | (.03799) | (.05768) | (.04018) | (.0585) | (.08176) |
| L1.Efficiency-improving | .01012 | .06886 | .0401 | -.00051 | .3624*** |
| | (.04104) | (.0728) | (.04048) | (.05797) | (.1072) |
| *Past innovation knowledge* | | | | | |
| L1.Renewable | -.00055*** | -.00046 | -.00045*** | 5.3e-05 | -.00077 |
| | (.00013) | (.00043) | (.00016) | (.00052) | (.00062) |
| L1.Fossil fuel | 4.9e-05 | .00025*** | | | |
| | (.00017) | (4.9e-05) | | | |
| L1.Baseload | | | -.001*** | -.00076*** | .00036 |
| | | | (.00027) | (.00023) | (.00049) |
| L1.Peakload | | | .00098*** | .00082*** | .00017 |
| | | | (.0002) | (.00017) | (.00031) |
| *Past innovation spillovers* | | | | | |
| L1.Renewable | -2.3e-05 | -3.0e-05 | -5.8e-06 | -1.4e-05 | -5.2e-05 |
| | (2.0e-05) | (2.7e-05) | (1.8e-05) | (2.1e-05) | (5.1e-05) |
| L1.Fossil fuel | -3.7e-05*** | -5.7e-06 | | | |
| | (1.4e-05) | (1.6e-05) | | | |
| L1.Baseload | | | 2.2e-05 | 2.3e-05 | 5.5e-05 |
| | | | (1.9e-05) | (2.3e-05) | (3.5e-05) |
| L1.Peakload | | | -.00013*** | -9.9e-05* | -2.7e-05 |
| | | | (4.8e-05) | (5.5e-05) | (9.4e-05) |
| *Macroeconomic indicators* | | | | | |
| L1.GDP | -.1463 | -.1171 | -.1941** | -.1632* | -.4785** |
| | (.08928) | (.1004) | (.09409) | (.09283) | (.1935) |
| L1.GDP per capita | -.362 | .591 | .2939 | 1.267** | .6879 |
| | (.815) | (.8263) | (.8069) | (.644) | (1.629) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 39293 | 27233 | 39317 | 25194 | 9782 |

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table 3.3: Fixed-effect Poisson estimates of fossil fuel price effect in renewable and fossil fuel technologies.

| | **Dependent variable: firm-level number of patents** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Renewable | | | | Fossil fuel | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Energy prices including taxes* | | | | | | | | |
| L1.Coal price | -.3864** | -.3381* | | -.3385* | -.2919 | -.2275 | | -.2416 |
| | (.1801) | (.2105) | | (.201) | (.2197) | (.183) | | (.1902) |
| L1.Natural gas price | | | -.1464 | .00125 | | | -.03939 | .04175 |
| | | | (.1206) | (.1275) | | | (.1146) | (.1248) |
| L1.Electricity price | .1745 | | .1184 | | .2533 | | .1633 | |
| | (.222) | | (.2632) | | (.2845) | | (.2433) | |
| *Research subsidies* | | | | | | | | |
| L1.Renewable | .1589** | .1505** | .1175 | .1507** | .04735 | .04613 | .03395 | .05016 |
| | (.07334) | (.07605) | (.07551) | (.07337) | (.1122) | (.1125) | (.1117) | (.1121) |
| L1.Fossil fuel | .00146 | -.01132 | -.02565 | -.01126 | .0569 | .04474 | .04178 | .04705 |
| | (.03799) | (.03848) | (.04143) | (.03969) | (.05768) | (.05448) | (.06002) | (.0564) |
| L1.Efficiency-improving | .01012 | .02349 | .03183 | .02339 | .06887 | .08057 | .08037 | .07852 |
| | (.04104) | (.04398) | (.0407) | (.04351) | (.0728) | (.07036) | (.06754) | (.06932) |
| *Past innovation knowledge* | | | | | | | | |
| L1.Renewable | -.00055*** | -.00056*** | -.00055*** | -.00056*** | -.00046 | -.00049 | -.00042 | -.00049 |
| | (.00013) | (.00013) | (.00013) | (.00013) | (.00043) | (.00042) | (.00045) | (.00042) |
| L1.Fossil fuel | 4.9e-05 | 5.0e-05 | 6.3e-05 | 5.0e-05 | .00025*** | .00025*** | .00025*** | .00025*** |
| | (.00017) | (.00017) | (.00017) | (.00017) | (4.9e-05) | (4.7e-05) | (4.8e-05) | (4.7e-05) |
| *Past innovation spillovers* | | | | | | | | |
| L1.Renewable | -2.3e-05 | -2.7e-05 | -3.1e-05 | -2.7e-05 | -3.0e-05 | -3.4e-05 | -3.3e-05 | -3.3e-05 |
| | (2.0e-05) | (1.8e-05) | (2.1e-05) | (1.9e-05) | (2.7e-05) | (2.6e-05) | (2.6e-05) | (2.6e-05) |
| L1.Fossil fuel | -3.7e-05*** | -3.6e-05*** | -3.1e-05** | -3.6e-05** | -5.7e-06 | -4.6e-06 | -4.6e-06 | -6.1e-06 |
| | (1.4e-05) | (1.3e-05) | (1.3e-05) | (1.4e-05) | (1.6e-05) | (1.5e-05) | (1.5e-05) | (1.6e-05) |
| *Macroeconomic indicators* | | | | | | | | |
| L1.GDP | -.1463 | -.1571* | -.09257 | -.157* | -.1171 | -.1473 | -.07268 | -.1499 |
| | (.08928) | (.0882) | (.09196) | (.08751) | (.1004) | (.1003) | (.1013) | (.1015) |
| L1.GDP per capita | -.362 | -.1069 | .1375 | -.1098 | .5909 | .8459 | .7526 | .8235 |
| | (.815) | (.9062) | (.7839) | (.7866) | (.8263) | (.8207) | (.828) | (.8104) |
| Pre-sample patents | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pre-sample activity | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 39293 | 39293 | 39293 | 39293 | 27233 | 27233 | 27233 | 27233 |

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table 3.4: Fixed-effect Poisson estimates of fossil fuel price effect in renewable, base- and peak-load technologies.

| | Dependent variable: firm-level number of patents | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Renewable | | | | Base load | | | | Peak load | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| *Energy prices including taxes* | | | | | | | | | | | | |
| L1.Coal price | -.4144** | -.3437* | | -.3522* | -.4051** | -.2934** | | -.2999** | -.5788 | -.5825 | | -.5652 |
| | (.1666) | (.1838) | | (.1862) | (.1695) | (.1492) | | (.1466) | (.3614) | (.3366) | | (.3329) |
| L1.Natural gas price | | | -.1594 | .0267 | | | -.1061 | .02338 | | | -.1955 | -.06678 |
| | | | (.1274) | (.124) | | | (.1158) | (.135) | | | (.2452) | (.2031) |
| L1.Electricity price | .2498 | | .1497 | | .3674 | | .2335 | | -.02734 | | -.05545 | |
| | (.1925) | | (.2376) | | (.2372) | | (.2114) | | (.37) | | (.3948) | |
| *Research subsidies* | | | | | | | | | | | | |
| L1.Renewable | .1273* | .1285* | .1017 | .1302* | -.02835 | -.02006 | -.03171 | -.02055 | .1749 | .1747 | .1394 | .1732 |
| | (.0738) | (.07463) | (.07427) | (.07368) | (.08402) | (.0842) | (.08214) | (.08432) | (.2144) | (.2137) | (.2059) | (.2126) |
| L1.Fossil fuel | .02175 | -.00256 | -.01638 | -.00101 | .06796 | .04559 | .04525 | .04696 | .06561 | .06759 | .02104 | .06334 |
| | (.04014) | (.04278) | (.04187) | (.04555) | (.0585) | (.05426) | (.05941) | (.05406) | (.08176) | (.08105) | (.08605) | (.08102) |
| L1.Efficiency-improving | .03971 | .05236 | .05897 | .05143 | -.00051 | .01431 | .01779 | .0136 | .3624*** | .3622*** | .3746*** | .3634*** |
| | (.04047) | (.0409) | (.04037) | (.04201) | (.05797) | (.05757) | (.05633) | (.05767) | (.1072) | (.1071) | (.1036) | (.1057) |
| *Past innovation knowledge* | | | | | | | | | | | | |
| L1.Renewable | -.00045*** | -.00046*** | -.00045*** | -.00046*** | 5.3e-05 | 2.4e-05 | 8.6e-05 | 2.2e-05 | -.00077 | -.00076 | -.00063 | -.00077 |
| | (.00016) | (.00016) | (.00016) | (.00016) | (.00052) | (.00051) | (.00054) | (.00051) | (.00062) | (.00062) | (.00061) | (.00062) |
| L1.Baseload | -.001*** | -.00102*** | -.00097*** | -.00102*** | -.00076*** | -.00078*** | -.00074*** | -.00078*** | .00036 | .00036 | .00037 | .00036 |
| | (.00027) | (.00027) | (.00027) | (.00027) | (.00023) | (.00023) | (.00024) | (.00023) | (.00049) | (.00049) | (.00047) | (.00049) |
| L1.Peakload | .00098*** | .00102*** | .00101*** | .00101*** | .00082*** | .00086*** | .00084*** | .00085*** | .00017 | .00016 | .00019 | .00018 |
| | (.0002) | (.0002) | (.00021) | (.0002) | (.00017) | (.00018) | (.00019) | (.00018) | (.00031) | (.0003) | (.00029) | (.00029) |
| *Past innovation spillovers* | | | | | | | | | | | | |
| L1.Renewable | -5.7e-06 | -1.7e-05 | -2.4e-05 | -1.5e-05 | -1.4e-05 | -2.2e-05 | -2.5e-05 | -2.1e-05 | -5.2e-05 | -5.1e-05 | -6.3e-05 | -5.5e-05 |
| | (1.8e-05) | (1.8e-05) | (1.9e-05) | (1.8e-05) | (2.1e-05) | (2.1e-05) | (2.0e-05) | (2.0e-05) | (5.1e-05) | (4.8e-05) | (4.6e-05) | (4.5e-05) |
| L1.Baseload | 2.2e-05 | 1.4e-05 | 1.5e-05 | 1.4e-05 | 2.3e-05 | 1.8e-05 | 1.9e-05 | 1.9e-05 | 5.5e-05 | 5.6e-05 | 4.8e-05 | 5.3e-05 |
| | (1.9e-05) | (2.2e-05) | (1.8e-05) | (2.2e-05) | (2.3e-05) | (2.3e-05) | (2.3e-05) | (2.3e-05) | (3.5e-05) | (3.9e-05) | (3.9e-05) | (3.9e-05) |
| L1.Peakload | -.00013*** | -.0001** | -8.6e-05* | -.00011** | -9.9e-05* | -8.6e-05 | -7.6e-05 | -9.1e-05 | -2.7e-05 | -2.9e-05 | 2.2e-05 | -1.4e-05 |
| | (4.8e-05) | (5.1e-05) | (4.7e-05) | (5.3e-05) | (5.5e-05) | (5.4e-05) | (6.1e-05) | (6.1e-05) | (9.4e-05) | (9.7e-05) | (.00011) | (9.4e-05) |
| *Macroeconomic indicators* | | | | | | | | | | | | |
| L1.GDP | -.1944** | -.2132** | -.1444 | -.2111** | -.1632* | -.2097** | -.1189 | -.209** | -.4785** | -.4749** | -.3556* | -.477** |
| | (.09409) | (.09119) | (.09491) | (.09064) | (.09283) | (.09458) | (.09471) | (.09462) | (.1935) | (.1869) | (.189) | (.1865) |
| L1.GDP per capita | .287 | .4706 | .6094 | .4498 | 1.267** | 1.511** | 1.409** | 1.52** | .6879 | .6785 | .78 | .6797 |
| | (.8069) | (.8171) | (.8016) | (.7814) | (.644) | (.6394) | (.6565) | (.6585) | (1.629) | (1.65) | (1.575) | (1.64) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 39317 | 39317 | 39317 | 39317 | 25194 | 25194 | 25194 | 25194 | 9782 | 9782 | 9782 | 9782 |

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table 3.5: Fixed-effect Poisson estimates of innovation in general and efficiency-improving nonrenewable technologies using global data from 1978 to 2009.

| | **Dependent variable: firm-level number of patents** | | | | |
|---|---|---|---|---|---|
| | Renewable | Fossil fuel | Renewable | Fossil fuel general | Fossil fuel Eff.- improv. |
| | (1) | (2) | (3) | (4) | (5) |
| *Energy prices including taxes* | | | | | |
| L1.Coal price | -.3864** | -.2919 | -.2829* | -.2756 | -.4781** |
| | (.1801) | (.2197) | (.1734) | (.2306) | (.2044) |
| L1.Electricity price | .1745 | .2533 | .104 | .2184 | -.1111 |
| | (.222) | (.2845) | (.2284) | (.2966) | (.3321) |
| *Research subsidies* | | | | | |
| L1.Renewable | .1589** | .04735 | .1633** | .06486 | -.05534 |
| | (.07334) | (.1122) | (.07353) | (.1074) | (.1177) |
| L1.Fossil fuel | .00146 | .0569 | -.01499 | .07245 | .1021 |
| | (.03799) | (.05768) | (.03968) | (.05756) | (.07579) |
| L1.Efficiency-improving | .01012 | .06886 | .0225 | .07435 | .1242 |
| | (.04104) | (.0728) | (.0416) | (.07893) | (.1022) |
| *Past innovation knowledge* | | | | | |
| L1.Renewable | -.00055*** | -.00046 | -.00055*** | -.00054 | -.00016 |
| | (.00013) | (.00043) | (.00014) | (.00045) | (.00043) |
| L1.Fossil fuel | 4.9e-05 | .00025*** | | | |
| | (.00017) | (4.9e-05) | | | |
| L1.Pure fossil fuel | | | .00013 | .00033*** | .00033*** |
| | | | (.00034) | (6.5e-05) | (8.9e-05) |
| L1.Efficiency-improving | | | -.00072 | -.00064 | -.00188*** |
| | | | (.00266) | (.00044) | (.00053) |
| *Past innovation spillovers* | | | | | |
| L1.Renewable | -2.3e-05 | -3.0e-05 | -2.9e-05 | -3.8e-05 | -2.6e-05 |
| | (2.0e-05) | (2.7e-05) | (2.3e-05) | (2.7e-05) | (3.0e-05) |
| L1.Fossil fuel | -3.7e-05*** | -5.7e-06 | | | |
| | (1.4e-05) | (1.6e-05) | | | |
| L1.Pure fossil fuel | | | -5.0e-05** | -5.8e-06 | -2.7e-05 |
| | | | (2.0e-05) | (2.1e-05) | (2.9e-05) |
| L1.Efficiency-improving | | | 7.9e-05 | 4.6e-05 | 9.3e-05 |
| | | | (5.9e-05) | (8.9e-05) | (.00013) |
| *Macroeconomic indicators* | | | | | |
| L1.GDP | -.1463 | -.1171 | -.1616 | -.07996 | -.1449* |
| | (.08928) | (.1004) | (.1012) | (.09475) | (.08561) |
| L1.GDP per capita | -.362 | .5909 | -.1454 | .6122 | .6944 |
| | (.815) | (.8263) | (.8161) | (.7438) | (.5516) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 39293 | 27233 | 39292 | 26221 | 10768 |

Significance levels: ***: 1% **: 5% *: 10%
Numbers in parentheses are standard errors.

## 3.6 Robustness analysis

To complete our empirical analysis, we discuss potential caveats associated with our analysis. Specifically, we investigate common estimation issues of dynamic count data models, alternative energy tax specifications, the selection of the most innovative countries and firms, alternative definitions of spillovers, adequate lag structures and other macroeconomic controls.

We start by considering the choice of estimator. One distinguishing feature of patent data is that in each period, the number of patents that a firm applies for depends on two factors. First, it depends on whether they decide to engage in research on a given technology. Second, it depends on whether the firm's R&D activity is successful (i.e., results in a patent application). In other words, a firm can have a zero patent count in a given period either because its R&D activity was not successful or simply because it chose not to enter the research market. This explains why we typically observe a large number of zeros in patent data. To account for this over-dispersion in the data, we employ a zero-inflated Poisson estimator, where we first use a logit model to determine whether a firm engaged in research in a given period, i.e., the extensive margin. Then we use a Poisson estimator to determine whether the firm is successful at innovating, conditional on a positive R&D decision, i.e., the intensive margin.

Table C-10 presents zero-inflated Poisson estimation results for the baseline specification in equation (3.3). We lag the explanatory variables by one period to account for the delayed responses of firms and to reduce contemporaneous feedback effects. Columns (1) and (2) present Poisson estimates of firm-level patent counts; i.e. the intensive margin which explains whether a firm's research activity successfully leads to the application of a new patent. On the other hand, columns (3) and (4) present our logit estimates of the extensive margin which explains a firm-level likelihood to engage in research in a given period.[22] These results confirm our main findings.

Another issue to consider when working with count panel data is the degree of over-dispersion, a situation where the variance exceeds the mean. The negative binomial distribution is more appropriate than a fixed-effects Poisson specification when data exhibits a high degree of over-dispersion. Our data do not represent a high over-dispersion problem as we control for entry and exit of firms in the market; therefore, our baseline estimates use a Poisson fixed effects estimator. However, one might argue that firms in our unbalanced panel appear to be more productive than in reality because we only include them in the sample after they apply for their first patent. To address this, we consider fully balanced panel data where all firms are active from 1978 to 2009. The fully balanced panel data exhibits an over-dispersion problem because the variance is 88 times larger than the mean; therefore, we use a negative binomial specification. Poisson estimates are used as a starting point for the negative binomial estimation. Table C-11 shows that our main results are robust to a negative binomial specification.

Another potential issue to consider with a Poisson regression specification is unobserved heterogeneity. Our baseline estimates include technology-specific average patenting activity prior to our sampling period of 1978-2009 (Blundell et al., 1995). These controls are not statistically significant for any technology type, which suggests that pre-sampling patenting activity is not a strong determinant of the likelihood of innovation during the sampling period.[23] However, controlling for pre-sampling activity allows us to take the wide heterogeneity in firms' innovation success rate into consideration. In addition, we estimate our baseline specification with alternative definitions of patenting activity in the sampling period. In particular, we consider the average number of total patents prior to 1978 and the technology-specific average patenting activity only in the years a

[22]Because the logit estimates explain the probability of observing excess zero patent counts, a negative impact on the likelihood of excess zero patents is interpreted as a positive probability of engaging in research.

[23]In Table C-22, we exclude pre-sample activity from our sample and find results consistent with our main estimation results.

firm was active in the pre-sampling period. Because our main results and the estimated values are unchanged, we do not report a table with these estimates; however, they are available upon request.

In addition to considering alternative estimators, we also choose alternative variables to represent the effect of fossil fuels, past innovations, and macroeconomic indicators. Regarding the effect of fossil fuel prices in innovation, Table C-12 presents additional fossil fuel prices. In particular, we consider the square term of coal prices and the gaps between electricity, coal, and oil prices. These estimates suggest that a higher gap between electricity and coal prices promotes innovation in renewable technologies, which implies a complementary relationship between renewable energy innovation and base-load fossil fuel innovation. We do not find evidence for a statistically significant effect of oil prices on innovation. We do not find this surprising because at the global level, the use of oil in electricity generation is modest (see Table 3.1).

In addition to energy prices, we analyze past innovation in more detail. One might argue that it takes several years before past innovation affects current innovation levels. To address this, we include past firm-level and spillover innovations lagged by 2 and 3 years in Tables C-13 and C-14. Our main conclusions about the impact of past innovation are still valid with these alternative lag structures.

Another issue related to past innovations relates to the definition of spillovers. Our baseline estimates, which include 11 regions, show that spillovers are not strong determinants of innovation. One reason for this low significance is that we are using triadic patents, which by construction, have a global nature. We do, however, consider alternative definitions of regions. In particular, we consider one global innovation spillover as well as five geographical regions: Africa, Asia and the Pacific, Europe, Latin America and the Caribbean, and North America. Overall, Table C-15 shows that these coefficients are similar to our earlier estimates in Table 3.2; therefore, our main results are robust to different definitions of regional spillovers.

Finally, we consider alternative macroeconomic characteristics in addition to controlling for the size of the economy and its wealth. Following Carlino et al. (2007), who present evidence for a positive effect of employment density on the innovation rate, we also control for population density. Table C-16 shows that population density is not statistically significant and that our main results are robust. One might also argue that energy consumption could be a determinant of innovation. Because the correlation between GDP and energy consumption is 85%, we exclude country-level energy consumption from our estimates. We include a country fixed effect in all our specifications to control for other macroeconomic indicators.

In addition to considering different specifications of our main equation, we categorize our data into sub-groups to identify whether groups of firms behave differently systematically. First, we analyze the choice of countries. While our data set contains 26 countries, the majority of patent applications are concentrated in a small number of countries. In Table C-17, we conduct a firm-level fixed-effect Poisson estimation using data from France, Germany, Japan, U.K. and U.S., which are the five countries with the largest number of patents in the sample. Compared to our full sample estimates, we find a stronger negative impact of coal prices on renewable innovation in these five countries, which reassures our prediction about the complementarity between renewable energy and base-load fossil fuel in electricity generation.

Our second group categorization involves firms. Our data contain a diverse set of 13,054 firms. We separate these firms into large and small research firms in Table C-18. We consider a firm large if they applied for more than 15 patents in total during the sampling period. These firms represent the top 15% of innovators in our sample. We consider alternative definitions of large firms, including 20 (top 11,7%) and 10 (top 21,7%) patents per firm, but these results are consistent with those in Table C-18, and we exclude them from the Appendix. Finally, we categorize firms as specialized or mixed firms in Table C-19. We consider a firm specialized if they only apply for patents in either renewable, base-, or peak-load technologies while mixed firms are those that applied for a patent in more than one technology. Specialized firms represent 53% of our sample. Table C-19 shows that firms that specialized in renewable technologies are more likely to be negatively affected by an increase in the price of coal than other types of firms. Moreover, compared with mixed firms, specialized firms also respond more strongly to changes in research subsidies and past innovation.

A final issue we address is the definition of renewable technologies. While most patent applications in renewable technologies involve solar and wind technologies (see Table C-8), a small number of patents include technologies that can be used for base-load electricity generation. To address this, we exclude patent applications from hydro, geothermal, and biomass technologies from renewable technologies in Table C-20. These results show that our main results are robust. In addition, we found that increasing coal prices produces a more negative impact on the innovation of these peak-load renewable energies, which is in line with the complementary relationship between base- and peak-load electricity. Finally, in Table C-21, we categorize all patent applications into technologies used for base- and peak-load electricity generation, instead of renewable and fossil fuel technologies. We found that increasing the coal price negatively affects innovation in both base- and peak-load technologies. As explained earlier, this is due to the fact that base- and peak-load power plants complement each other in electricity generation.

Overall, these alternative specifications show that our main results presented in Section 3.5 are robust to different assumptions and econometric specifications. This suggests idiosyncrasies in the responses of innovation to changes in energy prices in the electricity sector. Specifically, because renewable energies like the sun or wind complement base-load fossil fuels such as coal in electricity generation, discouraging fossil fuel innovation through coal or carbon taxes may produce unintended negative consequences on renewable innovation. On the other hand, taxing peak-load fossil fuels such as natural gas may steer the direction of innovation in the electricity sector towards more renewable energy by lowering fossil fuel innovation. Finally, our results also suggest that to effectively promote innovation in renewable energy, a combination of tax and research subsidy policies is desirable.

## 3.7 Policy recommendations and concluding remarks

As scientists and policymakers seek options to reconcile concerns about climate change with economic growth targets, increasing the use of renewable technologies seems crucial, particularly for carbon-intensive sectors such as electricity generation. The idiosyncrasies in the substitution relationship between renewable technologies and various types of fossil fuel technologies imply that an all-inclusive tax policy that raises the price of all fossil fuels may have unintended consequences in the development of renewable technologies. In the present paper, we explore this issue by analyzing the specific roles of various fossil fuel taxes on renewable innovation in the global electricity market.

Our study supports the idea that policymakers interested in using energy price signals to induce renewable innovation in the electricity sector must carefully structure energy regulations and taxes. In contrast to previous work, we are able to infer about the relationship between energy prices and innovation in base- and peak-load fossil fuel technologies. While many expect energy taxes to reduce the innovation gap by promoting the invention of renewable technologies, we find that coal prices have a negative impact on the invention of renewable technologies. This implies that until we are able to replace the use of coal from base-load electricity generation, renewable energy sources and coal are complements in electricity generation. Thus, taxing coal and a carbon tax that raises coal prices have negative effects not only on the development of base-load technologies, but also on the development of renewable technologies.

We also find evidence in support of research subsidies to reduce the innovation gap between fossil fuels and renewables. In fact, policymakers can foster new inventions in renewable technologies by increasing renewable research subsidies and/or reducing subsidies for general fossil fuel technologies.

Finally, a third mechanism to change the direction of innovation relates to historical research activity. Successful past research in fossil fuel technologies encourages more fossil fuel innovation in the future. Unfortunately, we do not observe such a relationship when we consider renewable energy innovation, potentially due to the absence of storable forms of renewable energy given the current state of technology. Finally, we find that economic growth policy can successfully enhance renewable innovation in the electricity sector through discouraging the development of fossil fuel technologies.

In short, our results suggest that regulations that raise the prices of all fossil fuels may be ineffective at fostering the invention of new renewable technologies in the electricity sector because of the imperfect substitution relationship between renewable energy and fossil fuels in electricity production. Researchers and policymakers interested in fostering renewable innovation in the electricity sector should consider this heterogeneity in their analysis.

# Chapter 4

# What are the leading contributors to growth of private firms in transitional economies?

## 4.1 Introduction

Private enterprises are known to be the main contributor to employment and local development in developing countries. Specifically, the private sector in developing countries provides 90% of jobs, therefore, promoting the development of the private sector is critical in alleviating global poverty. For decades, research on firms' performance in developing countries have identified a long list of factors that contribute to firm-level efficiency.[1] Yet, little is known about the relative importance of these efficiency determinants, primarily due to availability of data. This makes it challenging for policymakers to identify the most effective policy targets to promote the development of the private sector in developing countries. For this reason, many efforts have been made to improve the quality of the firm-level data in developing countries. In light of the recent improvements in firm-level data for developing countries, this paper presents a comprehensive analysis on the contribution of various internal and external factors to the profitability of private enterprises in developing countries.

Specifically, I ask the following research questions. First, how efficient are firms in developing countries? Second, what are the most important determinants of efficiency? Finally, what policy is the most effective at improving the firm-level efficiency? I answer these questions by combining the stochastic frontier framework, an econometric technique commonly used in the study of productive

[1] For example, Tybout (2000) and Bloom et al. (2010) summarize the factors that contribute to the productivity of firms in developing countries.

efficiency, with a detailed firm-level panel dataset of Vietnamese firms between 2005 and 2013.

Vietnam is an interesting site to study the above research questions. First, as a transitional economy, Vietnam shared many similarities to other developing countries. For example, small and medium firms comprise the majority (95%) of the Vietnamese private sector and hire the largest share of the Vietnamese labor force (Ho et al., 2014). Moreover, like other transitional economies, Vietnam has undergone a number of reforms, which transformed the country from a closed economy to an open market economy.[2] Second, the ranking of the determinants of efficiency requires detailed data on firms' various internal and external characteristics such as their financial accounts, human capital, age, size and many other factors. Unfortunately, such data are not widely available across all developing countries. In Vietnam, since 2005, the Vietnam Central Institute for Economic Management (CIEM) has collaborated with the University of Copenhagen to establish the Small and Medium Enterprise survey in an effort to improve the understanding of firms' performance in Vietnam (Tarp and Rand, 2013).[3] This comprehensive firm-level survey spans between 2005 and 2013, covers multiple industries and geographical regions and includes both formally-registered firms and informal firms. The detailed information provided by this dataset is useful to analyze the relative importance of various determinants of firm-level profitability in a transitional economy.

To study the relative importance of the firm-level efficiency determinants, I employ a stochastic profit frontier framework, an econometric techniques commonly used in the study of productive efficiency.[4] Under this framework, firms maximize profits by choosing a combination of inputs and

[2]One of the most significant reforms is the Enterprise Law of 2000, which simplifies the business registration process from 3 months to 15 days and removes discrimination in terms of access to resources (e.g. finance, capital, labor) between different types of business, for example, between state-owned and private-owned firms or between domestic and foreign firms. While these reforms provide a more level playing field in the Vietnamese business environment, they also come with challenges, especially for private small and medium firms who are now exposed to a larger market with tougher competition.

[3]This dataset has been used to answer a number of research questions. For example, Hansen et al. (2009) study the role of government support on firm-level growth. Larsen et al. (2011) study the employment structure while Rand (2007) studies the credit and capital structure of Vietnamese manufacturing firms.

[4]For example, Kumbhakar and Lovell (2003) provides an overview of stochastic frontier analysis and its applications.

outputs, taking as given technology and prices. Compared to the regular linear regression model, this profit frontier model has two advantages. First, it allows the estimation of the gap between firms' actual profit and their maximum attainable profit. Second, the stochastic frontier model allows the separation of firms' deviations from the optimal profit into two categories, in contrast to regular linear regression models which lump all deviations from a firm's optimal profit level into one symmetrically distributed random error term. The first type of deviation is due to randomness in the production process such as weather or other acts of nature, therefore, it either positively or negatively influences firm's profitability and is modeled using the symmetrically distributed error term, as in traditional linear regression models. The second type of deviation comes from the firms' inability to allocate their resources efficiently, given technology, prices and the existence of random events. This resource allocation failure negatively impacts the firm's profitability, therefore, it is modeled as a one-sided error that only takes negative values. In addition, the direct modeling of this resource allocation failure is a useful tool to study the relative importance between the main determinants of firm-level efficiency.

The estimation results show that on average, private manufacturing firms in Vietnam lose about 30.5% or approximately 285,493,400 Vietnam dongs (12,900 U.S. dollars) of annual profit due to inefficiency.[5] Moreover, the problem of inefficiency is more severe in heavy industries than light industries. The average annual profit loss in heavy industries due to inefficiency is 336,316,300 Vietnam dongs (approximately 15,288 U.S. dollars) while the average annual profit loss in light industries is only 245,824,100 Vietnam dongs (approximately 11,174 U.S. dollars). Previous studies in other developing countries also found similar level of inefficiency. For example, Wang and Wong (2012) find an average efficiency score of 70% in developing countries. Tybout (2000) provides a summary of the inefficiency loss in various developing countries across different industries.

[5]The exchange rate between Vietnam dongs and U.S. dollars is approximately 22,000 Vietnam dongs per U.S. dollar as of October 2016.

Therefore, Vietnam provides a good case study for other private firms in the developing world.

In addition to estimating the efficiency gap, this paper reveals the relative importance of various efficiency determinants on the firm-level profitability. I find that firm-specific characteristics are more important in shaping the profitability of a firm than characteristics of the external environment in which the firm operates. This may be an optimistic signal for private enterprises in developing countries, as their active efforts in bettering their production structure can be well-rewarded. Moreover, policies that encourage firms to improve their own internal strength are crucial to promote the firm-level efficiency. For example, improved access to the labor market, innovation incentives to upgrade the production process and labor training programs are found to be the most significant policies for the development of the private sector. The results also imply the importance of designing policies that meet the specific needs of each business segment in the private sector. For example, the light industries are more likely to benefit from inter-business partnerships and formalization while government support in the forms of technology and human resource training is more beneficial for the heavy industries. Finally, the design of enterprise development policy needs to be coupled with efforts to reduce corruption, as corruption has been found to crowd out the positive impacts of other factors.

This paper is related to the extensive literature studying firm-level productivity growth. This literature has identified a long list of factors that influence the firm-level productivity, however, little has been known about the relative importance of these factors, due to the lack of a comprehensive firm-level dataset in developing countries (Tybout, 2000; Syverson, 2011). Therefore, while previous studies gain useful insights into the role of individual factors in determining productivity growth, they also present a challenge for policymakers to identify the most important policy targets. Using a detailed firm-level panel dataset in Vietnam, this paper provides practical policy recommendations to increase productivity growth in developing countries through ranking various efficiency determinants by their orders of effectiveness. As the firm-level productivity is known to be an important indicator of aggregate industry- or country-level productivity (Hopenhayn, 2014), this paper also contributes to the literature studying the sources of aggregate productivity growth by identifying the most important productivity drivers at the micro level.

The rest of the paper is organized as follow. Section 4.2 presents the econometric framework while section 4.3 describes the empirical context of the study. Section 4.4 discusses the main estimation results and section 4.5 presents the robustness analysis. Finally, a concluding remark is provided in section 4.6.

## 4.2 Econometric framework

The goal of this study is to understand the relative importance of various factors in determining productive efficiency in developing countries. The literature studying productive efficiency is extensive and can be dated back to the theoretical work by Farrell (1957), who defines firms' efficiency as the distance between firms' current productive status and their maximum attainable outcome based on criteria such as production output, cost or profit. Econometric specification of firms' production behavior that allows for the existence of inefficiency is known as stochastic frontier analysis. This technique assumes that firms operate on or beneath a productive frontier, which captures the optimal allocations of production activities such that firms' production cost (profit) is minimized (maximized). Firms who operate on the productive frontier are considered efficient while firms who operate underneath the productive frontier are considered inefficient. The further a firm is from its productive frontier, the more inefficient it is.

Stochastic frontier analysis assumes two factors that affect firms' deviations from their productive frontier. The first characterizes the randomness in the production process (for example, weather or other acts of nature) and thus takes on both positive and negative values. The second characterizes the possibility that the firm is operating inefficiently and thus takes on only negative values. Thus, econometric specification under stochastic frontier analysis departs from the assumption of a symmetric random error in traditional ordinary least squares (OLS) regressions. Instead, it involves both a two-sided error term that captures the randomness in production and a one-sided error term that captures firms' inefficiency. This allows the estimation of the mean and variance of efficiency, thereby informing policymakers about the extent to which efficiency vary among firms (Kumbhakar and Lovell, 2003).

Many previous studies rely on the estimation of production or cost frontiers to determine the efficiency level of a decision-making unit. Under this approach, firms choose between different combinations of inputs to produce an exogenous level of output. While the assumption of exogenous output is appropriate in some settings, in most cases, producers are responsible for choosing both the input and output quantities.[6] To account for this, the estimation of firms' efficiency measurement should involve a profit frontier specification. In this paper, I employ the stochastic profit frontier framework to estimate the profit efficiency of Vietnamese SMEs and to analyze the factors that contribute to the performance of these firms. Following Kumbhakar and Lovell (2003), the specification of the stochastic profit frontier model is as follow:

$$\ln \pi_{it}^{a} = \ln \pi \left(p_{it}, \mathbf{w_{it}}, k_{it}\right) + \epsilon_{it} - u_{it} + \eta_s + \eta_t + \eta_{st}, \tag{4.1}$$

where $i$ denotes firm and $t$ denotes time. $\pi_{it}^{a}$ denotes a firm's actual short-run profit, which is calculated as its revenue minus its variable costs (the sum of labor and material costs). $\pi\left(p_{it}, \mathbf{w_{it}}, k_{it}\right)$ represents the firm's short-run profit frontier, which is the maximum attainable profit the firm could achieve, given the variable input price vector ($\mathbf{w_{it}}$), the output price ($p_{it}$) and the quantity

[6] See (Kumbhakar and Lovell, 2003) for examples of stochastic frontier analysis using production and cost functions.

of fixed input ($k_{it}$).[7] This econometric framework assumes that firms are price-takers, which is a reasonable assumption for small and medium firms.[8]

Two factors contribute to the deviation of firm's actual profit from its profit frontier. First, there exists randomness in the production process, due to an unusually favorable (or unfavorable) operating environment (for example, weather or other acts of nature), which may cause firms to perform better (or worse) than their potential. This randomness in the production process is captured in the mean-zero error term $\epsilon_{it}$. Second, a firm can deviate from its profit frontier because it was not operating efficiently. In other words, the firm was unsuccessful in solving its optimization problem and chose a combination of outputs and inputs that does not lead to the maximum attainable profit. These mistakes in the production of outputs and uses of inputs are captured in the non-negative random variable $u_{it}$ (hereafter, the inefficiency parameter). Finally, $\eta_s$, $\eta_t$, and $\eta_{st}$ capture industry-, time- and industry$\times$time fixed effects. The fixed effects capture the variations between industries and over time of the profit frontier.[9]

Estimating the model in (4.1) requires parametric specifications of the functional form of $\ln \pi \left(p_{it}, \mathbf{w_{it}}, k_{it}\right)$ as well as the distributions of $\epsilon_{it}$ and $u_{it}$. I assume that the profit frontier $\ln \pi \left(p_{it}, \mathbf{w_{it}}, k_{it}\right)$ takes the form of a translog profit function.[10] The translog profit function must satisfy homogeneity of degree one in input and output prices. This can be achieved by normalizing

[7]Since the time frame of the data is only between 2005-2013, a short-run profit frontier seems to be a more appropriate specification than a long-run version. In the short run, firms decide the quantity of output to produce and the quantity of each input to use in order to produce that output taking as given prices and fixed inputs such as machinery and equipment. Therefore, the short-run profit frontier is a function of the input and output prices, which include the quantity of fixed inputs as a control variable.

[8]While firm-level data on total revenue and expenditures are available, unfortunately, firm-level price data are not available, thus in this paper, I use input and output price indices to infer about the price level faced by each firm. Section 4.3 describes in details the construction of these indices.

[9]As described later in the data section, firms enter and exit the Vietnamese SMEs dataset at various points in time, therefore, an inclusion of a firm fixed effects may distort the results. I return to the impact of entries and exits in the robustness check section 4.5.

[10]Compared to the Cobb-Douglas specification, the translog profit function is a more widely used functional form because of its flexibility and its provision for economies of scale to vary with different output and input levels. Hence, the translog profit function has been widely applied in various settings. For example, Fitzpatrick and McQuinn (2008) uses the translog profit function to study bank efficiency, while Rahman (2003) and Wang et al. (1996) applies this framework to study agricultural productivity.

the input prices and profit by the output price.[11] Let $\ln \pi_{it} = \ln \pi\left(p_{it}, \mathbf{w_{it}}, k_{it}\right)$, the normalized translog profit frontier ($\ln \frac{\pi_{it}}{p_{it}}$) can be written as follow:

$$\begin{aligned}\ln \frac{\pi_{it}}{p_{it}} =& \alpha_0 + \sum_j \alpha_j \ln \frac{w_{jit}}{p_{it}} + \alpha_k \ln k_{it} + \frac{1}{2}\sum_j \sum_q \delta_{jq} \ln \frac{w_{jit}}{p_{it}} \ln \frac{w_{qit}}{p_{it}} + \frac{1}{2}\delta_{kk}(\ln k_{it})^2 \\ &+ \sum_j \delta_{jk} \ln \frac{w_{jit}}{p_{it}} \ln k_{it},\end{aligned} \tag{4.2}$$

where $w_{jit}$ denotes the price of variable input $j$ for firm $i$ during period $t$ and $j$ is equal to $m$ (raw materials) or $l$ (labor).

Combining (4.1) and (4.2) yields the following estimation equation:

$$\begin{aligned}\ln \frac{\pi^a_{it}}{p_{it}} =& \alpha_0 + \sum_j \alpha_j \ln \frac{w_{jit}}{p_{it}} + \alpha_k \ln k_{it} + \frac{1}{2}\sum_j \sum_q \delta_{jq} \ln \frac{w_{jit}}{p_{it}} \ln \frac{w_{qit}}{p_{it}} + \frac{1}{2}\delta_{kk}(\ln k_{it})^2 \\ &+ \sum_j \delta_{jk} \ln \frac{w_{jit}}{p_{it}} \ln k_{it} + \epsilon_{it} - u_{it} + \eta_s + \eta_t + +\eta_{st}.\end{aligned} \tag{4.3}$$

In addition to the homogeneity restriction, the translog profit function (4.3) also satisfies a symmetry condition, that is $\delta_{jq} = \delta_{qj}$ and $\delta_{jk} = \delta_{kj}$ for all $j, q, k$. Finally, $\epsilon_{it}$ is assumed to follow a normal distribution ($\epsilon \sim N(0, \sigma^2_\epsilon)$) and $u_{it}$ follows a truncated (at zero) normal distribution ($u \sim N^+(0, \sigma^2_u)$).

The objective of this paper is not only to estimate the level of efficiency for Vietnamese SMEs but also to identify the factors that contribute to inefficiency. To do so, I model the distribution function of the inefficiency parameter $u_{it}$ as a function of other explanatory variables. Specifically:[12]

$$\sigma^2_{u,it} = \exp(\mathbf{z}^T_{it}\beta_u), \tag{4.4}$$

[11] One concern with this normalization process is that it may cause endogeneity issues as output price appears on both the left-hand and right-hand sides of the estimation equation. I account for this issue in the robustness section 4.5 by estimating a non-normalized profit function.

[12] See Kumbhakar and Lovell (2003) for a summary of the literature.

where $\mathbf{z}_{it} = (z_{1it}, z_{2it}, ..., z_{kit}, ..., z_{Kit})$ is a firm-specific vector of variables which may influence the efficiency of a firm and $\beta_u = (\beta_{1u}, \beta_{2u}, ...\beta_{ku}, ...\beta_{Ku})$ is the corresponding coefficient vectors. The efficiency explanatory vector $\mathbf{z}_{it}$ includes firm-specific characteristics that determine a firm's success or failure at allocating their resources in a profit-maximizing manner, for example, the firm's age, size and various aspects of the business and legal environment that the firms operate in (e.g., competition, access to credit and government support). Since $u_{it}$ captures the amount of profit lost due to inefficiency, a positive $\beta_{ku}(k = 1, ...K)$ indicates a positive relationship between the efficiency explanatory variable $z_{kit}, (k = 1, ...K)$ and a firm's inefficiency level, thereby suggesting a negative relationship between $z_{kit}$ and a firm's profit efficiency. On the other hand, a negative $\beta_{ku}(k = 1, ...K)$ suggests a positive relationship between $z_{kit}, (k = 1, ...K)$ and a firm's profit efficiency.

To infer about the firm-level profit efficiency, I simultaneously estimate equations (4.3) and (4.4) using a maximum likelihood estimator. The estimation results allow us to understand the profit efficiency level of individual firms in the sample and the marginal effects of the efficiency explanatory variables $\mathbf{z}_{it}$ on firm-level profit efficiency. Specifically, profit efficiency can be defined as:

$$PE_{it} = \frac{\pi^a_{it}}{\pi^a_{it|u_{it}=0}}, \tag{4.5}$$

where $PE_{it}$ measures the actual profit for firm $i$ at time $t$ relative to the profit of a fully efficient firm who is subject to the same prices and fixed input quantity. Finally, following Wang (2002) and Kumbhakar and Lovell (2003), the implied changes in expected profit from changes in the efficiency explanatory variables ($\frac{\Delta E[\ln \pi^a_{it}]}{\Delta \mathbf{z}_{it}}$) are derived from the estimated values of $\beta_u$ and $\sigma^2_{u,it}$. Specifically, the marginal effect of the $k$th element of $\mathbf{z}_{it}$ is given by:

$$\frac{\Delta E[\ln \pi^a_{it}]}{\Delta z_{kit}} = -\beta_{ku} \frac{\sigma_{u,it}}{2} \left[ \frac{\phi(0)}{\Phi(0)} \right], \tag{4.6}$$

where $z_{kit}$ denotes the $k$th element of $\mathbf{z}_{it}$ and $\beta_{ku}$ is the corresponding coefficient estimated from equation (4.4). $\phi(.)$ and $\Phi(.)$ are the probability density and probability distribution functions of a standard normal variable. The magnitudes of the estimated marginal effects in equation (4.6) allows us to quantify the relative importance of various factors on the firm-level efficiency.

## 4.3 Data and Identification Strategy

To understand the role of different variables on firm-level efficiency in developing countries, I analyze the stochastic profit frontier model in the context of Vietnam, an Asian developing country located in one of the fastest growing regions of the world. As a transitional economy, Vietnam shares a number of similarities with other developing countries. First, the structure of the Vietnamese business sector is similar to that of other developing countries, where the private sector plays an important role in shaping the standards of living. According to the General Statistics Office of Vietnam, the private sector the largest employer, accounting for 85% of total employment in Vietnam (Ho et al., 2014). In addition, this sector contributes the largest share to GDP (49% in 2013) (General Statistics Office of Vietnam, 2013).[13] The majority (95%) of this private sector consists of small and medium enterprises (SMEs). 70% of these private SMEs operate in wholesale or retail trade, manufacturing, and construction sectors, with the manufacturing sector being the largest contributor to local employment (Ho et al., 2014). Second, like many other transitional economies, Vietnam has undergone a number of reforms for the last three decades, in an effort to

[13] The contributions of the state-owned and the foreign direct investment sectors to Vietnam GDP in 2013 were 33% and 18% (General Statistics Office of Vietnam, 2013).

transform from a closed, centrally-planned economy to an open, market oriented economy.[14]

The common characteristics between Vietnam and other developing countries make Vietnam a good case study of the business environment in developing countries. As the private sector contributes a significant share to the standards of living, it is important to identify the policy that contributes the most to their success. To evaluate the effectiveness of different policies in the business sector, the first step is to understand the production structure of Vietnam and the relative importance of various determinants of the firm-level performance. While previous studies have documented a long list of possible determinants of firm-level efficiency in developing countries, little has been known about the relative importance of these determinants, as well as their interaction with one another. This is partly due to the lack of a comprehensive firm-level dataset in developing countries. In Vietnam, since 2005, the Vietnam Center Institute for Economic Management (CIEM) has collaborated with the University of Copenhagen to establish the Small and Medium Enterprise (SME) survey, in an effort to better understand various aspects in the operation of SMEs, the largest component of the Vietnamese private sector. This comprehensive dataset covers different types of ownership, industries and geographical regions of Vietnam.[15] The dataset also contains rich firm-level information, such as their financial accounts, production and sales structure, employment and cost structure, economic constraints and potentials. Therefore, the data collected from the Vietnam

[14]The first major reform in Vietnam was the launch of *Doi moi* (Rennovation) in 1986, whose aim was to transform the economy from central planning to market orientation. Yet, progress was slow during the decade following *Doi moi*. Before the turn of the 21st century, the Vietnamese private sector faced a number of constraints such as complicated and time-consuming business registration process, lack of access to land, capital and credit. It was until the early 2000s that Vietnam began to implement more drastic reforms as the country entered into a number of international trade agreements such as the ASEAN Free Trade Agreement (AFTA), the Vietnam-U.S. bilateral trade agreement, and particularly the accession to the World Trade Organization. The participation in these trade agreements has required Vietnam to commit to a number of reforms that promote fair competition, provide protection for intellectual property, and improve the transparency of the legal system. The most important milestone for the development of the private sector was the Enterprise Law of 2000 and its revision in 2005. This law simplifies the business registration process and shortens the registration waiting time from 3 months to only 15 days. The law also eliminates all legal discrimination between different types of enterprises, for example, between state-owned and private enterprises, or between domestic and foreign enterprises. Since the passage of the Enterprise Law, the private sector in Vietnam has experienced drastic growth from only 47,158 enterprises in the period of 1991-1999 to nearly 250,000 active enterprises in 2010, accounting for 85% of total employment (Ho et al., 2014).

[15]Figure D-1 in Appendix D-1 shows the geographical coverage of the survey.

SME survey are in line with the objective of this study, which is to evaluate the relative importance of various efficiency determinants on the firm-level productivity.

Using the Vietnamese private sector as a case study and taking advantage of the rich Vietnam SME dataset, this paper aims at ranking the contributions of various factors to the productivity of firms. Rand and Tarp (2010) provide a detailed discussion of the Vietnam SME survey methodology.[16] Table 4.1 shows the distribution of firms across types of ownership and industry. Each round of the survey includes approximately 2,500 firms. The majority of firms in the sample are light-industry household businesses such as food producers, textile manufacturers, furniture manufacturers and printing and publishing businesses. Table 4.1 also shows that there has been an increase in the share of light-industry firms in the sample between 2005 and 2013. This is in line with the overall population statistics of all Vietnamese non-state manufacturing enterprises and with the dominance of light manufacturing in developing and transitional economies (General Statistics Office of Vietnam, 2013; Dinh et al., 2012).

I employ the stochastic profit frontier approach discussed in section 4.2 as the main empirical framework. The econometric specification of a firm's stochastic profit frontier consists of two component: (i) the profit frontier component that describes firms' optimal level of profits given their input and output prices (equation (4.3)); and (ii) a component that models the sources of inefficiency for each firm (equation (4.4)). Therefore, it requires two sets of variables. First, the estimation of the firm-level profit frontier in equation (4.3) requires information on firms' financial performance measured by annual profits, fixed inputs, and firm-level prices of output and variable inputs. Second, the estimation of the efficiency explanatory equation (4.4) and the marginal effects of different variables on efficiency (equation (4.6)) require data on the firm-specific internal and

[16] The firms in the survey are selected randomly from the population of non-state manufacturing enterprises based on the Establishment Census and the Industrial Survey conducted by the Vietnam General Statistics Office. Each firm is followed over time for as long as it continues operation, where exiting firms are replaced using the same sampling methods (Rand and Tarp, 2010).

Table 4.1: Distribution of firms across ownership types and industries.

| Survey year | Industry | Ownership type | | | | | Total |
|---|---|---|---|---|---|---|---|
| | | Household | Sole proprietorship | Partnership/ Collective/ Cooperative | Limited liability | Joint stock | |
| 2005 | Heavy | 878 | 171 | 65 | 246 | 29 | 1,389 |
| | Light | 1,012 | 109 | 31 | 183 | 25 | 1,360 |
| | **Total** | 1,890 | 280 | 96 | 429 | 54 | 2,749 |
| 2007 | Heavy | 602 | 86 | 53 | 177 | 22 | 940 |
| | Light | 1,155 | 111 | 49 | 261 | 32 | 1,608 |
| | **Total** | 1,757 | 197 | 102 | 438 | 54 | 2,548 |
| 2009 | Heavy | 535 | 83 | 40 | 217 | 40 | 915 |
| | Light | 1,170 | 121 | 34 | 290 | 50 | 1,665 |
| | **Total** | 1,705 | 204 | 74 | 507 | 90 | 2,580 |
| 2011 | Heavy | 482 | 86 | 41 | 231 | 42 | 882 |
| | Light | 1,143 | 116 | 27 | 287 | 59 | 1,632 |
| | **Total** | 1,625 | 202 | 68 | 518 | 101 | 2,514 |
| 2013 | Heavy | 453 | 89 | 29 | 244 | 55 | 870 |
| | Light | 1,141 | 113 | 26 | 307 | 59 | 1,646 |
| | **Total** | 1,594 | 202 | 55 | 551 | 114 | 2,516 |

Note: Light industries include firms producing food, beverages and tobacco products; textile and leather-related products; paper and printing products; and furniture manufacture. Heavy-industries include manufacturers of machinery and equipment, chemical, metal, rubber and non-metallic products.
Source: Tarp and Rand (2013)

external factors that potentially contribute to the discrepancy between firms' current profit and their optimal profit level. Next, I describe in detail the variables needed to estimate the profit efficiency model specified in section 4.2.

### 4.3.1 Profit frontier variables

The analysis of the profit frontier equation (4.3) requires the construction of firm-level profit ($\pi_{it}^{a}$), output price ($p_{it}$), variable input prices ($w_{jit}$), and fixed input ($k_{it}$), where variable inputs consist of labor ($l$) and raw materials ($m$).

Profit ($\pi_{it}^{a}$) is measured by the annual gross margin, which is the difference between a firm's revenue from production and its variable costs. Fixed inputs ($k_{it}$) is measured by the value of all productive physical assets, which includes the values of buildings, machinery and equipment. The price of labor ($w_{lit}$) is calculated by dividing the total wage expenditure by the number of employees (i.e. the quantity of labor).[17]

While firm-level data on gross margin ($\pi_{it}^{a}$), capital stock ($k_{it}$), labor, total revenue and total input expenditure are available, unfortunately, firm-level data are not available on the price of raw materials and output. One approach to generate input and output price indices is to use the industry-level price indices (e.g. Wang et al. (1996); Blancard et al. (2006); Sandleris and Wright (2014)). To account for the price variations among firms, each price used in this study is weighed by the transactions made during the year through different market channels. Specifically, the price

[17]While the wage rate per worker is a common measure of the price of labor, this approach does not account for the specific characteristics of the labor market, such as the number of working hours or part-time work. Unfortunately, data on the numbers of working hours are not available in the dataset, therefore, in this case, the wage rate per worker seems to be the most appropriate proxy for labor price.

of output ($p_{it}$) and raw materials ($w_{mit}$) are proxied by:

$$p_{it} = s^o_{d,it} * P_{dt} + s^o_{f,it} * P_{ft}, \tag{4.7}$$

$$w_{mit} = s^m_{d,it} * W_{dt} + s^m_{f,it} * W_{ft}, \tag{4.8}$$

where $i$, $t$ denotes firm and time. $s^o_{d,it}$ ($s^m_{d,it}$) is the share of output (raw materials) that is sold (acquired) domestically, while $s^o_{f,it}$ ($s^m_{f,it}$) is the share of output (raw materials) that is sold (acquired) internationally through exports (imports). $P_{dt}$ represents the price index of domestic goods while $P_{ft}$ is the price index of exported goods. Finally, $W_{dt}$ is the price index of domestic raw materials and $W_{ft}$ is the price index of imported raw materials. Data for the price indices are extracted from the Statistical Yearbook of Vietnam (General Statistics Office of Vietnam, 2013). The construction of the prices in equation (4.7) is based on two assumptions. First, firms are price takers in the output and input markets. And second, firms produce a single output and use only one type of raw material in production. In this case, the price-taking assumption is reasonable because small and medium firms in the dataset often operate industries with a large number of firms such as the food, tobacco and beverage industry or the textile industry, therefore, given their smaller sizes, these firms have little power over the market prices. Moreover, most firms in the dataset produce only one type of output and the average number of products that each firm produces is 1.16, therefore, without loss of generality, we can assume a single output price for every firm. On the other hand, raw materials typically include a number of different items. However, it is common in the literature to treat materials as a homogeneous input (Levinsohn and Petrin, 2003) and this paper simply follows this tradition.

Table 4.2 reports the average profit, raw material expenditure, wage expenditure and value of the capital stock for all SMEs over the period of 2005-2013. Overall, firms in heavy industries have higher profits and physical capital stock than firms in light industries. Heavy-industry firms also spend more on raw material and labor than their light-industry counterparts. In addition, there exists more heterogeneity in the financial accounts of light-industry firms than their heavy-industry counterparts. This is in line with the fact that compared to the heavy industry, the light industry consist of a diverse set of sectors, each of which possesses a distinct production structure.[18] The separation of the sample by ownership status shows that non-household firms make more profit than household firms, possess more physical capital and spend more on raw material and labor. These suggests that firms of different industries and ownership status may have different production structure, therefore, it is important for the profit efficiency analysis to control for these variations in the production structure, either through the use of interactive dummy variables or through estimating the profit frontier model for each subset of the sample. Sections 4.4 and 4.5 discuss each of these approaches in details.

Table 4.2: Summary statistics of profit frontier variables by industry and by ownership status

| | (1) Log profit | (2) Log raw material expenditure | (3) Log wage expenditure | (4) Log physical capital |
|---|---|---|---|---|
| By industry: | | | | |
| Light industries | 7.605 | 12.736 | 11.796 | 13.384 |
| | (1.434) | (1.833) | (1.516) | (1.904) |
| Heavy industries | 7.918 | 13.107 | 11.838 | 13.699 |
| | (1.480) | (1.909) | (1.489) | (1.853) |
| By ownership status: | | | | |
| Household firms | 7.118 | 12.125 | 11.038 | 12.814 |
| | (1.049) | (1.443) | (1.133) | (1.681) |
| Non-household firms | 8.941 | 14.367 | 12.901 | 14.872 |
| | (1.407) | (1.722) | (1.270) | (1.496) |
| Whole sample | 7.726 | 12.880 | 11.814 | 13.506 |
| | (1.460) | (1.871) | (1.505) | (1.890) |

Numbers in parentheses are standard deviations.

Source: Own calculation.

[18]Firms in the food, textile, paper and printing, and furniture sectors comprise the light industry. On the other hand, the heavy industry consists of manufacturers of chemicals, metal, rubber, plastic, machinery and equipment.

### 4.3.2 Efficiency explanatory variables

The profit frontier variables discussed above are helpful in estimating firms' maximum attainable profit, given the quantity of fixed inputs and the prices of output and variable inputs. The gap between this maximum profit and the actual profit allows us to infer about the level of profit efficiency for each firm. Possible factors that might affect this efficiency gap are modeled using the efficiency explanatory equation (4.4). These factors are either inherent within the firms themselves (the internal environment) or capture characteristics of the business and legal environment in which the firms operate (the external environment). Both the internal and external factors are available at the firm level and are discussed in detail below.

#### The internal determinants of profit efficiency

Internal factors such as human capital, firm's age, size and improvements of the production process have been known in the literature as important determinants of firm's performance (for example, Bloom et al. (2010); Nichter and Goldmark (2009); Tybout (2000)). In this paper, human capital is proxied by both the characteristics of the firms' owner-managers and labor training activity. A firm's effort to upgrade its production process is captured by a dummy variable which equal 1 if the firm introduces a new product, modifies its existing product, or modify its production process in the previous year. Firm's age is measured as the number of years since the firm's establishment up until the survey year while firm's size is measured using the number of employees.

#### The external determinants of profit efficiency

Besides the internal characteristics of the businesses, external environmental factors also play a role in determining firm-level performance (Tybout, 2000; Nichter and Goldmark, 2009). These external factors represent the business and legal environment in which the firms operate.

**Business environment.** The business environment is captured by dummy variables which show the various relationships between the firms and other business entities. Competition is measured by a dummy variable which equals 1 if the firm reports that they faced competition. A firm's exporting activity is measured by a dummy variable that equals 1 if the firm exports, while a firm's subcontracting activity is measured by a dummy variable that equals 1 if the firm is a subcontractor. Besides competition and business partnership, the ability to obtain capital also determines firm-level success (Fafchamps and Schündeln, 2013; Barslund and Tarp, 2008). In this paper, a firm's access to formal credit is measured by a dummy variable which equals 1 if the firm has difficulty in obtaining formal credit while a firm's use of informal credit is measured by a dummy variable which equals 1 if the firm use informal credit as a source of financing. Finally, to capture other characteristics of the business environment, dummy variables which indicate a firm's locations are also included in the analysis.

**Legal environment.** It is commonly agreed that poor legal systems can hinder firm's performance (Tybout, 2000; Rand and Torm, 2012; Hansen et al., 2009). In this paper, I consider three main indicators of the legal environment, which are formalization, government assistance and corruption. Formalization is measured by a dummy variable which equals 1 if the firm is formally registered while government assistance is captured by a dummy variable which equals 1 if the firm receives assistance from the government. Finally, corruption is measured by the amount of bribery that firms pay as a percentage of total revenue.

Table 4.3 provides the description of the efficiency explanatory variables included in this study. Column (1) of table 4.4 presents the summary statistics of each efficiency explanatory variable for the whole sample and columns (2)-(5) provide the summary statistics by industry and ownership status. Overall, heavy-industry firms are larger in size and younger in age and they are more likely to face constraints in the formal credit market. Moreover, a larger fraction of heavy-industry firms are formally registered businesses. This may allow them to have better access to government support while at the same time making them more vulnerable to bribery and corruption. In addition, the characteristics of the internal and external environment faced by each firm vary by the firm's ownership status. Compared to household businesses, non-household businesses are younger, have better human capital (as indicated by the owner's level of education and the provision of labor training), are more likely to engage in innovation, and operate on a larger scale (as indicated by their larger size). Non-household businesses are also more actively involved in the external business environment, as a larger fraction of them face competition or participates in subcontracting and exporting activity than household firms. Finally, the share of formally registered firms differs vastly between non-household and household businesses. 98.4% of non-household businesses in the sample are formally registered, while only 54% of household businesses are formally registered. Yet, the fraction of firms receiving government support does not vary across ownership status. In contrast, the severity of bribery varies substantially between firms, where on average, incidence of bribery was more popular among non-household businesses than among household businesses.

Table 4.3: Summary of efficiency explanatory variables.

| Variable | Description | Mean | Std. Dev. |
|---|---|---|---|
| Internal environment: | | | |
| Owner's education | Number of years of education by the owners | 12.15338 | 2.96007 |
| Labor training | Equals 1 if the firm has provided training for its labor force since the last survey | 0.15322 | 0.36021 |
| Production upgrading | Equals 1 if the firm introduces a new product, modifies its existing product, or modify its production process in the last survey. | 0.45084 | 0.49760 |
| Firm's age | Number of years since the firm's establishment up until the survey year. | 13.70018 | 10.23987 |
| Firm's size | Log of the number of workers. | 2.01427 | 1.15766 |
| Business environment: | | | |
| Competition | Equals 1 if the firm faces competition. | 0.87563 | 0.33002 |
| Subcontracting | Equals 1 if the firm is a subcontractor. | 0.10475 | 0.30625 |
| Exporting | Equals 1 if the firm exports. | 0.06178 | 0.24077 |
| Formal credit constraint | Equals 1the firm has has any difficulty in obtaining formal credit since last survey. | 0.37086 | 0.48305 |
| Informal credit usage | Equals 1 if the firm has relied on informal credit as a source of financing since last survey. | 0.25296 | 0.43473 |
| Industrial zone location | Equals 1 if the firm is located inside an industrial zone). | 0.06155 | 0.24035 |
| Urban location | Equals 1 if the firm is located in an urban area. | 0.43419 | 0.49567 |
| Legal environment: | | | |
| Formalization | Equals 1 if the firm is formally registered. | 0.68899 | 0.46292 |
| Government assistance | Equals 1 if the firm has received any assistance from the government since last survey. | 0.37047 | 0.48295 |
| Bribery and corruption | Amount of bribery as percentage of revenue. | 0.14613 | 1.13297 |

Source: Own calculation.

Table 4.4: Summary statistics of efficiency explanatory variables.

| | All firms | By industry: Light | By industry: Heavy | By ownership status: Household | By ownership status: Non-household |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Internal environment: | | | | | |
| Owner's education | 12.153 | 12.035 | 12.339 | 11.454 | 13.534 |
| | (2.960) | (2.995) | (2.898) | (3.157) | (1.876) |
| Labor training | 0.153 | 0.129 | 0.190 | 0.082 | 0.294 |
| | (0.360) | (0.336) | (0.392) | (0.274) | (0.456) |
| Innovation | 0.451 | 0.409 | 0.517 | 0.389 | 0.573 |
| | (0.498) | (0.492) | (0.500) | (0.488) | (0.495) |
| Firm's age | 13.700 | 14.352 | 12.665 | 15.204 | 10.741 |
| | (10.240) | (10.451) | (9.816) | (10.521) | (8.955) |
| Firm's size | 2.014 | 1.919 | 2.165 | 1.483 | 3.065 |
| | (1.158) | (1.169) | (1.122) | (0.772) | (1.071) |
| Business environment: | | | | | |
| Competition | 0.876 | 0.861 | 0.899 | 0.846 | 0.934 |
| | (0.330) | (0.346) | (0.302) | (0.361) | (0.248) |
| Subcontracting | 0.105 | 0.092 | 0.125 | 0.089 | 0.137 |
| | (0.306) | (0.289) | (0.330) | (0.284) | (0.344) |
| Exporting | 0.062 | 0.070 | 0.048 | 0.014 | 0.157 |
| | (0.241) | (0.256) | (0.215) | (0.116) | (0.364) |
| Formal credit constraint | 0.371 | 0.351 | 0.403 | 0.350 | 0.412 |
| | (0.483) | (0.477) | (0.490) | (0.477) | (0.492) |
| Use of informal credit | 0.253 | 0.236 | 0.279 | 0.221 | 0.315 |
| | (0.435) | (0.425) | (0.449) | (0.415) | (0.465) |
| Industrial zone location | 0.062 | 0.058 | 0.067 | 0.032 | 0.120 |
| | (0.240) | (0.234) | (0.251) | (0.176) | (0.325) |
| Urban location | 0.434 | 0.373 | 0.531 | 0.319 | 0.661 |
| | (0.496) | (0.484) | (0.499) | (0.466) | (0.473) |
| Legal environment: | | | | | |
| Formalization | 0.689 | 0.629 | 0.784 | 0.540 | 0.984 |
| | (0.463) | (0.483) | (0.412) | (0.498) | (0.127) |
| Government support | 0.370 | 0.346 | 0.408 | 0.363 | 0.385 |
| | (0.483) | (0.476) | (0.491) | (0.481) | (0.487) |
| Bribery | 0.146 | 0.125 | 0.180 | 0.116 | 0.206 |
| | (1.133) | (0.769) | (1.545) | (1.157) | (1.082) |
| Observations | 12,916 | 7,917 | 4,979 | 8,571 | 4,345 |

Numbers in parentheses are standard deviations.
Source: Own calculation.

## 4.4 Main empirical results

This section presents the main estimation results. Table 4.5 reports the estimation results of the profit frontier equation (4.3), the efficiency explanatory equation (4.4) and the marginal effects on expected profit of each efficiency explanatory variable ($\frac{\Delta E[\ln \pi_{it}^a]}{\Delta \mathbf{z}_{it}}$) for the full sample (columns(1)-(3)), the light industries (columns (4)-(6)) and the heavy industries (columns (7)-(9)) between 2005 and 2013. Light industries include manufacturers of products such as food, beverages and tobacco products; textile and leather-related products; paper and printing products; and furniture manufacture. Heavy-industry firms include manufacturers of machinery and equipment, chemical, metal, rubber and non-metallic products.

### 4.4.1 How efficient are private firms in Vietnam?

The estimation results for the whole sample in table 4.5 show that the average profit efficiency of non-state manufacturing firms between 2005 and 2013 is 69.5%. In other words, on average, firms earn 30.5% less than their estimated maximum attainable profit due to inefficiency. To get a sense of the potential loss in profit, I compare this to the average profit of a firm in this dataset. The average reported annual profit for a firm in the dataset is 648,101,800 Vietnam dongs (approximately 29,450 U.S. dollars). An average efficiency level of 69.5% implies that firms could increase their annual profit by about 285,493,400 Vietnam dongs (approximately 12,900 U.S. dollars) if they perform at their best potentials. The industry-specific estimation results indicate that on average, firms in the light industries are slightly more efficient than firms in the heavy industries. The average profit efficiency is 70.11% for light-industry firms and 69.43% for heavy industry firms. The average reported profit for firms in the light industries is 574,683,600 Vietnam dongs (approximately 26,122 U.S. dollars), which implies that light-industry firms could increase their profit by 245,824,100 Vietnam dongs (approximately 11,174 U.S. dollars) if they operate efficiently. Similarly, the average reported profit for firms in the heavy industries is 762,038,700 Vietnam dongs (approximately 34,638 U.S. dollars) and a profit efficiency level of 69.43% implies that the average loss due to inefficiency of heavy-industry firms in the dataset is 336,316,300 Vietnam dongs (approximately 15,288 U.S. dollars).

In short, the estimation results show that firms are not operating at their full potential. This finding is consistent with previous studies in other countries. For example, Wang and Wong (2012) find an average efficiency score of 70% in developing countries. Tybout (2000) provides a summary of the inefficiency loss in various developing countries across different industries.

So, what causes this efficiency gap? And more importantly, what are the largest contributors to the firm-level efficiency in developing countries? While previous studies have identified a number of determinants of efficiency, little has been known about the relative importance of these factors and the results vary depending on the availability of data. In this context, the Vietnam SME survey provides an advantage, as it contains extensive information about the firm-level internal and external characteristics. The analysis of the efficiency explanatory equation (4.4) and the marginal effect equation (4.6) allows us to infer about the most important determinants of efficiency.

### 4.4.2 What internal characteristics should an efficient firm possess?

The profit frontier model in section 4.2 not only reveals about the distance between a firm's current level profit and its maximum attainable profit, but also allows the identification of the determinants of efficiency. The bottom half of table 4.5 presents the estimation results of the efficiency explanatory equation (4.4) and the implied change or marginal effect of each variable that explains efficiency on expected profit. Overall, the profit efficiency level of a firm depends on characteristics of its internal environment, regardless of which industry it is in, therefore, a firm's action to improve

Table 4.5: Maximum likelihood estimation of the profit frontier and determinants of profit efficiency between 2005 and 2013

| | Whole sample | | | Light industries | | | Heavy industries | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) Coef. | (2) Std.Err. | (3) $\frac{\Delta E[\ln \pi_{it}^a]}{\Delta \mathbf{z}_{it}}$ | (4) Coef. | (5) Std.Err. | (6) $\frac{\Delta E[\ln \pi_{it}^a]}{\Delta \mathbf{z}_{it}}$ | (7) Coef. | (8) Std.Err. | (9) $\frac{\Delta E[\ln \pi_{it}^a]}{\Delta \mathbf{z}_{it}}$ |
| Profit frontier equation: | | | | | | | | | |
| $\alpha_m$ | 0.028** | (0.013) | | 0.052*** | (0.020) | | 0.058*** | (0.022) | |
| $\alpha_l$ | 0.305*** | (0.010) | | 0.287*** | (0.013) | | 0.337*** | (0.015) | |
| $\alpha_k$ | 0.766*** | (0.010) | | 0.688*** | (0.014) | | 0.687*** | (0.017) | |
| $\delta_{mm}$ | 0.040*** | (0.004) | | 0.055*** | (0.007) | | 0.032*** | (0.007) | |
| $\delta_{ll}$ | 0.070*** | (0.009) | | 0.086*** | (0.012) | | 0.038*** | (0.014) | |
| $\delta_{kk}$ | 0.272*** | (0.014) | | 0.228*** | (0.018) | | 0.289*** | (0.023) | |
| $\delta_{ml}$ | 0.000 | (0.008) | | -0.011 | (0.012) | | 0.011 | (0.015) | |
| $\delta_{mk}$ | 0.013 | (0.010) | | -0.013 | (0.014) | | 0.031* | (0.018) | |
| $\delta_{lk}$ | 0.054*** | (0.010) | | 0.065*** | (0.012) | | 0.043*** | (0.016) | |
| Constant | 7.972*** | (0.017) | | 7.872*** | (0.020) | | 8.015*** | (0.027) | |
| Average profit efficiency | 69.53% | | | 70.11% | | | 69.43% | | |
| Efficiency explanatory equation: | | | | | | | | | |
| Internal environment: | | | | | | | | | |
| Owner's education | -0.023** | (0.010) | 0.005 | -0.014 | (0.011) | 0.003 | -0.036** | (0.016) | 0.008 |
| Labor training | -0.189 | (0.145) | 0.043 | -0.358 | (0.222) | 0.082 | -0.158 | (0.158) | 0.036 |
| New product | -0.065 | (0.141) | 0.015 | 0.074 | (0.194) | -0.017 | -0.214 | (0.159) | 0.049 |
| Product modification | -0.330*** | (0.076) | 0.076 | -0.364*** | (0.091) | 0.083 | -0.295*** | (0.101) | 0.068 |
| Process upgrading | -0.406*** | (0.135) | 0.093 | -0.519*** | (0.168) | 0.118 | -0.057 | (0.159) | 0.013 |
| Firm's age | 0.017*** | (0.003) | -0.004 | 0.018*** | (0.003) | -0.004 | 0.010** | (0.004) | -0.002 |
| Firm's size | -1.444*** | (0.059) | 0.333 | -1.568*** | (0.074) | 0.358 | -1.334*** | (0.083) | 0.308 |
| Business environment: | | | | | | | | | |
| Competition | -0.232*** | (0.072) | 0.053 | -0.265*** | (0.079) | 0.061 | -0.167 | (0.122) | 0.039 |
| Subcontracting | 0.271*** | (0.101) | -0.062 | 0.300** | (0.127) | -0.068 | 0.104 | (0.128) | -0.024 |
| Exporting | -1.527** | (0.635) | 0.352 | -0.417 | (0.528) | 0.095 | -1.952 | (1.278) | 0.451 |
| Formal credit barrier | 0.189** | (0.087) | -0.044 | 0.156 | (0.100) | -0.035 | 0.135 | (0.125) | -0.031 |
| Use of informal credit | -0.245** | (0.104) | 0.056 | -0.232* | (0.121) | 0.053 | -0.218 | (0.145) | 0.050 |
| Industrial zone location | -0.282 | (0.180) | 0.065 | -0.294 | (0.185) | 0.067 | -0.325 | (0.316) | 0.075 |
| Urban location | -0.160 | (0.174) | 0.036 | 0.064 | (0.214) | -0.015 | -0.284 | (0.204) | 0.066 |
| Legal environment: | | | | | | | | | |
| Formalization | -0.027 | (0.080) | 0.006 | -0.177* | (0.093) | 0.040 | -0.110 | (0.111) | 0.025 |
| Financial support | -0.086 | (0.082) | 0.020 | 0.003 | (0.092) | -0.001 | -0.140 | (0.123) | 0.032 |
| Technical support | -0.386** | (0.180) | 0.089 | -0.221 | (0.201) | 0.050 | -0.502* | (0.259) | 0.116 |
| Other support | -0.251* | (0.135) | 0.058 | -0.230 | (0.162) | 0.052 | -0.136 | (0.183) | 0.031 |
| Bribery | 0.031 | (0.023) | -0.007 | 0.084 | (0.085) | -0.019 | 0.024 | (0.021) | 0.006 |
| Constant | 2.187*** | (0.277) | | 2.479*** | (0.707) | | 1.669*** | (0.562) | |
| Log likelihood | -16263.37 | | | -9595.62 | | | -6159.05 | | |
| Observations | 12,757 | | | 7,835 | | | 4,902 | | |
| Sub-industry FE | YES | | | YES | | | YES | | |
| Year FE | YES | | | YES | | | YES | | |
| Sub-industry*Year FE | YES | | | YES | | | YES | | |

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

its internal environment can be beneficial for its efficiency.

The estimation results in table 4.5 show that the three most important internal determinants of firm-level efficiency are its size, its effort to upgrade the production process or to improve its products, with firms' size being the most significant contributor to the firm-level profitability. The marginal effects of a firm's size on its profitability are 33%, followed by process upgrading efforts (9.3%) and product modification (7.6%). Interestingly, the significance of improved human capital on firms' performance is modest, where an extra year of education by the owner only increases the firm-level efficiency by 0.5% and a firm with labor training programs is only 4.3% more efficient than other firms without labor training programs. These results are consistent when the whole sample is divided into light-industry firms and heavy-industry firms (columns (4)-(9) of table 4.5). One explanation is that while the benefits from expanding a firm's size can be realized in the short run, the impact lag of other variables on efficiency is longer. For example, it takes more time for a new production process to be fully efficient and for new products to be accepted by consumers. Similarly, it takes more time for human capital improvements to be translated into higher profitability.

The analysis above suggests that in the short run, firms could improve their profitability by expanding their labor force, therefore, policy that improves firms' access to the labor market could be beneficial. In the long run, firms should invest in upgrading their production structure and improving their human resources, therefore, innovation incentives or labor training programs are beneficial for firm-level performance in the long run.

### 4.4.3 How does the external environment affect the firm-level efficiency?

In addition to the firm-specific characteristics, the external environment in which the firms operate also plays a role in shaping their efficiency. However, there exist vast differences in the extent to which firms in different industries respond to their environment.

In light industries (columns (4)-(6) of table 4.5), the most influential external determinants of efficiency are subcontracting, competition, use of informal credit and formalization. Specifically, competition increases the firm-level efficiency (6.1%) while a subcontracting relationship decreases the firm-level efficiency (-6.8%). One explanation is that competition motivates firms to better their operation and encourages inefficient firms to exit the market (Nickell, 1996). On the other hand, a subcontracting relationship reduces the flexibility of firms' operation, thereby reducing profit efficiency. This suggests the role of policy that encourages healthy inter-business competition and partnership on firms' performance.

In addition to competition and subcontracting, light-industry firms can also benefit from better access to credit. Interestingly, the estimation results from table 4.5 suggests the more important role of informal credit, compared to formal credit, on the firm-level profitability. One explanation is that fast growing firms require a larger amount of capital to expand their business, therefore, they must rely on both formal and informal credit to meet their financing needs. In fact, firms who experience faster sales growth in the dataset are less likely to face constraints in the formal credit market while at the same time are more likely to utilize informal credit.[19] Finally, formalization also positively affect the efficiency of firms in light industries, however, compared to other factors, the impact of formalization as well as other legal factors (e.g. government support and bribery) is modest. More importantly, I found a stronger impact of formalization on the firm-level efficiency when an interactive variable between formalization and bribery is included.[20] This implies that while formalization allows firms to gain access to resources such as better human resources and technology, it also makes firms more vulnerable to bribery. In other words, the positive impact

[19] This finding is consistent with Rand et al. (2009) who find that informal credit is crucial for the growth of Vietnamese SMEs.

[20] I did not include the estimation results with the interactive variable formalization*bribery in the paper, since they are very similar to the baseline results in table 4.5.

of formalization may have been crowded out by increasing incidence of bribery when the firm is formally registered. This suggests that to be effective, formalization incentives and government support policies have to be coupled with corruption reduction efforts.

While the profitability of firms in light industries is sensitive to changes in the external environment, the impacts of these external factors on the performance of heavy-industry firms are more modest and less statistically significant. The most significant determinant of efficiency in the heavy industries is technical support in the form of human resource training, trade promotion and quality improvement programs. The marginal impact of receiving technical support from the government on the firm-level profitability is 11.6%. Two explanations are possible. First, it is likely that changing the profit efficiency of heavy-industry firms takes more time and effort, therefore, within the short time frame of the sampling period, we are unable to capture a statistically significant impact of changes in the external environment in heavy industries compared to light industries. Second, heavy-industry firms are more likely to receive government support, which lowers their vulnerability to the business environment. In fact, 41% of all heavy-industry firms in the sample receive government support, while only 34% of all light-industry firms receive government support.

In summary, the results 4.5 in table suggest that the relative importance of business and legal environmental factors on the firm-level profitability varies largely from industry to industry, where light industries are more sensitive to external changes than heavy industries. This implies that it is important to develop industry-specific policy. For example, policy that encourage healthy inter-business relationships and formalization incentives is more beneficial for the light industries. On the other hand, the heavy industries are more likely to benefit from increasing government technical support. Finally, targeting the light industries in the short run can boost the overall performance of the Vietnamese private sector, as the marginal effects of the efficiency determinants on the firm-level profitability is generally larger in light industries than in heavy industries.

### 4.4.4 Summary of key findings and policy implications

The analysis in sections 4.4.2 and 4.4.3 reveals the most influential drivers of firm-level efficiency. Overall, the profitability of a firm depends on both its internal characteristics as well as the characteristics of the external environment in which the firm operates. Specifically, promoting healthy inter-firm partnership and encouraging formalization is more beneficial for light industries while improving technical support is more beneficial for heavy industries. However, as the previous analysis suggests, the firm-level profitability is more likely to be shaped by the firms' internal characteristics, rather than characteristics of the external environment. In both light and heavy industries, the marginal impacts of the firm-specific internal characteristics are larger, both in size and statistical significance level, compared to those of the external environment. This suggests that firms are more likely to benefit from policy that encourages firms to improve their own internal strength, such as improved availability of labor, incentives to upgrade and expand production structure, and labor training programs. From the policymaking standpoint, this result may be an optimistic signal, as influencing firm-specific characteristics can be less challenging than changing the characteristics of the whole business or legal environment.

## 4.5 Robustness checks

This section presents some robustness check of the main estimation results in section 4.4. Specifically, I consider alternative sub-samples in the dataset and alternative specifications of the profit frontier models.

To account for the fact the different types of firms have access to different technology, I apply the stochastic profit frontier model in section 4.2 to various subsamples in the dataset. Specifically, I re-estimate the profit frontier model using only incumbent firms who are present in all five rounds of the survey between 2005 and 2013. This is to account for the potential bias from the inclusion of firms who are not present in all five rounds of the survey. In addition, I further classify firms into household (family-owned) businesses and non-household businesses. Table 4.6 presents a summary of the estimation results of the above robustness checks for the whole sample (columns (1)-(4)), the light industries (columns (5)-(8)) and the heavy industries (columns (9)-(12)) and tables D-1, D-2 and D-3 in Appendix D-2 present the detailed estimation results.[21] Overall, the main estimation results still hold for these alternative sub-samples. However, household firms are more likely to benefit from formalization while non-household firms are more prone to bribery. This reflects that on average, non-household businesses pay bribery more frequently than household businesses. Thus, this also suggests the existence of a crowding-out effect between formalization and corruption.

Next, I estimate the profit efficiency for all firms in the sample under alternative specifications of the model described in section 4.2. This is to account for the potential correlations between closely related variables.[22] Table 4.7 shows the marginal effects of each efficiency explanatory variable on the profit efficiency of the full sample, under alternative measures of human capital (columns (2)-(3)), production upgrading activities (columns (4)-(6)), access to credit (columns (7)-(8)) and firm's location (columns (9)-(10)).[23] It can be seen from the table that the main estimation results in table 4.5 still hold under these alternative specifications.

To capture the interaction between different variables, I also incorporate interactive variables

[21]Note that the average profit efficiency reported in tables D-1, D-2 and D-3 measures the efficiency of each firms compared to the best performing firm in each subsample, therefore, they are not readily comparable. Also, the coefficients reported in tables D-1, D-2 and D-3 show the relationship between the efficiency explanatory variables and a firm's *inefficiency* level. On the other hand, the summary in table 4.6 reports the sign of the marginal effect of each efficiency explanatory variable on the *expected profit* of a firm, therefore, they are of opposite signs to the coefficients reported in tables D-1, D-2 and D-3.

[22]For example, owner's education and labor training are both proxies for the firm-level human capital.

[23]Tables D-4-D-7 in Appendix D-2 present the detailed robustness results under each of these alternative measures. Note that the average profit efficiency reported in these tables measures the efficiency of each firms compared to the best performing firm in each subsample, therefore, they are not readily comparable. Also, the coefficients reported in tables D-4-D-7 show the relationship between the efficiency explanatory variables and a firm's *inefficiency* level. On the other hand, the summary in table 4.7 reports the sign of the marginal effect of each efficiency explanatory variable on the *expected profit* of a firm, therefore, they are of opposite signs to the coefficients reported in tables D-4-D-7.

into the analysis. Columns (11) and (12) of table 4.7 summarize the marginal effects of the efficiency explanatory variables with interactive variables between firm's age and size (column (11)) and between labor training and firm's size (column (12)).[24] The marginal effects of the interaction variable between firm's age and size is negative and statistically significant (column (11)). This suggests that, while larger firms are more efficient, the marginal effect of expanding a firm's size on profit efficiency declines as the firm ages. This is in line with the fact that older firms are more likely to use older technology than their younger counterparts. Column (12) of table 4.7 explores the interaction between a firm's size and whether the firm provides training to their workers. The marginal effects of firm's size and the labor training×size interaction variable are positive and statistically significant, which implies that larger firms with labor training programs are more efficient than other firms. Finally, to capture the crowding-out effect between corruption and formalization, I also include the interactive variable in one of the robustness checks and find evidence for a crowding-out effect.[25]

One of the assumption of the profit efficiency model is that firms take prices as given. Firms who do not face competition are often price setters, therefore the inclusion of those firms may bias the results. Table 4.8 report the estimation results, excluding firms not facing competition from the sample. The table shows that the main estimation results still hold under this specification. This is in line with the fact that nearly all firms in the sample report that they face some competition.

Finally, to account for the potential endogeneity issue from the normalization of the profit function, I re-estimate the profit frontier model in section 4.2 using a non-normalized profit function, where the estimation equation is:

[24] Table D-8 in Appendix D-2 shows the detailed estimation results.

[25] Since other results are the same as the main estimation results, I did not include the estimation table in the paper.

$$
\begin{aligned}
\ln \pi_{it}^{a} =& \alpha_0 + \alpha_p \ln p_{it} + \sum_j \alpha_j \ln w_{jit} + \alpha_k \ln k_{it} + \frac{1}{2}\delta_{pp}(\ln p_{it})^2 + \frac{1}{2}\sum_j \sum_q \delta_{jq} \ln w_{jit} w_{qit} + \frac{1}{2}\delta_{kk}(\ln k_{it})^2 \\
&+ \sum_q \delta_{pq} \ln p_{it} \ln w_{qit} + \ln p_{it} \ln k_{it} + \sum_j \delta_{jk} \ln w_{jit} \ln k_{it} + \epsilon_{it} - u_{it} + \eta_s + \eta_t,
\end{aligned}
\tag{4.9}
$$

where the notations have the same meanings as described in section 4.2. Note that this profit function does not impose any price homogeneity constraint, which makes it computationally difficult to estimate the profit frontier model with the full set of time-, industry-, and time*industry- fixed effects. Therefore, the estimation of this non-normalized profit frontier only includes time- and industry- fixed effects. Overall, the main estimation results are still valid under this non-normalized profit frontier, as shown in table 4.9.

Table 4.6: Marginal effects on profit efficiency ($\frac{\Delta E[\ln \pi_{it}^{a}]}{\Delta \mathbf{z}_{it}}$), alternative sub-samples

| | Whole sample | | | | Light industries | | | | Heavy industries | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) All firms | (2) Incumbent firms only | (3) Household firms only | (4) Non-household firms only | (5) All firms | (6) Incumbent firms only | (7) Household firms only | (8) Non-household firms only | (9) All firms | (10) Incumbent firms only | (11) Household firms only | (12) Non-household firms only |
| <u>Internal environment</u> | | | | | | | | | | | | |
| Owner's education | +** | +** | +** | + | + | + | + | + | +** | +* | +** | + |
| Labor training | + | + | +** | - | + | + | +** | + | + | + | + | - |
| New product introduction | + | - | + | + | - | - | - | + | + | + | +* | - |
| Product modification | +*** | +** | +*** | + | +*** | +* | +*** | - | +*** | + | +*** | + |
| New process introduction | +*** | +** | +** | + | +*** | +* | +*** | + | + | + | + | + |
| Firm's age | -*** | -*** | -*** | -*** | -*** | -*** | -*** | -*** | -** | - | -** | -*** |
| Firm's size | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** |
| <u>Business environment</u> | | | | | | | | | | | | |
| Competition | +*** | +*** | +*** | + | +*** | +*** | +*** | + | + | + | + | + |
| Subcontracting | -*** | - | -** | - | -** | - | -** | - | - | - | - | - |
| Exporting | +** | +* | + | +** | + | + | + | + | + | + | + | +** |
| Formal credit constraint | -** | -* | -* | -** | - | - | - | - | - | - | - | -** |
| Use of informal credit | +** | +** | +*** | + | +* | +* | +* | + | + | + | +* | + |
| Industrial zone location | + | + | + | - | + | +* | + | - | + | + | + | - |
| Urban location | + | + | +*** | +** | - | - | + | +** | + | + | +*** | + |
| <u>Legal environment</u> | | | | | | | | | | | | |
| Formalization | + | + | +*** | - | +* | + | +*** | - | + | + | +*** | - |
| Financial support | + | + | + | -** | - | - | + | -* | + | + | + | - |
| Technical support | +** | +* | + | - | + | + | + | + | +* | + | + | - |
| Other support | +* | + | + | + | + | + | +* | + | + | + | + | - |
| Bribery | - | -* | - | -** | - | - | - | - | - | -*** | - | -* |
| Observations | 12757 | 5854 | 8499 | 4258 | 7835 | 3588 | 5581 | 2254 | 4902 | 2259 | 2904 | 1998 |
| Industry FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Industry*Year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

The table summarizes the marginal effects of each efficiency explanatory variable on the profit efficiency ($\frac{\Delta E[\ln \pi_{it}^{a}]}{\Delta \mathbf{z}_{it}}$) of various types of Vietnamese SMEs between 2005 and 2013.

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

Table 4.7: Marginal effects on profit efficiency ($\frac{\Delta E[\ln \pi^a_{it}]}{\Delta \mathbf{z}_{it}}$), alternative specifications of the profit frontier model

| | Baseline | Alternative human capital measures | | Alternative production upgrading measures | | | Alternative credit access measures | | Alternative location measures | | Interactive variables | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| <u>Internal environment</u> | | | | | | | | | | | | |
| Owner's education | +** | +** | | +** | +** | +** | +** | +** | +** | +** | +** | +** |
| Labor training | + | | + | + | + | + | + | + | + | + | + | -** |
| New product | + | + | + | +* | | | + | + | + | + | + | + |
| Product modification | +*** | +*** | +*** | | +*** | | +*** | +*** | +*** | +*** | +*** | +*** |
| Process upgrading | +*** | +*** | +*** | | | +*** | +*** | +*** | +*** | +*** | +*** | +*** |
| Firm's age | -*** | -*** | -*** | -*** | -*** | -*** | -*** | -*** | -*** | -*** | + | -*** |
| Firm's size | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** |
| Firm's age*Size | | | | | | | | | | | -*** | |
| Labor training*Size | | | | | | | | | | | | +*** |
| <u>Business environment</u> | | | | | | | | | | | | |
| Competition | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** | +*** |
| Subcontracting | -*** | -*** | -*** | -** | -*** | -** | -*** | -*** | -*** | -*** | -*** | -*** |
| Exporting | +** | +** | +** | +** | +** | +** | +** | +** | +** | +** | +** | +** |
| Formal credit barrier | -** | -** | -** | -** | -** | -** | - | | -** | -** | -** | -** |
| Use of informal credit | +** | +** | +** | +** | +** | +** | | + | +** | +** | +** | +** |
| Industrial zone location | + | + | + | + | + | + | + | + | + | | + | + |
| Urban location | + | + | + | + | + | + | + | + | | + | + | + |
| <u>Legal environment</u> | | | | | | | | | | | | |
| Formalization | + | + | + | + | + | + | + | + | + | + | + | + |
| Financial support | + | + | + | + | + | + | + | + | + | + | + | + |
| Technical support | +** | +** | +** | +*** | +** | +** | +** | +** | +** | +** | +** | +** |
| Other support | +* | +* | +* | +** | +** | +** | +* | +* | +* | +* | +* | +* |
| Bribery | - | - | - | - | - | - | - | - | - | - | - | - |
| Observations | 12757 | 12757 | 12757 | 12757 | 12757 | 12757 | 12761 | 12757 | 12757 | 12757 | 12757 | 12757 |
| Industry FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Industry*Year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

The table summarizes the marginal effects of each efficiency explanatory variable on the profit efficiency ($\frac{\Delta E[\ln \pi^a_{it}]}{\Delta \mathbf{z}_{it}}$) for the full sample of Vietnamese SMEs between 2005 and 2013 under various specifications of the profit frontier model.
The baseline column (1) summarizes the marginal effects reported in column (3) of table 4.5.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.8: Profit efficiency for firms that face competition

| | Whole sample | | | Light industries | | | Heavy industries | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) Coef. | (2) Std.Err. | (3) $\frac{\Delta E[\ln \pi^a_{it}]}{\Delta \mathbf{z}_{it}}$ | (4) Coef. | (5) Std.Err. | (6) $\frac{\Delta E[\ln \pi^a_{it}]}{\Delta \mathbf{z}_{it}}$ | (7) Coef. | (8) Std.Err. | (9) $\frac{\Delta E[\ln \pi^a_{it}]}{\Delta \mathbf{z}_{it}}$ |
| Profit frontier equation | | | | | | | | | |
| $\alpha_m$ | 0.031** | (0.014) | | 0.056*** | (0.021) | | 0.058** | (0.023) | |
| $\alpha_l$ | 0.313*** | (0.011) | | 0.299*** | (0.014) | | 0.337*** | (0.016) | |
| $\alpha_k$ | 0.748*** | (0.011) | | 0.665*** | (0.015) | | 0.696*** | (0.018) | |
| $\delta_{mm}$ | 0.038*** | (0.004) | | 0.054*** | (0.007) | | 0.030*** | (0.007) | |
| $\delta_{ll}$ | 0.083*** | (0.010) | | 0.105*** | (0.013) | | 0.055*** | (0.016) | |
| $\delta_{kk}$ | 0.294*** | (0.015) | | 0.255*** | (0.020) | | 0.310*** | (0.025) | |
| $\delta_{ml}$ | 0.001 | (0.008) | | -0.011 | (0.013) | | 0.013 | (0.016) | |
| $\delta_{mk}$ | 0.014 | (0.010) | | -0.012 | (0.015) | | 0.027 | (0.018) | |
| $\delta_{lk}$ | 0.039*** | (0.011) | | 0.048*** | (0.014) | | 0.031* | (0.017) | |
| Constant | 8.012*** | (0.019) | | 7.899*** | (0.022) | | 8.045*** | (0.029) | |
| Average profit efficiency | 69.50% | | 70.86% | | 69.33% | | | | |
| Efficiency explanatory equation: | | | | | | | | | |
| Internal environment: | | | | | | | | | |
| Owner's education | -0.021* | (0.011) | 0.005 | -0.015 | (0.013) | 0.003 | -0.036** | (0.017) | 0.008 |
| Labor training | -0.120 | (0.136) | 0.028 | -0.171 | (0.207) | 0.037 | -0.167 | (0.155) | 0.039 |
| New product | -0.050 | (0.145) | 0.011 | -0.013 | (0.207) | 0.002 | -0.174 | (0.166) | 0.040 |
| Product modification | -0.324*** | (0.079) | 0.075 | -0.360*** | (0.097) | 0.079 | -0.289*** | (0.105) | 0.067 |
| Process upgrading | -0.389*** | (0.135) | 0.089 | -0.577*** | (0.180) | 0.127 | -0.003 | (0.159) | 0.008 |
| Firm's age | 0.016*** | (0.003) | -0.004 | 0.017*** | (0.003) | -0.003 | 0.011** | (0.004) | -0.003 |
| Firm's size | -1.449*** | (0.063) | 0.333 | -1.618*** | (0.082) | 0.356 | -1.357*** | (0.089) | 0.315 |
| Business environment: | | | | | | | | | |
| Competition | N/A | | | N/A | | | N/A | | |
| Subcontracting | 0.293*** | (0.102) | 0.067 | 0.345** | (0.134) | -0.075 | 0.067 | (0.132) | -0.016 |
| Exporting | -1.697** | (0.805) | 0.390 | -0.123 | (0.549) | 0.027 | -1.466 | (0.904) | 0.339 |
| Formal credit barrier | 0.161* | (0.094) | 0.036 | 0.169 | (0.113) | -0.037 | 0.069 | (0.133) | -0.016 |
| Use of informal credit | -0.212* | (0.110) | 0.049 | -0.200 | (0.133) | 0.044 | -0.196 | (0.152) | 0.045 |
| Industrial zone location | -0.259 | (0.206) | 0.060 | -0.379* | (0.224) | 0.084 | -0.139 | (0.307) | 0.032 |
| Urban location | -0.196 | (0.175) | 0.045 | -0.020 | (0.225) | 0.004 | -0.214 | (0.207) | 0.049 |
| Legal environment: | | | | | | | | | |
| Formalization | 0.016 | (0.083) | -0.004 | -0.133 | (0.099) | 0.029 | -0.121 | (0.118) | 0.028 |
| Financial support | -0.102 | (0.088) | 0.024 | -0.022 | (0.101) | 0.005 | -0.130 | (0.131) | 0.030 |
| Technical support | -0.382* | (0.195) | 0.088 | -0.281 | (0.223) | 0.062 | -0.592** | (0.297) | 0.137 |
| Other support | -0.207 | (0.145) | 0.048 | -0.151 | (0.176) | 0.033 | -0.204 | (0.198) | 0.047 |
| Bribery | 0.031 | (0.023) | -0.007 | 0.099 | (0.075) | -0.021 | 0.022 | (0.021) | -0.005 |
| Constant | 2.070*** | (0.301) | | 2.410*** | (0.708) | | 2.074*** | (0.416) | |
| Log-likelihood | -14194.85 | | | -8241.46 | | | -5514.84 | | |
| Observations | 11,184 | | | 6,757 | | | 4,410 | | |
| Industry FE | YES | | | YES | | | YES | | |
| Year FE | YES | | | YES | | | YES | | |
| Industry*Year FE | YES | | | YES | | | YES | | |

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

Table 4.9: Profit efficiency using non-normalized data

| | | Whole sample | | Light industries | | Heavy industries | |
|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| | | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| Profit frontier equation | $\alpha_p$ | -12.336*** | (2.795) | -14.564*** | (3.366) | -4.280 | (5.764) |
| | $\alpha_m$ | 17.459*** | (2.799) | 18.109*** | (3.454) | 12.996** | (5.651) |
| | $\alpha_l$ | -1.629*** | (0.196) | -2.051*** | (0.250) | -0.869*** | (0.323) |
| | $\alpha_k$ | -0.422*** | (0.082) | -0.345*** | (0.110) | -0.389*** | (0.123) |
| | $\delta_{pp}$ | 9.474*** | (0.787) | 9.967*** | (1.090) | 6.485*** | (1.540) |
| | $\delta_{mm}$ | -0.046 | (1.002) | 0.254 | (1.234) | -0.826 | (2.022) |
| | $\delta_{ll}$ | 0.185*** | (0.022) | 0.239*** | (0.029) | 0.084** | (0.035) |
| | $\delta_{kk}$ | 0.087*** | (0.004) | 0.079*** | (0.005) | 0.099*** | (0.007) |
| | $\delta_{pm}$ | -5.024*** | (0.552) | -5.162*** | (0.810) | -3.670*** | (0.913) |
| | $\delta_{pl}$ | -0.366** | (0.155) | -0.269 | (0.192) | -0.524* | (0.278) |
| | $\delta_{pk}$ | -0.207*** | (0.064) | -0.202** | (0.081) | -0.234** | (0.111) |
| | $\delta_{ml}$ | 0.295* | (0.162) | 0.153 | (0.204) | 0.562* | (0.289) |
| | $\delta_{mk}$ | 0.007 | (0.067) | -0.005 | (0.085) | 0.018 | (0.116) |
| | $\delta_{lk}$ | 0.049*** | (0.008) | 0.055*** | (0.011) | 0.033** | (0.013) |
| | Constant | 4.553* | (2.630) | 9.206*** | (3.396) | -6.597 | (4.353) |
| | Average profit efficiency | 71.25% | | 71.53% | | 69.65% | |
| Efficiency explanatory equation | Internal environment: | | | | | | |
| | Owner's education | -0.023** | (0.010) | -0.015 | (0.013) | -0.033* | (0.018) |
| | Labor training | -0.280 | (0.172) | -0.480* | (0.292) | -0.078 | (0.182) |
| | New product | 0.069 | (0.137) | 0.210 | (0.212) | -0.184 | (0.177) |
| | Product modification | -0.359*** | (0.077) | -0.336*** | (0.104) | -0.283** | (0.110) |
| | Process upgrading | -0.347** | (0.139) | -0.592*** | (0.205) | -0.018 | (0.177) |
| | Firm's age | 0.018*** | (0.003) | 0.020*** | (0.003) | 0.014*** | (0.005) |
| | Firm's size | -1.515*** | (0.062) | -1.604*** | (0.084) | -1.347*** | (0.088) |
| | Business environment: | | | | | | |
| | Competition | -0.218*** | (0.074) | -0.233*** | (0.089) | -0.174 | (0.137) |
| | Subcontracting | 0.275*** | (0.104) | 0.310** | (0.146) | 0.189 | (0.137) |
| | Exporting | -2.103** | (1.032) | -1.127 | (0.826) | -26.75 | (745.1) |
| | Formal credit barrier | 0.179** | (0.091) | 0.214* | (0.116) | 0.171 | (0.143) |
| | Use of informal credit | -0.257** | (0.109) | -0.284** | (0.141) | -0.224 | (0.165) |
| | Industrial zone location | -0.426** | (0.190) | -0.410* | (0.225) | -0.486 | (0.367) |
| | Urban location | -0.202 | (0.188) | -0.050 | (0.276) | -0.456* | (0.241) |
| | Legal environment: | | | | | | |
| | Formalization | -0.081 | (0.083) | -0.121 | (0.110) | -0.052 | (0.123) |
| | Financial support | -0.095 | (0.084) | -0.072 | (0.106) | -0.158 | (0.138) |
| | Technical support | -0.311* | (0.180) | - 0.242 | (0.233) | -0.388 | (0.299) |
| | Other support | -0.210 | (0.135) | -0.228 | (0.181) | -0.199 | (0.209) |
| | Bribery | 0.030 | (0.024) | 0.115** | (0.053) | 0.023 | (0.022) |
| | Constant | -1.328 | (1.177) | -0.898** | (0.353) | -2.104*** | (0.418) |
| | Log-likelihood | -16193.30 | | -9816.86 | | -6292.74 | |
| | Observations | 12,757 | | 7,835 | | 4,902 | |
| | Industry FE | YES | | YES | | YES | |
| | Year FE | YES | | YES | | YES | |
| | Industry*Year FE | NO | | NO | | NO | |

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

## 4.6 Conclusion

As private firms play an important role in fostering local economic development, it is important to understand which factor is the most significant at boosting their performance. Yet, few studies have explored the relative importance of different variables on the firm-level efficiency, primarily because of the availability of data. Using a comprehensive dataset about firms in Vietnam, a transitional economy, this paper is among the first attempt at ranking the relative importance of various commonly-known efficiency determinants on private enterprises' profitability.

The results suggest that Vietnamese private firms are operating at about two-thirds of their potential profitability. This result is in line with previous studies in other developing countries, therefore, Vietnam provides a good case study for other private firms in the developing world. In addition to estimating the efficiency gap, this paper also documents the marginal impact of various commonly-known determinants of efficiency on the firm-level profitability. Specifically, firm-specific characteristics are more important in shaping the profitability of a firm than characteristics of the external environment in which the firm operates. This implies that policies that encourage firms to improve their own internal strength are crucial to promote the firm-level efficiency. For example, improved access to the labor market, innovation incentives to upgrade the production process and labor training programs are found to be the most significant policies for the development of the private sector.

In addition, the results also imply the importance of designing policies that meet the specific needs of each business segment in the private sector. For example, the light industries are more likely to benefit from inter-business partnerships and formalization while government support in the forms of technology and human resource training is more beneficial for the heavy industries. Finally, the design of enterprise development policy needs to be coupled with efforts to reduce corruption, as corruption has been found to crowd out the positive impacts of other factors.

The findings in this paper provide directions for future research on firm-level productivity. For example, one finding suggests that the most influential policies on the firm-level profitability are to improve the firms' internal strength, therefore, further insights into the optimal policy mix would be helpful. In addition, studies that compare the costs and benefits of various profitability-enhancement investments are also needed. Finally, the paper could benefit from the inclusion of a dataset with a longer time frame, as the SME survey will continue to be conducted in the future.

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# Appendices

## Appendix A: Appendix to Chapter 1

### A-1 Variable elasticity of substitution between energy and capital

In this part, we derive the elasticity of substitution between energy and capital in the VES production function. Recall that the elasticity of substitution between two inputs X and Y can be calculated using the following formula: $\sigma(X,Y) = \frac{\delta \ln(X/Y)}{\delta \ln(MP_y/MP_x)}$, where $X/Y$ denotes the input mix and $MP_y/MP_x$ denotes the ratio of the marginal products of the two inputs.

From equations (1.1) and (1.2) and assuming $v_1 = v_2 = 1$, we derive the marginal product of capital and energy to be:

$$\begin{aligned} MP_{K_t} &= \frac{\partial Y_t}{\partial K_t} = \frac{\partial Y_t}{\partial P_t}\frac{\partial P_t}{\partial K_t} = \frac{\partial Y_t}{\partial P_t} a_2 K_t^{a_2-1}(E_t + b_2 a_2 K_t)^{-a_2}(E_t + b_2 K_t), && \text{(A-1)} \\ MP_{E_t} &= \frac{\partial Y_t}{\partial E_t} = \frac{\partial Y_t}{\partial P_t}\frac{\partial P_t}{\partial E_t} = \frac{\partial Y_t}{\partial P_t}(1-a_2) K_t^{a_2}(E_t + b_2 a_2 K_t)^{-a_2}, && \text{(A-2)} \end{aligned}$$

where $\frac{\partial Y_t}{\partial P_t} = A_t a_1 P_t^{a_1-1}(L_t + b_1 a_1 P_t)^{-a_1}(L_t + b_1 P_t)$.

Combining equations (A-1) and (A-2) yields the ratio between the marginal products of energy and capital:

$$\frac{MP_{K_t}}{MP_{E_t}} = \frac{a_2(E_t + b_2 K_t)}{(1-a_2)K_t} = \frac{a_2(1 + b_2 \frac{K_t}{E_t})}{(1-a_2)\frac{K_t}{E_t}}. \tag{A-3}$$

Moreover, using chain rules, we have: $\frac{\partial \ln(MP_{K_t}/MP_{E_t})}{\partial(E_t/K_t)} = \frac{1}{MP_K/MP_E} * \frac{\partial(MP_K/MP_E)}{\partial(E_t/K_t)}$

$\implies \partial \ln(MP_{K_t}/MP_{E_t}) = \frac{1}{MP_K/MP_E} * \frac{\partial(MP_K/MP_E)}{\partial(E_t/K_t)} * \partial(E_t/K_t)$

Plugging equation (A-3) into the above expression and simplifying, we have:

$$\partial \ln(MP_{K_t}/MP_{E_t}) = \frac{1}{\frac{E_t}{K_t}(1 + b_2 \frac{E_t}{K_t})} \partial(E_t/K_t). \tag{A-4}$$

Furthermore:

$$\frac{\partial \ln(E_t/K_t)}{\partial (E_t/K_t)} = \frac{1}{E_t/K_t} \implies \partial \ln(E_t/K_t) = \frac{1}{E_t/K_t} * \partial (E_t/K_t). \tag{A-5}$$

Combining equations (A-4) and (A-5) yield the elasticity of substitution between capital and energy:

$$\sigma(E_t, K_t) = \frac{\partial \ln(E_t/K_t)}{\partial \ln(MP_{K_t}/MP_{E_t})} = 1 + b_2 \left(\frac{E_t}{K_t}\right), \tag{A-6}$$

where $\sigma(E_t, K_t)$ is the elasticity of substitution between energy and capital and $(E_t/K_t)$ is the energy-capital ratio.

## A-2 The shares of capital, energy and labor in a three-input VES production function

In this section, we derive the shares of capital, energy and labor in the VES production function described in equations (1.1) and (1.2). We assume constant returns to scale, that is $v_1 = v_2 = 1$ in this section.[26] Let $s_{K_t}$, $s_{E_t}$, $s_{L_t}$ be the shares of capital $K_t$, energy $E_t$ and labor $L_t$ in final output $Y_t$. Assume perfect competition in all factor markets, we can write the above shares as:

$$\begin{aligned} s_{L_t} &= \frac{MP_{L_t} L_t}{Y_t}, \\ s_{K_t} &= \frac{MP_{K_t} K_t}{Y_t}, \\ s_{E_t} &= \frac{MP_{E_t} E_t}{Y_t}, \end{aligned} \tag{A-7}$$

where $MP_{J_t} = \frac{\partial Y_t}{\partial J_t}$ denotes the marginal product of input $J$ at time $t$ $(J = K, E, L)$.

Let us first derive the share of labor $s_{L_t}$ in final output. Using equation (1.1) and assuming

[26] The derivations of input shares still hold when $v_1 \neq 1$ and $v_2 \neq 1$.

$v = 1$, we have: $MP_{L_t} = \frac{\partial Y_t}{\partial L_t} = A_t(1-a_1)P_t^{a_1}\left(L_t + b_1 a_1 P_t\right)^{-a_1}$. Thus,

$$s_{L_t} = \frac{MP_{L_t} L_t}{Y_t} = \frac{L_t - a_1 L_t}{L_t + b_1 a_1 P_t} = \frac{1 - a_1}{1 + b_1 a_1 p_t}, \tag{A-8}$$

where $p_t$ denotes physical inputs per capita.

Let $s_{P_t}$ be the share of physical inputs in final output production. Since physical input production is a function of capital and energy, we can interpret this $s_{P_t}$ as the combined shares of capital and energy in final output. Thus, we have:

$$s_{P_t} = 1 - s_{L_t} = \frac{a_1 + b_1 a_1 p_t}{1 + b_1 a_1 p_t}. \tag{A-9}$$

Next we will derive the share of energy in final output. We have:

$$s_{K_t} = \frac{MP_{K_t} K_t}{Y_t} = \frac{\frac{\partial Y_t}{\partial K_t} K_t}{Y_t} = \frac{\frac{\partial Y_t}{\partial P_t}\frac{\partial P_t}{\partial K_t} K_t}{Y_t} = \frac{\frac{\partial Y_t}{\partial P_t} P_t}{Y_t}\frac{\frac{\partial P_t}{\partial K_t} K_t}{P_t}. \tag{A-10}$$

From equations (1.1) and (1.2) we have:

$$\begin{aligned}
\frac{\partial Y_t}{\partial P_t} &= A_t a_1 P_t^{a_1 - 1}(L_t + b_1 a_1 P_t)^{1-a_1} + A_t b_1 a_1 (1-a_1) P_t^{a_1}(L_t + b_1 a_1 P_t)^{-a_1}, \\
\frac{\partial P_t}{\partial K_t} &= a_2 K_t^{a_2 - 1}(E_t + b_2 a_2 K_t)^{1-a_2} + b_2 a_2 (1-a_2) K_t^{a_2}(E_t + b_2 a_2 K_t)^{-a_2}.
\end{aligned} \tag{A-11}$$

Plugging equations (1.1), (1.2) and (A-11) into equation (A-10) and simplifying gives us the share of capital in final output as:

$$s_{K_t} = \frac{a_1 + b_1 a_1 p_t}{1 + b_1 a_1 p_t} * \frac{a_2 + b_2 a_2 \frac{K_t}{E_t}}{1 + b_2 a_2 \frac{K_t}{E_t}} = s_{P_t} * \frac{a_2 + b_2 a_2 \frac{K_t}{E_t}}{1 + b_2 a_2 \frac{K_t}{E_t}}. \tag{A-12}$$

Finally, the share of energy in final output is given by:

$$s_{E_t} = 1 - s_{L_t} - s_{K_t} = \frac{a_1 + b_1 a_1 p_t}{1 + b_1 a_1 p_t} * \frac{1 - a_2}{1 + b_2 a_2 \frac{K_t}{E_t}} = s_{P_t} * \frac{1 - a_2}{1 + b_2 a_2 \frac{K_t}{E_t}}. \tag{A-13}$$

In the case of $b_1 = 0$, that is, the elasticity of substitution between labor and physical input is constant, the shares of labor, capital and energy reduce to:

$$\begin{aligned} s_{L_t} &= 1 - a_1, \\ s_{K_t} &= a_1 * \frac{a_2 + b_2 a_2 \frac{K_t}{E_t}}{1 + b_2 a_2 \frac{K_t}{E_t}}, \\ s_{E_t} &= a_1 * \frac{1 - a_2}{1 + b_2 a_2 \frac{K_t}{E_t}}. \end{aligned} \tag{A-14}$$

## A-3 Pre-bootstrapping estimations

In this section, we present the pre-bootstrapping results of equation (1.11). Our post-estimation analysis of these analytical results suggests that the residuals are not white-noise. One solution to this issue is to bootstrap the data and re-estimate equation (1.11). The comparison between the bootstrapped and analytical estimates show a lower significance level for the bootstrapped estimates.

Table A-1: Marginal effects of capital-labor VES and income levels – pre-bootstrapping results.

| Dependent variable: GDP | | | | | | |
|---|---|---|---|---|---|---|
| | Global | | Income group | | HDI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $a_1$ | .8961*** | .8676*** | .8729*** | .8644*** | .8794*** | .8645*** |
| | (.00511) | (.00479) | (.00438) | (.00449) | (.00425) | (.00466) |
| $v_1$ | 1.005*** | 1.037*** | 1.026*** | 1.043*** | 1.021*** | 1.04*** |
| | (.00412) | (.00413) | (.00397) | (.00411) | (.0038) | (.00401) |
| $b_1$ (Global) | 2.9e-06 | -1.4e-06 | – | – | – | – |
| | (2.8e-06) | (1.3e-06) | – | – | – | – |
| $b_1$ (High income: OECD) | – | – | 2.1e-05*** | -4.3e-06*** | – | – |
| | – | – | (4.3e-06) | (9.4e-07) | – | – |
| $b_1$ (High income: Non-OECD) | – | – | 1.9e-05*** | 9.5e-06* | – | – |
| | – | – | (6.1e-06) | (5.6e-06) | – | – |
| $b_1$ (Upper middle income) | – | – | -1.7e-05*** | -1.7e-05*** | – | – |
| | – | – | (2.9e-07) | (5.1e-07) | – | – |
| $b_1$ (Lower middle income) | – | – | -4.2e-05*** | -4.3e-05*** | – | – |
| | – | – | (2.2e-07) | (4.7e-07) | – | – |
| $b_1$ (Low income) | – | – | -.00028*** | -.00028*** | – | – |
| | – | – | (1.4e-06) | (1.7e-06) | – | – |
| $b_1$ (Very high HDI) | – | – | – | – | 9.9e-06*** | -5.0e-07 |
| | – | – | – | – | (2.8e-06) | (1.6e-06) |
| $b_1$ (High HDI) | – | – | – | – | -2.4e-05*** | -2.2e-05*** |
| | – | – | – | – | (4.0e-07) | (2.2e-06) |
| $b_1$ (Medium HDI) | – | – | – | – | -1.7e-05*** | -1.7e-05*** |
| | – | – | – | – | (3.9e-07) | (6.3e-07) |
| $b_1$ (Low HDI) | – | – | – | – | -.00015*** | -.00015*** |
| | – | – | – | – | (9.1e-07) | (3.4e-06) |
| Regional fixed effect | No | Yes | No | Yes | No | Yes |
| Time fixed effect | No | Yes | No | Yes | No | Yes |
| Number of observations | 3277 | 3277 | 3277 | 3277 | 3277 | 3277 |
| R-squared | 0.9989 | 0.9992 | 0.9990 | 0.9993 | 0.9990 | 0.9993 |

* p-value < 10%, ** p-value < 5%, *** p-value < 1%.
Numbers in parentheses are standard errors.

Table A-2: Marginal effects of capital-energy VES and income levels – pre-bootstrapping results.

| Dependent variable: GDP | | | | | | |
|---|---|---|---|---|---|---|
| | Global | | Income group | | HDI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $a_1$ | 1.062*** | 1.066*** | 1.042*** | 1.053*** | 1.051*** | 1.058*** |
| | (.00373) | (.00436) | (.00382) | (.00457) | (.0042) | (.00484) |
| $a_2$ | .4165*** | .3618*** | .547*** | .447*** | .4809*** | .3925*** |
| | (.01961) | (.02644) | (.01578) | (.02049) | (.02013) | (.0265) |
| $b_2$ (Global) | .05401*** | .09723*** | – | – | – | – |
| | (.01017) | (.01949) | – | – | – | – |
| $b_2$ (High income: OECD) | – | – | .00903** | .05022*** | – | – |
| | – | – | (.00378) | (.00979) | – | – |
| $b_2$ (High income: Non-OECD) | – | – | .01584*** | .06112*** | – | – |
| | – | – | (.00407) | (.00972) | – | – |
| $b_2$ (Upper middle income) | – | – | -.00078 | .02898*** | – | – |
| | – | – | (.00364) | (.00794) | – | – |
| $b_2$ (Lower middle income) | – | – | -.00397 | .02349*** | – | – |
| | – | – | (.00446) | (.00871) | – | – |
| $b_2$ (Low income) | – | – | -.08541*** | -.08796*** | – | – |
| | – | – | (.00257) | (.0052) | – | – |
| $b_2$ (Very high HDI) | – | – | – | – | .03351*** | .08641*** |
| | – | – | – | – | (.00697) | (.01658) |
| $b_2$ (High HDI) | – | – | – | – | .02893*** | .07205*** |
| | – | – | – | – | (.0077) | (.01608) |
| $b_2$ (Medium HDI) | – | – | – | – | .01958** | .06589*** |
| | – | – | – | – | (.00785) | (.01708) |
| $b_2$ (Low HDI) | – | – | – | – | -.00822 | .04542** |
| | – | – | – | – | (.00663) | (.01969) |
| Regional fixed effect | No | Yes | No | Yes | No | Yes |
| Time fixed effect | No | Yes | No | Yes | No | Yes |
| Oil crisis dummy | No | Yes | No | Yes | No | Yes |
| Number of observations | 3277 | 3277 | 3277 | 3277 | 3277 | 3277 |
| R-squared | 0.9994 | 0.9995 | 0.994 | 0.995 | 0.994 | 0.995 |

* p-value < 10%, ** p-value< 5%, *** p-value<1%.
Numbers in parentheses are standard errors.

Table A-3: Marginal effects of capital-energy VES and environmental performance – pre-bootstrapping results.

| Dependent variable: GDP | | | | | | |
|---|---|---|---|---|---|---|
| | Global estimates | | Kyoto Annex B | | EPI | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $a_1$ | 1.062*** | 1.066*** | 1.06*** | 1.075*** | 1.046*** | 1.054*** |
| | (.00373) | (.00436) | (.00397) | (.00471) | (.00387) | (.00468) |
| $a_2$ | .4165*** | .3618*** | .4263*** | .3497*** | .498*** | .3874*** |
| | (.01961) | (.02644) | (.02037) | (.02621) | (.01839) | (.02696) |
| $b_2$ (Global) | .05401*** | .09723*** | – | – | – | – |
| | (.01017) | (.01949) | – | – | – | – |
| $b_2$ (Kyoto Annex B) | – | – | .054*** | .08127*** | – | – |
| | – | – | (.00987) | (.0183) | – | – |
| $b_2$ (No Kyoto Annex B) | – | – | .04908*** | .1085*** | – | – |
| | – | – | (.01005) | (.02072) | – | – |
| $b_2$ (Very high EPI) | – | – | – | – | .03462*** | .1069*** |
| | – | – | – | – | (.00664) | (.01989) |
| $b_2$ (High EPI) | – | – | – | – | .03425*** | .08335*** |
| | – | – | – | – | (.00717) | (.01787) |
| $b_2$ (Medium EPI) | – | – | – | – | .01445** | .06153*** |
| | – | – | – | – | (.00618) | (.01627) |
| $b_2$ (Low EPI) | – | – | – | – | .00175 | .07651*** |
| | – | – | – | – | (.00559) | (.01878) |
| $b_2$ (Very low EPI) | – | – | – | – | -.01395 | .06878*** |
| | – | – | – | – | (.00872) | (.02322) |
| Regional fixed effect | No | Yes | No | Yes | No | Yes |
| Time fixed effect | No | Yes | No | Yes | No | Yes |
| Oil crisis dummy | No | Yes | No | Yes | No | Yes |
| Number of observations | 3277 | 3277 | 3277 | 3277 | 3277 | 3277 |
| R-squared | 0.9994 | 0.9995 | 0.9994 | 0.9995 | 0.9994 | 0.9995 |

* p-value < 10%, ** p-value< 5%, *** p-value<1%.
Numbers in parentheses are standard errors.

## A-4 Classifications of countries

Table A-4: Classification of countries, by income.

| |
|---|
| *High income - OECD:* |
| Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, United Kingdom, United States. |
| *High-income - non-OECD:* |
| Bahrain, Brunei Darussalam, Cyprus, Kuwait, Malta, Oman, Qatar, Saudi Arabia, Singapore, Trinidad and Tobago, United Arab Emirates. |
| *Upper middle income:* |
| Algeria, Angola, Argentina, Botswana, Brazil, Bulgaria, Chile, China, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, Gabon, Iran, Jamaica, Jordan, Lebanon, Libyan Arab Jamahiriya, Malaysia, Mexico, Namibia, Panama, Peru, Romania, South Africa, Thailand, Tunisia, Turkey, Uruguay, Venezuela. |
| *Lower middle income:* |
| Albania, Bolivia, Cameroon, Congo, Cote d'Ivoire, Egypt, El Salvador, Ghana, Guatemala, Honduras, India, Indonesia, Iraq, Mongolia, Morocco, Nicaragua, Nigeria, Pakistan, Paraguay, Philippines, Senegal, Sri Lankan, Syrian Arab Republic, Vietnam, Yemen, Zambia. |
| *Low income:* |
| Bangladesh, Benin, Cambodia, Democratic Republic of Congo, Eritrea, Ethiopia, Haiti, Kenya, Mozambique, Myanmar, Nepal, Togo, United Republic of Tanzania, Zimbabwe. |

*Source: World Bank.*

Table A-5: Classification of countries, by HDI level.

| |
|---|
| *Very high HDI:* |
| Argentina, Australia, Austria, Bahrain, Belgium, Brunei Darussalam, Canada, Chile, Cuba, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Kuwait, Luxembourg, Malta, Netherlands, New Zealand, Norway, Poland, Portugal, Qatar, Saudi Arabia, Singapore, Slovakia, Spain, Sweden, Switzerland, United Arab Emirates, United Kingdom, United States. |
| *High HDI:* |
| Albania, Algeria, Brazil, Bulgaria, China, Colombia, Costa Rica, Dominican Republic, Ecuador, Iran, Jamaica, Jordan, Lebanon, Libyan Arab Jamahiriya, Malaysia, Mexico, Oman, Panama, Peru, Romania, Sri Lanka, Thailand, Trinidad and Tobago, Tunisia, Turkey, Uruguay, Venezuela. |
| *Medium HDI:* |
| Bangladesh, Bolivia, Botswana, Cambodia, Congo, Egypt, El Salvador, Gabon, Ghana, Guatemala, Honduras, India, Indonesia, Iraq, Mongolia, Morocco, Namibia, Nicaragua, Paraguay, Philippines, South Africa, Syrian Arab Republic, Vietnam, Zambia. |
| *Low HDI:* |
| Angola, Benin, Cameroon, Cote d'Voire, Democratic Republic of Congo, Eritrea, Ethiopia, Haiti, Kenya, Mozambique, Myanmar, Nepal, Nigeria, Pakistan, Senegal, Togo, United Republic of Tanzania, Yemen, Zimbabwe. |

*Source: United Nation Development Programme.*

Table A-6: Kyoto Annex B countries.

| |
|---|
| Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Latvia, Liechtenstein, Lithuania, Luxembourg, Monaco, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Russian Federation, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom, United States of America. |

*Source: United Nation Framework Convention on Climate Change.*

Table A-7: Classification of countries, by EPI.

| |
|---|
| *Very high EPI:* |
| Switzerland, Luxembourg, Australia, Singapore, Czech Republic, Germany, Spain, Austria, Sweden, Norway, Netherlands, United Kingdom, Denmark, Iceland, New Zealand, Portugal, Finland, Ireland, Slovakia, Italy, Greece, Canada, United Arab Emirates, Japan, France, Hungary, Chile, Poland, United States of America, Malta. |
| *High EPI:* |
| Albania, Qatar, Tunisia, Cuba, Ecuador, Venezuela, Saudi Arabia, Mexico, Panama, Malaysia, Syrian Arab Republic, Costa Rica, Jamaica, Brunei Darussalam, Belgium, Turkey, Jordan, Israel, Cyprus, Bulgaria, Kuwait, Egypt. |
| *Medium EPI:* |
| Argentina, Thailand, Botswana, Nicaragua, Dominican Republic, Oman, Lebanon, Honduras, Bahrain, Gabon, Trinidad and Tobago, Uruguay, Romania, South Africa, Algeria, Bolivia, Iran, Guatemala, Colombia, Morocco, Sri Lanka, Brazil, Zimbabwe. |
| *Low EPI:* |
| Nepal, Zambia, Libyan Arab Jamahiriya, Indonesia, El Salvador, China, Ethiopia, Senegal, Nigeria, Namibia, Kenya, Mongolia, Paraguay, Congo, Peru, Vietnam, Philippines, Cote d'Ivoire. |
| *Very Low EPI:* |
| Myanmar, Yemen, Tanzania, Bangladesh, Ghana, Angola, Eritrea, Benin, Iraq, Democratic Republic of the Congo, Mozambique, Cameroon, Haiti, Togo, India, Cambodia, Pakistan. |

*Source: Yale University.*

## A-5 Estimations of full specifications without restrictions on $b_1$

The estimates reported in Tables 1.6 and 1.7 in Section 3.5 are based on the restrictions that $b_1 = 0$ and $v_1 = v_2 = 1$. One concern is that these restrictions may distort the results, thereby altering the true capital-energy relationship. In fact, our preliminary estimations of equation (1.11) in Table A-8 show that the imposition of these restrictions do not fundamentally affect the main results while having clear computational advantages. Due to the complexity of our model, it is computationally challenging to simultaneously estimate all parameters. Therefore, to test the validity of our restrictions, we impose the constraints on one parameter at a time in our preliminary estimations. Then we perform a post-estimation hypothesis test to verify whether our estimates provide supports for imposing the constraints on other parameters in the model. Specifically, Column (1) of Table A-8 shows the estimations of equation (1.11) where we impose $v_1 = 1$, while Column (2) shows the estimation results under the constraint $v_2 = 1$. Our post-estimation hypothesis test shows that under these restrictions, the returns-to-scale parameters $v_1$ and $v_2$ are not significantly different from 1. In other words, our estimates provide support for a production function with constant returns to scale, Therefore, in Column (3) of Table A-8, we present the estimates of equation (1.11) where we restrict both $v_1$ and $v_2$ to be 1. Our results also show that parameter $b_1$ is close to 0 and the magnitude of parameter $b_1$ is very small compared to that of $b_2$. This suggests that the elasticity of substitution between capital and energy is more likely to vary over time than the elasticity of substitution between labor and physical inputs. Therefore, we restrict the value of $b_1$ to be 0.

Table A-8: Full specification without restrictions on $b_1$.

| Dependent variable: GDP | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | $v_1 = 1$ | $v_2 = 1$ | $v_1 = v_2 = 1$ |
| $a_1$ | 1.1069*** | 1.1075*** | 1.1134*** |
| | (0.0079) | (0.0079) | (0.0065) |
| $a_2$ | 0.1873*** | 0.1882*** | 0.1914*** |
| | (0.0351) | (0.0350) | (0.0348) |
| $b_1$ | 0.0006*** | 0.0006*** | 0.0006*** |
| | (0.0002) | (0.0002) | (0.0002) |
| $b_2$ | 0.3230*** | 0.3205*** | 0.3116*** |
| | (0.0965) | (0.0954) | (0.0914) |
| $v_1$ | – | 1.0039*** | – |
| | – | (0.0031) | – |
| $v_2$ | 1.0041*** | – | – |
| | (0.0029) | – | – |

* p-value < 10%, ** p-value < 5%, *** p-value < 1%.
Numbers in parentheses are standard errors.

# Appendix B: Appendix to Chapter 2

## B-1 Testing for asymmetric leverage effects

One stylized fact in the financial world is that volatility tends to be higher in response to negative shocks than to positive shocks. This section presents a simple framework to uncover this possible asymmetric leverage effects in a given time series, according to Zivot (2008).

Let $\{R_t\}$ be a time series of asset returns. To test for the presence of asymmetric leverage effects in $\{R_t\}$, we first obtain the residuals from the following conditional mean regression:

$$E_{t-1}[R_t] = c + \sum_{h=1}^{r} \phi_h(y_{t-h}) + \sum_{k=1}^{s} \psi_k \epsilon_{t-k} + \epsilon_t, \tag{B-1}$$

where the lag lengths $r$ and $s$ are determined using the Schwartz information criteria.

Next, we estimate the following regression:

$$\hat{\epsilon}_t^2 = \gamma_0 + \gamma_1 \hat{\omega}_{t-1} + \zeta_t, \tag{B-2}$$

where $\hat{\epsilon}_t$ is the estimated residuals from equation (B-1), $\hat{\omega}_t$ is a dummy variable that equals 1 when $\hat{\epsilon}_t < 0$ and 0 otherwise. A significant $\gamma_1$ provides evidence for asymmetric leverage effects in the ARCH/GARCH model.

# Appendix C: Appendix to Chapter 3

## C-1 A directed technological change model of the electricity sector

In this section, we present a directed technological change model of the electricity sector where we distinguish between innovation in renewable and nonrenewable technologies. Our goal is to derive the equilibrium condition that explains firm-level innovation that guides our empirical analysis in section 3.4. Aghion et al. (2016) used the directed technological change framework by Acemoglu et al. (2012) to study innovation in the automobile industry. We follow a similar approach but focus instead on the electricity sector.

There are two types of agents in this economy: consumers and electricity producers. Consumers derive their utility from the consumption of goods and electricity:

$$U = c_0 + \frac{\beta}{\beta - 1}\left(\int_0^1 Y_i^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}\frac{\beta-1}{\beta}}, \tag{C-1}$$

where $U$ denotes utility, $c_0$ is consumption good and $Y_i$ is electricity purchased from retailer $i$. $\beta$ is the elasticity of substitution between electricity and the consumption good while $\sigma$ is the elasticity of substitution between electricity from different electricity retailers. Consumers allocate their budget between the consumption goods and electricity such that their utility is maximized. This maximization process yields the consumers' electricity demand function:

$$Y_i = P^{\sigma-\beta} P_i^{-\sigma}, \tag{C-2}$$

where $Y_i$ is consumer electricity demand from retailer $i$, $P_i$ is the price of electricity charged by retailer $i$, while $P$ is the market price of electricity. In this model, we consider tax-inclusive electricity prices.

Two types of firms participate in the electricity sector: the generators and the retailers. Electricity generators produce electricity using either renewable or non-renewable resources while electricity retailers buy electricity from the generators and deliver it to the consumers. Let us start with electricity generators.

There are two types of electricity generators: renewable and nonrenewable. Renewable electricity generators produce electricity using renewable resources ($r$) while nonrenewable electricity generators use fossil fuels ($f$). At the beginning of each period, they engage in research to develop new electricity-generating technologies. Research efforts can improve firms' existing technology by $A_{i,j} = (1 + x_{i,j})A^0_{i,j}$, where $A_{i,j}$ measures generator $i$'s advancement in technology $j$ and $A^0_{i,j}$ is the firm's initial knowledge in technology $j$ for $j = r, f$. At the end of the period, newly developed technologies are used to generate electricity, which is then sold to electricity retailers. All electricity generators engage in research, thus there exists a continuum of renewable and nonrenewable electricity generators with local market power, which allows them to seek monopoly rents from electricity retailers.[27]

Electricity retailers buy electricity from renewable and nonrenewable generators, which are substitutes. There are multiple electricity retailers and they take the consumer demand for electricity in equation (C-2) as given. Retailers maximize profits by choosing the amount of renewable and nonrenewable electricity to buy. The profit function for electricity retailers is given as:

$$\pi_i^R = \max_{y_{i,r}, y_{i,f}} \{P_i Y_i - p_{i,r} y_{i,r} - p_{i,f} y_{i,f}\}, \tag{C-3}$$

[27]In reality, each electricity generator would be able to decide whether to conduct research at the beginning of each period. While this distinction is important to study the impact of policies on innovation from an empirical standpoint, note that there is no change in firms' level of technology when they choose not to conduct research or when they conduct unsuccessful research. In other words, from a theoretical standpoint, the economic outcome resulting from firms' decision not to engage in research is the same as those resulting from firms' unsuccessful research. Therefore, we assume that all electricity generators engage in research in our theoretical model while our empirical model separately analyzes the impact of policies on firms' decision to engage in research and on the probability that the research is successful.

where $\pi_i^R$ are the profits of retailer $i$, $P_i$ is the price of electricity that retailer $i$ charges its consumers, $y_{i,j}$ $(j = r, f)$ is electricity purchased from renewable and nonrenewable sources, and $p_{i,j}$ $(j = r, f)$ are their corresponding prices. Electricity for final consumption, $Y_i$, combines electricity from renewable and nonrenewable sources:

$$Y_i \equiv \left( y_{i,r}^{\frac{\epsilon-1}{\epsilon}} + y_{i,f}^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{C-4}$$

where $\epsilon$ is the ease of substitution between renewables and nonrenewables.[28] Retailers maximize profits in (C-3) and determine their demands for renewable and nonrenewable electricity: $y_{i,j} = Y_i \left( \frac{P_i}{p_{i,j}} \right)^{\epsilon}$ for $j = r, f$. Since electricity generators earn monopoly profits from their research by exerting their market power over the prices of electricity sold to retailers (i.e. $p_{i,j}$ for $j = r, f$), using (C-2), we rewrite the retailers' inverse demand function for electricity generated from source $j$ $(j = r, f)$ in terms of prices as:

$$y_{i,j} = P^{\sigma-\beta} P_i^{\epsilon-\sigma} p_{i,j}^{-\epsilon}. \tag{C-5}$$

We consider two types of environmental policies: energy taxes and research subsidies. Energy taxes affect firms through the price of electricity $(P)$ while research subsidies $(\tau_j)$ affect firms by reducing the cost of innovation.[29]

With the retailers' inverse demand function in place, we can calculate the profit maximization of electricity generators and their equilibrium level of investment in research. At the beginning of each period, electricity generator $i$ invest $\frac{1}{2}\psi x_{i,j}$ of the consumption goods in research for technology

[28] There is much debate about how ease it is to substitute renewable and nonrenewable technologies in electricity generation. While some people argue that they are easily substitutable, others find evidence for a complementary relationship.

[29] We can think of these subsidies as lowering the costs of doing research.

type $j$ $(j = r, f)$. The equilibrium level of research $x_{i,j}$ maximizes:

$$\max_{x_{i,j}} \left\{ \pi_{i,j} - \frac{1}{2} \frac{\psi x_{i,j}}{\tau_j} \right\}, \tag{C-6}$$

where $\pi_{i,j}$ are generator $i$'s expected profits from selling electricity generated by source $j$ to the retailers and $\tau_j$ are research subsidies for technology type $j$ $(j = r, f)$. We calculate the equilibrium level of research backwards. First, we calculate electricity generators' equilibrium profits $\pi_{i,j}$ and second, we calculate their equilibrium level of research intensity $x_{i,j}$. Profit maximization becomes: $\pi_{i,j} = \max_{y_{i,j}} \{p_{i,j} y_{i,j} - \frac{1}{A_{i,j}} y_{i,j}\}$ where $p_{i,j}$ is the inverse demand function in equation (C-5). From this maximization problem, we obtain the equilibrium demand for renewable and nonrenewable electricity, $y_{i,j} = \left(\frac{\epsilon-1}{\epsilon}\right)^{\epsilon}$, their corresponding equilibrium prices, $p_{i,j} = \frac{\epsilon}{\epsilon-1} \frac{1}{A_{i,j}}$, and equilibrium profits, $\pi_{i,j} = \left(\frac{(\epsilon-1)^{\epsilon-1}}{\epsilon^{\epsilon}}\right) P_i^{\epsilon-\sigma} P^{\sigma-\beta} A_{i,j}^{\epsilon-1}$, for $j = r, f$. We use these equilibrium profits in (C-6) to calculate the equilibrium level of innovation.

Innovation intensity for each electricity generator satisfies the first order condition:

$$x_{i,j} = \left(\frac{\epsilon - 1}{\epsilon}\right)^{\epsilon} \frac{\tau_j}{\psi} P_i^{\epsilon-\sigma} P^{\sigma-\beta} \left( \frac{A_{i,j}^0}{\left((1 + x_{i,j}) A_{i,j}^0\right)^{2-\epsilon}} \right). \tag{C-7}$$

Equation (C-7) describes each firm's incentives to innovate. This equation shows that the equilibrium innovation intensity depends on environmental policies, such as energy taxes and research subsidies, energy prices and firms' past research. More importantly, the impact of energy prices and taxes on the direction of innovation depends on the ease at which firms can substitute between electricity generated from fossil fuels and renewable energy ($\epsilon$), as well as the ease at which consumers can substitute between electricity and the consumption good ($\beta$) and between electricity supplied by different producers ($\sigma$).

## C-2 Data appendix

Table C-1: Variables and sources of data.

| Variable | Unit of measure | Source |
|---|---|---|
| Patents | Number of applications | OECD Triadic Patent Families Database |
| | Firms' name and location | OECD REGPAT Database |
| | Firms' name and location | OECD HAN database |
| Research subsidies | Constant 2005 national prices (in millions of 2005 U.S. $ ) | IEA Energy Technology RD&D Statistics |
| Energy prices including taxes | Constant 2005 national prices (in millions of 2005 U.S. $ ) | IEA Energy Prices & Taxes |
| Real GDP | Constant 2005 national prices (in millions of 2005 U.S. $ ) | Penn World Table |
| Population | Millions of people | Penn World Table |
| Population density | People per square km of land area | World Development Indicator |

Table C-2: List of countries.

*Patents:*

Argentina, Australia, Austria, Bahamas, Barbados, Belgium, Belize, Bermuda, Brazil, Bulgaria, Canada, Cayman Islands, Chile, China, Colombia, Croatia, Cyprus, Czech Republic, Denmark, Dominica, Finland, France, Georgia, Germany, Greece, Hong Kong, Hungary, Iceland, Indonesia, India, Iran, Ireland, Italy, Israel, Japan, Jordan, Korea, Kenya, Kuwait, Lithuania, Luxembourg, Malaysia, Mauritius, Mexico, Netherlands, New Zealand, Norway, Panama, Philippines, Poland, Portugal, Russian Federation, Saudi Arabia, Seychelles, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, St. Kitts and Nevis, Sweden, Switzerland, Taiwan, Thailand, Turkey, Ukraine, United Arab Emirates, United Kingdom, United States of America, Venezuela.

*Energy prices and research subsidies:*

Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States of America.

*Countries in the estimations:*

Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States of America.

### International patent classifications (IPC)

Table C-3: Patent classes for renewable electricity generation technologies.

| IPC code | Description |
|---|---|
| H01M 4/86-4/98, 8/00-8/24, 12/00-12/08 | **Fuel cells** |
| H01M 4/86-4/98 | Electrodes |
| H01M 4/86-4/98 | Inert electrodes with catalytic activity |
| H01M 2/00-2/04 , 8/00-8/24 | Non-active parts |
| H01M 12/00-12/08 | Within hybrid cells |
| C10B 53/00, C10J | **Pyrolysis or gasification of biomass** |
| | **Harnessing energy from manmade waste** |
| C10L 5/00 | Agricultural waste |
| C10L 5/42, 5/44 | Fuel from animal waste and crop residues |
| F23G 7/00, 7/10 | Incinerators for field, garden or wood waste |
| C10J 3/02, 3/46, F23B 90/00, F23G 5/027 | Gasification |
| B09B 3/00, F23G 7/00 | Chemical waste |
| C10L 5/48, F23G 5/00, F23G 7/00 | Industrial waste |
| C21B 5/06 | Using top gas in blast furnaces to power pigiron production |
| D21C 11/00 | Pulp liquors |
| A62D 3/02, C02F 11/04, 11/14 | Anaerobic digestion of industrial waste |
| F23G 7/00, 7/10 | Industrial wood waste |
| B09B 3/00, F23G 5/00 | Hospital waste |
| B09B | Landfill gas |

**Table C-3 – continued from previous page**

| IPC code | Description |
|---|---|
| B01D 53/02, 53/04, 53/047, 53/14, 53/22, 53/24, C10L 5/46 | Separation of components |
| F23G 5/00 | Municipal waste |
| | **Hydro energy** |
| E02B 9/00-9/06 | Water-power plants |
| E02B 9/08 | Tide or wave power plants |
| F03B, F03C | Machines or engines for liquids |
| F03B 13/12-13/26 | Using wave or tide energy |
| F03B 15/00-15/22 | Regulating, controlling or safety means of machines or engines |
| B63H 19/02, 19/04 | Propulsion of marine vessels using energy derived from water movement |
| F03G 7/05 | **Ocean thermal energy conversion (OTEC)** |
| F03D | **Wind energy** |
| H02K 7/18 | Structural association of electric generator with mechanical driving motor |
| B63B 35/00, E04H 12/00, F03D 11/04 | Structural aspects of wind turbines |
| B60K 16/00 | Propulsion of vehicles using wind power |
| B60L 8/00 | Electric propulsion of vehicles using wind power |
| B63H 13/00 | Propulsion of marine vessels by wind-powered motors |
| | **Solar energy** |
| H01L 27/142, 31/00 31/078, H01G 9/20, H02N 6 | Devices adapted for the conversion of radiation energy into electrical energy |
| H01L 27/30, 51/42-51/48 | Using organic materials as the active part |
| H01L 25/00, 25/03, 25/16, 25/18, 31/042 | Assemblies of a plurality of solar cells |
| C01B 33/02, C23C 14/14, 16/24, C30B 29/06 | Silicon; single-crystal growth |

**Table C-3 – continued from previous page**

| IPC code | Description |
|---|---|
| G05F 1/67 | Regulating to the maximum power available from solar cells |
| F21L 4/00, F21S 9/03 | Electric lighting devices with, or rechargeable with, solar cells |
| H02J 7/35 | Charging batteries |
| H01G 9/20, H01M 14/00 | Dye-sensitised solar cells (DSSC) |
| F24J 2/00-2/54 | Use of solar heat |
| F24D 17/00 | For domestic hot water systems |
| F24D 3/00, 5/00, 11/00, 19/00 | For space heating |
| F24J 2/42 | For swimming pools |
| F03D 1/04, 9/00, 11/04, F03G 6/00 | Solar updraft towers |
| C02F 1/14 | For treatment of water, waste water or sludge |
| F02C 1/05 | Gas turbine power plants using solar heat source |
| H01L 31/058 | Hybrid solar thermal-PV systems |
| B60K 16/00 | Propulsion of vehicles using solar power |
| B60L 8/00 | Electric propulsion of vehicles using solar power |
| F03G 6/00-6/06 | Producing mechanical power from solar energy |
| E04D 13/00, 13/18 | Roof covering aspects of energy collecting devices |
| F22B 1/00, F24J 1/00 | Steam generation using solar heat |
| F25B 27/00 | Refrigeration or heat pump systems using solar energy |
| F26B 3/00, 3/28 | Use of solar energy for drying materials or objects |
| F24J 2/06, G02B 7/183 | Solar concentrators |
| F24J 2/04 | Solar ponds |
| | **Geothermal energy** |
| F01K, F24F 5/00, F24J 3/08, H02N 10/00, F25B 30/06 | Use of geothermal heat |
| F03G 4/00-4/06, 7/04 | Production of mechanical power from geothermal energy |

**Table C-3 – continued from previous page**

| IPC code | Description |
|---|---|
| F24J 1/00, 3/00, 3/06 | Other production or use of heat, not derived from combustion, e.g. natural heat |
| F24D 11/02 | Heat pumps in central heating systems using heat accumulated in storage masses |
| F24D 15/04 | Heat pumps in other domestic- or space-heating systems |
| F24D 17/02 | Heat pumps in domestic hot-water supply systems |
| F24H 4/00 | Air or water heaters using heat pumps |
| F25B 30/00 | Heat pumps |
| | **Using waste heat** |
| F01K 27/00 | To produce mechanical energy |
| F01K 23/06-23/10, F01N 5/00, F02G 5/00-5/04, F25B 27/02 | Of combustion engines |
| F01K 17/00;23/04 | steam engine plants |
| F02C 6/18 | Of gas-turbine plants |
| F25B 27/02 | As source of energy for refrigeration plants |
| C02F 1/16 | For treatment of water, waste water or sewage |
| D21F 5/20 | Recovery of waste heat in paper production |
| F22B 1/02 | For steam generation by exploitation of the heat content of hot heat carriers |
| F23G 5/46 | Recuperation of heat energy from waste incineration |
| F24F 12/00 | Energy recovery in air conditioning |
| F27D 17/00 | Arrangements for using waste heat from furnaces, kilns, ovens or retorts |
| F28D 17/00-20/00 | Regenerative heat-exchange apparatus |
| C10J 3/86 | Of gasification plants |
| F03G 5/00-5/08 | Devices for producing mechanical power from muscle energy |

Source: IPC Green Inventory, World Intellectual Property Organization.

Table C-4: Patent classes for efficiency-improving electricity generation technologies.

| IPC code | Description |
|---|---|
| **Coal gasification** | |
| C10J3 | Production of combustible gases containing carbon monoxide from solid carbonaceous fuels |
| **Improved burners** | [Classes listed below excluding combinations with B60,B68,F24,F27] |
| F23C1 | Combustion apparatus specially adapted for combustion of two or more kinds of fuel simultaneously or alternately,at least one kind of fuel being fluent |
| F23C5/24 | Combustion apparatus characterised by the arrangement or mounting of burners; disposition of burners to obtain a loop flame |
| F23C6 | Combustion apparatus characterised by the combination of two or more combustion chambers |
| F23B10 | Combustion apparatus characterised by the combination of two or more combustion chambers |
| F23B30 | Combustion apparatus with driven means for agitating the burning fuel; combustion apparatus with driven means for advancing the burning fuel through the combustion chamber |
| F23B70 | Combustion apparatus characterised by means for returning solid combustion residues to the combustion chamber |
| F23B80 | Combustion apparatus characterised by means creating a distinct flow path for fluegases or for non-combusted gases given off by the fuel |
| F23D1 | Burners for combustion of pulverulent fuel |
| F23D7 | Burners in which drops of liquid fuel impinge on a surface |
| F23D17 | Burners for combustion simultaneously or alternatively of gaseous or liquid or pulverulent fuel |
| **Fluidised bed combustion** | |
| B01J8/20-22 | Chemical or physical processes in general, conducted in the presence of fluids and solid particles; apparatus for such processes; with liquid as a fluidising medium |

**Table C-4 – continued from previous page**

| IPC code | Description |
|---|---|
| B01J8/24-30 | Chemical or physical processes in general, conducted in the presence of fluids and solid particles; apparatus for such processes; according to “fluidised-bed” technique |
| F27B15 | Fluidised bed furnaces; Other furnaces using or treating finely divided materials in dispersion |
| F23C10 | Apparatus in which combustion takes place in afluidised bed of fuel or other particles |
| **Improved boilers for steam generation** | |
| F22B31 | Modifications of boiler construction, or of tube systems, dependent on installation of combustion apparatus; Arrangements or dispositions of combustion apparatus |
| F22B33/14-16 | Steam generation plants,e.g.comprising steam boilers of different types in mutual association; combinations of low-and high-pressure boilers |
| **Improved steam engines** | |
| F01K3 | Plants characterised by the use of steam or heat accumulators, or intermediate steam heaters, therein |
| F01K5 | Plants characterised by use of means for storing steam in an alkali to increases team pressure,e.g. of Honigmann or Koenemann type |
| F01K23 | Plants characterised by more than one engine delivering power external to the plant, the engines being driven by different fluids |
| **Super-heaters** | |
| F22G | Steam super heating characterised by heating method |
| **Improved gas turbines** | |
| F02C7/08-105 | Features, component parts, details or accessories; heating air supply before combustion,e.g. by exhaust gases |
| F02C7/12-143 | Features, component parts, details or accessories; cooling of plants |
| F02C7/30 | Features, component parts, details or accessories; preventing corrosion in gas-swept spaces |
| **Combined cycles** | |

**Table C-4 – continued from previous page**

| IPC code | Description |
|---|---|
| F01K23/02-10 | Plants characterised by more than one engine delivering power external to the plant, the engines being driven by different fluids; the engine cycles being thermally coupled |
| F02C3/20-36 | Gas turbine plants characterised by the use of combustion products as the working fluid; using special fuel, oxidant or dilution fluid to generate the combustion products |
| F02C6/10-12 | Plural gas-turbine plants; combinations of gas-turbine plants with other apparatus; supplying working fluid to a user,e.g. a chemical process, which returns working fluid to a turbine of the plant |
| **Improved compressed-ignitionengines** | |
| [Classes listed below excluding combinations with B60,B68,F24,F27] | |
| F02B1/12-14 | Engines characterised by fuel-air mixture compression; with compression ignition |
| F02B3/06-10 | Engines characterised by fuel-air mixture compression; with compression ignition |
| F02B7 | Engines characterised by the fuel-air charge being ignited by compression ignition of an additional fuel |
| F02B11 | Engines characterised by both fuel-air mixture compression and air compression, or characterised by both positive ignition and compression ignition,e.g.indifferent cylinders |
| F02B13/02-04 | Engines characterised by the introduction of liquid fuel into cylinders by use of auxiliary fluid; compression ignition engines using air or gas for blowing fuel into compressed air in cylinder |
| F02B49 | Methods of operating air- compressing compression-ignition engines involving introduction of small quantities of fuel in the form of a fine mist into the air in the engine's intake |
| **Co-generation** | |
| F01K17/06 | Use of steam or condensate extracted or exhausted from steam engine plant; returning energy of steam, in exchanged form,to process,e.g. use of exhaust steam for drying solid fuel of plant |
| F01K27 | Plants for converting heat or fluid energy into mechanical energy |

**Table C-4 – continued from previous page**

| IPC code | Description |
|---|---|
| F02C6/18 | Plural gas-turbine plants; combinations of gas-turbine plants with other apparatus; using the waste heat of gas-turbine plants outside the plants themselves, e.g. gas-turbine power heat plants |
| F02G5 | Profiting from waste heat of combustion engines |
| F25B27/02 | Machines, plant, or systems, using particular sources of energy; using waste heat, e.g. from internal-combustion engines |

Source: Lanzi et al. (2011).

Table C-5: Patent classes for general fossil-fuel technologies.

| **IPC code** | **Description** |
|---|---|
| C10J | Production of fuel gases by carburetting air or other gases without pyrolysis |
| F01K | Steam engine plants; steam accumulators; engine plants not otherwise provided for; engines using special working fluids or cycles |
| F02C | Gas-turbine plants; air intakes for jet-propulsion plants; controlling fuel supply in air-breathing jet-propulsion plants |
| F02G | Hot-gas or combustion-product positive-displacement engine; use of waste heat of combustion engines,not otherwise provided for |
| F22 | Steam generation |
| F23 | Combustion apparatus; combustion processes |
| F27 | Furnaces; kilns; ovens; retorts |

Source: Lanzi et al. (2011).

Table C-6: Patent classes for base load electricity generation technologies.

| IPC code | Description |
|---|---|
| C10J3 | Coal gassification–production from solid carbonaceous fuels |
| F23C1 | Integrated coal gasification combined cycle (IGCC) |
| F23C5/24 | Burners used for combustion are used in base load activities |
| F23C6 | Burners used for combustion are used in base load activities |
| F23B10 | Other coal-fire technology, in general |
| F23B30 | Burners used for combustion are used in base load activities |
| F23B70 | Burners used for combustion are used in base load activities |
| F23B80 | Burners used for combustion are used in base load activities |
| F23D1 | Pulverized coal combustion (PCC) in steam cycle |
| F23D7 | Burners used for combustion are used in base load activities |
| F23D17 | Integrated coal gasification combined cycle (IGCC) |
| B01J8/20-22 | FBC burns coal or any combustable material. Coal is mainly used in base load operations |
| B01J8/24-30 | FBC burns coal or any combustable material. Coal is mainly used in base load operations |
| F27B15 | FBC burns coal or any combustable material. Coal is mainly used in base load operations |
| F23C10 | FBC burns coal or any combustable material. Coal is mainly used in base load operations |
| F22B31 | Used in steam generation. From p 24 ref 7 “baseload steam generating units (e.g., boilers)” |
| F22B33/14-16 | Used in steam generation. From p 24 ref 7 “baseload steam generating units (e.g., boilers)” |
| F01K3 | Steam engines used in base load ops |
| F01K5 | Steam engines used in base load ops |
| F01K23 | IGCC |
| F22G | PCC in steam cycle |
| F01K23/02-10 | CCGT is the dominant gas-based technology for intermediate and base-load power generation |
| F02C3/20-36 | CCGT is the dominant gas-based technology for intermediate and base-load power generation |
| F02C6/10-12 | CCGT is the dominant gas-based technology for intermediate and base-load power generation |

Source: own calculations.

Table C-7: Patent classes for peak load electricity generation technologies.

| IPC code | Description |
|---|---|
| F02C7/08-105 | Gas Turbines used in peak load operations |
| F02C7/12-143 | Gas Turbines used in peak load operations |
| F02C7/30 | Gas Turbines used in peak load operations |
| F02B1/12-14 | Compressed-ignition engines (or diesel engines) are used in peak load production |
| F02B3/06-10 | Compressed-ignition engines (or diesel engines) are used in peak load production |
| F02B7 | Compressed-ignition engines (or diesel engines) are used in peak load production |
| F02B11 | Compressed-ignition engines (or diesel engines) are used in peak load production |
| F02B13/02-04 | Compressed-ignition engines (or diesel engines) are used in peak load production |
| F02B49 | Compressed-ignition engines (or diesel engines) are used in peak load production |
| F01K17/06 | Cogeneration is used dring peak load hours mainly using natural gases |
| F01K27 | Cogeneration is used dring peak load hours mainly using natural gases |
| F02C6/18 | Cogeneration is used dring peak load hours mainly using natural gases |
| F02G5 | Cogeneration is used dring peak load hours mainly using natural gases |
| F25B27/02 | Cogeneration is used dring peak load hours mainly using natural gases |

Source: own calculations.

**Summary statistics**

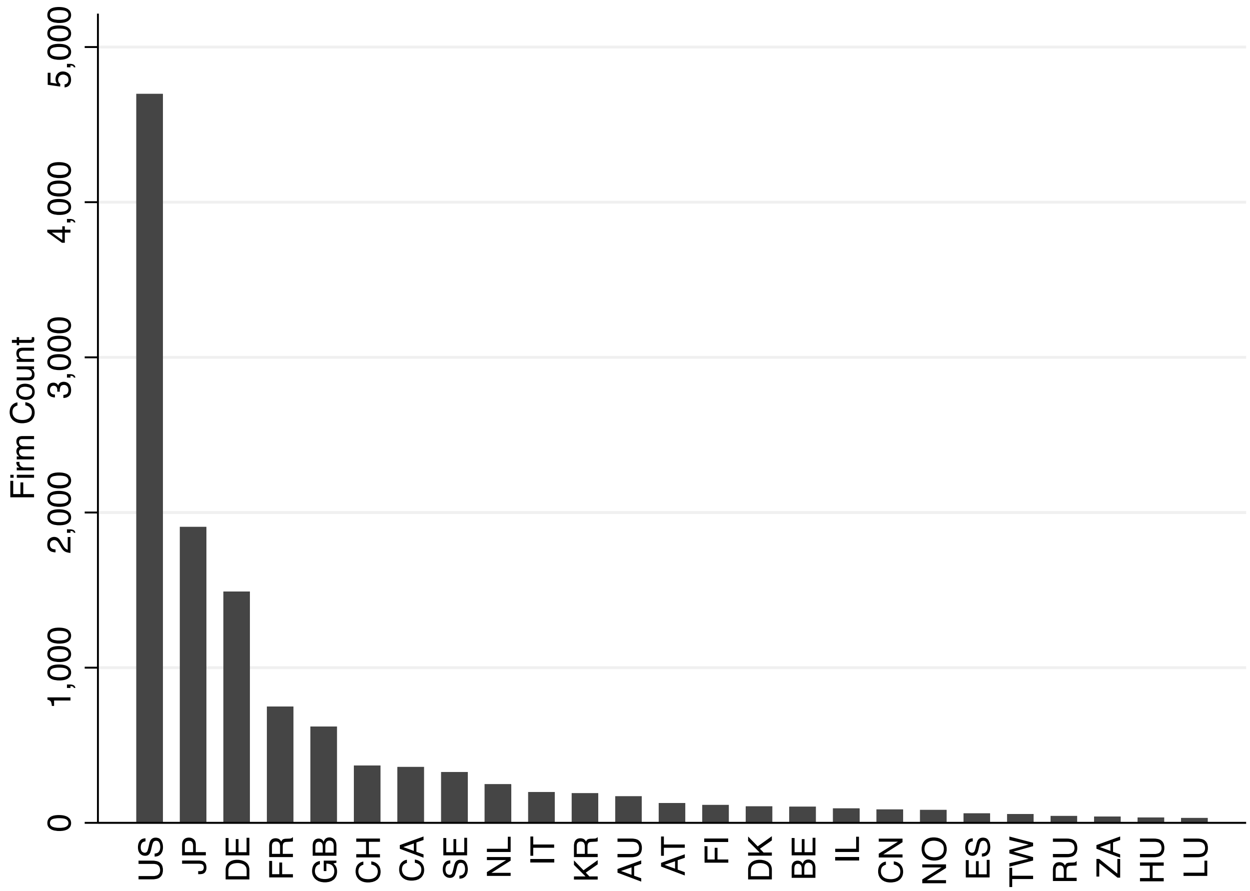


Figure C-1: Innovating firms by country.

Table C-8: Total number of patents in each renewable and fossil fuel technology.

| Technology | Global |
|---|---|
| *Renewables* | |
| Geothermal | 2,123 |
| Hydro | 6,337 |
| Natural heat | 2,351 |
| Solar | 59,905 |
| Thermal | 43 |
| Waste | 17,361 |
| Waste heat | 2,351 |
| Wind | 5,770 |
| Fuel cells | 22,994 |
| Biomass | 808 |
| Muscle energy | 16 |
| *Total* | *120,059* |
| *Fossil fuels* | |
| Base load (coal and natural gas) | 89,425 |
| Peak load (natural gas and diesel) | 27, 121 |
| *Total* | *116,546* |

Table C-9: Cross-correlation table of energy prices in the most innovative regions.

**United States**

| | Coal price | Natural gas price | Oil price | Electricity price |
|---|---|---|---|---|
| Coal price | 1.000 | | | |
| Natural gas price | 0.503 | 1.000 | | |
| Oil price | 0.766 | 0.867 | 1.000 | |
| Electricity price | 0.769 | 0.779 | 0.775 | 1.000 |

**Europe**

| | Coal price | Natural gas price | Oil price | Electricity price |
|---|---|---|---|---|
| Coal price | 1.000 | | | |
| Natural gas price | 0.858 | 1.000 | | |
| Oil price | 0.902 | 0.921 | 1.000 | |
| Electricity price | 0.961 | 0.913 | 0.902 | 1.000 |

**Japan**

| | Coal price | Natural gas price | Oil price | Electricity price |
|---|---|---|---|---|
| Coal price | 1.000 | | | |
| Natural gas price | 0.376 | 1.000 | | |
| Oil price | 0.858 | 0.206 | 1.000 | |
| Electricity price | -0.014 | 0.386 | 0.164 | 1.000 |

## C-3 Robustness analysis

This section presents the detailed estimation results of the robustness analysis discussed in section 3.6. Specifically, tables C-10 and C-11 show the zero-inflated Poisson and negative binomial estimates while Table C-12 shows additional fossil fuel prices. In tables C-13 and C-14 we consider alternative lag structures of past innovation and table C-15 presents the estimation results using the five geographical regions as an alternative definition of regional spillovers. Table C-16 controls for additional macroeconomic indicators while Table C-17 considers only firms in France, Germany, Japan, United Kingdom and United States, the five most innovative countries in the dataset. Table C-18 separates firms between large and small firms while table C-19 separates them between specialized and mixed firms. Finally, tables C-20 and C-21 looks at different definitions of base load and peak load technologies.

Table C-10: Zero-inflated Poisson estimates of the determinants of firm-level innovation in renewable and non-renewable technologies using global data from 1978 to 2011.

| | **Dependent variable: firm-level number of patents** | | | |
|---|---|---|---|---|
| | Probability to apply for a patent (Poisson – intensive margin) | | Probability to engage in research (Logit – extensive margin) | |
| | Renewable | Fossil fuel | Renewable | Fossil fuel |
| | (1) | (2) | (3) | (4) |
| *Energy prices including taxes* | | | | |
| L1.Coal price | -.36010*** | -.30060* | -.05183 | -.16450*** |
| | (.10370) | (.16440) | (.04318) | (.04526) |
| L1.Electricity price | -.50680*** | -.72890*** | -.10040* | .01906 |
| | (.10470) | (.18690) | (.05896) | (.06581) |
| *Research subsidies* | | | | |
| L1.Renewable | .08301*** | .04699 | -.02661 | -.06508*** |
| | (.03033) | (.05693) | (.01890) | (.02014) |
| L1.Fossil fuel | -.10610*** | -.04926 | -.01698 | -.00639 |
| | (.02006) | (.03995) | (.01332) | (.01473) |
| L1.Efficiency-improving | .03313 | .06965 | .03944* | .06440*** |
| | (.03131) | (.06131) | (.02245) | (.02431) |
| *Past innovation* | | | | |
| L1.Renewable knowledge | .00345*** | .00007 | -.01313*** | .00055 |
| | (.00018) | (.00068) | (.00082) | (.00049) |
| L1.Renewable spillovers | -.00002*** | -.00003* | -.00002*** | -.00000 |
| | (.00001) | (.00001) | (.00000) | (.00000) |
| L1.Fossil-fuel knowledge | .00004 | .00054*** | .00068*** | -.00792*** |
| | (.00006) | (.00007) | (.00017) | (.00092) |
| L1.Fossil-fuel spillover | .00003*** | .00003** | .00000 | .00000 |
| | (.00001) | (.00001) | (.00000) | (.00000) |
| *Macroeconomic indicators* | | | | |
| L1.GDP | -.00629 | -.00417 | .01788 | .03257 |
| | (.05982) | (.1028) | (.02037) | (.022) |
| L1.GDP per capita | .12320 | -2.8430*** | -.10140 | .87870*** |
| | (.35030) | (.68200) | (.12240) | (.13720) |
| Constant term | 55.55000* | -36.84000 | 2.96400** | -7.34800*** |
| | (29.40000) | (53.14000) | (1.26300) | (1.38500) |
| Firm pre-sample FE | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Observations | 30597 | 30597 | 30597 | 30597 |

* p-value < 10%, ** p-value < 5%, *** p-value < 1%.
Numbers in parentheses are standard errors.

Table C-11: Negative binomial estimates of the determinants of firm-level innovation in renewable, base load and peak load technologies in the five most innovative countries.

| | **Dependent variable: firm-level number of patents** | | |
|---|---|---|---|
| | | Fossil fuel | |
| | Renewable | Base load | Peak load |
| *Energy prices including taxes* | | | |
| L1.Coal price | -.4939*** | -.4275*** | -.3169* |
| | (.06604) | (.09596) | (.1721) |
| L1.Electricity price | -.00157 | .0215 | -.1107 |
| | (.07439) | (.1032) | (.1803) |
| *Research subsidies* | | | |
| L1.Renewable | .01648 | .03532 | .03243 |
| | (.0292) | (.03803) | (.07431) |
| L1.Fossil fuel | .04571** | .02959 | -.02929 |
| | (.02059) | (.02778) | (.05324) |
| L1.Efficiency-improving | .04731*** | .00883 | .1616*** |
| | (.01664) | (.02333) | (.04631) |
| *Past innovation knowledge* | | | |
| L1.Renewable | .00072*** | .00063*** | .00115*** |
| | (5.5e-05) | (.00011) | (.00019) |
| L1.Base load | .00046*** | .00135*** | .00055*** |
| | (.0001) | (.00011) | (.00017) |
| L1.Peak load | 2.8e-05 | -.00048*** | 6.0e-05 |
| | (.0001) | (.0001) | (.00013) |
| *Past innovation spillovers* | | | |
| L1.Renewable | 1.2e-05 | 2.4e-05* | 1.1e-05 |
| | (7.6e-06) | (1.3e-05) | (2.1e-05) |
| L1.Base load | -3.6e-05*** | -6.0e-05*** | -3.1e-05 |
| | (8.9e-06) | (1.4e-05) | (2.5e-05) |
| L1.Peak load | 8.1e-05*** | 7.0e-05** | 4.7e-05 |
| | (1.8e-05) | (2.9e-05) | (4.8e-05) |
| *Macroeconomic indicators* | | | |
| L1.GDP | -.8157*** | -.7045*** | -.4787*** |
| | (.04811) | (.05605) | (.108) |
| L1.GDP per capita | .7797** | 1.275*** | .5734 |
| | (.3149) | (.4848) | (.8579) |
| Constant term | 2.69 | -5.711 | -1.588 |
| | (3.382) | (5.33) | (9.151) |
| Pre-sample history | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 196903 | 100955 | 31494 |

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table C-12: Fossil fuel price effect in base load and peak load technologies using global data from 1978 to 2009 (firms with more than 10 patents – top 22% innovators).

| | **Dependent variable: firm-level number of patents** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Renewable | | | Base load | | | Peak load | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Energy prices including taxes* | | | | | | | | | |
| L1.Coal price | -.8366 | | | .5183 | | | .3937 | | |
| | (.6063) | | | (.5667) | | | (.8791) | | |
| L1.Coal price squared | .9411 | | | -1.661 | | | -1.866 | | |
| | (1.236) | | | (1.151) | | | (1.593) | | |
| L1.Oil price | | .03736 | | | .1095 | | | .2135 | |
| | | (.2032) | | | (.2426) | | | (.3715) | |
| L1.Electricity price | | .03578 | | | .1439 | | | -.2071 | |
| | | (.2612) | | | (.2195) | | | (.3621) | |
| L1.Elec-coal price gap | | | .5675** | | | .6421*** | | | .4826 |
| | | | (.23) | | | (.2405) | | | (.5954) |
| *Research subsidies* | | | | | | | | | |
| L1.Renewable | .1335* | .1106 | .1156 | -.03796 | -.03609 | -.03989 | .1625 | .1661 | .1591 |
| | (.07896) | (.07847) | (.0785) | (.08523) | (.08647) | (.08577) | (.2126) | (.2099) | (.2125) |
| L1.Fossil fuel | .00747 | -.01113 | .0197 | .04053 | .0531 | .06869 | .04789 | .02528 | .06499 |
| | (.04556) | (.04263) | (.04456) | (.05576) | (.0606) | (.05687) | (.07685) | (.08678) | (.07989) |
| L1.Efficiency-improving | .04536 | .05442 | .04606 | .01864 | .01824 | .00855 | .3811*** | .3864*** | .3819*** |
| | (.04251) | (.04163) | (.04222) | (.05867) | (.05716) | (.05868) | (.1092) | (.1076) | (.1057) |
| *Past innovation knowledge* | | | | | | | | | |
| L1.Renewable | -.00041** | -.0004** | -.0004** | 7.6e-05 | .00012 | .0001 | -.00068 | -.00059 | -.00059 |
| | (.00017) | (.00017) | (.00017) | (.00051) | (.00053) | (.00052) | (.00059) | (.0006) | (.00062) |
| L1.Fossil-fuel | -.00098*** | -.00096*** | -.00097*** | -.00079*** | -.0007*** | -.00074*** | .00031 | .00037 | .0004 |
| | (.00027) | (.00028) | (.00026) | (.00022) | (.00023) | (.00023) | (.00049) | (.00046) | (.00048) |
| L1.Peak load | .00101*** | .001*** | .00099*** | .00088*** | .0008*** | .00083*** | .00022 | .00015 | .00012 |
| | (.0002) | (.00021) | (.0002) | (.00017) | (.00018) | (.00018) | (.00031) | (.0003) | (.00031) |
| *Past innovation spillovers* | | | | | | | | | |
| L1.Renewable | -1.1e-05 | -1.2e-05 | -4.0e-06 | -2.5e-05 | -1.9e-05 | -1.8e-05 | -6.0e-05 | -5.0e-05 | -4.3e-05 |
| | (1.9e-05) | (2.0e-05) | (1.9e-05) | (2.1e-05) | (2.1e-05) | (2.2e-05) | (5.1e-05) | (5.0e-05) | (5.1e-05) |
| L1.Base load | 1.3e-05 | 1.3e-05 | 2.0e-05 | 1.7e-05 | 1.8e-05 | 1.8e-05 | 5.2e-05 | 5.2e-05 | 6.3e-05* |
| | (2.3e-05) | (1.9e-05) | (2.4e-05) | (2.3e-05) | (2.3e-05) | (2.3e-05) | (3.9e-05) | (3.9e-05) | (3.8e-05) |
| L1.Peak load | -.00011** | -.00012** | -.00013** | -8.9e-05 | -9.7e-05* | -9.5e-05* | -2.1e-05 | -2.0e-05 | -4.1e-05 |
| | (5.4e-05) | (4.8e-05) | (5.7e-05) | (5.5e-05) | (5.7e-05) | (5.5e-05) | (9.8e-05) | (.0001) | (9.9e-05) |
| *Macroeconomic indicators* | | | | | | | | | |
| L1.GDP | -.2366** | -.1505 | -.196** | -.2274** | -.1188 | -.1754* | -.5012*** | -.3641* | -.3744** |
| | (.09645) | (.09981) | (.09779) | (.09345) | (.09634) | (.09547) | (.1872) | (.1906) | (.1788) |
| L1.GDP per capita | .5374 | .5634 | .4427 | 1.551** | 1.552** | 1.42** | .6351 | .7471 | .6453 |
| | (.842) | (.7767) | (.8344) | (.6495) | (.6648) | (.6434) | (1.638) | (1.6) | (1.661) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 21433 | 21433 | 21433 | 17801 | 17801 | 17801 | 7730 | 7730 | 7730 |

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table C-13: Estimates with second lags of explanatory variables.

| | Dependent variable: firm-level number of patents | | | | |
|---|---|---|---|---|---|
| | | | | Fossil fuel | |
| | Renewable | Fossil fuel | Renewable | Base load | Peak load |
| | (1) | (2) | (3) | (4) | (5) |
| *Energy prices including taxes* | | | | | |
| L1.Coal price | -.4123** | -.3538* | -.3801** | -.4599*** | -.5508 |
| | (.1621) | (.2064) | (.1481) | (.1652) | (.3651) |
| L1.Electricity price | .2079 | .3064 | .1687 | .3595 | -.2256 |
| | (.2098) | (.2732) | (.187) | (.2313) | (.3913) |
| *Research subsidies* | | | | | |
| L1.Renewable | .1538** | .04959 | .1668** | -.0118 | .1749 |
| | (.07187) | (.113) | (.06896) | (.08075) | (.2059) |
| L1.Fossil fuel | .00717 | .05446 | -.00955 | .0623 | .06368 |
| | (.03757) | (.05815) | (.03977) | (.05977) | (.08687) |
| L1.Efficiency-improving | .00229 | .03965 | -.0096 | -.02493 | .3045*** |
| | (.03686) | (.06079) | (.03812) | (.0544) | (.09123) |
| *Past innovation knowledge* | | | | | |
| L2.Renewable | -.00104*** | -.00079 | -.00095*** | -5.9e-05 | -.00104 |
| | (.00014) | (.00054) | (.00012) | (.00066) | (.0007) |
| L2.Fossil fuel | -1.8e-06 | .00019*** | | | |
| | (.0002) | (6.4e-05) | | | |
| L2.Base load | | | -.0011*** | -.00125*** | .00031 |
| | | | (.0003) | (.0003) | (.00057) |
| L2.Peak load | | | .00105*** | .00114*** | .00023 |
| | | | (.00025) | (.00022) | (.00036) |
| *Past innovation spillovers* | | | | | |
| L2.Renewable | -2.3e-05 | -1.4e-05 | -2.9e-05* | -3.7e-05 | -7.7e-05 |
| | (1.6e-05) | (2.4e-05) | (1.7e-05) | (2.3e-05) | (5.4e-05) |
| L2.Fossil fuel | -3.9e-05** | -5.4e-06 | | | |
| | (1.5e-05) | (1.5e-05) | | | |
| L2.Base load | | | -3.5e-05** | 4.9e-06 | 8.9e-06 |
| | | | (1.6e-05) | (2.0e-05) | (3.0e-05) |
| L2.Peak load | | | -3.7e-05 | -3.0e-05 | 7.8e-05 |
| | | | (4.4e-05) | (5.5e-05) | (8.9e-05) |
| *Macroeconomic indicators* | | | | | |
| L1.GDP | -.1764* | -.1321 | -.1792* | -.2485*** | -.6646*** |
| | (.09771) | (.1077) | (.1015) | (.08802) | (.1872) |
| L1.GDP per capita | -.4653 | .4265 | -.6343 | .7695 | .4334 |
| | (.7823) | (.8231) | (.7311) | (.6287) | (1.466) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 46590 | 31316 | 46620 | 28779 | 9782 |

Significance levels: ***: 1% **: 5% *: 10%
Numbers in parentheses are standard errors.

Table C-14: Estimates with third lags of explanatory variables.

| | Dependent variable: firm-level number of patents | | | | |
|---|---|---|---|---|---|
| | | | | Fossil fuel | |
| | Renewable | Fossil fuel | Renewable | Base load | Peak load |
| | (1) | (2) | (3) | (4) | (5) |
| *Energy prices including taxes* | | | | | |
| L1.Coal price | -.4294*** | -.3924** | -.4012*** | -.4787*** | -.5158 |
| | (.1496) | (.1959) | (.1383) | (.1662) | (.3949) |
| L1.Electricity price | .2292 | .3448 | .2845 | .3623* | -.2149 |
| | (.199) | (.2579) | (.179) | (.2201) | (.3932) |
| *Research subsidies* | | | | | |
| L1.Renewable | .1512** | .04769 | .1408** | .00381 | .1709 |
| | (.06923) | (.109) | (.06488) | (.07456) | (.2099) |
| L1.Fossil fuel | .01373 | .05483 | .00358 | .06109 | .07089 |
| | (.0378) | (.05881) | (.04003) | (.05967) | (.0935) |
| L1.Efficiency-improving | -.00734 | .01646 | -.00943 | -.04462 | .2936*** |
| | (.0357) | (.06259) | (.03483) | (.05181) | (.08994) |
| *Past innovation knowledge* | | | | | |
| L3.Renewable | -.00148*** | -.00103* | -.00134*** | -7.6e-05 | -.00093 |
| | (.00027) | (.0006) | (.0002) | (.00078) | (.00065) |
| L3.Fossil fuel | -7.0e-05 | .00015* | | | |
| | (.00024) | (8.1e-05) | | | |
| L3.Base load | | | -.00123*** | -.00174*** | .00018 |
| | | | (.00038) | (.00035) | (.00058) |
| L3.Peak load | | | .00106*** | .00147*** | .00029 |
| | | | (.00032) | (.00027) | (.00038) |
| *Past innovation spillovers* | | | | | |
| L3.Renewable | -2.8e-05 | -8.7e-06 | -1.6e-05 | -3.8e-05* | -7.7e-05 |
| | (1.7e-05) | (2.7e-05) | (1.9e-05) | (2.2e-05) | (6.1e-05) |
| L3.Fossil fuel | -3.6e-05** | -9.1e-06 | | | |
| | (1.6e-05) | (1.9e-05) | | | |
| L3.Base load | | | -9.5e-06 | -2.5e-06 | 7.1e-06 |
| | | | (1.7e-05) | (2.2e-05) | (3.5e-05) |
| L3.Peak load | | | -9.4e-05* | -9.9e-06 | 1.0e-04 |
| | | | (4.9e-05) | (6.0e-05) | (.00011) |
| *Macroeconomic indicators* | | | | | |
| L1.GDP | -.1981* | -.1141 | -.1734* | -.2491*** | -.6602*** |
| | (.112) | (.1196) | (.1037) | (.09158) | (.1985) |
| L1.GDP per capita | -.4775 | .3075 | -.3941 | .6358 | .4153 |
| | (.7639) | (.8435) | (.7155) | (.62) | (1.498) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 53642 | 35200 | 53676 | 32180 | 9782 |

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table C-15: Alternative definition of regional spillovers: five regions.

| | Dependent variable: firm-level number of patents | | | | |
|---|---|---|---|---|---|
| | | | | Fossil fuel | |
| | Renewable | Fossil fuel | Renewable | Base load | Peak load |
| | (1) | (2) | (3) | (4) | (5) |
| *Energy prices including taxes* | | | | | |
| L1.Coal price | -.3964** | -.2992 | -.4168** | -.4081** | -.5841 |
| | (.1809) | (.2168) | (.1664) | (.1703) | (.3599) |
| L1.Electricity price | .1641 | .2415 | .2467 | .3653 | -.02527 |
| | (.2259) | (.2857) | (.194) | (.2404) | (.3832) |
| *Research subsidies* | | | | | |
| L1.Renewable | .1567** | .0485 | .1288* | -.0253 | .1756 |
| | (.07383) | (.1129) | (.07403) | (.08381) | (.2168) |
| L1.Fossil fuel | .00263 | .0551 | .02039 | .06659 | .06384 |
| | (.03797) | (.05722) | (.03945) | (.05826) | (.08065) |
| L1.Efficiency-improving | .00187 | .06258 | .0385 | -.00404 | .3642*** |
| | (.0406) | (.06928) | (.04008) | (.05664) | (.1052) |
| *Past innovation knowledge* | | | | | |
| L1.Renewable | -.00056*** | -.00049 | -.00045*** | 4.3e-05 | -.00077 |
| | (.00013) | (.00044) | (.00016) | (.00053) | (.00062) |
| L1.Fossil-fuel | 4.4e-05 | .00025*** | | | |
| | (.00017) | (4.9e-05) | | | |
| L1.Base load | | | -.001*** | -.00076*** | .00036 |
| | | | (.00027) | (.00024) | (.0005) |
| L1.Peak load | | | .00098*** | .00082*** | .00016 |
| | | | (.0002) | (.00018) | (.00032) |
| *Past innovation spillovers* | | | | | |
| L1.Renewable | -2.6e-05 | -3.6e-05 | -6.0e-06 | -1.4e-05 | -5.0e-05 |
| | (2.3e-05) | (3.2e-05) | (2.1e-05) | (3.1e-05) | (5.6e-05) |
| L1.Fossil-fuel | -4.3e-05*** | -1.1e-05 | | | |
| | (1.5e-05) | (1.6e-05) | | | |
| L1.Base load | | | 2.2e-05 | 2.1e-05 | 5.9e-05 |
| | | | (2.3e-05) | (3.0e-05) | (3.8e-05) |
| L1.Peak load | | | -.00013*** | -.0001* | -3.7e-05 |
| | | | (5.0e-05) | (6.0e-05) | (9.4e-05) |
| *Macroeconomic indicators* | | | | | |
| L1.GDP | -.1662* | -.1112 | -.1941** | -.1636* | -.4713** |
| | (.09153) | (.1016) | (.09364) | (.09356) | (.1953) |
| L1.GDP per capita | -.3539 | .5974 | .2637 | 1.255** | .7033 |
| | (.8199) | (.8274) | (.7974) | (.6389) | (1.634) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 39293 | 27233 | 39317 | 25194 | 9782 |

Significance levels: ***: 1% **: 5% *: 10%
Numbers in parentheses are standard errors.

Table C-16: Baseline estimates with additional macroeconomic indicators (population density).

| | **Dependent variable: firm-level number of patents** | | | | |
|---|---|---|---|---|---|
| | | | | Fossil fuel | |
| | Renewable (1) | Fossil fuel (2) | Renewable (3) | Base load (4) | Peak load (5) |
| *Energy prices including taxes* | | | | | |
| L1.Coal price | -.3871* | -.2869 | -.403** | -.4036** | -.5892 |
| | (.1986) | (.2195) | (.1798) | (.1695) | (.347) |
| L1.Electricity price | .1767 | .2685 | .2707 | .3659 | -.03229 |
| | (.2265) | (.2847) | (.1989) | (.2412) | (.39) |
| *Research subsidies* | | | | | |
| L1.Renewable | .1575** | .04417 | .126* | -.03284 | .1754 |
| | (.07461) | (.1154) | (.07477) | (.08704) | (.2151) |
| L1.Fossil fuel | .0012 | .05684 | .0213 | .06772 | .06437 |
| | (.03916) | (.05764) | (.04196) | (.05867) | (.0804) |
| L1.Efficiency-improving | .01003 | .06804 | .03807 | .00048 | .366*** |
| | (.04124) | (.0738) | (.04069) | (.0585) | (.1142) |
| *Past innovation knowledge* | | | | | |
| L1.Renewable | -.00055*** | -.00046 | -.00045*** | 5.4e-05 | -.00077 |
| | (.00013) | (.00043) | (.00016) | (.00053) | (.00062) |
| L1.Fossil-fuel | 4.8e-05 | .00025*** | | | |
| | (.00017) | (4.9e-05) | | | |
| L1.Base load | | | -.001*** | -.00076*** | .00036 |
| | | | (.00027) | (.00023) | (.00049) |
| L1.Peak load | | | .00098*** | .00082*** | .00017 |
| | | | (.0002) | (.00017) | (.00031) |
| *Past innovation spillovers* | | | | | |
| L1.Renewable | -2.3e-05 | -3.0e-05 | -5.1e-06 | -1.4e-05 | -5.2e-05 |
| | (2.0e-05) | (2.7e-05) | (1.8e-05) | (2.2e-05) | (5.1e-05) |
| L1.Fossil-fuel | -3.7e-05*** | -5.7e-06 | | | |
| | (1.4e-05) | (1.6e-05) | | | |
| L1.Base load | | | 2.5e-05 | 2.2e-05 | 5.5e-05 |
| | | | (2.0e-05) | (2.4e-05) | (3.5e-05) |
| L1.Peak load | | | -.00013*** | -9.9e-05* | -2.6e-05 |
| | | | (5.0e-05) | (5.9e-05) | (9.5e-05) |
| *Macroeconomic indicators* | | | | | |
| L1.GDP | -.1374 | -.1152 | -.1765* | -.1622* | -.4801** |
| | (.09599) | (.09859) | (.1038) | (.09144) | (.1942) |
| L1.GDP per capita | -.3662 | .6039 | .2445 | 1.287** | .6931 |
| | (.8814) | (.819) | (.8643) | (.6551) | (1.53) |
| L1.Pop. density | -.00289 | -.03837 | -.03412 | .00132 | .00953 |
| | (.07262) | (.1259) | (.08817) | (.1257) | (.2721) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 39099 | 27020 | 39123 | 24981 | 9767 |

Significance levels: ***: 1% **: 5% *: 10%



Numbers in parentheses are standard errors.

Table C-17: Five most innovative countries: France, Germany, Japan, United Kingdom, United States.

| | Dependent variable: firm-level number of patents | | | | |
|---|---|---|---|---|---|
| | | | | Fossil fuel | |
| | Renewable | Fossil fuel | Renewable | Base load | Peak load |
| | (1) | (2) | (3) | (4) | (5) |
| *Energy prices including taxes* | | | | | |
| L1.Coal price | -.5212** | -.0764 | -.6175*** | -.3273 | .02017 |
| | (.2215) | (.2669) | (.208) | (.2093) | (.4524) |
| L1.Electricity price | .2901 | .06645 | .5866** | .5353 | -.5389 |
| | (.2539) | (.3515) | (.229) | (.3435) | (.4916) |
| *Research subsidies* | | | | | |
| L1.Renewable | .1383* | .06597 | .1274 | .02422 | .1783 |
| | (.08316) | (.1258) | (.08085) | (.0935) | (.2117) |
| L1.Fossil fuel | .02769 | .06799 | .07531 | .115* | -.05627 |
| | (.04436) | (.06448) | (.04806) | (.06856) | (.08894) |
| L1.Efficiency-improving | -.02535 | .09217 | .01101 | -.00632 | .4546*** |
| | (.04325) | (.06963) | (.04223) | (.05709) | (.1068) |
| *Past innovation knowledge* | | | | | |
| L1.Renewable | -.00053*** | -.00059 | -.00041** | -1.7e-05 | -.00086 |
| | (.00014) | (.00044) | (.00018) | (.00051) | (.00067) |
| L1.Fossil-fuel | 4.2e-05 | .00029*** | | | |
| | (.00017) | (4.7e-05) | | | |
| L1.Base load | | | -.00101*** | -.00066** | .00048 |
| | | | (.00028) | (.00027) | (.00056) |
| L1.Peak load | | | .00095*** | .00078*** | .00018 |
| | | | (.00021) | (.00022) | (.00036) |
| *Past innovation spillovers* | | | | | |
| L1.Renewable | -2.4e-05 | -6.1e-05* | 1.2e-05 | -1.7e-05 | -8.4e-05 |
| | (2.4e-05) | (3.5e-05) | (2.4e-05) | (4.0e-05) | (6.6e-05) |
| L1.Fossil-fuel | -4.4e-05*** | -3.1e-06 | | | |
| | (1.5e-05) | (1.7e-05) | | | |
| L1.Base load | | | 4.4e-05 | 3.8e-05 | 5.6e-05 |
| | | | (2.7e-05) | (3.9e-05) | (5.3e-05) |
| L1.Peak load | | | -.00018*** | -.00012 | -1.7e-05 |
| | | | (5.8e-05) | (8.6e-05) | (.00011) |
| *Macroeconomic indicators* | | | | | |
| L1.GDP | -.2038* | -.1909 | -.2624** | -.1796 | -.3594* |
| | (.1196) | (.1759) | (.1271) | (.1184) | (.1837) |
| L1.GDP per capita | -.3636 | .8395 | .2975 | .3559 | .6358 |
| | (.9212) | (.8435) | (.9344) | (.8418) | (1.557) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 33586 | 23139 | 33652 | 21394 | 8525 |

Significance levels: ***: 1% **: 5% *: 10%
Numbers in parentheses are standard errors.

Table C-18: Baseline estimates with large and small firms.

| | **Dependent variable: firm-level number of patents** | | | | | |
|---|---|---|---|---|---|---|
| | Large firms (> 15 total patents) | | | Small firms (< 15 total patents) | | |
| | Renewable (1) | Base load (2) | Peak load (3) | Renewable (4) | Base load (5) | Peak load (6) |
| *Energy prices including taxes* | | | | | | |
| L1.Coal price | -.4436** | -.4003** | -.5758 | .09776 | .00012 | -.5506 |
| | (.1832) | (.1785) | (.3713) | (.2114) | (.3373) | (1.074) |
| L1.Electricity price | .2726 | .3507 | -.02502 | .06325 | 1.397*** | 1.441 |
| | (.2116) | (.2488) | (.3782) | (.2339) | (.4325) | (1.312) |
| *Research subsidies* | | | | | | |
| L1.Renewable | .1324* | -.02993 | .184 | .01987 | -.1885 | .2159 |
| | (.08045) | (.08819) | (.2226) | (.09456) | (.1535) | (.3421) |
| L1.Fossil fuel | .02327 | .071 | .06291 | .00138 | -.07014 | .1345 |
| | (.04323) | (.06038) | (.08314) | (.06061) | (.09505) | (.2693) |
| L1.Efficiency-improving | .04037 | -.00082 | .3782*** | -.08224 | .064 | -.1454 |
| | (.04303) | (.0603) | (.109) | (.05443) | (.09466) | (.287) |
| *Past innovation knowledge* | | | | | | |
| L1.Renewable | -.00039** | .00012 | -.00072 | -.6293*** | -.2323*** | -.2383 |
| | (.00017) | (.00052) | (.00062) | (.03314) | (.08897) | (.1725) |
| L1.Base load | -.00098*** | -.00071*** | .00036 | -.03261 | -.9332*** | -.4581 |
| | (.00028) | (.00023) | (.00049) | (.05756) | (.07653) | (.3674) |
| L1.Peak load | .001*** | .00081*** | .00018 | -.139 | -.5253* | -1.434*** |
| | (.00021) | (.00017) | (.00032) | (.0958) | (.3102) | (.2648) |
| *Past innovation spillovers* | | | | | | |
| L1.Renewable | 1.1e-06 | -1.3e-05 | -4.9e-05 | -9.4e-05** | .00015** | -.00024 |
| | (2.0e-05) | (2.2e-05) | (5.3e-05) | (3.7e-05) | (7.7e-05) | (.00016) |
| L1.Base load | 2.4e-05 | 2.0e-05 | 5.9e-05 | .00011*** | .00038*** | .00015 |
| | (2.1e-05) | (2.3e-05) | (3.6e-05) | (3.1e-05) | (6.6e-05) | (.00026) |
| L1.Peak load | -.00014*** | -.0001* | -3.4e-05 | -2.4e-05 | 7.7e-05 | -.00035 |
| | (5.3e-05) | (5.7e-05) | (9.7e-05) | (.00013) | (.0003) | (.00207) |
| *Macroeconomic indicators* | | | | | | |
| L1.GDP | -.2284** | -.1731* | -.4857** | .5648 | .8201** | -24.85 |
| | (.1015) | (.0953) | (.1963) | (.3449) | (.3744) | (111.1) |
| L1.GDP per capita | .3592 | 1.344** | .6504 | .7158 | .523 | 23.17 |
| | (.8471) | (.6641) | (1.669) | (1.547) | (2.657) | (110.9) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 18064 | 15544 | 7028 | 20736 | 9250 | 2601 |

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table C-19: Baseline estimates with specialized and mixed firms.

| | Dependent variable: firm-level number of patents | | | | | |
|---|---|---|---|---|---|---|
| | Specialized firms | | | Mixed firms | | |
| | Renewable (1) | Base load (2) | Peak load (3) | Renewable (4) | Base load (5) | Peak load (6) |
| *Energy prices including taxes* | | | | | | |
| L1.Coal price | -.802*** | -.2684 | -3.039* | -.2009 | -.3744** | -.5976 |
| | (.3003) | (.3301) | (1.843) | (.1433) | (.1854) | (.364) |
| L1.Electricity price | -.5917* | .2668 | 5.37*** | .4349** | .3449 | -.02659 |
| | (.3043) | (.3646) | (1.938) | (.2196) | (.2579) | (.3743) |
| *Research subsidies* | | | | | | |
| L1.Renewable | .1288 | -.1609 | -1.347 | .1171 | -.01907 | .1965 |
| | (.1047) | (.1403) | (.9019) | (.0888) | (.09345) | (.2183) |
| L1.Fossil fuel | .123** | -.04512 | .1831 | -.01608 | .09057 | .06972 |
| | (.0604) | (.08581) | (.5875) | (.05007) | (.06612) | (.08219) |
| L1.Efficiency-improving | -.01507 | .2294** | -.04686 | .03205 | -.01894 | .3669*** |
| | (.07171) | (.1059) | (.8053) | (.04585) | (.06322) | (.1085) |
| *Past innovation knowledge* | | | | | | |
| L1.Renewable | -.00315** | | | -.00036* | .00016 | -.00076 |
| | (.0014) | | | (.00021) | (.00052) | (.00062) |
| L1.Base load | | -.04717*** | | -.00096*** | -.00065*** | .00036 |
| | | (.01288) | | (.00028) | (.00023) | (.0005) |
| L1.Peak load | | | -.327 | .00098*** | .00078*** | .00018 |
| | | | (.2278) | (.00021) | (.00018) | (.00031) |
| *Past innovation spillovers* | | | | | | |
| L1.Renewable | -7.5e-05** | 9.7e-05** | -.00038 | 5.0e-06 | -9.1e-06 | -5.0e-05 |
| | (3.2e-05) | (5.0e-05) | (.00029) | (2.3e-05) | (2.4e-05) | (5.1e-05) |
| L1.Base load | .00012** | .00016*** | .00026 | 2.4e-06 | 1.5e-05 | 5.6e-05 |
| | (5.0e-05) | (4.7e-05) | (.00017) | (1.9e-05) | (2.5e-05) | (3.5e-05) |
| L1.Peak load | -.00014 | -.00031* | 1.5e-05 | -.00014** | -.0001* | -2.7e-05 |
| | (9.0e-05) | (.00017) | (.00107) | (5.6e-05) | (6.0e-05) | (9.5e-05) |
| *Macroeconomic indicators* | | | | | | |
| L1.GDP | .095 | .2788 | -10.43 | -.2037* | -.2012** | -.4989** |
| | (.1785) | (.7883) | (81.37) | (.1089) | (.09996) | (.1954) |
| L1.GDP per capita | -1.713 | .2664 | 20.45 | .7907 | 1.316* | .5791 |
| | (1.496) | (2.998) | (86.99) | (.8294) | (.6796) | (1.651) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 21223 | 7187 | 891 | 18094 | 18007 | 8891 |

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table C-20: FE Poisson estimates for top five innovating countries excluding hydro, geothermal, and biomass from renewable technologies.

| | Dependent variable: firm-level number of patents | | | | |
|---|---|---|---|---|---|
| | | | | Fossil fuel | |
| | Renewable | Fossil fuel | Renewable | Base load | Peak load |
| | (1) | (2) | (3) | (4) | (5) |
| *Energy prices including taxes* | | | | | |
| L1.Coal price | -.525** | -.03552 | -.6438*** | -.5085** | -.05094 |
| | (.2237) | (.2706) | (.2142) | (.2105) | (.4438) |
| L1.Electricity price | .2791 | .1139 | .4469* | .4667 | -.6124 |
| | (.2621) | (.3462) | (.2359) | (.3284) | (.5269) |
| *Research subsidies* | | | | | |
| L1.Renewable | .1353 | .0826 | .1429* | .0567 | .1857 |
| | (.08524) | (.1266) | (.08516) | (.1024) | (.197) |
| L1.Fossil fuel | .03507 | .04622 | .06106 | .07373 | -.04772 |
| | (.04678) | (.06331) | (.04904) | (.06969) | (.08827) |
| L1.Efficiency-improving | -.04022 | .05854 | -.02912 | -.01993 | .4737*** |
| | (.04234) | (.07206) | (.0424) | (.05729) | (.1115) |
| *Past innovation knowledge* | | | | | |
| L1.Renewable | -.00055*** | -.00068 | -.00047*** | 6.4e-05 | -.00087 |
| | (.00015) | (.00044) | (.00018) | (.00057) | (.00069) |
| L1.Fossil-fuel | 7.6e-08 | .00029*** | | | |
| | (.00018) | (4.3e-05) | | | |
| L1.Base load | | | -.00108*** | -.00086** | .00047 |
| | | | (.00028) | (.00034) | (.00057) |
| L1.Peak load | | | .00098*** | .00097*** | .00018 |
| | | | (.00021) | (.00025) | (.00035) |
| *Past innovation spillovers* | | | | | |
| L1.Renewable | -2.3e-05 | -6.0e-05* | -1.3e-05 | -5.0e-05 | -6.8e-05 |
| | (2.4e-05) | (3.6e-05) | (2.2e-05) | (3.4e-05) | (5.8e-05) |
| L1.Fossil-fuel | -4.8e-05*** | -1.4e-05 | | | |
| | (1.6e-05) | (1.6e-05) | | | |
| L1.Base load | | | 2.7e-07 | -1.9e-05 | 7.1e-05 |
| | | | (2.6e-05) | (3.8e-05) | (5.7e-05) |
| L1.Peak load | | | -.00012** | -1.7e-07 | -3.4e-05 |
| | | | (5.6e-05) | (7.8e-05) | (.0001) |
| *Macroeconomic indicators* | | | | | |
| L1.GDP | -.271** | -.07988 | -.1046 | -.4305*** | -.6013** |
| | (.1292) | (.1968) | (.1409) | (.1445) | (.2375) |
| L1.GDP per capita | -.3806 | .1371 | -.3618 | -.2393 | .6567 |
| | (.9774) | (.9394) | (.9623) | (.851) | (1.768) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 32134 | 22914 | 32124 | 21167 | 8393 |

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table C-21: All patents separated between base load and peak load technologies.

| | **Dependent variable: firm-level number of patents** | |
|---|---|---|
| | Base load | Peak load |
| *Energy prices including taxes* | | |
| L1.Coal price | -.3075* | -.2522 |
| | (.165) | (.1795) |
| L1.Electricity price | .3366 | .1447 |
| | (.2217) | (.1772) |
| *Research subsidies* | | |
| L1.Renewable | .0294 | .149* |
| | (.08583) | (.07837) |
| L1.Fossil fuel | .07615 | .03047 |
| | (.05487) | (.03866) |
| L1.Efficiency-improving | .02353 | .09496** |
| | (.05639) | (.04487) |
| *Past innovation knowledge* | | |
| L1.Base load | -.00062** | .00037 |
| | (.00025) | (.00037) |
| L1.Peak load | .00065*** | -.00013 |
| | (.00016) | (.00021) |
| *Past innovation spillovers* | | |
| L1.Base load | 8.3e-06 | 5.4e-06 |
| | (2.0e-05) | (1.7e-05) |
| L1.Peak load | -2.9e-05* | -2.6e-05 |
| | (1.7e-05) | (1.8e-05) |
| *Macroeconomic indicators* | | |
| L1.GDP | -.1686 | -.2283* |
| | (.1375) | (.119) |
| L1.GDP per capita | 1.359** | .2075 |
| | (.665) | (.6933) |
| Pre-sample history | Yes | Yes |
| Pre-sample active | Yes | Yes |
| Firm FE | Yes | Yes |
| Country FE | Yes | Yes |
| Year FE | Yes | Yes |
| Observations | 27660 | 40011 |

Significance levels: ***: 1% **: 5% *: 10%
Numbers in parentheses are standard errors.

Table C-22: Baseline estimates without pre-sample patenting activity.

| | Dependent variable: firm-level number of patents | | | | |
|---|---|---|---|---|---|
| | | | | Fossil fuel | |
| | Renewable (1) | Fossil fuel (2) | Renewable (3) | Base load (4) | Peak load (5) |
| *Energy prices including taxes* | | | | | |
| L1.Coal price | -.3891** | -.344* | -.4584*** | -.4162*** | -.4352 |
| | (.1825) | (.2087) | (.1675) | (.1539) | (.3699) |
| L1.Electricity price | .1098 | .4099* | .2111 | .3791 | .00688 |
| | (.2178) | (.2434) | (.1965) | (.2337) | (.4163) |
| *Research subsidies* | | | | | |
| L1.Renewable | .1465* | .07793 | .1423* | .00574 | .1372 |
| | (.07475) | (.1089) | (.07332) | (.08518) | (.1997) |
| L1.Fossil fuel | .00359 | .06335 | .01328 | .0859* | .05623 |
| | (.03823) | (.05416) | (.03941) | (.05561) | (.08003) |
| L1.Efficiency-improving | .01639 | .05165 | .03249 | -.00465 | .3396*** |
| | (.04148) | (.07135) | (.04022) | (.05517) | (.1128) |
| *Past innovation knowledge* | | | | | |
| L1.Renewable | -.00054*** | -.00046 | -.00047*** | 3.6e-05 | -.00083 |
| | (.00013) | (.00043) | (.00016) | (.00054) | (.0006) |
| L1.Fossil-fuel | 4.4e-05 | .00024*** | | | |
| | (.00017) | (4.4e-05) | | | |
| L1.Base load | | | -.00098*** | -.00075*** | .0004 |
| | | | (.00027) | (.00023) | (.0005) |
| L1.Peak load | | | .00097*** | .00085*** | .00011 |
| | | | (.0002) | (.00016) | (.00031) |
| *Past innovation spillovers* | | | | | |
| L1.Renewable | -2.3e-05 | -3.6e-05 | -1.3e-05 | -3.7e-05* | -4.9e-05 |
| | (2.1e-05) | (2.8e-05) | (1.7e-05) | (2.2e-05) | (4.6e-05) |
| L1.Fossil-fuel | -3.5e-05** | -1.0e-05 | | | |
| | (1.4e-05) | (1.6e-05) | | | |
| L1.Base load | | | 6.3e-06 | 2.0e-06 | 6.9e-05 |
| | | | (2.0e-05) | (2.9e-05) | (5.0e-05) |
| L1.Peak load | | | -.00011** | -4.9e-05 | -9.2e-05 |
| | | | (4.8e-05) | (5.8e-05) | (9.5e-05) |
| *Macroeconomic indicators* | | | | | |
| L1.GDP | -.1322 | -.07117 | -.04709 | -.00821 | -.1083 |
| | (.08913) | (.1212) | (.09775) | (.1007) | (.1636) |
| L1.GDP per capita | -.03711 | .8073 | .3347 | .6445 | .7332 |
| | (.8216) | (.7256) | (.7642) | (.65) | (1.462) |
| Pre-sample history | No | No | No | No | No |
| Pre-sample active | No | No | No | No | No |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 39303 | 27240 | 39319 | 25183 | 9774 |

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table C-23: Fossil fuel price effect in renewable, base and peak load technologies.

| | Dependent variable: firm-level number of patents | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Renewable | | | Base load | | | Peak load | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Energy prices including taxes* | | | | | | | | | |
| L1.Coal price | -.4144** | | | -.4051** | | | -.5788 | | |
| | (.1666) | | | (.1695) | | | (.3614) | | |
| L1.Electricity price | .2498 | .05752 | | .3674 | .1926 | | -.02734 | -.134 | |
| | (.1925) | (.2238) | | (.2372) | (.2171) | | (.37) | (.3591) | |
| L1.Nat gas | | | -.09758 | | | -.04992 | | | -.2119 |
| | | | (.133) | | | (.1336) | | | (.2261) |
| *Research subsidies* | | | | | | | | | |
| L1.Renewable | .1273* | .1099 | .1075 | -.02835 | -.0337 | -.02588 | .1749 | .1421 | .1385 |
| | (.0738) | (.07479) | (.07474) | (.08402) | (.08249) | (.08222) | (.2144) | (.2052) | (.2028) |
| L1.Fossil fuel | .02175 | -.0137 | -.02473 | .06796 | .04855 | .03606 | .06561 | .02525 | .02358 |
| | (.04014) | (.041) | (.04301) | (.0585) | (.05952) | (.05586) | (.08176) | (.08467) | (.08698) |
| L1.Efficiency-improving | .03971 | .05677 | .06301 | -.00051 | .01673 | .02346 | .3624*** | .3718*** | .3747*** |
| | (.04047) | (.04007) | (.041) | (.05797) | (.05622) | (.05651) | (.1072) | (.1059) | (.1036) |
| *Past innovation knowledge* | | | | | | | | | |
| L1.Renewable | -.00045*** | -.00045*** | -.00046*** | 5.3e-05 | 7.7e-05 | 5.8e-05 | -.00077 | -.00062 | -.00062 |
| | (.00016) | (.00016) | (.00016) | (.00052) | (.00054) | (.00053) | (.00062) | (.00061) | (.00062) |
| L1.Baseload | -.001*** | -.00098*** | -.00099*** | -.00076*** | -.00073*** | -.00076*** | .00036 | .00037 | .00037 |
| | (.00027) | (.00027) | (.00027) | (.00023) | (.00023) | (.00024) | (.00049) | (.00047) | (.00047) |
| L1.Peakload | .00098*** | .00099*** | .00102*** | .00082*** | .00081*** | .00085*** | .00017 | .00015 | .00018 |
| | (.0002) | (.00021) | (.00021) | (.00017) | (.00018) | (.00019) | (.00031) | (.0003) | (.00029) |
| *Past innovation spillovers* | | | | | | | | | |
| L1.Renewable | -5.7e-06 | -1.7e-05 | -2.6e-05 | -1.4e-05 | -2.0e-05 | -2.7e-05 | -5.2e-05 | -5.3e-05 | -6.1e-05 |
| | (1.8e-05) | (1.9e-05) | (1.8e-05) | (2.1e-05) | (2.1e-05) | (2.0e-05) | (5.1e-05) | (4.9e-05) | (4.4e-05) |
| L1.Base load | 2.2e-05 | 1.3e-05 | 1.0e-05 | 2.3e-05 | 2.1e-05 | 1.7e-05 | 5.5e-05 | 5.1e-05 | 5.0e-05 |
| | (1.9e-05) | (1.8e-05) | (2.1e-05) | (2.3e-05) | (2.3e-05) | (2.3e-05) | (3.5e-05) | (3.7e-05) | (4.3e-05) |
| L1.Peak load | -.00013*** | -.00011** | -8.3e-05* | -9.9e-05* | -9.5e-05* | -7.8e-05 | -2.7e-05 | -1.5e-05 | 2.0e-05 |
| | (4.8e-05) | (4.6e-05) | (4.8e-05) | (5.5e-05) | (5.6e-05) | (6.2e-05) | (9.4e-05) | (9.8e-05) | (.00011) |
| *Macroeconomic indicators* | | | | | | | | | |
| L1.GDP L.firm_rgdpna | -.1944** | -.1378 | -.1567* | -.1632* | -.1172 | -.1575* | -.4785** | -.349* | -.348** |
| | (.09409) | (.09611) | (.09331) | (.09283) | (.09342) | (.09506) | (.1935) | (.189) | (.174) |
| L1.GDP per capita | .287 | .5262 | .6477 | 1.267** | 1.479** | 1.565** | .6879 | .8118 | .7658 |
| | (.8069) | (.8107) | (.7902) | (.644) | (.6448) | (.6549) | (1.629) | (1.602) | (1.586) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 39317 | 39317 | 39317 | 25194 | 25194 | 25194 | 9782 | 9782 | 9782 |

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

Table C-24: Country and year fixed effects in the five most innovative countries.

| | **Dependent variable: firm-level number of patents** | | | | | |
|---|---|---|---|---|---|---|
| | Renewable | | Base load | | Peak load | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Energy prices including taxes* | | | | | | |
| L.PFuel | -.6175*** | -.3613 | -.3273 | -.2707 | .02017 | -.8996 |
| | (.208) | (.2288) | (.2093) | (.4153) | (.4524) | (.7334) |
| L.PElectricity | .5866** | .2084 | .5353 | 1.113 | -.5389 | .6276 |
| | (.229) | (.2793) | (.3435) | (.7796) | (.4916) | (.8478) |
| *Research subsidies* | | | | | | |
| L.firm_RD_RENEW | .1274 | -.01015 | .02422 | .3215 | .1783 | 1.264 |
| | (.08085) | (.1712) | (.0935) | (.2512) | (.2117) | (1.14) |
| L.firm_RD_EFF | .01101 | .05404 | -.00632 | -.2038 | .4546*** | -.1688 |
| | (.04223) | (.1092) | (.05709) | (.2824) | (.1068) | (.5013) |
| L.firm_RD_FUEL | .07531 | .02057 | .115* | .309** | -.05627 | .4451* |
| | (.04806) | (.1158) | (.06856) | (.1231) | (.08894) | (.252) |
| *Past innovation knowledge* | | | | | | |
| L.knowledge_c | -.00041** | -.00045** | -1.7e-05 | -.00016 | -.00086 | -.00118 |
| | (.00018) | (.00019) | (.00051) | (.0005) | (.00067) | (.00078) |
| L.knowledge_d | -.00101*** | -.00093*** | -.00066** | -.00063** | .00048 | .00095 |
| | (.00028) | (.00033) | (.00027) | (.00028) | (.00056) | (.0007) |
| L.knowledge_b | .00095*** | .00098*** | .00078*** | .00117*** | .00018 | .0004 |
| | (.00021) | (.00024) | (.00022) | (.00038) | (.00036) | (.00065) |
| *Past innovation spillovers* | | | | | | |
| L.Regionspillover_c | 1.2e-05 | 1.3e-05 | -1.7e-05 | -5.6e-05 | -8.4e-05 | -.00025** |
| | (2.4e-05) | (3.7e-05) | (4.0e-05) | (.00015) | (6.6e-05) | (.0001) |
| L.Regionspillover_d | 4.4e-05 | 4.4e-05 | 3.8e-05 | -3.9e-05 | 5.6e-05 | -6.2e-05 |
| | (2.7e-05) | (3.4e-05) | (3.9e-05) | (.00012) | (5.3e-05) | (.00011) |
| L.Regionspillover_b | -.00018*** | -5.6e-05 | -.00012 | .00034 | -1.7e-05 | .00065 |
| | (5.8e-05) | (9.3e-05) | (8.6e-05) | (.00037) | (.00011) | (.00047) |
| *Macroeconomic indicators* | | | | | | |
| L.firm_rgdpna | -.2624** | -.1772 | -.1796 | -.505** | -.3594* | -.8915 |
| | (.1271) | (.1524) | (.1184) | (.2416) | (.1837) | (.6065) |
| L.firm_rgdpna_capita | .2975 | -.2448 | .3559 | -1.392 | .6358 | -5.345 |
| | (.9344) | (.8176) | (.8418) | (1.375) | (1.557) | (6.901) |
| Pre-sample history | Yes | Yes | Yes | Yes | Yes | Yes |
| Pre-sample active | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country*Year FE | No | Yes | No | Yes | No | Yes |
| Observations | 33652 | 33652 | 21394 | 21394 | 8525 | 8525 |

Significance levels: ***: 1% **: 5% *: 10%

Numbers in parentheses are standard errors.

# Appendix D: Appendix to Chapter 4

## D-1 Geographical distribution of the Vietnam SME survey

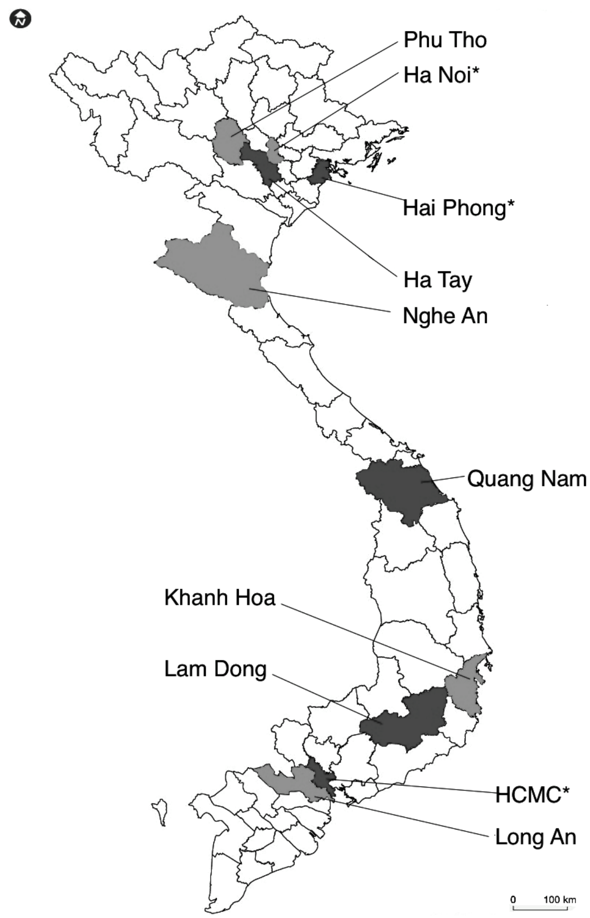


Figure D-1: Geographical coverage of the Vietnam SME survey. (*: Urban areas)

## D-2 Robustness checks: Detailed estimation results

This section presents the detailed estimation results for the robustness checks described in section 4.5 for both the whole sample and each industry. Specifically, table D-1 shows the results for incumbent firms, table D-2 shows the results for household firms and table D-3 shows the results for non-household firms. These tables are summarized in Table 4.6 of the Section 4.5. Tables D-4-D-8 show the estimation results for the alternative specifications summarized in Table 4.7 in Section 4.5. Note that the average profit efficiency reported in these tables measures the efficiency of each firms compared to the best performing firm in each subsample, therefore, they are not readily comparable. Also, the coefficients reported in these appendix tables show the relationship between the efficiency explanatory variables and a firm's *inefficiency* level. On the other hand, the summary in tables 4.6 and 4.7 reports the sign of the marginal effect of each efficiency explanatory variable on the *expected profit* of a firm, therefore, they are of opposite signs to the coefficients reported in the tables in this appendix.

Table D-1: Profit efficiency among incumbent firms

| | | Whole sample | | Light industries | | Heavy industries | |
|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| | | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| Profit frontier equation | $\alpha_m$ | 0.080*** | (0.021) | 0.087*** | (0.028) | 0.048 | (0.033) |
| | $\alpha_l$ | 0.277*** | (0.015) | 0.232*** | (0.019) | 0.340*** | (0.023) |
| | $\alpha_k$ | 0.765*** | (0.015) | 0.766*** | (0.019) | 0.748*** | (0.025) |
| | $\delta_{mm}$ | 0.051*** | (0.006) | 0.052*** | (0.009) | 0.039*** | (0.009) |
| | $\delta_{ll}$ | 0.063*** | (0.013) | 0.065*** | (0.016) | 0.010 | (0.024) |
| | $\delta_{kk}$ | 0.242*** | (0.020) | 0.212*** | (0.026) | 0.290*** | (0.035) |
| | $\delta_{ml}$ | 0.005 | (0.013) | -0.002 | (0.017) | 0.009 | (0.021) |
| | $\delta_{mk}$ | 0.002 | (0.015) | -0.016 | (0.019) | 0.039 | (0.026) |
| | $\delta_{lk}$ | 0.077*** | (0.014) | 0.079*** | (0.017) | 0.053** | (0.024) |
| | Constant | 7.898*** | (0.025) | 7.826*** | (0.031) | 8.053*** | (0.040) |
| | Average profit efficiency | 70.21% | | 70.14% | | 69.45% | |
| Efficiency explanatory equation | Internal environment: | | | | | | |
| | Owner's education | -0.032** | (0.016) | -0.025 | (0.019) | -0.046* | (0.027) |
| | Labor training | -0.092 | (0.206) | -0.251 | (0.352) | -0.070 | (0.223) |
| | New product | 0.068 | (0.209) | 0.148 | (0.315) | -0.115 | (0.258) |
| | Product modification | -0.271** | (0.112) | -0.271* | (0.157) | -0.207 | (0.154) |
| | Process upgrading | -0.477** | (0.209) | -0.503* | (0.273) | -0.354 | (0.285) |
| | Firm's age | 0.017*** | (0.004) | 0.022*** | (0.005) | 0.007 | (0.007) |
| | Firm's size | -1.429*** | (0.089) | -1.469*** | (0.118) | -1.309*** | (0.121) |
| | Business environment: | | | | | | |
| | Competition | -0.316*** | (0.102) | -0.355*** | (0.124) | -0.177 | (0.188) |
| | Subcontracting | 0.232 | (0.149) | 0.289 | (0.207) | 0.120 | (0.200) |
| | Exporting | -1.713* | (0.893) | -0.946 | (0.802) | -28.131 | (1,723) |
| | Formal credit constraint | 0.218* | (0.126) | 0.162 | (0.160) | 0.249 | (0.200) |
| | Use of informal credit | -0.307** | (0.152) | -0.338* | (0.196) | -0.183 | (0.231) |
| | Industrial zone location | -0.345 | (0.232) | -0.465* | (0.277) | -0.056 | (0.388) |
| | Urban location | -0.079 | (0.260) | 0.083 | (0.415) | -0.297 | (0.322) |
| | Legal environment: | | | | | | |
| | Formalization | -0.134 | (0.118) | -0.236 | (0.157) | -0.136 | (0.183) |
| | Financial support | -0.047 | (0.118) | 0.064 | (0.146) | -0.304 | (0.207) |
| | Technical support | -0.473* | (0.282) | -0.513 | (0.375) | -0.422 | (0.442) |
| | Other support | -0.139 | (0.201) | -0.129 | (0.266) | -0.054 | (0.310) |
| | Bribery | 0.139* | (0.081) | 0.078 | (0.093) | 0.232*** | (0.086) |
| | Constant | 2.067*** | (0.408) | 1.188** | (0.463) | 2.583*** | (0.541) |
| | Log-likelihood | -7197.77 | | -4297.11 | | -2837.36 | |
| | Observations | 5,854 | | 3,588 | | 2,259 | |
| | Industry FE | YES | | YES | | YES | |
| | Year FE | YES | | YES | | YES | |
| | Industry*Year FE | YES | | YES | | YES | |

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

Table D-2: Profit efficiency among household businesses

| | | Whole sample | | Light industries | | Heavy industries | |
|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| | | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| Profit frontier equation | $\alpha_m$ | 0.146*** | (0.022) | 0.186*** | (0.029) | 0.083** | (0.035) |
| | $\alpha_l$ | 0.279*** | (0.012) | 0.256*** | (0.015) | 0.318*** | (0.019) |
| | $\alpha_k$ | 0.504*** | (0.013) | 0.523*** | (0.017) | 0.467*** | (0.022) |
| | $\delta_{mm}$ | 0.069*** | (0.011) | 0.073*** | (0.016) | 0.086*** | (0.017) |
| | $\delta_{ll}$ | 0.058*** | (0.010) | 0.062*** | (0.012) | 0.026 | (0.016) |
| | $\delta_{kk}$ | 0.091*** | (0.018) | 0.078*** | (0.022) | 0.119*** | (0.031) |
| | $\delta_{ml}$ | -0.035** | (0.017) | -0.024 | (0.021) | -0.057* | (0.032) |
| | $\delta_{mk}$ | 0.048** | (0.021) | 0.030 | (0.025) | 0.114*** | (0.041) |
| | $\delta_{lk}$ | 0.060*** | (0.011) | 0.062*** | (0.014) | 0.062*** | (0.019) |
| | Constant | 7.704*** | (0.016) | 7.701*** | (0.020) | 7.706*** | (0.029) |
| | Average profit efficiency | 70.10% | | 69.19% | | 72.00% | |
| Efficiency explanatory equation | Internal environment: | | | | | | |
| | Owner's education | -0.027** | (0.011) | -0.018 | (0.013) | -0.045** | (0.021) |
| | Labor training | -0.431** | (0.211) | -0.644** | (0.327) | -0.286 | (0.273) |
| | New product | -0.104 | (0.164) | 0.117 | (0.242) | -0.407* | (0.225) |
| | Product modification | -0.519*** | (0.088) | -0.508*** | (0.112) | -0.511*** | (0.147) |
| | Process upgrading | -0.433** | (0.170) | -0.659*** | (0.230) | -0.020 | (0.250) |
| | Firm's age | 0.018*** | (0.003) | 0.021*** | (0.003) | 0.011** | (0.005) |
| | Firm's size | -1.866*** | (0.073) | -1.900*** | (0.092) | -1.790*** | (0.126) |
| | Business environment: | | | | | | |
| | Competition | -0.252*** | (0.077) | -0.287*** | (0.089) | -0.159 | (0.158) |
| | Subcontracting | 0.256** | (0.116) | 0.320** | (0.149) | 0.137 | (0.184) |
| | Exporting | -0.934 | (0.825) | -1.016 | (0.875) | -0.348 | (1.711) |
| | Formal credit constraint | 0.176* | (0.097) | 0.170 | (0.118) | 0.156 | (0.178) |
| | Use of informal credit | -0.323*** | (0.118) | -0.267* | (0.143) | -0.375* | (0.211) |
| | Industrial zone location | -0.322 | (0.196) | -0.309 | (0.216) | -0.515 | (0.508) |
| | Urban location | -0.641*** | (0.213) | -0.443 | (0.299) | -0.954*** | (0.308) |
| | Legal environment: | | | | | | |
| | Formalization | -0.409*** | (0.090) | -0.395*** | (0.113) | -0.387*** | (0.149) |
| | Financial support | -0.062 | (0.091) | -0.021 | (0.109) | -0.164 | (0.168) |
| | Technical support | -0.323 | (0.199) | -0.181 | (0.247) | -0.560 | (0.354) |
| | Other support | -0.185 | (0.150) | -0.323* | (0.196) | -0.033 | (0.245) |
| | Bribery | 0.032 | (0.025) | 0.130 | (0.105) | 0.027 | (0.028) |
| | Constant | 2.682*** | (0.298) | 1.837*** | (0.323) | 3.018*** | (0.443) |
| | Log-likelihood | -9242.19 | | -6044.52 | | -3135.41 | |
| | Observations | 8,499 | | 5,581 | | 2,904 | |
| | Industry FE | YES | | YES | | YES | |
| | Year FE | YES | | YES | | YES | |
| | Industry*Year FE | YES | | YES | | YES | |

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

Table D-3: Profit efficiency among non-household businesses

| | | Whole sample | | Light industries | | Heavy industries | |
|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| | | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| Profit frontier equation | $\alpha_m$ | -0.018 | (0.018) | -0.052** | (0.023) | 0.024 | (0.028) |
| | $\alpha_l$ | 0.372*** | (0.024) | 0.409*** | (0.035) | 0.332*** | (0.035) |
| | $\alpha_k$ | 0.652*** | (0.032) | 0.627*** | (0.045) | 0.684*** | (0.045) |
| | $\delta_{mm}$ | 0.012*** | (0.004) | 0.014** | (0.006) | -0.004 | (0.007) |
| | $\delta_{ll}$ | 0.058*** | (0.018) | 0.116*** | (0.025) | 0.012 | (0.028) |
| | $\delta_{kk}$ | 0.297*** | (0.034) | 0.292*** | (0.051) | 0.291*** | (0.047) |
| | $\delta_{ml}$ | 0.008 | (0.010) | -0.003 | (0.012) | 0.025 | (0.015) |
| | $\delta_{mk}$ | 0.045*** | (0.012) | 0.048*** | (0.016) | 0.048** | (0.021) |
| | $\delta_{lk}$ | -0.044** | (0.022) | -0.042 | (0.032) | -0.038 | (0.031) |
| | Constant | 8.733*** | (0.038) | 8.725*** | (0.053) | 8.742*** | (0.055) |
| | Average profit efficiency | 62.35% | | 61.90% | | 62.79% | |
| Efficiency explanatory equation | Internal environment: | | | | | | |
| | Owner's education | -0.025 | (0.026) | -0.021 | (0.036) | -0.021 | (0.037) |
| | Labor training | 0.032 | (0.111) | -0.033 | (0.156) | 0.128 | (0.156) |
| | New product | -0.025 | (0.168) | -0.264 | (0.255) | 0.077 | (0.232) |
| | Product modification | -0.039 | (0.101) | 0.001 | (0.140) | -0.104 | (0.149) |
| | Process upgrading | -0.090 | (0.130) | -0.140 | (0.177) | -0.036 | (0.195) |
| | Firm's age | 0.023*** | (0.005) | 0.022*** | (0.007) | 0.026*** | (0.006) |
| | Firm's size | -1.234*** | (0.079) | -1.217*** | (0.105) | -1.188*** | (0.116) |
| | Business environment: | | | | | | |
| | Competition | -0.245 | (0.171) | -0.227 | (0.250) | -0.276 | (0.242) |
| | Subcontracting | 0.072 | (0.126) | 0.154 | (0.188) | 0.035 | (0.174) |
| | Exporting | -0.446** | (0.226) | -0.095 | (0.252) | -1.660** | (0.693) |
| | Formal credit constraint | 0.347** | (0.152) | 0.147 | (0.211) | 0.511** | (0.221) |
| | Use of informal credit | -0.132 | (0.160) | -0.033 | (0.227) | -0.169 | (0.225) |
| | Industrial zone location | 0.151 | (0.164) | 0.102 | (0.233) | 0.067 | (0.254) |
| | Urban location | -0.654** | (0.264) | -0.671** | (0.334) | -0.665 | (0.428) |
| | Legal environment: | | | | | | |
| | Formalization | 0.483 | (0.295) | 0.160 | (0.431) | 0.504 | (0.410) |
| | Financial support | 0.278** | (0.122) | 0.280* | (0.164) | 0.169 | (0.188) |
| | Technical support | 0.024 | (0.181) | -0.061 | (0.250) | 0.064 | (0.264) |
| | Other support | -0.004 | (0.205) | -0.087 | (0.286) | 0.007 | (0.305) |
| | Bribery | 0.074** | (0.033) | 0.061 | (0.039) | 0.116* | (0.065) |
| | Constant | 2.164*** | (0.585) | 2.490** | (1.165) | 1.781** | (0.791) |
| | Log-likelihood | -5816.96 | | -3094.50 | | -2688.18 | |
| | Observations | 4,258 | | 2,254 | | 1,998 | |
| | Industry FE | YES | | YES | | YES | |
| | Year FE | YES | | YES | | YES | |
| | Industry*Year FE | YES | | YES | | YES | |

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

Table D-4: Profit efficiency of the full sample under alternative measures of human capital

| | | Baseline estimates | | Owner's education | | Labor training | |
|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| | | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| Profit frontier equation | $\alpha_m$ | 0.028** | (0.013) | 0.028** | (0.013) | 0.028** | (0.013) |
| | $\alpha_l$ | 0.305*** | (0.010) | 0.306*** | (0.010) | 0.306*** | (0.010) |
| | $\alpha_k$ | 0.766*** | (0.010) | 0.766*** | (0.010) | 0.767*** | (0.010) |
| | $\delta_{mm}$ | 0.040*** | (0.004) | 0.040*** | (0.004) | 0.040*** | (0.004) |
| | $\delta_{ll}$ | 0.070*** | (0.009) | 0.070*** | (0.009) | 0.070*** | (0.009) |
| | $\delta_{kk}$ | 0.272*** | (0.014) | 0.272*** | (0.014) | 0.270*** | (0.014) |
| | $\delta_{ml}$ | 0.000 | (0.008) | -0.000 | (0.008) | 0.000 | (0.008) |
| | $\delta_{mk}$ | 0.013 | (0.010) | 0.013 | (0.010) | 0.013 | (0.010) |
| | $\delta_{lk}$ | 0.054*** | (0.010) | 0.054*** | (0.010) | 0.054*** | (0.010) |
| | Constant | 7.972*** | (0.017) | 7.973*** | (0.017) | 7.973*** | (0.017) |
| | Average profit efficiency | 69.53% | | 69.50% | | 69.52% | |
| Efficiency explanatory equation | Internal environment: | | | | | | |
| | Owner's education | **-0.023**** | **(0.010)** | **-0.023**** | **(0.010)** | | |
| | Labor training | **-0.189** | **(0.145)** | | | **-0.195** | **(0.145)** |
| | New product | -0.065 | (0.141) | -0.073 | (0.141) | -0.065 | (0.141) |
| | Product modification | -0.330*** | (0.076) | -0.329*** | (0.076) | -0.336*** | (0.076) |
| | Process upgrading | -0.406*** | (0.135) | -0.408*** | (0.135) | -0.415*** | (0.135) |
| | Firm's age | 0.017*** | (0.003) | 0.017*** | (0.003) | 0.017*** | (0.003) |
| | Firm's size | -1.444*** | (0.059) | -1.454*** | (0.058) | -1.452*** | (0.059) |
| | Business environment: | | | | | | |
| | Competition | -0.232*** | (0.072) | -0.234*** | (0.072) | -0.236*** | (0.072) |
| | Subcontracting | 0.271*** | (0.101) | 0.268*** | (0.101) | 0.269*** | (0.101) |
| | Exporting | -1.527** | (0.635) | -1.528** | (0.635) | -1.567** | (0.643) |
| | Formal credit barrier | 0.189** | (0.087) | 0.194** | (0.087) | 0.190** | (0.087) |
| | Use of informal credit | -0.245** | (0.104) | -0.251** | (0.104) | -0.241** | (0.104) |
| | Industrial zone location | -0.282 | (0.180) | -0.277 | (0.179) | -0.279 | (0.181) |
| | Urban location | -0.160 | (0.174) | -0.179 | (0.173) | -0.169 | (0.174) |
| | Legal environment: | | | | | | |
| | Formalization | -0.027 | (0.080) | -0.028 | (0.080) | -0.035 | (0.080) |
| | Financial support | -0.086 | (0.082) | -0.088 | (0.082) | -0.084 | (0.082) |
| | Technical support | -0.386** | (0.180) | -0.386** | (0.180) | -0.378** | (0.180) |
| | Other support | -0.251* | (0.135) | -0.250* | (0.135) | -0.256* | (0.135) |
| | Bribery | 0.031 | (0.023) | 0.031 | (0.023) | 0.032 | (0.023) |
| | Constant | 2.187*** | (0.277) | 2.199*** | (0.276) | 2.019*** | (0.266) |
| | Log-likelihood | -16263.37 | | -16264.26 | | -16265.88 | |
| | Observations | 12,757 | | 12,757 | | 12,757 | |
| | Industry FE | YES | | YES | | YES | |
| | Year FE | YES | | YES | | YES | |
| | Industry*Year FE | YES | | YES | | YES | |

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

Table D-5: Profit efficiency of the full sample under alternative measures of production upgrading activities

| | Baseline estimates | | New product | | Product modification | | Process upgrading | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Coef. | Std.Err. | Coef. | Std.Err. | Coef. | Std.Err. | Coef. | Std.Err. |
| Profit frontier equation | | | | | | | | |
| $\alpha_m$ | 0.028** | (0.013) | 0.026* | (0.013) | 0.028** | (0.013) | 0.026* | (0.013) |
| $\alpha_l$ | 0.305*** | (0.010) | 0.306*** | (0.010) | 0.306*** | (0.010) | 0.306*** | (0.010) |
| $\alpha_k$ | 0.766*** | (0.010) | 0.766*** | (0.010) | 0.766*** | (0.010) | 0.765*** | (0.010) |
| $\delta_{mm}$ | 0.040*** | (0.004) | 0.040*** | (0.004) | 0.040*** | (0.004) | 0.040*** | (0.004) |
| $\delta_{ll}$ | 0.070*** | (0.009) | 0.069*** | (0.009) | 0.071*** | (0.009) | 0.068*** | (0.009) |
| $\delta_{kk}$ | 0.272*** | (0.014) | 0.270*** | (0.014) | 0.271*** | (0.014) | 0.270*** | (0.014) |
| $\delta_{ml}$ | 0.000 | (0.008) | -0.000 | (0.008) | -0.000 | (0.008) | 0.000 | (0.008) |
| $\delta_{mk}$ | 0.013 | (0.010) | 0.014 | (0.010) | 0.013 | (0.010) | 0.014 | (0.010) |
| $\delta_{lk}$ | 0.054*** | (0.010) | 0.055*** | (0.010) | 0.054*** | (0.010) | 0.054*** | (0.010) |
| Constant | 7.972*** | (0.017) | 7.975*** | (0.017) | 7.973*** | (0.017) | 7.975*** | (0.017) |
| Average profit efficiency | 69.53% | | 69.41% | | 69.51% | | 69.43% | |
| Efficiency explanatory equation: | | | | | | | | |
| Internal environment: | | | | | | | | |
| Owner's education | -0.023** | (0.010) | -0.026** | (0.010) | -0.024** | (0.010) | -0.025** | (0.010) |
| Labor training | -0.189 | (0.145) | -0.185 | (0.144) | -0.202 | (0.145) | -0.184 | (0.144) |
| New product | **-0.065** | **(0.141)** | **-0.255*** | **(0.138)** | | | | |
| Product modification | **-0.330*** ** | **(0.076)** | | | **-0.382*** ** | **(0.074)** | | |
| Process upgrading | **-0.406*** ** | **(0.135)** | | | | | **-0.518*** ** | **(0.131)** |
| Firm's age | 0.017*** | (0.003) | 0.018*** | (0.003) | 0.017*** | (0.003) | 0.017*** | (0.003) |
| Firm's size | -1.444*** | (0.059) | -1.489*** | (0.059) | -1.463*** | (0.059) | -1.466*** | (0.059) |
| Business environment: | | | | | | | | |
| Competition | -0.232*** | (0.072) | -0.253*** | (0.072) | -0.234*** | (0.072) | -0.254*** | (0.072) |
| Subcontracting | 0.271*** | (0.101) | 0.249** | (0.100) | 0.262*** | (0.100) | 0.252** | (0.100) |
| Exporting | -1.527** | (0.635) | -1.447** | (0.590) | -1.582** | (0.654) | -1.410** | (0.583) |
| Formal credit barrier | 0.189** | (0.087) | 0.183** | (0.087) | 0.176** | (0.087) | 0.198** | (0.087) |
| Use of informal credit | -0.245** | (0.104) | -0.251** | (0.104) | -0.237** | (0.104) | -0.258** | (0.104) |
| Industrial zone location | -0.282 | (0.180) | -0.248 | (0.178) | -0.273 | (0.180) | -0.264 | (0.178) |
| Urban location | -0.160 | (0.174) | -0.174 | (0.174) | -0.154 | (0.173) | -0.161 | (0.174) |
| Legal environment: | | | | | | | | |
| Formalization | -0.027 | (0.080) | -0.039 | (0.080) | -0.038 | (0.080) | -0.026 | (0.080) |
| Financial support | -0.086 | (0.082) | -0.096 | (0.082) | -0.095 | (0.082) | -0.087 | (0.082) |
| Technical support | -0.386** | (0.180) | -0.466*** | (0.181) | -0.444** | (0.179) | -0.413** | (0.181) |
| Other support | -0.251* | (0.135) | -0.283** | (0.134) | -0.263** | (0.134) | -0.269** | (0.134) |
| Bribery | 0.031 | (0.023) | 0.028 | (0.022) | 0.032 | (0.023) | 0.028 | (0.022) |
| Constant | 2.187*** | (0.277) | 2.158*** | (0.274) | 2.213*** | (0.273) | 2.062*** | (0.273) |
| Log-likelihood | -16263.37 | | -16280.69 | | -16268.75 | | -16273.67 | |
| Observations | 12,757 | | 12,757 | | 12,757 | | 12,757 | |
| Industry FE | YES | | YES | | YES | | YES | |
| Year FE | YES | | YES | | YES | | YES | |
| Industry*Year FE | YES | | YES | | YES | | YES | |

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

Table D-6: Profit efficiency of the full sample under alternative measures of access to credit

| | | Baseline estimates | | Formal credit barrier | | Use of informal credit | |
|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| | | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| Profit frontier equation | $\alpha_m$ | 0.028** | (0.013) | 0.028** | (0.013) | 0.028** | (0.013) |
| | $\alpha_l$ | 0.305*** | (0.010) | 0.306*** | (0.010) | 0.306*** | (0.010) |
| | $\alpha_k$ | 0.766*** | (0.010) | 0.765*** | (0.010) | 0.765*** | (0.010) |
| | $\delta_{mm}$ | 0.040*** | (0.004) | 0.040*** | (0.004) | 0.040*** | (0.004) |
| | $\delta_{ll}$ | 0.070*** | (0.009) | 0.070*** | (0.009) | 0.070*** | (0.009) |
| | $\delta_{kk}$ | 0.272*** | (0.014) | 0.272*** | (0.014) | 0.272*** | (0.014) |
| | $\delta_{ml}$ | 0.000 | (0.008) | -0.000 | (0.008) | -0.000 | (0.008) |
| | $\delta_{mk}$ | 0.013 | (0.010) | 0.013 | (0.010) | 0.013 | (0.010) |
| | $\delta_{lk}$ | 0.054*** | (0.010) | 0.054*** | (0.010) | 0.054*** | (0.010) |
| | Constant | 7.972*** | (0.017) | 7.972*** | (0.017) | 7.972*** | (0.017) |
| | Average profit efficiency | 69.53% | | 69.51% | | 69.56% | |
| Efficiency explanatory equation | Internal environment: | | | | | | |
| | Owner's education | -0.023** | (0.010) | -0.023** | (0.010) | -0.023** | (0.010) |
| | Labor training | -0.189 | (0.145) | -0.199 | (0.145) | -0.202 | (0.146) |
| | New product | -0.065 | (0.141) | -0.065 | (0.141) | -0.062 | (0.141) |
| | Product modification | -0.330*** | (0.076) | -0.335*** | (0.076) | -0.335*** | (0.076) |
| | Process upgrading | -0.406*** | (0.135) | -0.399*** | (0.135) | -0.393*** | (0.135) |
| | Firm's age | 0.017*** | (0.003) | 0.017*** | (0.003) | 0.017*** | (0.003) |
| | Firm's size | -1.444*** | (0.059) | -1.449*** | (0.059) | -1.447*** | (0.059) |
| | Business environment: | | | | | | |
| | Competition | -0.232*** | (0.072) | -0.240*** | (0.072) | -0.234*** | (0.072) |
| | Subcontracting | 0.271*** | (0.101) | 0.265*** | (0.101) | 0.267*** | (0.101) |
| | Exporting | -1.527** | (0.635) | -1.555** | (0.645) | -1.556** | (0.643) |
| | Formal credit barrier | **0.189**** | **(0.087)** | **0.044** | **(0.062)** | | |
| | Use of informal credit | **-0.245**** | **(0.104)** | | | **-0.086** | **(0.074)** |
| | Industrial zone location | -0.282 | (0.180) | -0.279 | (0.180) | -0.277 | (0.180) |
| | Urban location | -0.160 | (0.174) | -0.142 | (0.173) | -0.134 | (0.173) |
| | Legal environment: | | | | | | |
| | Formalization | -0.027 | (0.080) | -0.030 | (0.080) | -0.033 | (0.080) |
| | Financial support | -0.086 | (0.082) | -0.085 | (0.082) | -0.093 | (0.082) |
| | Technical support | -0.386** | (0.180) | -0.385** | (0.181) | -0.391** | (0.181) |
| | Other support | -0.251* | (0.135) | -0.255* | (0.135) | -0.257* | (0.135) |
| | Bribery | 0.031 | (0.023) | 0.032 | (0.023) | 0.032 | (0.023) |
| | Constant | 2.187*** | (0.277) | 2.202*** | (0.277) | 2.223*** | (0.276) |
| | Log-likelihood | -16263.37 | | -16270.22 | | -16265.69 | |
| | Observations | 12,757 | | 12,761 | | 12,757 | |
| | Industry FE | YES | | YES | | YES | |
| | Year FE | YES | | YES | | YES | |
| | Industry*Year FE | YES | | YES | | YES | |

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

Table D-7: Profit efficiency of the full sample under alternative measures of location

| | | Baseline estimates | | Industrial zone location | | Urban location | |
|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| | | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| Profit frontier equation | $\alpha_m$ | 0.028** | (0.013) | 0.027** | (0.013) | 0.028** | (0.013) |
| | $\alpha_l$ | 0.305*** | (0.010) | 0.306*** | (0.010) | 0.306*** | (0.010) |
| | $\alpha_k$ | 0.766*** | (0.010) | 0.766*** | (0.010) | 0.766*** | (0.010) |
| | $\delta_{mm}$ | 0.040*** | (0.004) | 0.040*** | (0.004) | 0.040*** | (0.004) |
| | $\delta_{ll}$ | 0.070*** | (0.009) | 0.070*** | (0.009) | 0.070*** | (0.009) |
| | $\delta_{kk}$ | 0.272*** | (0.014) | 0.272*** | (0.014) | 0.273*** | (0.014) |
| | $\delta_{ml}$ | 0.000 | (0.008) | 0.000 | (0.008) | -0.000 | (0.008) |
| | $\delta_{mk}$ | 0.013 | (0.010) | 0.013 | (0.010) | 0.013 | (0.010) |
| | $\delta_{lk}$ | 0.054*** | (0.010) | 0.054*** | (0.010) | 0.054*** | (0.010) |
| | Constant | 7.972*** | (0.017) | 7.972*** | (0.017) | 7.973*** | (0.017) |
| | Average profit efficiency | 69.53% | | 69.55% | | 69.47% | |
| Efficiency explanatory equation | Internal environment: | | | | | | |
| | Owner's education | -0.023** | (0.010) | -0.023** | (0.010) | -0.023** | (0.010) |
| | Labor training | -0.189 | (0.145) | -0.199 | (0.145) | -0.184 | (0.144) |
| | New product | -0.065 | (0.141) | -0.059 | (0.141) | -0.065 | (0.141) |
| | Product modification | -0.330*** | (0.076) | -0.331*** | (0.076) | -0.327*** | (0.076) |
| | Process upgrading | -0.406*** | (0.135) | -0.406*** | (0.135) | -0.401*** | (0.135) |
| | Firm's age | 0.017*** | (0.003) | 0.017*** | (0.003) | 0.017*** | (0.003) |
| | Firm's size | -1.444*** | (0.059) | -1.450*** | (0.059) | -1.448*** | (0.059) |
| | Business environment: | | | | | | |
| | Competition | -0.232*** | (0.072) | -0.231*** | (0.072) | -0.227*** | (0.072) |
| | Subcontracting | 0.271*** | (0.101) | 0.274*** | (0.101) | 0.269*** | (0.100) |
| | Exporting | -1.527** | (0.635) | -1.532** | (0.635) | -1.512** | (0.621) |
| | Formal credit barrier | 0.189** | (0.087) | 0.184** | (0.087) | 0.187** | (0.087) |
| | Use of informal credit | -0.245** | (0.104) | -0.240** | (0.104) | -0.243** | (0.104) |
| | Industrial zone location | **-0.282** | **(0.180)** | **-0.275** | **(0.180)** | | |
| | Urban location | **-0.160** | **(0.174)** | | | **-0.148** | **(0.173)** |
| | Legal environment: | | | | | | |
| | Formalization | -0.027 | (0.080) | -0.031 | (0.080) | -0.023 | (0.080) |
| | Financial support | -0.086 | (0.082) | -0.077 | (0.082) | -0.085 | (0.082) |
| | Technical support | -0.386** | (0.180) | -0.379** | (0.180) | -0.386** | (0.180) |
| | Other support | -0.251* | (0.135) | -0.251* | (0.135) | -0.248* | (0.134) |
| | Bribery | 0.031 | (0.023) | 0.031 | (0.023) | 0.032 | (0.023) |
| | Constant | 2.187*** | (0.277) | 2.081*** | (0.253) | 2.162*** | (0.276) |
| | Log-likelihood | -16263.37 | | -16263.79 | | -16264.65 | |
| | Observations | 12,757 | | 12,757 | | 12,757 | |
| | Industry FE | YES | | YES | | YES | |
| | Year FE | YES | | YES | | YES | |
| | Industry*Year FE | YES | | YES | | YES | |

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

Table D-8: Profit efficiency of the full sample with interactive variables

| | | Baseline estimates | | Firm's age*Size | | Labor training*Size | |
|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) |
| | | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
| Profit frontier equation | $\alpha_m$ | 0.028** | (0.013) | 0.027** | (0.013) | 0.027** | (0.013) |
| | $\alpha_l$ | 0.305*** | (0.010) | 0.304*** | (0.010) | 0.304*** | (0.010) |
| | $\alpha_k$ | 0.766*** | (0.010) | 0.767*** | (0.010) | 0.764*** | (0.010) |
| | $\delta_{mm}$ | 0.040*** | (0.004) | 0.040*** | (0.004) | 0.040*** | (0.004) |
| | $\delta_{ll}$ | 0.070*** | (0.009) | 0.070*** | (0.009) | 0.070*** | (0.009) |
| | $\delta_{kk}$ | 0.272*** | (0.014) | 0.275*** | (0.014) | 0.270*** | (0.014) |
| | $\delta_{ml}$ | 0.000 | (0.008) | -0.000 | (0.008) | -0.000 | (0.008) |
| | $\delta_{mk}$ | 0.013 | (0.010) | 0.014 | (0.010) | 0.013 | (0.010) |
| | $\delta_{lk}$ | 0.054*** | (0.010) | 0.053*** | (0.010) | 0.054*** | (0.010) |
| | Constant | 7.972*** | (0.017) | 7.972*** | (0.017) | 7.975*** | (0.017) |
| | Average profit efficiency | 69.53% | | 69.55% | | 69.53% | |
| Efficiency explanatory equation | Internal environment: | | | | | | |
| | Owner's education | -0.023** | (0.010) | -0.022** | (0.010) | -0.023** | (0.010) |
| | Labor training | -0.189 | (0.145) | -0.142 | (0.143) | 0.785** | (0.340) |
| | New product | -0.065 | (0.141) | -0.049 | (0.139) | -0.057 | (0.140) |
| | Product modification | -0.330*** | (0.076) | -0.331*** | (0.076) | -0.335*** | (0.076) |
| | Process upgrading | -0.406*** | (0.135) | -0.398*** | (0.134) | -0.386*** | (0.134) |
| | Firm's age | 0.017*** | (0.003) | -0.002 | (0.005) | 0.016*** | (0.003) |
| | Firm's size | -1.444*** | (0.059) | -1.693*** | (0.084) | -1.403*** | (0.059) |
| | Firm's age*Size | | | 0.017*** | (0.003) | | |
| | Labor training*Size | | | | | -0.580*** | (0.193) |
| | Business environment: | | | | | | |
| | Competition | -0.232*** | (0.072) | -0.223*** | (0.071) | -0.234*** | (0.071) |
| | Subcontracting | 0.271*** | (0.101) | 0.277*** | (0.100) | 0.273*** | (0.100) |
| | Exporting | -1.527** | (0.635) | -1.424** | (0.591) | -1.289** | (0.562) |
| | Formal credit barrier | 0.189** | (0.087) | 0.185** | (0.087) | 0.185** | (0.087) |
| | Use of informal credit | -0.245** | (0.104) | -0.231** | (0.104) | -0.242** | (0.104) |
| | Industrial zone location | -0.28 | (0.180) | -0.288 | (0.178) | -0.275 | (0.180) |
| | Urban location | -0.160 | (0.174) | -0.151 | (0.172) | -0.167 | (0.173) |
| | Legal environment: | | | | | | |
| | Formalization | -0.027 | (0.080) | -0.040 | (0.080) | -0.040 | (0.079) |
| | Financial support | -0.086 | (0.082) | -0.087 | (0.082) | -0.085 | (0.082) |
| | Technical support | -0.386** | (0.180) | -0.377** | (0.179) | -0.377** | (0.179) |
| | Other support | -0.251* | (0.135) | -0.257* | (0.135) | -0.243* | (0.134) |
| | Bribery | 0.031 | (0.023) | 0.031 | (0.023) | 0.031 | (0.023) |
| | Constant | 2.187*** | (0.277) | 2.486*** | (0.283) | 2.162*** | (0.275) |
| | Log-likelihood | -16263.37 | | -16263.79 | | -16253.66 | |
| | Observations | 12,757 | | 12,757 | | 12,757 | |
| | Industry FE | YES | | YES | | YES | |
| | Year FE | YES | | YES | | YES | |
| | Industry*Year FE | YES | | YES | | YES | |

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

# Curriculum Vitae

**Linh Pham**

## ACADEMIC APPOINTMENT

**Assistant Professor**, University of Central Oklahoma, Department of Economics, 2017-

## EDUCATION

**Ph.D.**, Economics, University of Wisconsin-Milwaukee, May 2017 *(expected)*, GPA: 4.00/4.00.

**B.S.**, Finance & Economics, *summa cum laude*, University of Wisconsin-La Crosse, 2011.

## FIELDS OF INTEREST

**Research:** Development Economics, Environmental & Energy Economics.

**Teaching:** Development Economics, Environmental & Energy Economics, Macroeconomics, Microeconomics, Statistics, Personal Finance.

## RESEARCH EXPERIENCE

**Research Assistant** for Prof. Itziar Lazkano, UW-Milwaukee, 2014 -2015.

**Research Analyst**, Brooklyn Bridge to Cambodia (BB2C), 2011.

## TEACHING EXPERIENCE

**Lecturer**, UW-Whitewater, Department of Economics, 2016-2017.

**Associate Lecturer**, UW - Milwaukee, School of Freshwater Sciences, 2016.

**Graduate Assistant**, UW - Milwaukee, Department of Economics, 2012-2016.

## PEER-REVIEWED PUBLICATIONS

- ‘Can Capital-Energy Substitution Foster Economic Growth?’, **Land Economics**, 92(3): 491-514, August 2016 (with Itziar Lazkano).
- ‘Is It Risky to Go Green? Volatility Modeling of the Green Bond Market.’, **Journal of Sustainable Finance and Investment**, 6(4): 263-291, October 2016.

## WORKING PAPERS

- 'Do Fossil-Fuel Taxes Promote Innovation in Renewable Electricity Generation?' (with Itziar Lazkano).
- 'What Are the Leading Contributors to Growth of Private Enterprises in Developing Countries?'.

## OTHER PUBLICATIONS

### White Papers:

- 'Bottom-Up Development Strategy: A New Approach to Solving the Developmental Puzzle of the World', **BB2C White Papers,** 2011.
- 'Research on the Plight of Cambodian Women', **BB2C White Papers,** 2011.

### Book Reviews:

- Review of *'Water Resource Economics: The Analysis of Scarcity, Policies, and Projects'*, 2nd edition by Ronald C. Griffin, **Water Economics and Policy,** 2(4), December 2016.

## REFERRING ACTIVITY

Journal of Environmental Economics and Management (2); Natural Resource Modeling (1); Environment, Development and Sustainability (1).

## PRESENTATIONS

Midwest Economic Association Annual Conference, Cincinnati, OH, April 2017.

Midwest Economic Association Annual Conference, Evanston, IL, April 2016.

Wisconsin Economic Association Annual Conference, Stevens Point, WI, October 2015.

Midwest Economics Association Annual Conference, Minneapolis, MN, March 2015.

Honor Program Seminar, UW - La Crosse, La Crosse, WI, December 2011.

## AWARDS AND SCHOLARSHIPS

Graduate Student Excellence Fellowship, UW-Milwaukee (2016-2017).

Asian Faculty and Staff Association (AFSA) Award, UW-Milwaukee (2016).

UW-Milwaukee Chapter Scholarship, Golden Key International Honour Society (2015).

Student Association Award, UW-Milwaukee (2015).

J. Walter Elliott Memorial Award for Excellence in Macroeconomics, UW-Milwaukee (2013).

Chancellor's Graduate Student Fellowship - UW-Milwaukee (2012-2014).

UW-La Crosse Chapter Scholarship, Golden Key International Honour Society (2011).

Maurice and Elizabeth Graff Scholarship in Economics - UW-La Crosse (2011).

Global Link Scholarship - UW-La Crosse (2008-2009).

Undergraduate Full Scholarship - UW-La Crosse (2008-2011).

Odon Vallet Scholarship (2007).

## HONOR SOCIETY MEMBERSHIPS

Golden Key International Honour Society; Beta Gamma Sigma International Honor Society; Omicron Delta Epsilon International Honor Society in Economics.

## CAMPUS AND COMMUNITY SERVICES

Vice President of UW-Milwaukee Golden Key International Honour Society, 2015-2016.

Judge for UW System Undergraduate Research and Creative Activity Symposium, 2015.

Graduate School Senator and Economics Rep, UW-Milwaukee Student Association, 2015.

Math and Science Tutor, Upward Bound Program, 2013-2016.

Translator, Youth Leader Magazine, 2011.

Translator, Professional Educational Organization International (PEOI), 2011.

Math and Science Tutor, UW - La Crosse, 2009-2011.

## ACADEMIC PROFESSIONAL AFFILIATIONS

Wisconsin Economics Association, Midwest Economics Association, European Association of Environmental and Resource Economists, American Economic Association.

## NON-ACADEMIC PROFESSIONAL POSITIONS

**Advisory Board Member**, Brooklyn Bridge to Cambodia (BB2C), 2012.

**Accountant**, GE Energy, General Electric Company, 2012.

## COMPUTER SKILLS

STATA, R, EViews, SPSS, GAUSS, LaTeX, Microsoft Office.

## INTERESTS

Instrumental music (listening and playing), photography, cooking, yoga.