university of groningen

Imperfect Information and Incentives for Renewable Energy

Daan Hulshof

Theses in Economics and Business

Imperfect Information and Incentives for Renewable Energy

Daan Hulshof

Publisher: University of Groningen, Groningen, The Netherlands.

Printed by: Ipskamp Printing.

rijksuniversiteit
groningen

Imperfect Information and Incentives for Renewable Energy

Proefschrift

ter verkrijging van de graad van doctor aan de
Rijksuniversiteit Groningen
op gezag van de
rector magnificus prof. dr. C. Wijmenga
en volgens besluit van het College voor Promoties.

De openbare verdediging zal plaatsvinden op

Donderdag 22 April 2021 om 16:15 uur

door

Daan Hulshof

geboren op 14 October 1990
te Drachten

Promotores
Prof. dr. M. Mulder
Prof. dr. mr. C. J. Jepma

Beoordelingscommissie
Prof. dr. T. Jamasb
Prof. dr. J. L. Moraga-González
Prof. dr. H. Vollebergh

Acknowledgements

Several individuals other than myself have made key contributions to this thesis. To them, I want to say thanks. In particular, I am very thankful to Machiel, my supervisor. Machiel, you are responsible for catalysing my interest in the fields of energy economics and energy policy, already while writing my bachelor's thesis. Owing to my personality, the opportunity to pursue a PhD thesis came as a surprise to many people close to me, and myself. Thank you for this opportunity, and for the countless invaluable lessons. I learned a lot and enjoyed our collaboration. In addition, I want to thank Catrinus, my other supervisor, for facilitating my PhD position, constructive supervision and supporting me in the, sometimes rigid, discussions with the STORE&GO-project coordinator.

I also want to thank Tooraj Jamasb, José Luis Moraga-González and Herman Vollebergh, the members of the reading committee. I highly appreciate your willingness and time to read and evaluate this thesis, and your instructive comments.

Apart from doing research, the past few years I also enjoyed and learned a lot from being around Daniel, Jos, Mart, Nick and Ruben at and outside of the faculty. Daniel, it was a pleasure to receive non-voluntary debating lessons from you during lunch–I like to think that I benefited non-negligibly. Jos, your interest in others and pleasant company, while limited to afternoons at times, greatly contributed to an enjoyable life at the office. Mart, you were an excellent office mate, and our discussions of all sorts sincerely contributed to my thinking and writing. Nick, our field experiment regarding the functioning of crypto currencies in the form of jointly investing €30, at the very peak of the market, was great fun. Ruben, learning about your extremely broad definition of luxuriance (as well as your level of intelligence) was a very valuable lesson for my humility. Furthermore, thank you Anouk, Arjan, Christiaan, Jann, Juliette, Lennard, Peter, Roel and Tobias, and numerous others, for being around. I enjoyed your presence.

Beyond the faculty walls, I wish to express gratitude to my friends and family.

To my good friends: I appreciate you and your enthusiasm for bikes, sports, good food and drinks, bars, cars and/or games, and your tolerance towards me and my quirks. To my family: Mom, you are the very best; Dad, you are the wisest; Floor, you are the star; Loes, when I look at you I see myself; and your support is important to me.

Finally, to Merel: You are an exceptional woman and I am grateful for having you on my side. The future looks bright.

Groningen,

March 2021,

Daan Hulshof

Contents

Chapter 1

Introduction

1.1 Market imperfections and renewable energy

In academic literature and societies, a consensus is emerging regarding the need to reduce greenhouse gas emissions. Failing to do so will result in climate change associated with significant economic and social damages (e.g. IPCC, 2014; Nordhaus, 2006; Stern, 2007). This consensus has recently resulted in an international agreement to limit the average temperature increase to two degree Celsius above pre-industrial levels, the so-called Paris Agreement (United Nations, 2015). Realising this ambition requires, among other things, a rigorous structural economic change from non-renewable to renewable energy systems: the energy transition. A key issue for governments is realising this transition as efficiently as possible in order to keep the costs of this dramatic change under control.

Supportive to these ambitions and the energy transition, many governments have set targets for CO_2 emission reductions in general, and renewable energy use in particular. For instance, in 2030, the EU targets to use 32% of its final energy consumption from renewable sources and to emit 40% less CO_2 compared to 1990 (European Parliament, 2018), while many national governments have set similar targets.

The energy transition in general and meeting targets for renewable energy in particular will in principal not occur without government intervention because, generally, the production costs of non-renewable energy remain considerably lower than the production costs of renewable energy. As energy prices are largely based on the lower production costs of non-renewable energy sources, unregulated energy markets do not yet incentivise investment in renewable energy. However, the production costs are not the only costs to society associated with non-renewable energy. Consuming non-renewable energy results in harmful CO_2 emissions which contribute to climate change. In the absence of regulatory measures, the costs associated with climate change, while borne by society, are not borne by energy producers or consumers and therefore not reflected in energy prices. Compared to the economic optimum, this results in energy prices which are too low and, as a result, underinvestment in renewable energy. In economic terms, energy markets fail due to the presence of a negative externality. This is the economic justification underlying the desire to transition away from non-renewable to renewable energy sources.

In the economic literature, two policy tools have been formulated that are regarded as the most efficient responses to a negative externality, including emissions from non-renewable-energy use. These so called first-best solutions, are (see e.g. Stavins, 2011): a carbon tax conform Pigou (1920), and an emission-rights trading scheme (ETS) conform Coase (1960). Theoretically, these policies result in exact internalization of the external costs associated with emitting CO_2 and, as a result, the socially optimal level of consumption of renewable and non-renewable energy. In practice, however, attaining maximum efficiency with first-best policies is complicated by uncertainty regarding the optimal tax level or cap on the amount of emission permits that would result in the firs-best outcome (Weitzman, 1974). Other available policy tools that may contribute to emission reductions include subsidies, renewable portfolio standards and command-and-control measures. These policy tools are theoretically sub-optimal and sometimes referred to as second-best climate policies, given that they typically do not result in exact internalization of the external costs of non-renewable energy use and, therefore, maximum efficiency (e.g. Borenstein, 2012; Schmalensee, 2012). The explanation for this is that second-best policies usually focus on and support a particular reduction option (e.g. subsidies for renewable electricity) while other, potentially less costly, reduction options may be available.[1][2]

Although we observe that first-best policies have been implemented in practice (for instance the EU ETS), subsidies for renewable energy (or, more broadly, emission-reduction technologies) have become way more popular as policy response to the emissions externality. This is illustrated by the fact that, in 2018, out of 135 countries with some form of regulatory policy for renewable electricity in place, 111 have implemented a subsidy scheme (REN21, 2020). The expenditures associated with these subsidies are substantial. For example, in the EU in 2017, governments spent €78.4 billion on subsidies for renewable electricity (Taylor, 2020), which constitutes 0.5% of GDP. On the benefit side, this contributed to a share of renewables in total electricity production in 2017 of 30.4% (Eurostat, 2020a). However, the fact that the renewable-electricity share in 1990 (a time without material support for renewables) was 12.6%, and that the electricity sector is not the only energy sector with emissions (electricity currently has a share in energy consumption of 21%) highlights that the energy transition will involve large expenditures (Eurostat, 2020a,d). In turn, this underlines the importance of realising the transition as efficiently as possible.

Another market failure present in energy markets is information asymmetry and, when left unaddressed, this market failure may increase the required amount of subsidy expenditure (or other type of climate-policy action) to attain climate goals. Information asymmetry in this respect results from producers knowing all characteristics of the energy that they supply, while end-users typically cannot observe these characteristics, such as whether energy is produced from renewable resources. If end-users prefer and are willing to pay a premium for renewable energy, all energy producers, including producers of non-renewable energy, have an incentive to claim that their energy is renewable. Considering that rational energy users understand the producers' incentives, information asymmetry may re-

[1]Dutch climate policy is illustrative for this problem. In the Netherlands in 2020, the primary subsidy scheme for emission reductions (the SDE++; mainly targeted at production technologies for renewable energy), does not subsidise technologies that achieve emission reductions at costs in excess of €300 per tonne of CO_2, whereas the subsidy scheme for electric cars achieves emission reductions at costs of €1300–€1700 per tonne of CO_2 (Algemene Rekenkamer, 2020).

[2]When addressing positive externalities that are associated with the adoption of clean technologies, targeted subsidies for research and development may constitute a theoretical first-best response (Schneider and Goulder, 1997). The market failure of knowledge spillovers is particularly relevant when cost reductions stem from learning-by-doing, as opposed to other sources, such as economies of scale or an exogenous decrease in input prices (Borenstein, 2012). While this appears to be an ongoing debate, empirical evidence suggests learning-by-doing was not the key driver of the decrease in costs of solar PV (Nemet, 2006). Similarly, Egli et al. (2018) find that learning-by-doing was hardly relevant for the decrease in financing costs (responsible for almost half of the total cost reductions) of on-shore wind and solar PV. Arguably, this implies that, realizing the energy transition in a cost-efficient manner requires, compared with knowledge spillovers, relatively more attention for addressing the emissions externality.

sult in adverse selection: end-users with preferences for renewable energy end up buying fewer renewable energy than they would buy in a situation of perfect information, because they cannot sufficiently trust the claims of producers (Akerlof, 1970). Hence, if not resolved, information asymmetry raises the required amount of climate-policy intervention.

While information asymmetry is present in virtually all renewable energy markets, the degree to which it is a problem and adverse selection occurs depends critically on whether end-users prefer renewable energy in the sense that they are willing to pay more for it. Economic models frequently assume that renewable and non-renewable energy are perfect substitutes, such that consumers will only opt for renewable energy when its price is lower than the price for non-renewable energy (e.g. Van der Ploeg and Withagen, 2014; Golosov et al., 2014). However, research shows that consumers appear willing to pay a premium for renewable energy (e.g Andor et al., 2017). Higher retail prices for several renewable types are also observed in practice. For example, several renewable electricity retail contracts are priced above similar non-renewable contracts (Mulder and Zomer, 2016). Considering that subsidies are usually based on wholesale energy prices, which are uniform for all types of energy (i.e. not differentiated by renewable vs. non-renewable), this could imply that less government subsidies are required to realise the energy transition when this premium for renewable energy is taken into account.

To address information asymmetry, governments have introduced certification schemes. A certification scheme typically involves a third party monitoring relevant information (such as who produces how much renewable energy and where, how and when did production occur) and making this information available in certificates. In this way, these schemes intend to overcome the informational gap between producers and consumers of renewable energy. A primary example is the European Guarantees of Origin scheme for the electricity market. This scheme monitors producers of renewable electricity and provides them with a certificate for their production, enabling them to proof to end-users that they sell renewable electricity. In principle, this type of policy tool can function considerably better in reducing information asymmetry than unregulated solutions such as reputation signals or “cheap talk” mechanisms (Cason and Gangadharan, 2002). However, in practice, there appears to be some lack of trust in Guarantees of Origin for electricity (Aasen et al., 2010; Veum et al., 2015). Somewhat comparable problems appear to be present in the EU market for (clean) passenger cars, where consumers cannot trust the information provided by the EU-imposed CO_2 labelling scheme (Fontaras et al., 2017; Haq and Weiss, 2016). As a result of these issues, it is questionable whether information asymmetry is properly addressed and adverse selection prevented in energy (and energy-related) markets, and if current market prices and quantities are efficient in the sense that they reflect end-user preferences.

1.2 Thesis overview

Against the background of a lack of appropriate incentives for renewable energy due to the presence of information asymmetry and negative externalities, this dissertation aims to improve our understanding of the conditions for the functioning of renewable energy markets. The dissertation studies in the subsequent two chapters to what extent end-users prefer renewable energy, where Chapter 2 focuses on consumers and Chapter 3 on firms. Chapter 2 studies the willingness-to-pay (WTP) for renewable energy of consumers when they have perfect information. Chapter 3 studies whether, next to consumers, firms are also willing to pay a premium for renewable energy. Chapters 4 and 5 shift attention towards policy measures addressing the respective market failures of information asymmetry and negative externalities. Specifically, Chapter 4 analyses the effectiveness of certification schemes in addressing the information problem. Chapter 5 analyses the extent to which support schemes for renewable energy result in windfall profits as a result of asymmetrical information between governments and investors. These four chapters are titled:

2. Willingness to pay for CO_2 emission reductions in passenger car transport
3. The impact of renewable energy use on firm profit
4. Performance of markets for European renewable energy certificates
5. Design of renewable support schemes and windfall profits: a Monte Carlo analysis for the Netherlands

Because of the relative distinct nature of the chapters, this thesis does not contain a separate literature chapter. Instead, each chapter separately discusses the related literature. Finally, Chapter 6 concludes this thesis with a brief overview of the conclusions and policy implications.

1.2.1 Preferences for renewable energy: Chapters 2 and 3

Chapters 2 and 3 about the potential for a market premium for renewable energy relate intrinsically to the preferences of end-users for renewable energy. These chapters study, separately, the preferences of two types of end-users: consumers and firms. Both chapters analyse to what extent there is a willingness to pay (WTP) a premium for renewable energy over non-renewable energy. Consumers and firms are treated in separate chapters because economic theory assumes that the behaviour of these two types of agents is motivated by different objectives. Chapter 2 posits that consumers prefer renewable energy when contributing financially to climate-change mitigation maximises their personal welfare as measured by utility, despite not benefiting in material or financial terms. In contrast, Chapter 3 posits that firms prefer renewable energy when that is aligned with their central objective of maximising profit.

Chapter 2

Chapter 2 investigates consumer WTP for the environmental benefits of renewable energy: CO_2 emission reductions. In contrast to much of the other papers in the literature, this investigation decomposes the WTP for renewable energy into components for CO_2 emissions and for other attributes of renewable energy. Such a decomposition is desirable because various types of renewable energy have in common that they reduce emissions but differ in many other respects (e.g. molecular nature versus electrical nature). The chapter estimates the WTP by means of a discrete-choice experiment, a stated-preference approach, applied to the passenger-car market. The advantage of estimating the WTP by means of a discrete-choice experiment is that it does not depend on actual transactions in renewable energy markets, which may not reflect the true preferences for emission due to information asymmetry. The passenger-car market is a suitable application because, in practice, consumers already trade-off between a range of renewable and non-renewable energy types (e.g. gasoline, biofuel, electric, hybrid-electric, CNG, hydrogen) in choosing a single good, a passenger car. In addition, in contrast to, for instance, a (renewable-)electricity contract, the level of CO_2 emissions is typically an explicit attribute faced by passenger-car buyers. The experiment is based on a sample of Dutch adults with the intention to buy a passenger car. The main results are that the mean WTP for emission reductions is in the neighbourhood of €200 per tonne, and that there is large degree of heterogeneity in preferences across individuals. These results suggest that there is a considerable market potential for emission reductions in passenger car transport.

Chapter 3

Chapter 3 investigates firm preferences for renewable energy. This chapter applies a revealed-preference approach in order to verify firms' environmental claims and concerns of firms that often accompany corporate use of renewable energy. This chapter adopts a fundamental microeconomic framework for analysing firm behaviour in relation to renewable energy use: firms maximise profit and choose to use renewable when that enables product differentiation, which in turn enables charging a higher price. This framework predicts that firms only use renewable energy when they are compensated for the higher costs, and that, within a setting of perfect competition, this compensation cannot exceed the increase in costs. This chapter's empirical analysis, based on panel data for 911 firms, tests this prediction. Evidence for a sacrifice in profit as a consequence of renewable energy use would be interpreted as evidence for a positive willingness to pay for renewable energy of firms. The empirical results are in line with the prediction from the analytical framework: there appears to be no impact from renewable energy use on profit. This suggests that firms do not have a positive willingness to pay for renewable energy as contribution to the environment and that firms are only willing to contribute to climate-change mitigation through buying renewable energy when this is aligned with the profit-maximisation objective.

A joint lesson from Chapters 2 and 3

Chapters 2 and 3 jointly help our understanding of the severity of the information asymmetry problem in renewable energy markets. Intrinsically, a large part of the consumers appears quite willing to financially contribute to emission reductions by buying products with relatively lower emissions. In addition, despite that firms do not appear to be willing to use renewable energy at the expense of profit, consumer demand for products with renewable energy characteristics can induce them to use renewable energy and realise emission reductions on behalf of consumers. However, these emission reductions will only fully materialise when information asymmetry is adequately addressed and adverse selection prevented. For policy, this implies that providing consumers with trustworthy information can be considered an important tool for achieving emission reductions.

1.2.2 Climate policy: Chapters 4 and 5

Chapters 4 and 5 shift the attention from preferences to climate policy. Given that it appears desirable from the first part of the thesis to address information asymmetry between consumers and producers of renewable energy, Chapter 4 empirically analyses renewable energy certificates. Certificates are widely implemented as solution for information asymmetry in renewable electricity markets and frequently considered for addressing this issue in other renewable energy markets, such as renewable hydrogen an methane markets. Here, the chapter departs from the idea that, as renewable energy certificates are traded in separate markets, resolving information asymmetry with certificates is strongly associated with well-functioning certificate markets. Subsequently, Chapter 5 studies the design of subsidy schemes for renewable energy in relation to asymmetrical information between renewable energy producers and the government. With subsidy schemes, instead of relating to the characteristics of renewable energy, information asymmetry relates to the characteristics and costs of renewable energy projects. This chapter assumes that governments ideally set the subsidy for a renewable energy investor precisely at the investor's minimally required level. In practice, however, this is complicated by the prohibitively high costs for the government of obtaining information about individual investors' project characteristics and costs.

Chapter 4

Chapter 4 investigates the principal solution for information asymmetry that has been introduced in renewable energy markets: certification. While certificates appear to have become an important medium to exchange renewable energy in many parts of the world, certificate markets are relatively young and it is unclear whether they function as mature markets. Countries have also adopted relatively different designs for their certification schemes. To investigate this, Chapter 4 uses four market performance indicators (the churn rate, price volatility, the certification rate and the expiration rate) for European renewable-electricity certificate markets and analyses their development over 2001–2016. In addition, this chapter analyses with panel data whether market performance depends on two key design aspects of the certification scheme: the public/private nature of the certifier and presence of an international standard. The results show that, despite that increasing shares of renewable electricity are being certified, certificate markets suffer from poor liquidity and very volatile prices. In addition, this chapter finds that appointing a public certifier and adopting an international standard foster the development of certificate systems.

Chapter 5

Chapter 5 investigates the design of subsidy schemes for renewable energy in relation to information asymmetry between governments and renewable energy investors. At the outset, this chapter assumes that *optimal* subsidies are not only allocatively efficient (i.e. subsidies should not only trigger the lowest-cost emission-reduction options first), but also should not be higher than the minimally required level. In other words, renewable-energy subsidies should not result in windfall profits to investors. While less relevant from an efficiency perspective, this chapter deems the point of limiting windfall profits important because of public-finance concerns from potentially excessive subsidy expenditures, and because of equity concerns regarding the distribution of the costs and benefits of the energy transition. A key challenge for limiting windfall profits is that, due to asymmetrical information about the true costs between governments and investors, it is difficult to tailor the subsidy at the minimally required level for each project. As a consequence, many governments provide a uniform subsidy, resulting in windfall profits to favourable projects and, in turn, an unnecessary financial burden on those who finance the scheme (e.g. electricity consumers or general tax payers). This chapter analyses the development of windfall profits due to the Dutch subsidy scheme for renewable energy over 2003–2018 using Monte Carlo simulations. The Netherlands provides a relevant case to study as it has subsidised renewable energy since 2003. In addition, it has implemented a number of design adaptations to the scheme specifically aimed at reducing the degree of windfall profits, such as the introduction of differentiation in the subsidy between on-shore wind projects according to the average wind speed in the turbine's region. The results suggest that the average windfall profit of a randomly drawn project from the pool of available investments has decreased considerably over time, from €2.42 ct/kWh in 2003, to €0.85 ct/kWh in 2018. This decrease largely results from differentiating in the subsidy between projects. Despite the design changes, actual investments still experience substantially higher windfall profits, at an average of €1.28 ct/kWh in 2018. This implies that investors successfully seek out projects that yield the highest windfall profits. Overall, the results imply that differentiating between projects contributes to mitigating windfall profits.

1.2.3 Chapter 6

Chapter 6 concludes the thesis by integrating the respective lessons from the relatively independent chapters.

Chapter 2

Willingness to pay for CO_2 emission reductions in passenger car transport

2.1 Introduction

Passenger car transportation is a major contributor of harmful emissions. As the fleet of passenger cars remains running predominantly on gasoline and diesel, the sector accounted for 12% of total emissions in the European Union in 2016 (EEA, 2018). Moreover, while total emissions have fallen since 1990 in every other sector, emissions in transport have increased by 17% since then (EEA, 2018).

In order to reverse this trend, governments in many parts of the world have implemented a number of policy measures. Within the EU, CO_2 standards are imposed on car manufacturers and a CO_2-labelling scheme has been introduced to inform car buyers about the emissions of cars. On a national level, governments have introduced a variety of measures, including CO_2 taxes on the purchase of cars, taxes on fossil fuels, fuel-blending requirements for renewable fuels and subsidies on alternative-fuel cars, often combined with each other. Despite all these measures, 97% of the existing EU fleet in 2016 and 91% of the new cars in the Netherlands in 2018 were gasoline and diesel cars (ACEA, 2018).

It is clear that the market for clean cars remains underdeveloped but the ques-

This chapter is based on Hulshof and Mulder (2020a). I thank two anonymous referees and the co-editor of Environmental and Resource Economics, as well as Adriaan Soetevent and other participants at the 2019 SOM PhD conference for very valuable comments and suggestions.

tion is to what extent this can be attributed to the preferences of consumers for polluting cars. At least two other reasons hamper the development of the market for clean cars. The first is an information asymmetry problem. In the EU, consumers obtain information about the level of a car's emissions through CO_2 labels, which are based on laboratory measurements (Haq and Weiss, 2016). It is becoming increasingly apparent that real-world emissions of cars deviate from lab-tested emissions and that this gap has increased over time (Fontaras et al., 2017), partly caused by cheating behaviour on the emission measurements by some car manufacturers (Paton, 2015). As a result, these labels are untrustworthy and, therefore, consumers may not express their intrinsic willingness to pay (WTP) for clean cars in the market. The second reason is caused by the fact that alternative-fuel cars remain emerging technologies. In addition to a limited number of models to choose from, consumers worry about the unavailability of refuelling stations for alternative fuels (Ziegler, 2012; Hackbarth and Madlener, 2016) and long refuelling times in case of electric vehicles (Egbue and Long, 2012; Hackbarth and Madlener, 2016). This leads these type of cars not to be considered as serious alternatives to many consumers. To be able to assess the potential for emission reductions in passenger car transport, the intrinsic willingness to pay of consumers needs to be understood.

Studies that have assessed the WTP of consumers for cars with lower emissions find a wide range of estimates. These studies include Hackbarth and Madlener (2016), Achtnicht (2012), Tanaka et al. (2014) and Hidrue et al. (2011), where the last two focus only on electric cars. These studies report a WTP a one-time premium ranging from €5 to €1432 to reduce a vehicles emissions by one percent (Hackbarth and Madlener (2016, 2013), Tanaka et al. (2014), Hidrue et al. (2011)) or from €13 to €127 to reduce a vehicles emissions with 1g of CO_2 per kilometre for the median person (Achtnicht, 2012). This translates to minimum estimates of the WTP per tonne of CO_2 of €89 and €256 for two reference groups (Achtnicht, 2012). Also related to this paper are studies that use various other applications to study the valuation of consumers for climate change mitigation. These include Alberini et al. (2018) and Longo et al. (2008) (policy scenarios), Roe et al. (2001) (green electricity), Brouwer et al. (2008) and MacKerron et al. (2009) (airfare), and Löschel et al. (2013) and Diederich and Goeschl (2014) (EU ETS). The estimates of these studies for the WTP to reduce CO_2 emissions by one tonne range from €6 to $967 (approximately €780[1]). An overview of the estimates for CO_2 emission reductions in the stated-preference literature is included in Alberini et al. (2018). In contrast to

[1]Using the average annual US dollar/euro exchange rate in 2005, the study's (Longo et al., 2008) survey year, according to Eurostat.

the previously mentioned studies, Bigerna et al. (2017) estimate the WTP for emissions based on revealed preference data (converted from elasticities of demand for conventional fuels) and find a mean WTP of €7 per tonne.

Almost all papers that study the WTP within transport estimate the WTP for clean cars, except for Achtnicht (2012). From a policy perspective, however, it is more relevant to know the WTP for emission reductions because it are the emissions that lead to climate change and should therefore be targeted by policies. Not surprisingly, the benefits of climate change mitigation policies are typically denoted as the avoided damages in euros/dollars per tonne of emissions (i.e. the social cost of carbon).

This paper investigates the preferences of consumers for emission reductions in passenger car transport. Our main research question is: how much are consumers willing to pay to reduce CO_2 emissions in passenger car transport? In addition, based on our WTP estimates, we specifically investigate the distribution of the WTP for hybrids, a promising clean car type. Lastly, we want to understand the socio-economic factors that contribute to the heterogeneity in preferences for emissions and the implied required pay-back period for lower fuel costs.

The contribution of this paper is the estimation of the WTP for emission reductions in passenger car transport, expressed in euros per tonne of emissions (which is the conventional unit of measure in the climate policy debate). We follow a similar approach as Achtnicht (2012) but this paper uses a somewhat different method to translate the WTP for clean cars into WTP for emission reductions. Also, this paper makes an important different assumption about the distribution of the WTP for emissions, generally leading to more realistic WTP estimates. In addition, we have detailed socio-economic information about respondents that we relate to preferences for emission reductions, including income, age, gender and education. Lastly, we investigate the stated preferences for hybrids based on two real-life cars and compare the stated preferences with actual vehicle sales records.

We analyse preferences by adopting a discrete-choice experiment. Participants make trade-offs between cars that differ in four attributes: the purchase price, emissions, fuel type and fuel costs. Our sample consists of 1471 participants that represent the Dutch adult population with the intention to buy a passenger car. Participants were confronted with 10 choice questions, resulting in 14,638 observed choices. Choices are modelled based on a mixed logit approach to take into account that preferences may vary between individuals (Train, 1998). In addition, the paper uses the WTP estimates to analyse the driving costs of and WTP for two real-life hybrids that are also available in a nearly identical gasoline version.

We find a strong preference for emission reductions in passenger car transport. Our main estimate of the WTP for emission reductions equals €199 per tonne. In addition, the majority of consumers appears to be willing to pay at least the prevailing market premium for two selected hybrid cars. This implies a large potential for emission reductions in passenger car transport. We also find considerable differences in preferences amongst socio-economic groups along the lines of age, gender and education but not income. Finally, the results suggest that the average consumer has a short implicitly required pay-back period for expenditure on a vehicle's fuel cost attribute. For government policy, our findings suggest that policies that successfully reduce information asymmetry in passenger car transport can make a considerable contribution to achieving emission reductions.

The remaining of this paper is structured as follows. Section 2.2 discusses the theoretical framework. In Section 2.3, we describe the methods that we applied, particularly the set-up of the choice experiment, survey design and data. Section 2.4 provides the result. Finally, Section 2.5 provides the discussion and conclusion.

2.2 Theoretical framework

To analyse consumer preferences, we depart from the microeconomic theory of consumer behaviour and utility maximization. The central idea in this theory is that consumers choose a good within a set of alternatives that maximizes their utility. Basically, a budget-constrained consumer chooses the good that is most valuable to him.

Lancaster (1966) proposes that the utility someone derives from consuming a good is not driven by the good itself but by the good's attributes. Accordingly, selected alternatives represent the 'best' combinations of attributes to the decision maker in the sense that they yield the highest utility.

Choice experiments involve asking respondents to choose their preferred alternative out of a set of alternative options. The alternatives typically represent the same good (e.g. cars) that differ in certain attributes (e.g. emissions). By asking individuals to choose between alternatives that differ in attributes, the trade-offs that respondents make between these attributes are revealed.

The observed choices from the respondents are modelled according to Random Utility Theory (RUT). RUT posits that consumers maximize their utility (derived from a good's attributes), but exhibits a random component in the utility function to consider that the true utility functions of the observed decision makers are unknown. The utility function (U) therefore consists of two parts, a systematic part V and a random part ϵ. Utility of individual i for alternative j can be written as:

$$U_{ij} = V_{ij} + \epsilon_{ij} \tag{2.1}$$

Assuming a linear utility function, the systematic part can be written as:

$$V_{ij} = \beta_i' X_{ij} \tag{2.2}$$

where X is a vector of product attributes. Together with Eq. (2.1) and the assumption that ϵ_{ij} is I.I.D. extreme value type 1 distributed, this yields the mixed logit model:[2]

$$U_{ij} = \beta_i' X_{ij} + \epsilon_{ij} \tag{2.3}$$

Importantly, this model considers that decision makers differ in their taste parameters (the β's) (Train, 1998), as indicated by the subscript i. Intuitively, this reflects that individuals differ from each other and have their own respective utility function. Other studies confirm that people differ in their preferences for environmental goods, such as renewable electricity (Bollino, 2009). However, we do not observe exactly how preferences differ between individuals, i.e. the true distributions of the taste parameters $f(\beta|\theta)$ are unknown. Therefore, to estimate a model based on (3), the researcher has to assume a distribution for the random parameters. The chosen distributions can significantly affect the results of the model (Hensher and Greene, 2003). For a given distribution, the probability that alternative j is chosen out of the k available alternatives is given by (see e.g. Train, 2009):

$$P(j) = \int exp(\beta_i' X_{ij}) / \Sigma_k exp(\beta_i' X_{ik}), f(\beta|\theta) d\beta \tag{2.4}$$

No closed-form solution exists for this expression but an option is to estimate an approximate solution using simulated maximum likelihood.

Train and Weeks (2005) propose a reformulation of the model in Eq. (2.3) such that the researcher can assume distributions directly for the WTP coefficients rather than for the coefficients of the utility function. This reformulated model is referred

[2] In a setting where individuals make repeated choices, an additional subscript (t) in the utility function is appropriate: $U_{ijt} = \beta_i' X_{ijt} + \epsilon_{ijt}$.

to as the model in WTP space. An important advantage of this WTP-space model is that it enables specifying the distribution of the WTP directly, resulting in more convenient (Train and Weeks, 2005) and less "counter-intuitive" (Scarpa et al., 2008) distributions for the WTP. Additional conveniences of the WTP-space model is that the estimates can be directly interpreted as marginal WTPs and that the standard errors of the WTP need not be simulated or approximated (Scarpa and Willis, 2010). For these reasons we estimate the model in WTP space rather than in preference space. The WTP-space reformulation is now briefly discussed.

To arrive from Eq. (2.3) at the model in WTP space, Train and Weeks (2005) assume ϵ_{ij} is extreme value distributed with variance equal to $\mu_i^2(\pi^2/6)$, where μ_i is referred to as the individual-specific scale parameter. This scale parameter reflects that different individuals with the same preference parameters may be associated with different degrees of variance in the random part of the utility function. As an example, Train and Weeks (2005) note that in a repeated choice situation, unobserved factors may differ for each choice question. Separating the product attributes into a price attribute p (with taste parameter δ) and non-price attributes x (with taste parameters α) and dividing Eq. (2.3) by the scale parameter, which leaves behaviour unaffected (Train and Weeks, 2005), results in the utility function:

$$U_{ij} = (\alpha_i/\mu_i)'x_{ij} - (\delta_i/\mu_i)p_{ij} + \varepsilon_{ij} \tag{2.5}$$

which has a new error term ε which is I.I.D. extreme value type 1 distributed and has constant variance $\pi^2/6$. Let $c_i = (\frac{\alpha_i}{\mu_i})$ and $\lambda_i = \frac{\delta_i}{\mu_i}$, then this utility function (still in preference space) can be written as:

$$U_{ij} = c_i'x_{ij} - \lambda_i p_{ij} + \varepsilon_{ij} \tag{2.6}$$

Here, the WTP for an attribute is given by the marginal rate of substitution between the non-price attribute and the price attribute, i.e. the ratio of the attribute's coefficient to the price coefficient: $w_i = c_i/\lambda_i$. Finally, this definition of the WTP is used in Equation (2.6) to arrive at the model in WTP space:

$$U_{ij} = (\lambda_i w_i)'x_{ij} - \lambda_i p_{ij} + \varepsilon_{ij} \tag{2.7}$$

2.3 Method

2.3.1 Choice experiment

In this choice experiment, participants choose between two alternative cars that differ in four attributes. The survey was randomly administered to 2395 adult-aged Dutch persons. Prior to the actual choice questions, participants encountered a short text explaining the goal of the survey, the choice questions, and the attributes and corresponding levels.

The four attributes in the survey are the (i) purchase price, (ii) fuel type, (iii) CO_2 emissions per kilometre and (iv) fuel costs per 100 kilometre. The CO_2 emissions attribute is our main attribute of interest. The survey includes the purchase price as this enables estimating the WTP for the other attributes in monetary terms. The survey includes the fuel type and fuel costs per 100 kilometre because we are interested in the intrinsic preferences for emissions and want to exert explicit control over these two attributes in order to prevent respondents from associating low emissions with certain fuel types (e.g. electric) or low/high fuel costs.

Table 2.1 lists the attributes and corresponding levels. The levels of the purchase price depend on the participant's self-declared reference price for a new vehicle, as is common practice in the transportation literature (e.g. Ito et al., 2013). This ensures that the survey offers prices which the respondent would consider in practice. We include seven fuel types including the dominating fossil fuels and five primary alternative fuels that are currently on the market in the Netherlands. Five levels of emissions are shown, which are in line with papers from the transportation literature (e.g. Achtnicht, 2012). During pre-testing, some participants struggled with combinations between positive emissions and full-electric or hydrogen. Therefore, the survey clearly explains to participants that emissions from fuel production and transport are included (i.e. are based on a *well-to-wheel* approach). The levels of fuel costs per 100 kilometre are also based on the literature (e.g. Hackbarth and Madlener, 2016).

Regarding our experimental design, we only restrict combinations between zero emissions and the fuel types gasoline and diesel in order to display realistic combinations. This results in a total possible number of combinations of $4 \times (7 \times 5 \times 3) + 1 \times (5 \times 5 \times 3) = 495$, which were all included in the final experiment. Figure 2.A.1 in Appendix 2.A provides a screenshot of one of the choice sets.

Many relevant car attributes for car purchases are not included in this survey, such as reliability, size, body type and power (e.g. Train and Winston, 2007). If

Attribute	Number of levels	Levels
Purchase price	5	60%, 80%, 100%, 120%, 140% of reference (in €)
Fuel type	7	Gasoline, diesel, CNG, biofuel, full-electric, hybrid-electric, hydrogen
CO_2 emissions per kilometre (including emissions from fuel production)	5	0gr*, 90gr, 130gr, 170gr, 250gr
Fuel costs per 100 kilometre	3	€5, €15, €25

*Not combined with gasoline and diesel.

Table 2.1. Attributes and their levels

respondents would make implicit assumptions about omitted attributes in relation to attributes that are included (for instance that hydrogen vehicles are always large and luxurious), our estimates for the attribute associated to such omitted attributes would be biased. To prevent this, the introductory text of the survey and the actual choice questions contain explicit instructions to regard the alternatives as identical beyond the described characteristics. A transcript of these instructions can be found in Appendix 2.A.

Frequently, an attribute or one of its levels represents a number of (omitted) inherently related attributes or characteristics. While it prevents associations with omitted non-inherently related attributes (e.g. body type, power, colour, reliability, brand, transmission type or size), the survey's instruction to regard cars as identical beyond the described attributes does not prevent respondents from making assumptions about omitted inherently related characteristics. For example, diesel is inherently associated to more harmful NO_x emissions and full-electric to a currently relatively limited refuelling-station availability. The trade-offs by respondents are expected to reflect the preferences of consumers for inherently related characteristics. Importantly, by explicitly including fuel types and fuel costs as attributes, the survey design prevented respondents from making assumptions about fuel types and fuel costs and their inherently related characteristics when they encountered different levels of emissions. Moreover, beyond mitigating climate change, there appear to be no other inherently related characteristics of CO_2

emissions in passenger car transport. As a result, the estimates for the WTP for emission reductions reflect the consumer preferences for climate-change mitigation. This was verified during survey pre-testing, as interviews did not suggest that participants were choosing on the basis of implicit assumptions about (non-inherently related) omitted characteristics. Appendix 2.B provides details on the pre-test procedure of the survey.

The survey starts by announcing the goal of the survey (to study consumer preferences for different types of cars) and asking several preliminary questions. We ask (i) to indicate a reference price for their next vehicle, (ii) to indicate the type of car (e.g. small or SUV) that someone owns (or drives most in case they own more than one), and (iii) to indicate the approximate annual mileage.[3] As we are interested in car purchases, we discarded respondents that indicated they do not intend to buy a car again at question (i) in our statistical analysis (n=252). Therefore, our final sample represents the Dutch adult population with the intention to buy a car. Summary statistics of the responses to question (i) are included in Table 2.2. We used the second question to investigate a possible relationship between car types and preferences for emissions.

In the introductory text, we also briefly discuss the relation between fuel types, fuel costs and emissions. In addition, we explain the attributes and the levels. The survey then explains that the respondent is asked to choose ten times between two cars that differ in these four attributes. We also explain to the respondents that some of the fuel types are not yet widely available (e.g. hydrogen) but may become so in the near future. The actual choice question asks the respondent which car he/she would buy, taking into consideration his/her own budget. The last part is added as “cheap talk” strategy to minimize the hypothetical bias, referring to the tendency of people to overstate their true WTP in stated-preference research (e.g. List and Gallet, 2001).

Another concern with stated-preference surveys is that the questions are not incentive compatible because, depending on the type of good (public/private), payment obligation, question format and (expected) reaction of the relevant agency to the responses, respondents may have an incentive to respond strategically and not according to their true preferences (Carson and Groves, 2007). Particularly impor-

[3]Specifically, in the survey, people are asked to indicate what segment their car belongs to based on the following car segmentation proposed by the European Commission: A: mini cars, B: small cars, C: medium cars, D: large cars, E: executive cars, F: luxury cars, J: sport utility cars (including off-road vehicles), M: multi-purpose cars, S: sports cars (CEC, 1999). For each car segment, three (popular) example cars are shown based on the segment’s Wikipedia pages (see https://en.wikipedia.org/wiki/Euro_Car_Segment).

tant is how the respondent expects the survey results will be used. We note that, although the survey is administered by a university, car manufacturers in particular have a great interest in consumer preferences. Therefore, if respondents anticipated this, they may have felt that they exerted influence over the type of cars that will be produced in the future. In our binary choice setting, in case the choice questions were regarded independently, no incentive compatibility problem would have been present because participants chose between two private goods and may have expected that selecting an alternative resulted in a higher probability of the selected type being produced in the future. Respondents probably have not regarded the choice questions independently such that our repeated structure could imply some scope for making strategic choices. However, two reasons as discussed by Carson and Groves (2007) suggest this was not highly problematic in our survey. Firstly, car manufacturers are likely to produce a range of vehicle types such that respondents may have expected that only a few alternatives will not be produced. Secondly, strategic behaviour requires knowledge about the distribution of preferences and we believe that expectations about this distribution are highly uncertain. Carson and Groves (2007) note that meeting one of these two conditions is sufficient to induce responses close to the true preferences.

The survey is randomly administered to 2395 members of age 18 and above of the CentERpanel in December 2017. The CentERpanel is a high-quality sample, representing the Dutch population (CentERdata, 2018).[4] Out of 2395 invites, 1736 persons responded (72.5%) to the survey. Because socio-economic characteristics of all individuals in the sample are known to the research institute administering the CentERpanel, we do not need to ask additional questions.

Table 2.2 describes socio-economic characteristics of our sample and the Dutch adult population. The gender structure of our sample is similar to that of the adult population. The age structure of our sample tends to resemble the Dutch adult population as well, although the age group 65-79 years is somewhat overrepresented. The educational structure of the sample is also quite close to the structure of the population, although the share of higher educated people is about nine percentage points higher in the sample.[5] Finally, the income structure of our sample is not

[4]Members are not included based on self-selection but are randomly drawn from the pool of national addresses and invited to join the panel. Panel members are not required to own a computer or have an internet connection.

[5]Classification according to the ISCED (International Standard Classification of Education): lower education represents primary education and lower secondary education (basisonderwijs, VMBO and havo/vwo klas 1-3); middle education represents higher secondary education and post-secondary non-tertiary education (havo/vwo klas 4-6, MBO); and higher education represents bachelor's, master's and doctoral (HBO and WO).

very different from the income structure of the Dutch population. For 6% of the respondents, income is unknown.

Table 2.3 provides several key characteristics of Dutch households and their cars, and the Dutch passenger car fleet. The majority of households owns at least one car and the average household dedicates 10% of expenditure on cars. Regarding Dutch vehicle sales in 2018, hybrid and full-electric have reached market shares of 6% and 4%, respectively. Other alternative fuel technologies remain without significant market shares. The share of fossil fuel cars in sales remained high at 91%. Regarding the existing car fleet, hybrids and full-electric cars have higher shares amongst older people when compared to younger generations.

2.3.2 Model specification

In order to analyse the observed choices, several specification choices need to be made. We need to determine which parameters are randomly distributed and we need to assume a distribution for those parameters.

To determine the random parameters, we applied Lagrange Multiplier tests as proposed by McFadden and Train (2000) and log-likelihood ratio tests (as in e.g. Wang et al., 2007). These tests unambiguously suggest including all parameters as random coefficients. However, when we estimate the model with all random parameters, the simulated-maximum likelihood estimator does not converge to a global maximum, a known problem within simulated-maximum likelihood estimation that comes without a generally accepted solution (e.g. Myung, 2003). We overcome this by estimating the final model with only the coefficients of the purchase price, CO_2 emissions and hybrid fuel type as random. Inclusion of more random parameters is computationally not possible with simulated maximum likelihood estimation. The analysis retains the emissions parameter as random because it is the main parameter of interest. We retain the price attribute as random because fixing the price coefficient would imply that the scale parameter is constant over individuals (Train and Weeks, 2005). If in fact scale varies between individuals, and one fixes the price coefficient, the variation in scale would be "erroneously attributed to variation in WTP" for the other attributes (Scarpa et al., 2008). The coefficient for hybrid is allowed to be random to be able to analyse the driving costs and distribution of WTP for hybrid vehicles. The drawback of this solution is that we will not derive distributions for the WTP coefficients of the fuel cost and other

Variable	Sample	Population
Female*	54.6%	50.8%
Age		
18–39 years	27.8%	33.8%
40–64 years	40.6%	43.1%
65–79 years	27.4%	17.5%
80+	4.2%	5.6%
Education**		
Lower education	28.2%	31.4%
Middle education	34.6%	38.2%
Higher education	37.1%	28.9%
Unknown	0.1%	1.5%
Income (gross per year)***		
Less than €10,000	15.7%	16.0%
€10,000–€19,999	20.0%	26.3%
€20,000–€29,999	20.5%	18.0%
€30,000–€39,999	18.1%	14.3%
€40,000–€49,999	9.7%	9.5%
€50,000–€99,999	9.3%	13.4%
€100,000 and more	0.7%	2.4%
Unreported	6.0%	
Vehicle reference price		
€0–€20,000	62.4%	
€20,001–€40,000	19.3%	
€40,001–€60,000	3.1%	
More than €60,000	0.6%	
Will not buy a car	14.5%	

*Dutch population of 18 years and above; **Dutch population of 15 years and above. Schooling levels according to ISCED standard; ***Dutch population.
Source: Sample: CentERdata, own calculations. Population: CBS.

Table 2.2. Descriptive statistics of respondent characteristics

Avg. No. of cars per household (2019)	0.95				
Avg. household expenditure share dedicated to (operation of) car(s) (2015)	9.7%				
Avg. annual mileage (2015)	13,000km				
Avg. car ownership duration (2016)	4.1 years				
Percentage of households with (2015)	1 car	2 cars	3 or more		
	48.2%	18.8%	4.2%		
Avg. emissions of new car (gram/km)	2015	2016	2017		
	101	106	109		
%-share in vehicle sales, by fuel type (2018)	Gasoline	Diesel	Hybrid	Full-electric	Biofuel
	77%	14%	6%	4%	0%
	CNG	LPG	Hydrogen		
	0%	0%	0%		
Share in fleet of hybrid and full-electric cars, by age group (2016)	18-29	30-49	50-64	65-74	75+
	0.4%	1.1%	1.4%	1.7%	1.5%

Source: CBS, Eurostat, RDW

Table 2.3. Characteristics of Dutch households and their cars

fuel type attributes.[6]

After selecting the random coefficients, a distribution has to be assumed for these parameters. For our random coefficients, we considered the two most commonly applied distributions in practice, the normal and log-normal distributions (Train, 2009). The log-normal distribution is often assumed for coefficients that have a strong a priori assumption on the sign, typically following from economic theory (e.g. the price coefficient). This way, the coefficients are forced to be either strictly positive or negative. In contrast to the coefficient for hybrid, for both the signs of the coefficients of the purchase price and CO_2 emissions we have prior expectations. A negative coefficient is expected for the purchase price because utility

[6] Another solution would be to assume a constant coefficient for the price and link this attribute to income. This would facilitate including random coefficients for the fuel types and fuel costs and accommodate differences in the marginal utility of money to differ between income levels. The latter implies differences in scale between but not within income groups. However, as the marginal utility of money probably also differs in other respects than income, including “factors that are independent of observed socioeconomic covariates" (Scarpa et al., 2008), the drawback of this approach is that variation in scale due to these other factors may still affect our estimates for the (distribution of the) WTP for emission reductions. Given our focus on estimating the WTP for emission reductions, we opted for the current WTP-space model with a random price parameter.

decreases if the price of an ordinary good rises.[7] With respect to emissions, the environmental benefits of reducing emissions provide reasons to expect that some people prefer lower emissions. In contrast, it is hard to justify an expectation that some people prefer higher emissions since there appear to be no benefits at all.[8] Hensher and Greene (2003) propose an empirical approach to guide the decision on which distributions to assume. Their approach involves estimating empirical distributions for each of the random parameters based on kernel density plots and inspecting the shape of these distributions. Appendix 2.C discusses this approach in more detail and provides the kernel density plots (Figure 2.C.1) and two descriptive measures (Table 2.C.1). From these plots, the hybrid coefficient appears to be normally distributed, the price coefficient appears to be log-normally distributed and the distribution for emissions is not unambiguously normal or log-normal. Considering our reservations to assume a log-normal distribution for the emissions parameter (see Appendix 2.C), we assume a normal distribution for this coefficient.

Our final specification of the utility function is:

$$U_{ijt} = \boldsymbol{\alpha}\mathbf{F}_{ijt} + \gamma_i HY_{ijt} + \beta_i CO_{2ijt} + \theta_i PP_{ijt} + \delta CKM_{ijt} + \epsilon_{ijt} \tag{2.8}$$

where $\mathbf{F}$ is a vector of fuel type dummies (excluding hybrid), HY refers to the fuel type hybrid, CO_2 refers to $\mathrm{CO_2}$ emissions, PP refers to the purchasing price and CKM refers to fuel costs. The dummy for gasoline is omitted in the estimation procedure and serves as reference case for the other fuel types. Random coefficients are denoted with a subscript i. The subscript t represents the panel structure of our data, i.e. that respondents choose repeatedly. We estimate the model with the user-written Stata command `mixlogitwtp`, using 600 Halton draws.

In order to investigate the relationship between socio-economic characteristics and preferences for emissions, we estimate a second model that includes interactions of $\mathrm{CO_2}$ emissions with gender (female=1), age, education, income and car-type dummy variables. Regarding age, we divide the sample in three groups: 18-39, 40-64 and 65+. Regarding education, individuals are assigned to groups representing lower, medium and higher education based on the ISCED classifications. Regarding income, we distinct between five (gross yearly) income groups: low (€0–€19,999), medium (€20,000–€39,999), high (€40,000–€59,999), very high

[7]We assume cars are ordinary goods, i.e. that, conditional upon a set of characteristics, the probability that someone will buy a car decreases if the price increases.

[8]Based on anecdotal evidence, it appears that, in certain parts of the US, some individuals prefer polluting vehicles as a form of protest against liberalism. For the Dutch population, we are not aware of such preferences amongst subgroups of the population.

(€60,000–€79,999) and top (€80,000+). Lastly, we investigate a potential relationship between the car type someone owns and preferences for emissions. Based on self-reported information about the car type owned, respondents are assigned to one of three car segment groups: small segment (A, B and C segments), upper segment (D, E and M) or luxury segment (F, J and S). For each of these interaction variables, the first group is omitted in the estimation stage (18-39 years old, lower education, low income and small car segment, respectively). Variance inflation factors do not suggest the presence of multicollinearity in the interaction variables (not reported here, factors are below 3.6), which could be a worry due to an expected relationship between income and car type ownership.

2.4 Results

2.4.1 Estimation results

Table 2.4 reports the estimation results. The estimated coefficients can be directly interpreted as mean estimates of the WTP, except for the coefficient of the purchase price, which is the estimated mean of the log of the price coefficient. The estimates are in line with economic theory. A higher price, higher fuel costs or higher emissions are associated with lower levels of utility. The associated coefficients of these attributes are all statistically significant.

Regarding fuel types, the coefficients for diesel, CNG, biofuel and hydrogen are negative and statistically significant. This implies that these fuel types are, on average, valued less than gasoline (the reference fuel type). The least preferred fuel type is diesel with a WTP per vehicle that is €3230 lower than gasoline.[9] The coefficient for full-electric is negative but insignificant while only the coefficient for hybrid-electric is positive and significant. The mean WTP for a hybrid-electric vehicle, the most favoured fuel type, is €812 higher than for a gasoline counterpart. The estimated standard deviation for hybrid of € 3272 suggests there exists a very large degree of heterogeneity in preferences for this fuel type. Overall, consumers appear to favour gasoline and electric fuel types. These results may be driven by factors that are inherently related to (and therefore represented by) the respective

[9]In practice, diesel cars tend to be more expensive than gasoline cars in the Netherlands. However, despite the higher price and a lower WTP, diesel cars still have a market share of 14% in new car sales 2018. This may be explained by the considerably lower fuel price for diesel than gasoline in the Netherlands due to differences in fuel tax. I.e. in practice, the fuel type diesel is combined with low fuel costs. In addition, the estimate reflects the mean WTP for diesel whereas the distribution for this fuel type may be dispersed.

fuel type but omitted in our model, such as harmful NO_x emissions for diesel or the relatively limited availability of refuelling stations for full-electric and hydrogen cars.

Regarding fuel costs, the average respondent values a decrease of €1 in fuel costs per 100km at €434 at the moment of vehicle purchase. At an average annual mileage of 13,000km, this implies a required pay-back period of only 3.3 years. It appears that car buyers with respect to fuel costs do not display far-forward looking behaviour, apply very high discount rates or use decision rules that are not based on valuation principles which a rational agent would use. This finding is very much in line with the mean required pay-back periods for US car drivers estimated by Greene et al. (2013). On the other hand, the results of Espey and Nair (2005) imply that US car buyers apply much lower discount rates, more accurately reflecting the outcome of valuation based on the (discounted) net present value. Compared to the results of Achtnicht (2012) and Hackbarth and Madlener (2013, 2016) for German car buyers, our estimates for the WTP to reduce fuel costs are somewhat lower. The subsequent driving cost analysis in Section 2.4.4 further illustrates the short implicitly required pay-back periods in the context of driving a hybrid car.

The mean WTP to reduce a vehicle's emissions with 1 gram per kilometre is €36.70. This coefficient is highly significant. All else equal, the average consumer prefers a car with lower emissions. The degree of preference heterogeneity in emissions is large, considering the estimated standard deviation of €30.81.

The estimation results of the second model yield insights in the relationship between socio-economic characteristics and preferences for emission reductions. Particularly, we find differences in WTP along the lines of gender, age and education but not income and car segment. The mean WTP to reduce a vehicle's emissions with 1 gram per kilometre of the reference group in this model is €21.62 (male, age 19-39, low education and a small segment car; the group with the lowest WTP). Females have a significantly higher WTP than males. Regarding age, we do not find differences between groups 19-39 and 40-64 while the WTP amongst individuals older than 64 is €17.19 higher. With respect to education, we do not find a significant difference between lower and medium education groups while the higher education group has a significantly higher WTP. Regarding income, we do not find statistically significant differences between groups. Finally, we do not find a statistically significant relationship between car segment and the WTP for emissions.[10]

[10]These results are robust to omitting the interactions between emissions and car segments or specifying the marginal utility of emissions to depend linearly on income rather than the reported dummy specification.

Variable	MXL model		MXL with interactions	
	Coefficient	Standard error	Coefficient	Standard error
CO_2 emissions (gr/km)	-36.70***	1.82	-21.62***	4.84
Standard deviation of CO_2 emissions (gr/km)	30.81***	2.04	29.56***	2.02
CO_2*Female			-6.84*	3.03
CO_2*Age40-64			-2.80	3.42
CO_2*Age65+			-17.19***	3.91
CO_2*Medium education			-4.16	3.90
CO_2*Higher education			-12.26**	4.29
CO_2*Medium income			-0.68	3.76
CO_2*High income			-1.49	5.03
CO_2*Very high income			-4.70	6.95
CO_2*Top income			9.28	6.17
CO_2*Upper segment car			2.15	3.24
CO_2*Luxury segment car			16.46	10.40
Fuel costs (€/100km)	-433.84***	16.66	-430.97***	15.48
Diesel	-3173.19***	321.45	-3200.46***	309.97
CNG	-1937.15***	298.05	-1939.38***	292.36
Biofuel	-837.45**	281.67	-872.13**	272.83
Full-electric	-256.91	281.79	-270.40	272.29
Hybrid-electric	811.58*	319.34	771.33*	310.24
Standard deviation of Hybrid-electric	3271.69***	453.31	3296.97***	328.78
Hydrogen	-885.04**	276.67	-914.51**	272.15
Purchase price	-8.57***	0.05	8.57***	0.04
Standard deviation of purchase price	1.10***	0.05	1.10***	0.05
Observed choices	29,276		29,276	
Log-likelihood	-7605.20		-7583.83	

Note: Standard error in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 2.4. Mixed logit model estimation results

2.4.2 Willingness to pay for emission reductions

To translate the WTP for emission reductions per kilometre into the WTP for emission reductions, we need to consider the effect of the purchase on the car's emissions.[11] From the perspective of the car buyer, there is a direct effect on emissions during the period of ownership over the car. After re-selling the car, future owners are accountable for the car's reduced emissions. This complicates estimating the WTP for emission reductions based on the WTP for emissions per kilometre because we do not know after how many kilometres the car is sold and the emission-attribute's resale value at that point in time. By making the assumption that, during its entire lifetime, a car bought by individual i is owned by individuals that have the same WTP as individual i (and this WTP is fully paid), we can obtain an estimate for the WTP for emission reductions. Under this assumption, the WTP for emission reductions (WTP^{tonne}) equals the WTP for emission reductions per kilometre ($-WTP^{attribute}$ i.e. minus the emissions parameter estimate), divided over the car's expected lifetime mileage $E[Tkm]$, which in turn is divided by one million to transform grams into tonnes:

$$WTP_i^{tonne} = \frac{-WTP_i^{attribute}}{E[Tkm]/1,000,000} \tag{2.9}$$

Assuming an expected total mileage of 184,000km for cars (Ricardo-AEA, 2015), this results in a mean WTP per tonne of emission reductions of €199 and, since Eq. (2.9) is distributed according to the distribution of $WTP^{attribute}$, a standard deviation of €167.

Based on the method proposed by Revelt and Train (2000), we calculate individual-level coefficients for the emissions parameter. Figure 2.1 provides a graphical description of the WTP distribution using kernel density estimates, based on these individual level-estimates and Eq. (2.9). As a result of assuming a normal distribution for the emissions attribute and the fact that Eq. (2.9) does not affect the shape of this distribution, the distribution of WTP for emission reductions appears normal, has a mean of €199 and a minimum and maximum of -€94 and €562, respec-

[11] Archsmith et al. (2017) report a substitution effect between the emissions of different vehicles within a household, i.e. an indirect effect of the purchase of a vehicle with certain emissions on the total emissions of the household's vehicle portfolio. We do not explicitly consider this indirect effect in our paper but we have tested whether there is an impact of the number of vehicles in the household on the WTP for the emissions attribute and there appears to be no statistically significant effect. In addition, this substitution effect does not influence our proposed translations of the WTP for the emissions attribute into WTP for emission reduction (Equations 2.9 and 2.10).

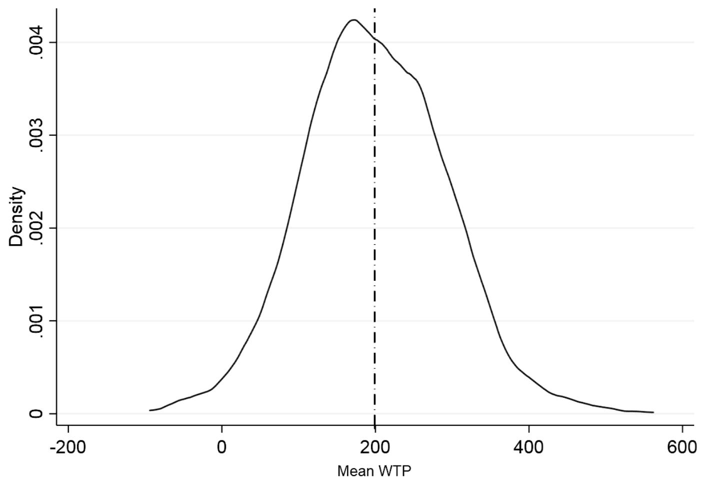


Figure 2.1. Distribution of individual-level WTP for emission reductions.

tively.[12] This highlights the considerable heterogeneity in preferences for emissions that we estimate.

In practice, people will not sell cars to others with a similar WTP because they have no incentive to do so nor can they differentiate between buyers on the basis of their WTP. Taking this into account, we could determine the WTP for emission reductions according to:

$$WTP_i^{tonne} = \frac{-WTP_i^{attribute} + E[P_{E[km_i]}^{attribute}]}{E[km_i]/1,000,000} \tag{2.10}$$

where $E[P_{E[km_i]}^{attribute}]$ refers to the expected resale value of the attribute after buyer i's expected mileage $E[km_i]$. This equation says that the WTP for emissions reductions is equal to the net WTP for the attribute, divided over the individual's mileage, which in turn is divided by one million to transform grams into tonnes. Unfortunately, information about individual mileage and expected resale value of the attribute is unavailable. By making several assumptions, we can get an estimate of the WTP for emission reductions based on this equation. For the expected mileage, we take the average annual mileage in the Netherlands (13,000km) and multiply

[12]A negative WTP for emission reductions is not in accordance with economic theory. However, we estimate a negative WTP for less than 1.4% of the individuals in the sample. This is the result of selecting the normal distribution for the emissions parameter, which does not force the parameter to be of a particular sign. Given that it concerns only a very small number of people, we are not highly worried about the relevance of our WTP estimates.

by the average ownership duration (4.1 years) to arrive at an assumption for $E[km]$ equal to 53,300km (CBS, 2017). Considering that we have very little information about the resale value of the attribute after 53,300km, our assumptions for this parameter are arbitrary. Suppose the resale value of the attribute decreases linearly in the mileage.[13] Let us further assume that the value of the attribute after 0km (i.e. with 184,000km remaining) is equal to €36.70, the mean WTP for the attribute. The expected resale value after 53,300km then equals €26.07.[14] According to (10), the mean WTP under these assumptions equals €199.[15] The most pessimistic assumption for the attribute's resale value would be to set it equal to €0 at any remaining mileage, resulting in an estimated mean WTP for emission reductions equal to €689.[16]

2.4.3 A driving cost and WTP comparison of hybrid and gasoline types

While there appears to be a latent preference for lower emissions, reductions will only materialise if actually available clean car types will be purchased. In that respect, hybrid cars seem to be promising considering that they generally emit less CO_2 and have lower fuel cost. Moreover, compared to gasoline, hybrid is the only fuel type for which we estimate a positive WTP. In addition, the number of actually available hybrid models in the Netherlands has increased from 13 in 2011 to 71 at this moment (November 2019). This subsection aims to further the understanding of the preferences for (non-plug-in) hybrid cars and of the degree of forward looking behaviour of buyers of hybrids. We make pair-wise comparisons of the driving costs and WTP of two actually available models that are sold with both a hybrid and gasoline engine. Importantly, the hybrid and gasoline types that we compare are nearly identical in the attributes for which we did not estimate the WTP.

Specifically, for the two hybrid-gasoline pairs, we estimate the (distribution of the) willingness to pay a premium for the hybrid versus the gasoline type based

[13]For example, if the market price of the attribute is €10 at an expected remaining mileage of 184,000km, the resale value at an expected remaining mileage of 92,000km equals €5.

[14]The car is sold with 71% of the expected mileage left ($\frac{184{,}000km-53{,}300km}{184{,}000km}$). $0.71 \times €36.70 = €26.07$.

[15]These assumptions yield the same outcome as the WTP estimate based on (9) as they imply scaling the numerator and denominator by the same factor of $53,300km/184,000km$.

[16]This follows from (10): with emissions, we do not attribute the (expected) future revenue from reselling the attribute to someone else to the individual's WTP for emission reductions. If you have a positive WTP only because you can sell the attribute at a later point to someone else for the same amount as your WTP, then this can hardly be considered a willingness to contribute to the environment. Therefore, (10) does not attribute the expected resale value to the individual's willingness to pay for the emission reductions that materialised during the period of ownership.

on the WTP estimates for emissions, fuel costs and fuel type. Consequently, we compare the WTP for the hybrid with (1) the estimated savings from lower fuel costs, and (2) the actual market premium and vehicle sales records. By comparing the WTP for the hybrid with the estimated fuel savings we gain further insight into the degree of forward looking behaviour of car buyers. By comparing the distribution of the WTP for the hybrid with the actual market premium and vehicle sales records we obtain anecdotal evidence of whether our stated-preference results appear aligned with revealed-preference data.

We compare the hybrid and gasoline types of a Toyota C-HR and Toyota Yaris.[17] These models are available with highly comparable gasoline and hybrid engines and are nearly identical in other respects. This analysis assumes that consumers regard the hybrid and gasoline types as identical, except for the fuel type, fuel costs and emissions. A drawback of using real-life models is that the reported emissions and fuel consumption levels are based on laboratory tests, which cannot be trusted. This is further complicated by the difference in accuracy of lab-tests for hybrid and gasoline types (ICCT, 2019). However, the differences in fuel consumption and emissions of the models in our comparison are somewhat reflective of the average real-world performance increase of hybrids of 23% in the EU (in terms of fuel consumption and emissions), as estimated by Emissions Analytics (2019). The hybrid's reported emissions and fuel consumption are 36% and 15% lower for the C-HR and Yaris, respectively. In addition to the results presented in the current subsection, we have repeated the analysis for two hypothetical hybrid-gasoline pairs. The results of this sensitivity analysis are reported in Table 2.D.1 and Figures 2.D.1 and 2.D.2 in Appendix 2.D. The outcomes are comparable to the results reported here.

Table 2.5 and Figure 2.2 report the results of the driving cost comparison for

[17] Vehicle selection is based on a case-by-case inspection of all available hybrid models with a price below € 60,000 (96% of respondents indicated a reference price below € 60,000). Ideally, two models are identical except for the hybrid engine, which is why hybrid models that are not available with a gasoline engine do not qualify (e.g. Ford Mondeo, Kia Niro, Toyota Prius, Hyundai Ioniq). These two restrictions yield 8 potential models to be analysed. Consequently, hybrid models for which no comparable gasoline engine in terms of performance is available are excluded (Citroen C5 Aircross). Hybrid models for which a comparable gasoline engine is available but which are only available with different transmission or drive types are also excluded (Hyundai Kona). Further, as it appears more interesting to compare a hybrid alternative that is more expensive than the gasoline alternative, models for which vice versa is true are excluded (Honda CR-V). Finally, hybrid models with officially reported CO_2 emissions below 50 gram/km based on laboratory tests are not considered as it is generally acknowledged that these values greatly exaggerate the true level of emissions, and because (despite that fact) these models qualify for a 50% reduction in the Dutch fixed monthly vehicle tax (Audi A3). This results in four models to be considered for inclusion, all Toyota's: C-HR, Corolla, RAV4 and Yaris. The Corolla and RAV4 are excluded because the vehicle sales records are annual figures and the Corolla hybrid has only been on the market for a few months (as opposed to the Corolla gasoline) whereas the RAV4 was completely updated in the middle of 2019. This leaves the Toyota C-HR and Yaris to be included in the analysis.

the Toyota C-HR (first column) and Toyota Yaris (second column). The calculation of the WTP for the hybrid's lower fuel cost, lower emissions and hybrid fuel type attributes are based on the estimated mean WTP for those attributes, as reported in Table 2.4. For example, the WTP for the improvement in the hybrid C-HR's fuel cost (row b) is calculated as the estimated mean WTP for a decrease in fuel costs of €1 per 100km (€433.84) multiplied by the difference in fuel costs (in €per 100km) between the gasoline and hybrid types (i.e. €$1.65/l \times (6.1 - 3.8)l/100km$), which equals €1,646. The bottom of Table 2.5 shows the annual fuel savings at various annual mileages and reports the implied pay-back period of the WTP for the hybrid's fuel cost attribute (corresponding to row (b)), and the emissions and hybrid fuel type attributes (corresponding to row (c)) in between brackets. For example, at an annual mileage of $13,000km$, the annual fuel savings of the C-HR hybrid are calculated as the difference in litres of fuel consumption per 100km (i.e $(6.1 - 3.8)l/100km$) times the fuel price per litre (€$1.65/l$), multiplied by the annual mileage ($13,000km$), which equals €493.35. This implies a required pay-back period of 3.3 and 5.5 years for the fuel cost (row b), and fuel type and emissions attributes (row c), respectively.

For the Yaris, one important difference in the gasoline and hybrid type is the higher monthly vehicle tax (MRB) of the hybrid type (€7.33 per month) due to its slightly higher weight (+35kg).[18] The reported annual fuel savings for the Yaris are net of these higher taxes. Panel a and b of Figure 2.2 show the implied pay-back period in mileage terms for the hybrid C-HR and for the Yaris at an annual mileage of 13,000km (this only matters for the Yaris due to the difference in fixed monthly taxes).

The results for the C-HR display the short required pay-back period from fuel savings. For the mean respondent, the WTP for lower fuel costs is earned back after 43,300km or 3.3. years. The total premium (fuel costs, fuel type and emissions) is earned back after 115,000km, well below the expected lifetime mileage of a gasoline car (184,000km). For the Toyota Yaris, pay-back from 'gross' fuel savings takes slightly longer. When accounting for the higher MRB taxes, pay-back takes much longer.[19]

On the basis of the method proposed by Revelt and Train (2000), we can use the WTP estimates for the various characteristics from Section 2.4.1 to estimate the

[18]The C-HR hybrid is also slightly heavier than the gasoline version but falls in the same weight-dependent tax bracket as the gasoline type.

[19]For the Toyota Yaris, the total WTP premium in the graph excludes the negative WTP for higher MRB taxes to facilitate readability and to demonstrate the implied required pay-back periods under the assumption that the hybrid and gasoline types are identical beyond emissions and fuel consumption.

approximate distribution of the WTP for the hybrids. For the Yaris, we use the estimates for the WTP for fuel costs to control for the higher MRB taxes.[20] Figure 2.3 shows kernel density estimates of the distribution of the WTP for the hybrid types of the C-HR (panel a) and Yaris (panel b), respectively. The solid lines provide the distribution for the full sample whereas the dotted lines provide the distribution for individuals that currently own a similarly sized vehicle and indicated a reference price in the neighbourhood of the listing price, i.e. this concerns individuals who appear likely to be in the market for the respective vehicle. The vertical dash-dotted line indicates the actual price premium for the hybrid type.

Taking the actual price premium in consideration, our results indicate that nearly all respondents (98%) prefer the hybrid type of the C-HR over the gasoline type. In case of the Yaris, approximately two-thirds (67%) of the respondents prefers the hybrid over the gasoline type. Based on this, we would expect the share of hybrids in actual total sales to be higher for the C-HR than for the Toyota Yaris, which is also observed. Interestingly, despite that our model and results are not tailored for analysing revealed preferences, the actual share of the hybrid types in total sales (97% for the C-HR and 74% for the Yaris; see Table 2.6) quite closely matches the estimated share of respondents who are WTP at least the hybrid's actual premium. It is particularly interesting to note that, despite the higher purchase price and MRB taxes for the hybrid Yaris, which cause long pay-back periods, it is still the preferred type by most consumers, both in practice and based on this stated-preference analysis. For these two highly specific cases, the stated-preference results do not appear to be misaligned with revealed-preference data.

2.5 Discussion and conclusion

Passenger car transport is a major contributor to greenhouse gas emissions and the only key sector where emissions have not fallen since 1990 (EEA, 2018). Whether this can be attributed to a lack of WTP for lower emissions from car buyers is questionable for two reasons: (i) consumers cannot observe emissions themselves and

[20]We use the model's estimates of the WTP for savings of €1/100km in fuel costs and combine this with self-reported information about individuals' annual mileage. Specifically, we (i) estimate a separate model with the fuel costs as random parameter (due to the earlier mentioned convergence issue we are not able to obtain these estimates from a single model), (ii) use this to generate individual-level estimates of the WTP to reduce fuel costs by €1 per 100km, and (iii) combine this with information about respondents self-reported annual mileage to obtain an estimate of the WTP for a reduction in monthly taxes. For example, if an individual's WTP to reduce fuel costs by €1 per 100km is €400 and this individual drives 1,000km per month, this analysis imputes that the individual is WTP €40 to reduce monthly taxes by €1.

Model	Toyota C-HR		Toyota Yaris	
Type	1.2T CVT Style	1.8 Hybrid CVT Style	1.5 VVT-i CVT 5 door Active	1.5 Hybrid CVT 5 door Active
Fuel type	Gasoline	Hybrid	Gasoline	Hybrid
Emissions (gr/km)	135	87	96	82
(a) Fuel consumption (l/100km)	6.1	3.8	4.5	3.7
Fuel cost/100km=€ 1.65×(a)*	€ 10.07	€ 6.27	€ 7.43	€ 6.11
Listing price**	€ 32,960	€ 34,160	€ 19,465	€ 20,465
Monthly MRB tax***	€ 59.33	€ 59.33	€ 31	€ 38.33
0-100km/h (seconds)	11.1s	11.0s	11.8s	11.2s
Max. speed	170km/h	185km/h	175km/h	165km/h
Max. horse power	116hp	122hp	111hp	100hp
WTP for hybrid's+				
(b) fuel cost attribute++	€ 434×€ 1.65× (6.1 − 3.8)=€ 1,646		€ 434×€ 1.65× (4.5 − 3.7)=€ 573	
(c) fuel type and emissions attribute+++	€ 811+€ 37× (135 − 87)=€ 2,720		€ 811+€ 37× (96 − 82)=€ 1,211	
(d) MRB-tax attribute++++			–€ 63×(€ 38.33− € 31)=–€ 463	
Annual fuel savings of hybrid‡ [pay-back period of (b), (c)]				
6,500km/year	€ 247 [6.7 yrs, 11.0 yrs]		-€ 2 [never, never]	
13,000km/year	€ 493 [3.3 yrs, 5.5 yrs]		€ 84 [6.9 yrs, 14.5 yrs]	
19,500km/year	€ 740 [2.2 yrs, 3.7 yrs]		€ 169 [3.4 yrs, 7.1 yrs]	
26,000km/year	€ 987 [1.7 yrs, 2.8 yrs]		€ 255 [2.2 yrs, 4.7 yrs]	
Sales (2019)				
Total with this fuel type	95	2,897	1,305	3,651
Of which have a different engine type than specified (1.0 VVT-i for the Yaris)	0	0	513	0

Note: Larger values are rounded. * Fuel price assumption of € 1.65 per litre is based on the 2019 avg. gasoline price according to CBS. ** Corresponding to the listing price in 2019, with identical trim line, gearbox and drive type. Price difference between the hybrid and gasoline is sometimes smaller for other trim lines (e.g. Dynamic for the C-HR) but is never bigger than reported here. *** Based on Noord-Holland region. + The table reports the premium that the average respondent is willing to pay for the attributes of the hybrid. ++ (WTP for fuel cost attribute in €/100km)×(fuel price)×(difference in fuel consumption/100km). +++ (WTP for hybrid attribute)+(WTP for emissions attribute in gr/km)×(difference in gr of emissions/km). ++++ (WTP for car costs in € /month)×(difference in MRB tax in € /month). ‡ Net of MRB-tax premium for the Yaris.
Source: ANWB, Koninklijke RAI Vereniging, own calculations.

Table 2.5. Driving cost comparison based on existing hybrid and gasoline types of a Toyota C-HR and Toyota Yaris.

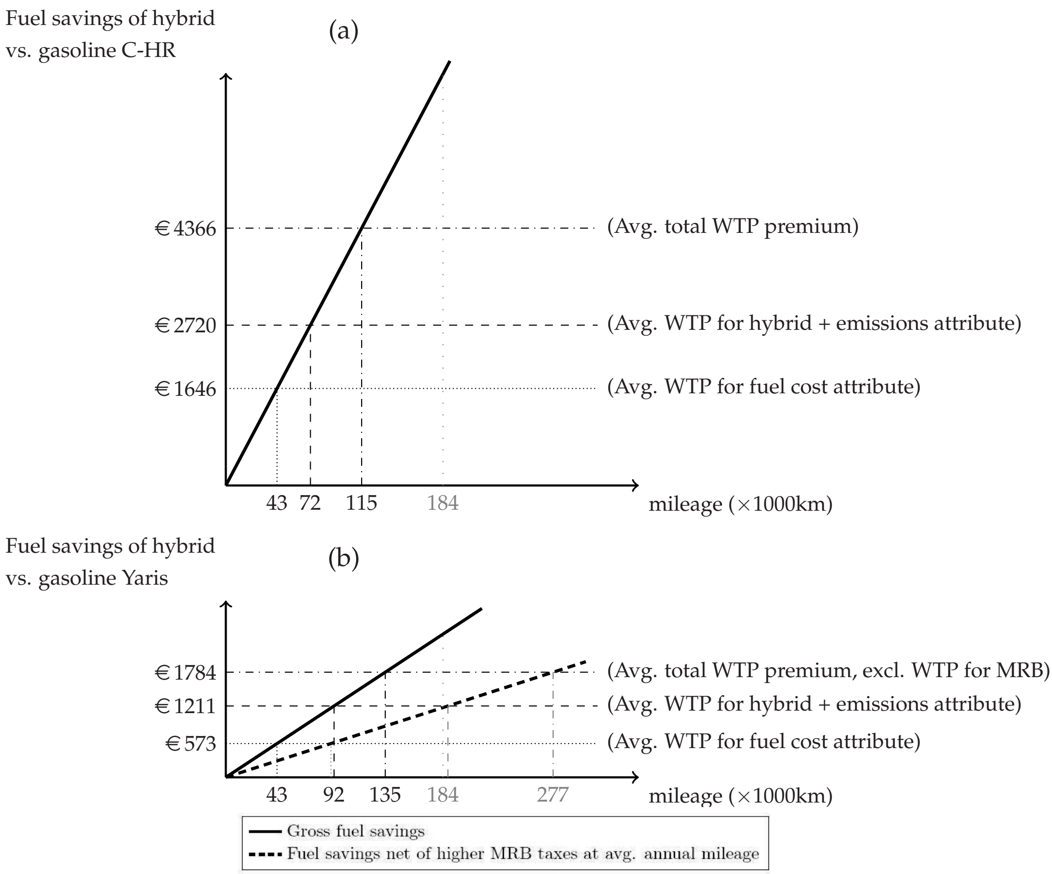
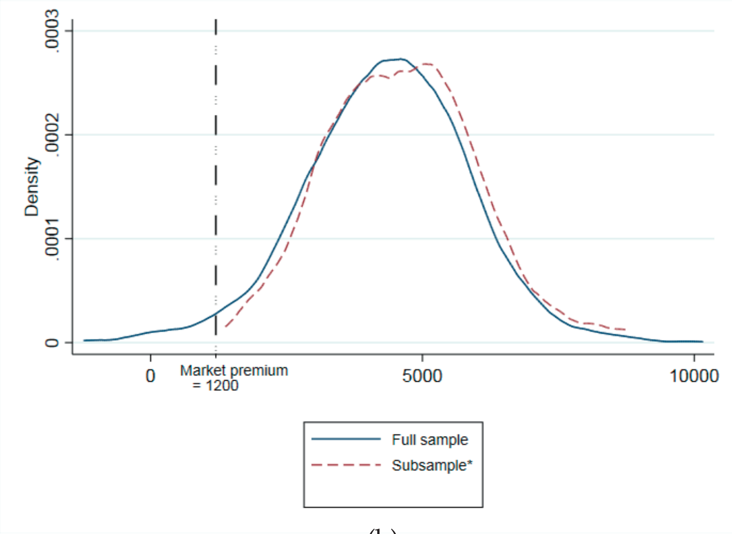
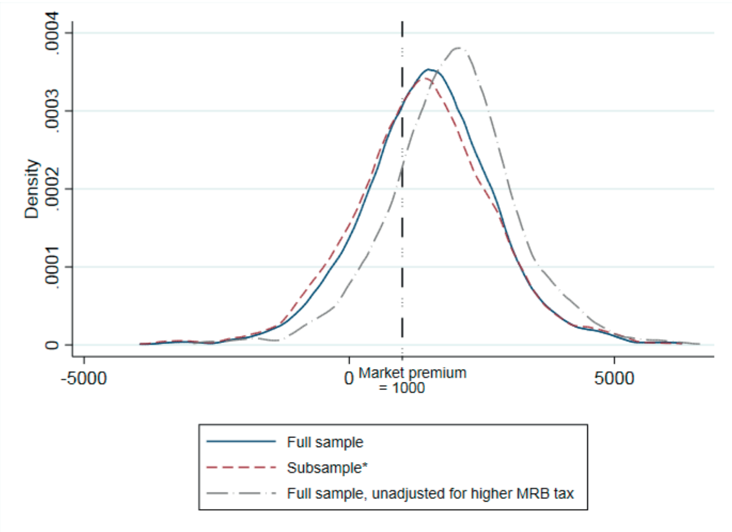


Figure 2.2. Fuel savings by mileage of a hybrid Toyota C-HR (a) and Toyota Yaris (b).

(a)



(b)



Note: Subsamples consist of respondents who indicated a reference price similar to the actual price and who currently own a similarly-sized vehicle: between €20k–€40k and medium-sized car for the C-HR (a); and below €40k and small car for the Yaris (b).

Figure 2.3. Distribution of individual-level WTP for hybrid instead of gasoline type of a Toyota C-HR (a) and Toyota Yaris (b), compared with the actual market premium.

emissions reported in CO_2 labels do not accurately reflect the true level of emissions (Fontaras et al., 2017), and (ii) alternative-fuel cars remain very much emerging technologies. This paper analyses the WTP for emission reductions from passenger car buyers on the basis of a choice experiment amongst a sample of Dutch adults with the intention to buy a passenger car.

We find that people prefer cars with lower emissions per kilometre (mean WTP of €36.70 per gram/km). Translated to emission reductions, we find that Dutch passenger car buyers are willing to pay €199 to reduce CO_2 emissions by one tonne and that there is a very considerable degree of heterogeneity in preferences amongst individuals. Our estimates appear to be in the lower range of the reported WTP estimates in Achtnicht (2012). The relatively lower estimates in this paper may be the result of studying a different population (Dutch vs. German passenger car buyers) and due to a number of different modelling decisions: this paper assumes a normally instead of a log-normally distributed emissions parameter, assumes a random instead of a fixed price coefficient, and estimates the model in WTP instead of preference space.

Despite our somewhat lower WTP estimates, our findings still indicate a considerable WTP for emission reductions. Based on these findings, we conclude that there is a large potential for voluntary contributions to emission reductions in passenger car transport in the Netherlands. This conclusion is confirmed by our analysis of preferences for two real-life cars that are available with very similar hybrid and gasoline engines. The majority of respondents is willing to pay more than the actual market premiums of the two existing hybrid types. This finding is reflected in actual vehicle sales of the two models.

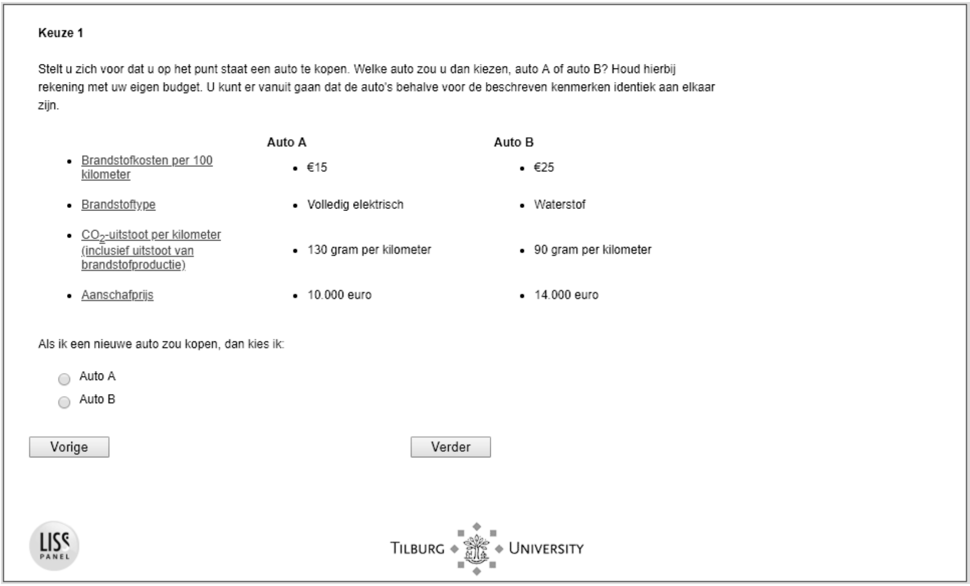
This paper also analysed to what extent the WTP is related to personal characteristics. We find differences in the WTP for emission reductions along the lines of gender, age and education but not income. The results show that females have a higher WTP than males; people aged 65+ have a higher WTP than people aged 18-64; and that individuals with higher education have a higher WTP than individuals with lower or medium education.

Our results regarding the relationship with personal characteristics are both supportive and contradictory to the results of several other papers. For a comparison with other findings in the literature, see Diederich and Goeschl (2014) for an overview. Particularly noteworthy is that our finding for the positive effect of age on the WTP for emission reductions contrasts the findings of most other studies on the WTP for emission reductions or climate-policy support. However, our results seem to be in line with a study into the attitudes of the Dutch population by the Institute for Social Research (SCP). The SCP finds that older and younger generations in the Netherlands are equally worried about climate change but older generations are more inclined to behave environmentally friendly and have a higher probability to contribute to a better environment (Verbeek and Boelhouwer, 2010).

Several caveats of this paper need to be mentioned. First, we tried to eliminate the hypothetical bias, referring to the tendency of people to overstate their true WTP in stated-preference research, by means of a "cheap talk" strategy (e.g. List and Gallet, 2001). We are not able to measure the hypothetical bias and, therefore, if our cheap talk did not fully eliminate the hypothetical bias, our WTP estimates may be biased upwards. Secondly, as we do not possess data for all relevant aspects (e.g. for the future resale value of a car's emission attribute), we required a number of assumptions to calculate the WTP for emission reductions. While we mostly based our assumptions on findings of others, changing the assumptions affects the WTP estimates.

From a policy perspective, our findings imply that providing consumers with trustworthy information can be considered a key policy tool for achieving emission reductions in passenger car transport. Given that a large portion of the Dutch passenger car buyers has a considerable WTP for emission reductions, there appears to be a substantial market potential for voluntary contributions to emission reductions. If the information asymmetry in the passenger car market can be reduced, less financial support is required to promote the use of cars with lower carbon emissions.

2.A Appendix: Example choice question and transcript of survey instructions


Keuze 1

Stelt u zich voor dat u op het punt staat een auto te kopen. Welke auto zou u dan kiezen, auto A of auto B? Houd hierbij rekening met uw eigen budget. U kunt er vanuit gaan dat de auto's behalve voor de beschreven kenmerken identiek aan elkaar zijn.

	Auto A	Auto B
Brandstofkosten per 100 kilometer	€15	€25
Brandstoftype	Volledig elektrisch	Waterstof
CO_2-uitstoot per kilometer (inclusief uitstoot van brandstofproductie)	130 gram per kilometer	90 gram per kilometer
Aanschafprijs	10.000 euro	14.000 euro

Als ik een nieuwe auto zou kopen, dan kies ik:

- Auto A
- Auto B

Vorige | Verder

LISS PANEL

TILBURG UNIVERSITY

Figure 2.A.1. Example of a choice question from the survey.

Instruction in introductory text:

> "In this survey, we ask you to choose between two cars that differ in four characteristics. The four characteristics are:
>
> 1 Fuel type
>
> 2 CO_2 emissions per kilometre (including emissions from fuel production)
>
> 3 Fuel costs per 100 kilometre
>
> 4 Purchase price
>
> There are probably other characteristics than the four previously mentioned that are important to you when choosing a car. You should assume that the presented cars in this survey are, except for the described characteristics, identical to each other."

The choice question, including instructions:

“Imagine you are about to buy a car. Which car would you choose, car A or car B? Please, mind your own budget. You should assume that the presented cars are, except for the described characteristics, identical to each other.”

2.B Appendix: Pre-test procedure and post-survey evaluation

The pre-testing of this survey consisted of three waves of one-to-one interviews, corresponding to three iterated versions of the survey. The first version was discussed with four other university staff members, including two colleagues with extensive experience in choice experiments.

In the second and third rounds, respectively nine and fourteen individuals participated, which were invited either personally or through acquaintances and relatives. Invitees were selected such that the groups reflected heterogeneity in age, education, income, profession and place of residence in the Netherlands.

The invitation to participate in the second and third pre-test rounds indicated to the participant that it concerned a pre-test and that the goal was to solicit feedback about the survey from the perspective of the respondent. Feedback was solicited face-to-face or via email or telephone, depending on the participant. The invitation further asked the respondent to pay particular attention to anything that is unclear, ambiguous or vague. Following the survey, we first gathered their general comments. Consequently, we specifically asked:

- Whether the task was sufficiently clear.
- What they thought the goal of the survey was.
- If the language in the survey in general and the questions in particular were clear, and if any specific words or terms were unclear.
- Whether it was difficult to answer the questions.
- Whether they had enough information to answer the choice questions.
- What they thought of the number of choices they had to make.
- Why they made the specific choice for A or B for several of their choices.
- Whether they thought the combinations were realistic.
- If they though it was realistic that they were forced to choose between two alternatives.
- If they regarded full-electric or hydrogen with zero emissions as a realistic combination (only the third round).

In addition, the survey was language-checked by an external communication expert and a survey researcher from the university administering the LISS panel with a focus on clarity and comprehensibility.

After the second round of pre-testing, three participants indicated that they did not understand why combinations of full-electric (all three participants) or hydrogen (one participant) with zero emissions were provided. To clarify this, the explanation of the emissions attribute more pronouncedly discussed that emissions from fuel production were included and the name of the attribute was changed to "CO_2 emissions per kilometre (including emissions from fuel production)" everywhere, where the part between parentheses was added. In the third pre-test round, this issue appeared resolved. Furthermore, after the second round of pre-testing, a participant indicated that the page that introduced the four attributes, together with the instruction to regard vehicles as identical in other respects and an explanation of the attributes and their levels contained a lot of information. The subsequent version of the survey split this into two pages, one containing the introduction of the four attributes and the instruction to regard vehicles as identical in other respects, and a separate page that explained the attributes and the levels. Another participant indicated after the second round that she thought it would be helpful if the attribute definitions and levels were visible while answering the choice questions. To accommodate this, the subsequent version showed the attribute and levels information when participants clicked on the respective attribute name (these were blue and underlined to highlight that they could be clicked on). Based on the suggestions of the communication and survey experts, several language adaptations were done. The interviews with the pre-test participants gave no further reasons to change the survey.

Upon completion of the choice questions, the survey finally asked the following five evaluation questions:

"Finally; what did you think of this questionnaire?

1 Was it difficult to answer the questions? [1 Certainly not; 2 ; 3 ; 4 ; 5 Certainly yes]

2 Were the questions sufficiently clear? [1 Certainly not; 2 ; 3 ; 4 ; 5 Certainly yes]

3 Did the questionnaire get you thinking about things? [1 Certainly not; 2 ; 3 ; 4 ; 5 Certainly yes]

4 Was it an interesting subject? [1 Certainly not; 2 ; 3 ; 4 ; 5 Certainly

yes]

5 Did you enjoy answering the questions? [1 Certainly not; 2 ; 3 ; 4 ; 5 Certainly yes]"

Table 2.B.1 provides summary statistics of the responses to these questions. In particular, most respondents thought the questions were not very difficult, thought the questions were clear and did not seem to derive dissatisfaction from participating in the survey.

Question	25th pctile	median	mean	75th pctile
Was it difficult to answer the questions?	1	2	2.54	4
Were the questions sufficiently clear?	3	4	3.92	5
Did the questionnaire get you thinking about things?	2	3	3.09	4
Was it an interesting subject?	3	3	3.45	4
Did you enjoy answering the questions?	3	4	3.62	5

Table 2.B.1. Summary statistics of final survey evaluation question. 1 = certainly not, 5 = certainly yes.

2.C Appendix: Determining distributions for the random parameters

Hensher and Greene (2003) propose an empirical approach to guide the decision on which distributions to assume for the random parameters in a mixed logit model. They suggest to inspect the profile of preference heterogeneity by estimating n+1 models, where n is the number of individuals in the sample. Apart from the full model, the model is estimated n times where each time a different individual is removed. The difference between the parameter estimate of the full model and the estimates of the reduced models represents the contribution of a specific individual to the mean parameter estimates. Consequently, kernel-density plots of the estimates of the reduced models are estimated to obtain an idea of the empirical profile of the parameters.

Figure 2.C.1 provides these graphical descriptions of the empirical profiles of the price, hybrid and emissions parameters. Table 2.C.1 reports two descriptive measures of the empirical distributions. The price coefficient appears to be log-normally distributed with an early peak and a very long tail. The hybrid coefficient appears normally distributed. The distribution for emissions is less apparent from this figure. The distribution is quite symmetric, while it also appears to have a somewhat longer tail. Both the normal and log-normal distributions do not appear to represent the true distribution. However, because we are somewhat reluctant to assume the log-normal distribution for the emissions parameter we assume it is normally distributed. Our reluctance is for two reasons: Firstly, a log-normally distributed coefficient takes strictly positive values and hence not zero. A number of papers find that (sometimes a considerable) part of the population is not willing to contribute anything to reducing emissions (e.g. Diederich and Goeschl, 2014). From that perspective, excluding zero as possible value of the coefficient is undesirable. Second, the log-normal distribution is characterized by a long right tail, possibly resulting in a too-large standard deviation and a mean that is biased upward (Sillano and de Dios Ortúzar, 2005). The drawback of assuming a normal distribution for a parameter with a strong expectation about the sign is that this quite commonly results in WTP estimates for some individuals that have the 'incorrect' sign (Murdock, 2006).

	Price	Emissions	Hybrid
Measures of distribution			
Skewness	-3.66	-0.72	0.12
Kurtosis	23.27	4.18	4.19

Table 2.C.1. Skewness and kurtosis measures of empirical distributions.

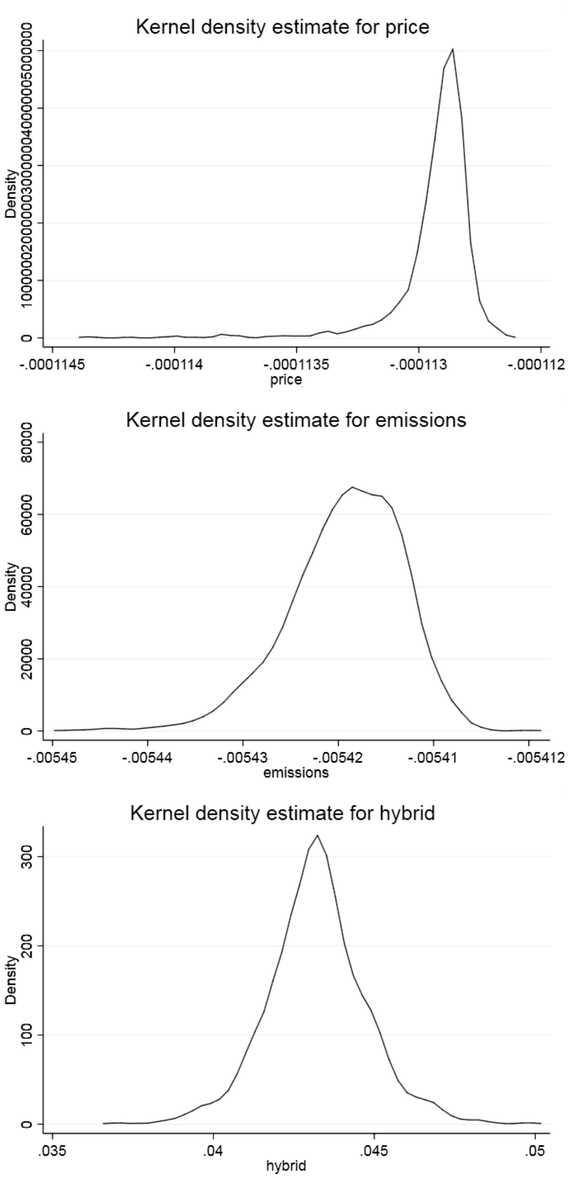


Figure 2.C.1. Empirical profile for distributions of random parameters using kernel density estimates.

2.D Appendix: Driving cost comparison for two hypothetical hybrid-gasoline pairs

Table 2.D.1 and Figures 2.D.1 an 2.D.2 report the results of a replication of the driving cost/WTP analysis in Section 2.4.4 for two hypothetical gasoline-hybrid vehicle pairs. The first column (Hypothetical Model X) compares an otherwise-identical gasoline type with a hybrid type that has 23% lower fuel consumption, emissions and fuel costs. This corresponds to the average real-world performance increase of existing hybrid engines compared to their closest gasoline equivalent in the EU (Emissions Analytics, 2019). The level of emissions are chosen such that the average level of emissions of a new Dutch passenger car (109 gram/km) is approximately in between the levels of the hybrid and gasoline type. The second column (Hypothetical Model Y) calibrates the levels of emissions, fuel consumption and fuel costs at the reported levels of a Toyota Prius hybrid model and the most comparable Volkswagen Golf gasoline model in terms of engine performance. For both vehicles, the reported fuel consumption levels are 0.3 lower than the real-world levels according to Emissions Analytics (2019), which means that the outcome of this analysis based on the real-world estimates would be identical.

The results display the short implied required pay-back period from fuel savings at various levels of annual mileage. At 50% of the average annual mileage, the implied required payback period is less than 7 years while at double the average annual mileage, the implied required payback period is even less than 2 years. For the mean respondent, the WTP for lower fuel costs is earned back after 43,300km. The combined WTP premium for the hybrid fuel type and improved emissions attribute is earned back only after an additional 92,900km for the 23% more efficient hybrid and 82,200km for the Prius. The implied pay-back period of the total WTP premium for both hypothetical hybrids is at 136,300km (23% more efficient hybrid) and 125,500km (Prius), well below the expected lifetime mileage of a gasoline car (184,000km). Furthermore, the vast majority of respondents appears willing to pay a premium for the hypothetical hybrid and Prius, compared to their gasoline equivalents. However, despite the improvement in fuel costs and emissions of the hybrid, a small minority of individuals still prefers the gasoline type. This illustrates the considerable heterogeneity in preferences for the hybrid and emissions attribute that we estimate.

Model	Hypothetical Model X		Hypothetical Model Y	
Type	Gasoline type	Hybrid type with 23% lower fuel consumption	Values of VW Golf 1.5TSI 130hp	Values of Toyota Prius 1.8 HEV 123hp
Fuel type	Gasoline	Hybrid	Gasoline	Hybrid
Emissions (gr/km)	124	96	115	78
(a) Fuel consumption (l/100km)	5.2	4.0	5.0	3.4
Fuel cost (€ /100km)= €1.65×(a)*	€8.58	€6.60	€8.25	€5.61
WTP for hybrid's+				
(b) fuel cost attribute	€434×€1.65× (5.2 − 4.0)=€859		€434×€1.65× (5.0 − 3.4)=€1145	
(c) fuel type and emissions attribute	€812+€37× (124 − 96)=€1839		€812+€37× (115 − 78)=€2169	
Annual fuel savings of hybrid [Pay-back period of (b), (c)]				
6,500km/year	€129 [6.7 yrs, 14.3 yrs]		€172 [6.7 yrs, 12.6 yrs]	
13,000km/year	€257 [3.3 yrs, 7.1 yrs]		€343 [3.3 yrs, 6.3 yrs]	
19,500km/year	€386 [2.2 yrs, 4.8 yrs]		€515 [2.2 yrs, 4.2 yrs]	
26,000km/year	€515 [1.7 yrs, 3.6 yrs]		€686 [1.7 yrs, 3.1 yrs]	

Note: Larger values are rounded. * Fuel price assumption of €1.65 per litre is based on the 2019 avg. gasoline price according to CBS. + The table reports the premium that the average respondent is willing to pay for the attributes of the hybrid. ++ (WTP for fuel cost attribute in €/100km)×(fuel price)×(difference in fuel consumption/100km). +++ (WTP for hybrid attribute)+(WTP for emissions attribute in gr/km)×(difference in gr of emissions/km).
Source: ANWB, own calculations.

Table 2.D.1. Driving cost comparison based on emissions and fuel consumption of a hypothetical car with a gasoline and hybrid engine, and on a Volkswagen Golf and Toyota Prius.

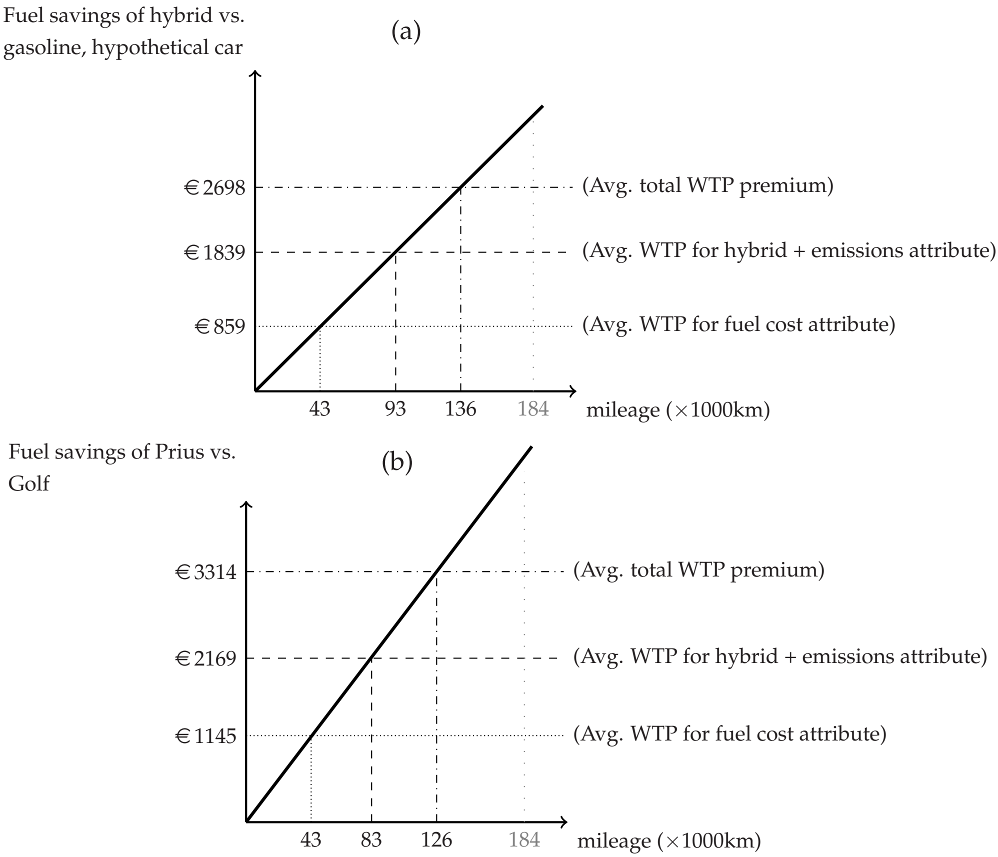


Figure 2.D.1. Fuel savings by mileage of a hypothetical hybrid vs. gasoline (a) and calibrated for a Toyota Prius hybrid vs. Volkswagen Golf gasoline (b).

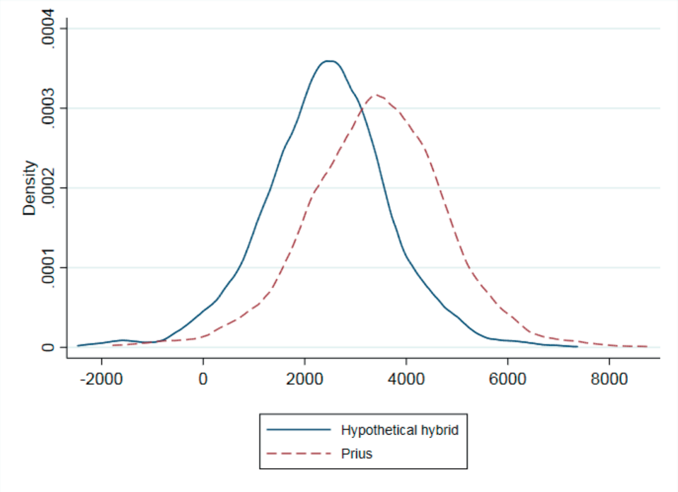


Figure 2.D.2. Distribution of individual-level WTP for a Prius and hypothetical hybrid vs. a VW Golf and hypothetical gasoline respectively, under the assumption that the gasoline alternative is otherwise identical.

Chapter 3

The impact of renewable energy use on firm profit

3.1 Introduction

An increasing number of firms uses renewable energy with the intention to "combat climate change" (Apple, 2018), "contribut[e] to the reduction of carbon [emissions]" (Nestle, 2018) or "reduc[e] the environmental footprint" (Volkswagen, 2017). These public announcements seem to suggest that these firms are motivated by environmental concerns when they buy renewable energy, particularly considering that renewable energy is generally more expensive than non-renewable energy. For example, in the case of renewable electricity (applying to the three cited firms), firms that want to claim the use of renewable electricity typically acquire renewable electricity certificates in addition to the electricity itself. The wholesale price of European renewable energy certificates (Guarantees of Origin) was approximately €2 per MWh in 2018 (Greenfact, 2018a). Prices of certain specific certificates are even much higher, such as Dutch wind certificates, which had a price of more than €7 per MWh in 2018.[1]

Considering that buying these renewable energy certificates does not affect at all firms' technological processes, the question emerges how renewable energy use is related to the general objective of the firm according to microeconomic theory,

---

This chapter is based on Hulshof and Mulder (2020b). I thank Mart van Megen, Arjan Trinks and two anonymous reviewers for highly valuable comments and suggestions.

[1]See the next chapter and Hulshof et al. (2019) for more information on renewable energy certificate prices in Europe. For reference, the average wholesale electricity price was about €45 per MWh in the past decade in Northwest Europe.

which is to maximize profit. More generally, this question appears relevant for most environmental corporate social responsibility (CSR) actions of firms. CSR may be referred to as actions that are beneficial to society, not directly beneficial to the firm and not required by law (McWilliams and Siegel, 2001). Environmental CSR can be considered the subgroup of CSR actions which are related to environmental concerns, such as reducing the use of fossil energy in order to contribute to the mitigation of climate change. This paper regards renewable energy use as a specific type of environmental CSR: it benefits society through climate change mitigation while it generally does not provide direct benefits to the firm (e.g. lower costs) and is not required by law.

An extensive amount of papers empirically investigates the impact of environmental CSR on firm profit, or, comparably, the impact of environmental performance on financial performance. While some papers find no relationship (e.g. Petitjean, 2019; Brzeszczynski et al., 2019), or even a negative impact (e.g. Oberndorfer et al., 2013), a large amount of papers find a positive impact of CSR on profit (e.g. Konar and Cohen, 2001; Kang et al., 2016). This positive relationship is corroborated in several meta-analyses, both for environmental CSR in particular (e.g. Dixon-Fowler et al., 2013; Margolis et al., 2009) and CSR in general (e.g. Margolis et al., 2009; Margolis and Walsh, 2001; Orlitzky et al., 2003). A positive impact of CSR on profit seems to imply the existence of a 'win-win': CSR activities that benefit the environment are associated with higher firm profit as well.

Taking on a microeconomic perspective, a structural positive effect of renewable energy use on profit may not be expected. On the one hand, renewable energy use can enable the firm to differentiate itself from competitors such that it can serve consumers with a higher willingness to pay (WTP) and charge them higher prices. On the other hand, competition for those consumers is expected to drive down prices to the level of marginal costs.[2] Furthermore, regarding firms' reported environmental concerns, it appears questionable as to whether firms are willing to use renewable energy at the expense of profit, as this directly contradicts the assumption that firms maximize profit. But if firms would be willing to use renewable energy at the expense of profit, the decline in profit may be seen as the revealed willingness to pay of firms to contribute to climate-change mitigation.

The main question we address is: what is the impact of renewable energy use on firm profit? The main contribution of this paper is that, to the best of our knowl-

[2] This may not be true in product-differentiation settings with entry barriers for selecting/switching between differentiation strategies. In Section 3.3, the paper argues that these are not relevant for differentiation on the basis of renewable energy.

edge, it is the first empirical analysis of the impact of renewable energy use on firm profit. The paper also contributes to the broader literature on the relationship between financial and environmental performance by using a concrete measure of a specific type of environmental CSR, instead of the frequently used indicator variables for environmental CSR (such as the Kinder, Lydenberg, Domini & Co. (KLD), environmental, social and governance (ESG), or ASSET4 score indicators), of which it is unclear whether they accurately reflect the true level of environmental performance (e.g. Dixon-Fowler et al., 2013).

This paper empirically investigates the impact of renewable energy use on firm profit. Our analytical framework relies on a theory of product differentiation in a profit-maximization framework, as discussed in a seminal paper by Rosen (1974). This framework appears appropriate since, from a profit-maximization perspective, the only justification for using renewable energy is that the firm can differentiate itself from competitors (e.g. gain a better reputation) and serve consumers with a higher willingness to pay for this type of product quality, as renewable energy is more expensive and provides no technological advantages. Based on this analytical framework, we expect no impact of renewable energy use on profit. Our empirical analysis tests this prediction. If the empirical findings are not in accordance with this prediction, this might suggest that other explanations for renewable energy use by firms are more appropriate, for instance altruistic environmental concerns.

The empirical analysis uses panel data for the period 2014–2018. The panel consists of 920 firms from 59 countries from a very large number of sectors. Our estimates of the impact of renewable energy use on firm profit are not statistically significant. These results do not corroborate the positive impact that has been established in the literature, and we conclude that there seems to be no 'win-win' from renewable energy use in the form of higher profit and a better environment. Instead, the impact appears to be neutral, as predicted by the theoretical framework, which would suggest that firms do not sacrifice profit when they use renewable energy. However, given that the coefficients are estimated with relative imprecision, we recommend further research to verify these findings.

The remaining of this paper is organized as follows. The second section reviews the theoretical and empirical literature. The third section discusses the analytical framework. The fourth section describes the methods applied in this paper, in particular the empirical model, data and estimation method. The fifth section provides the results and discussion. The sixth section concludes.

3.2 Literature review

A, by now substantial, literature has emerged that discusses the impact of environmental CSR on firm profit. This section first discusses the link between profit and (environmental) CSR from a theoretical perspective. Consequently, this section discusses the findings in the empirical literature. Finally, this section discusses renewable energy use by firms in particular. Considering the similarity between papers that focus on the general CSR-profit relationship and the environmental CSR-profit relationship, this section discusses papers from both the general CSR and environmental CSR literature.

3.2.1 Theoretical literature

Economic theory has suggested two main theoretical explanations for the presence of (environmental) CSR goods in firms' profit-maximizing bundle of inputs. First of all, (environmental) CSR can be part of profit maximization when it enables product differentiation. In contrast to firms active in markets with homogeneous goods, firms active in markets with differentiated goods may be able to charge a higher price than competitors (e.g. Rosen, 1974). Taking on a theory of the firm perspective, McWilliams and Siegel (2001) theorize that CSR expenditure can result in product attributes that are valued by consumers. The authors propose that firms, like for other inputs, trade-off the costs and benefits of CSR expenditure and select the quantity of CSR where the marginal costs and benefits are equalized. Considering the possibility to switch between CSR strategies, they theorize that CSR does not have an effect on profit. A primary example of how firms differentiate themselves from competitors is reputation building through (environmental) CSR expenditure (e.g. Siegel and Vitaliano, 2007; McWilliams and Siegel, 2011).

Secondly, the profit-maximizing way to produce any quantity is where the production costs are minimized. Besides that several clean production technologies or inputs may be cheaper than polluting alternatives,[3] some authors have pointed out more subtle mechanisms through which environmental CSR can be part of cost-minimization. Porter and Van der Linde (1995) note that many types of environmental CSR investments are characterized by high initial investment costs which

[3]E.g. energy efficiency measures. It must be noted that it is somewhat doubtful whether these type of production inputs can be considered as CSR because, in addition to external benefits, they also generate direct private benefits to the firm. This is not the case for renewable energy considering that it is generally more expensive than non-renewable energy.

ultimately lead to cost reductions that offset the initial investment costs.[4] Another argument is that costly environmental CSR may prevent governments from imposing even more costly regulation (e.g. Davis, 1973; Carroll and Shabana, 2010).

3.2.2 Empirical evidence

An extensive empirical literature regarding the impact of environmental CSR in particular or CSR in general and profit has emerged. Within this empirical literature, two major strands of papers exist. A first strand tries to relate measures of profit (e.g. net income or return on assets) to measures of (environmental) CSR (predominantly indicators of environmental CSR based on the KLD, ESG or ASSET4 scores).[5] A second strand tries to relate stock market performance (e.g. abnormal returns or Tobin's Q) to measures of (environmental) CSR (typically inclusion in a sustainability index or indicators of environmental CSR based on the KLD, ESG or ASSET4 scores). Some paper have used both measures of profit and measures of stock market performance in their analysis. With respect to the difference between environmental and general CSR, papers focusing on the former generally measure CSR over environmental aspects only, whereas papers focusing on the latter measure CSR over all aspects. In other respects, the methodology is typically very similar.

In both strands of literature, the empirical evidence is not fully consistent between studies. For the strand using measures of stock market performance, a large number of studies finds a positive relationship between (environmental) CSR and profit (e.g. King and Lenox, 2001; Kang et al., 2016). A considerable number of other studies find that no relationship exists (e.g. Petitjean, 2019; Brzeszczynski et al., 2019; Ng and Zheng, 2018). In addition, a very small minority of studies reports a negative relationship (e.g. Oberndorfer et al., 2013; Meznar et al., 1994). Likewise, for the strand using accounting-based measures of profit, many studies report a positive relationship (e.g. Russo and Fouts, 1997; Waddock and Graves, 1997), whereas other studies find no significant relationship (e.g. Petitjean, 2019). The positive relationship is confirmed by several meta-analyses, which typically

[4] Porter and Van der Linde (1995) also propose that regulation is required for firms to be willing to invest in many types of CSR because they suggest that firms generally fail at making optimal choices inter-temporally, i.e. fail at minimizing costs/maximizing profit over the long run.

[5] KLD, ESG and ASSET4 scores are typically managed by a research firm. This research firm scores and ranks other firms on the basis of a set of performance indicators relating to environmental, social and governance matters. Examples of two performance indicators in the KLD database are: (i) whether a company has "...notably strong pollution prevention programs including both emissions reductions and toxic-use reduction programs"; and (ii) whether a company uses recycled raw materials or is a major factor in the recycling industry in some other way.

include papers that use profit measures as well as stock market-performance measures. This is the case for environmental CSR in particular (e.g. Dixon-Fowler et al., 2013; Margolis et al., 2009), and for CSR in general (e.g Margolis et al., 2009; Margolis and Walsh, 2001; Orlitzky et al., 2003). In addition, the type of measure for firm performance (stock-market or profit based) does not appear to affect these meta-analytic results (Dixon-Fowler et al., 2013).

Barnett and Salomon (2012) theorize and empirically find a U-shaped relationship between CSR and firm profit. They propose that, in order to profit from CSR actions, the level of CSR needs to surpass a certain threshold for otherwise the firm's stakeholders will not react in a profitable manner. Their argument is based on a stakeholder argument, namely that a firm's capability to influence its stakeholders depends on the level of CSR. The paper argues that, at low levels of CSR, a firm has few abilities to influence its stakeholders because those stakeholders will not perceive social actions by the firm as very credible and therefore not respond in a profitable manner. In contrast, at high levels of CSR, a firm has the ability to influence its stakeholders because those stakeholders will perceive social actions by the firm as credible and therefore respond in a profitable manner (in this case "such actions are in consonance with the firms character").

Also related to this paper is Ziegler et al. (2011), who find that the stock market performance of firms who disclose their response to climate change is better than the stock market performance of firms who do not disclose their response.

Many papers in this literature have been criticized for the typical use of indicator variables for (environmental) CSR, often based on ESG, KLD and ASSET4 scores. This type of indicator variable is usually based on ranking firms on a large number of CSR-related aspects. The scores on the various aspects are then transformed into a single firm-level CSR score. These indicator variables have mainly become popular because it is difficult to measure CSR objectively. Inherently, there is a degree of subjectivity and arbitrariness present in the methodologies underlying such indicators (e.g. selection of aspects and aspect score calculation). Because of these problems, the validity of these indicators to represent actual environmental or social performance has been questioned (e.g. Dixon-Fowler et al., 2013; Margolis and Walsh, 2001; Chatterji et al., 2009; Semenova and Hassel, 2015). One notable exception is Konar and Cohen (2001), who use data regarding emissions of toxic chemicals and pending environmental lawsuits and also find a positive relationship with profit.

A second critique is the widespread (incorrect) use of ratio variables in this literature, both as dependent and independent variable (e.g. return on assets or toxic chemical emissions per dollar revenue) (Barnett and Salomon, 2012), which may lead to spurious results in regression analysis (e.g. Kronmal, 1993).

Another branch of papers has verified the direction of causality in the relationship between profit and CSR. The concern of these papers is that CSR activities may be determined by profitability, rather than the other way around, because these activities represent “inessential” expenditure. If valid and unaccounted for, this reverse causality problem could lead to biased estimates from conventional estimation techniques. However, explicitly addressing the direction of causality, Kang et al. (2016) and Scholtens (2008) find evidence that causality runs from CSR to profit and not the other way around.

3.2.3 Renewable energy use by firms

In recent years, there has been a marked increase in the demand for renewable energy from firms. This can be seen for example from the steep increase in participation by firms in voluntary renewable energy programs in which they pledge or articulate their intention to increase their renewable energy use. Two primary examples are the U.S. EPA’s Green Power Partnership (GPP) program and the RE100 initiative. The former experienced an increase in the number of participants from 656 in 2006 to 1532 in 2018 (including small, medium and very large firms from a wide number of sectors). Collectively, participants consumed 55TWh of renewable electricity in 2018 (EPA, 2019).[6] The RE100 initiative experienced an increase from 50 participating firms in 2015 to 155 in 2018 (including mostly large firms from a large number of sectors) with an aggregate renewable electricity consumption of 72TWh in 2017 (RE100, 2018). Based on survey findings, PWC (2016) reports that meeting sustainability goals and reducing greenhouse gas emissions is the primary motivation for firms in the U.S. to buy renewable energy.

The primary tool for firms to consume renewable energy is the procurement of renewable energy certificates (RECs), which has become the dominant market mechanism for consumption of renewable electricity (Hulshof et al., 2019). RECs are administered to renewable energy producers, which can then be sold separately from the energy to end-users who wish to claim the consumption of renewable energy. Firms buy RECs either (i) directly as unbundled product, i.e. separately from their electricity product, or (ii) as a bundled product consisting of both RECs

[6]For reference, total electricity consumption in 2017 in Chile, Italy and the U.S. was 75TWh, 315TWh and 4,098TWh, respectively (IEA, 2019).

and electricity from a retailer or producer. A third way to claim the consumption of renewable electricity, which does not involve the explicit purchase of RECs, is (iii) generating renewable electricity on-site at the firm.[7] Method (i) and (ii) accounted for 95% and 97% of the renewable electricity consumption of GPP partners in 2018 and RE100 participants in 2017, respectively (EPA, 2019; RE100, 2018).

3.3 Analytical framework

This paper's analytical framework is based on the seminal paper about vertical product differentiation by Rosen (1974). Products are vertically (as opposed to horizontally) differentiated when, at a given price, everybody prefers a product (or is indifferent) when more of a particular characteristic is present. This appears to be the suitable framework for our analysis because vertical product differentiation is the principal mechanism through which renewable energy use relates to (economic) profit of the firm. It is clear that some individuals prefer goods with environmental-friendly attributes (e.g. Bjørner et al., 2004) and, despite that some individuals may be indifferent, there seems to be no reason to dislike the use of renewable energy in production. This section provides an interpretation of Rosen's model when goods are vertically differentiated on the basis of firms' renewable energy use with several assumptions that are specific to this setting. We discuss the main insights and implications for the relationship between firm profit and renewable energy from adopting this framework.

A key element in Rosen's model is the dependence of the market price (p) on the presence of a number (n) of valuable characteristics ($z = (z_1, z_2, \cdots, z_n)$), which he refers to as the hedonic price function $p(z)$. Here, it is assumed that products are differentiated on the basis of a single attribute, renewable energy ($z = RE$). Firms are price takers in input and output markets, but face different market prices when they use more or less RE. We will make the specific assumption that firms can modify the product's renewable energy characteristic by simply buying the desired amount of renewable energy certificates at the prevailing market price, reflecting actual practice. In terms of the firm's cost function $C(M, RE)$, where M is the quantity produced, this translates to assuming that the marginal cost of adding renewable energy is constant i.e. $\frac{\partial C}{\partial RE} > 0$ and $\frac{\partial^2 C}{\partial RE^2} = 0$. Moreover, buying renewable energy certificates does not lead in any way to changes in the physical production

[7] Although method (iii) does not involve the explicit purchase of RECs, the opportunity cost of consuming on-site generated renewable electricity includes the foregone REC price.

process and there are basically no interactions with other production inputs.[8] Further, we assume that firms have the same cost function. While this may not reflect reality for other product characteristics and inputs, it can be justified for the case of renewable energy on the basis that firms do not transform other inputs into the renewable energy characteristic but simply buy it from certificate retailers.

Firms then maximize profit $\pi = Mp(RE) - C(M, RE)$ with respect to RE and M. The first order conditions that yield the optimum choices of $M = M^*$ and $RE = RE^*$ are given by:

$$p(RE) - \frac{\partial C}{\partial M} = 0 \tag{3.1}$$

and

$$M\frac{\partial p}{\partial RE} - \frac{\partial C}{\partial RE} = 0 \tag{3.2}$$

Equation (3.2) gives the relationship between profit and renewable energy use, when evaluated at M^*. The first term ($M\frac{\partial p}{\partial RE}$) gives the marginal revenue of increasing RE whereas the second term ($\frac{\partial C}{\partial RE}$) is the marginal cost of increasing RE. Notice that the marginal cost of RE *per unit of output* is equal to $\frac{\partial C}{\partial RE}/M^*$. This is the firm's minimally required price increase to be willing to increase its use of RE, i.e. the marginal reservation price for RE. Because of the assumption that firms have the same cost function, this is identical for all firms. According to (3.2), in the optimum, the marginal cost and revenue per unit should be equal, i.e. $\frac{\partial p}{\partial RE} = \frac{\partial C}{\partial RE}/M^*$. Furthermore, because we assume a competitive market, prices will equal the producers' reservation prices for RE and M. This implies that $\frac{\partial p}{\partial RE}$ is fully determined by $\frac{\partial C}{\partial RE}/M^*$.[9] Under these assumptions, the hedonic price curve and the producers' common RE marginal reservation price curve coincide and Eq. (3.2) is satisfied at any choice of RE. Moreover, since the marginal cost of certificates is constant, the slope of the marginal reservation price curve and therefore the hedonic price curve is also constant. In terms of Eq. (3.2), $\frac{\partial^2 p}{\partial RE^2} = 0$ because $\frac{\partial^2 C}{\partial RE^2} = 0$ by assump-

[8] The assumptions on the cost function are chosen to reflect differentiation on the basis of renewable energy in practice. This includes assuming there exist no entry barriers in the form of a fixed cost associated with choosing a certain renewable energy/quality level, as in Shaked and Sutton (1982, 1987). With renewable energy, firms change the desired amount of certificates and pay the associated marginal certificate price when choosing/changing the desired quality level instead of paying a significant fixed costs.

[9] Individual firms take the hedonic price curve and its slope as exogenous as they are assumed to be price takers.

tion.[10] Figure 3.1 draws the relevant producer reservation price curve ($p(RE)$) as a function of the renewable energy characteristic.[11]

From the perspective of some consumers, more of the renewable energy input may be preferred and the willingness to pay of these individuals increases with the amount of renewable energy accordingly. However, since buying a good with more renewable energy (at a higher price) means lower consumption of other goods, the marginal willingness to pay for the RE characteristic is decreasing, conform the usual properties of a utility function. In terms of Figure 3.1, this can be shown by introducing a special type of consumer indifference curve, which Rosen calls the bid curve (θ). The bid curve reflects a consumer's willingness to pay for the good at different RE levels, while holding the level of utility constant.[12] As with conventional indifference curves, a whole family of parallel bid curves exist. Consumers prefer bundles to the south-east corner (i.e. a lower price for a given amount of RE) but are constrained by the market price. Their optimal choice is characterized by a tangency condition between their indifference curve and the hedonic price curve (essentially the budget constraint), corresponding here to the competitive firm's reservation price curve. Figure 3.1 draws the bid curves of two example consumers, which optimally choose two different levels of RE. When the preferences of consumers for the RE characteristics are very heterogeneous or "spread out", as is assumed in Rosen (1974) and here, the points of tangency with the producer reservation price curve occur at all levels of RE. In other words, at any choice of RE, a firm can find consumers that prefer exactly that type.

[10] Assuming non-constant marginal cost of renewable energy merely changes the shape of the reservation price curve (e.g. convex), but not the qualitative conclusions regarding the expected relationship between profit and renewable energy from this theoretical framework.

[11] Where relevant refers to the reservation price curve corresponding to the competitive-industry profit level (π_{pc}). Rosen (1974) shows that a whole family of parallel reservations price curves exist (i.e. all with slope $\frac{\partial C}{\partial RE}/M^*$), each corresponding to a different profit level. From assuming a competitive market, the relevant reservation price is the one associated with π_{pc}.

[12] In Figure 3.1, the vertical axis measures the amount spend on the good, as it is assumed that consumers buy one unit, which therefore equals the foregone expenditure on other goods. The bid curve is therefore an inverted conventional indifference curve (trading off consumption of the good with varying levels of the RE attribute versus consumption of other goods), with a slope equal to the inverse of the slope of a conventional indifference curve.

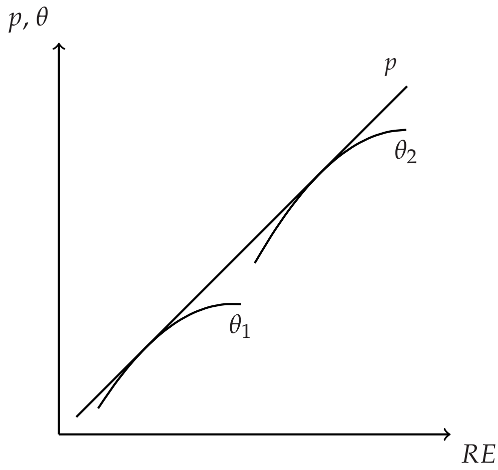


Figure 3.1. Producer (p) and consumer (θ_i) reservation prices for the renewable energy characteristic

What are the implications for the impact of renewable energy use on profit? The outcome of the model is that the choice of RE does not matter for profit as firms are always exactly compensated for the increased costs of using more renewable energy. By increasing RE, costs increase but, following the price increase, revenues also increase in an exactly offsetting manner.[13] In other words, this theoretical framework predicts that there is no impact of renewable energy use on profit.[14]

One of our critical (but arguably realistic) assumptions that drives this prediction is that firms have access to exactly the same technology/cost function to add the renewable energy characteristic, namely by simply buying the desired amount of certificates at a constant price. In contrast, assuming differences exist in firms'

[13]We assume in the model that consumers have perfect information on product qualities in terms of RE. In practice, information about the level of RE is usually not directly observed from a product, but may be accessed through annual or environmental reports. Suppose that the assumption is violated and information asymmetry regarding RE qualities exists. One would then expect that consumers lower their willingness-to-pay for products with a positive level of RE and that, as a consequence, adverse selection arises (cf. Akerlof, 1970). In terms of Figure 3.1, because of information asymmetry, the consumer reservation price curves shift to the left. The intrinsic costs of producing RE have not changed. In effect, the tangency points will shift to the left, resulting in products of relatively lower RE quality and lower average prices. Regarding the relationship between profit and renewable energy use, information asymmetry has no effect because it is still predicted to be neutral.

[14]From assuming there is perfect competition between firms at every level of RE, this theoretical framework implies that there exist few incentives to switch from RE strategy. However, our theoretical framework describes an equilibrium outcome and transition dynamics may partly explain the incentives for firms to switch from RE strategy. Consider, for example, that consumer preferences change towards preferring more green types. This change may create new niche markets that previously did not exist. First movers in these new niche markets may earn profit in the short run, providing an explanation for why firms may switch from RE strategy. With perfect competition and considering how easy it is to switch to/copy another RE strategy, these profit opportunities are expected to dissipate relatively quickly.

cost function, the general model in Rosen (1974) predicts that there will be a single optimal choice of RE for an individual firm and deviating in any direction from the optimum would hurt profit.

The subsequent empirical analysis tests the prediction of a neutral impact of renewable energy use on profit, which we derived from taking on a profit-maximization perspective with vertical product differentiation in a perfectly competitive environment. Given that alternative explanations for renewable energy use cannot be true at the same time (e.g. one alternative explanation being that firms engage in green behavior for environmental reasons and at the expense of profit), we investigate the specific explanation that renewable energy use follows from profit maximization and that firms will only do so if they are compensated for it (in an offsetting manner due to competition).

3.4 Method

3.4.1 Empirical model

Using panel data, we estimate an empirical model that relates firm profit (π) to renewable energy use (RE). The empirical model assumes that firms have the cost function $C(RE, M(K, L, TE))$: firms use capital (K), labor (L) and (total) energy (use) (TE) to produce the quantity of output (M), and can adjust the quality of output by procuring RE. We do not impose structure on the revenue or cost functions. Instead, we estimate a reduced-form regression model that relates profit to the four production factors: RE, K, L and TE:[15]

$$\pi_{ti} = \beta_0 + \beta_1 RE_{ti} + \beta_2 K_{ti} + \beta_3 L_{ti} + \beta_4 TE_{ti} + c_i + \boldsymbol{\alpha}\mathbf{Y}_{ti} + \epsilon_{ti} \tag{3.3}$$

where t refers to the time period, i to the firm and c to an unobserved time-invariant firm-specific effect. In this case, c may capture differences in the unobserved ability of firms' management. $\mathbf{Y}$ is a vector of year-sector interaction dummies which are equal to one for firm i in year t if the firm belongs to the respective sector and zero otherwise. This may capture for example macroeconomic fluctuations pertaining

[15] The empirical model implicitly assumes that the relationship between renewable energy use and profit, as given by β_1, is the same for all firm sizes. This is in line with our theoretical framework. However, we have also estimated Equation (3.3) with interactions included between RE and K, L and TE (separately) to investigate whether the marginal effect of renewable energy use differs with firm size. These interaction terms (and β_1) are not statistically significant in all three robustness estimations.

to a specific sector. ϵ is an error term which is assumed to be independent and identically distributed with a mean of zero.

To test for the presence of a U-shaped relationship between π and RE, as found by Barnett and Salomon (2012), we estimate a second specification that includes a quadratic RE term:

$$\pi_{ti} = \beta_0 + \beta_1 RE_{ti} + \beta_{11} RE_{ti}^2 + \beta_2 K_{ti} + \beta_3 L_{ti} + \beta_4 TE_{ti} + c_i + \boldsymbol{\alpha}\mathbf{Y}_{ti} + \epsilon_{ti} \quad (3.4)$$

The model deliberately omits R&D expenditure as control variable, which is suggested to be included by McWilliams and Siegel (2000) for empirical models linking CSR to profit. As the procurement of RECs from producers or retailers is a simple administrative act, renewable energy consumption is typically not expected to be relevant for firms' product innovations stemming from R&D expenditure. Including R&D expenditure does not materially change our conclusion regarding the impact of renewable energy use on profit. The first two columns of Table 3.A.1 in Appendix 3.A report the results of the model with R&D expenditure included as control variable. Another control variable that has often been included in the CSR literature that we omit is the level of debt. Including debt also does not materially change our conclusions, see the last two columns of Table 3.A.1 in Appendix 3.A.

3.4.2 Data

The data for this analysis comes from firms' financial and environmental reports over the period 2014–2018, which we collect using Bloomberg. For this period, renewable energy use (in GWh) is reported for 973 firms in one or more years, resulting in a total number of annual firm-year observations for this variable of 2,702 (including observations of zero renewable energy use).[16] The data on renewable energy use is complemented with data for the other variables in Eq. (3.3): net income (in thousand US$) as a measure of profit,[17] total energy use (in GWh),[18] assets (in million US$) as a measure of capital and the number of employees (in full-time equivalents) as a measure of labor.

The final panel dataset is unbalanced due to one or more missing observations

[16]Note that this includes all types of renewable energy, such as renewable electricity, renewable gas, renewable hydrogen etc.

[17]I.e. after taxes, interest payments, depreciation and all other expenses. Note that this is a measure of accounting profit and not economic profit.

[18]Including all types of energy.

in most of the variables. In total, the final sample includes 2,554 firm-year observations for 911 firms. Firms from all continents and sectors are included in the sample, where sectors are distinguished according to the Industry Classification Benchmark (ICB) by FTSE Russell. The ICB classification encompasses 114 sub-sectors, 41 sectors, 19 super-sectors and 10 industries, out of which 104, 39, 19 and 10 are represented in the sample. The ICB sectors are used for construction of the year-sector dummy variables (195 in total of which one is omitted in the estimations). Table 3.1 reports details about the geographical and industrial characteristics of the firms in our sample. Table 3.2 reports several key descriptive statistics of the variables.

Reporting about renewable energy use is voluntary and the incentive to report seems more obvious for firms that use considerable amounts of renewable energy (i.e. green firms) than for firms that do not. Therefore, a worry may be that the sample only includes relatively green firms, thereby introducing a potential selection bias. However, the kernel density plot of the distribution of the share of renewable energy (as percentage of total energy use) depicted in Figure 3.B.1 in Appendix 3.B shows that the large majority of the firm-years in the sample have a renewable energy share of or close to zero. Our results could still be prone to selection bias when these zero observations are 'early' observations of firms who start reporting positive renewable energy use in later time periods. However, 46% of the 'zero' observations for renewable energy use in our sample are from firms that never reported positive renewable energy use in the observed period.

	World	North America	South America	Europe	Africa	Asia	Oceania
All sectors	2,554	608	177	1,071	35	604	59
Oil & gas	88	21	9	33	0	25	0
Basic materials	316	84	35	93	5	81	18
Industrials	551	108	27	246	5	154	11
Consumer goods	429	74	26	181	9	135	4
Health care	124	46	3	47	2	26	0
Consumer services	180	51	8	92	10	19	0
Telecommunications	96	10	11	56	1	13	5
Utilities	135	24	46	51	0	14	0
Financials	458	115	12	246	3	61	21
Technology	177	75	0	26	0	76	0

Source: Bloomberg

Table 3.1. Number of firm-years in sample by geography and industry

	Mean	SD (within)	Min.	Max.
Net income (mln US$)	1,300	3,939 (2,235)	-16,265	94,209
Renewable energy use (GWh)	1,423	5,930 (1,935)	0	106,884
Total energy use (GWh)	10,672	37,656 (4,788)	0.2	563,957
Share of renewable energy	18.0%	24.8% (6.9%)	0%	100%
Assets (mln US$)	79,653	259,548 (18,998)	22	2,622,532
Employees (fte)	45,795	73,836 (8,104)	5	706,730

Source: Bloomberg

Table 3.2. Descriptive statistics

3.4.3 Estimation method

The analysis applies both a within-estimation procedure as well as a random-effects estimation procedure to estimate the coefficients of Equations (3.3) and (3.4). A within-estimation procedure is appropriate when the unobserved time-invariant firm-specific effect (c) is correlated with the independent variables, which is not unlikely. A drawback of using the within-estimator is that it only exploits variation in renewable energy use within firms, of which there is considerably less when compared to variation between firms (see Table 3.2). Therefore, we also apply a random-effects estimation procedure, which exploits both sources of variation. The random-effects estimator has the additional benefit that, in contrast to using within-firm variation only, using also between-firm variation in our static panel-data model means that potential lagged effects on revenue from renewable energy use are not neglected. This could be relevant when, for instance, reputation improvements from renewable energy use, and therefore the ability to charge higher prices, do not fully materialize instantly but take some time. The drawback of the random-effects model is that, because c is not explicitly modeled, unbiasedness of the estimates relies on the assumption that c is uncorrelated with firm profitability and the independent variables. We have tested for this assumption using the test proposed by Wooldridge (2010).[19] This test fails to reject that the firm-specific effect is uncorrelated with the other independent variables, providing support for the appropriateness of applying a random-effects estimation procedure.

To test for the presence of a linear relationship between profit and renewable energy use, we estimate the model in Eq. (3.3) and test the hypothesis that $\beta_1 = 0$

[19]In this case, the test of Wooldridge (2010) is more appropriate than the more conventionally applied Hausman test because the latter cannot accommodate the model's year-sector interactions and is not valid when the model suffers from heteroskedasticity.

against the alternative that $\beta_1 \neq 0$. To test for the presence of U-shaped relationship, we estimate Eq. (3.4) and apply the test proposed by Lind and Mehlum (2010). Their formal test provides the necessary and sufficient conditions for the presence of a(n) (inverse-)U shape. The test entails testing the null hypothesis that a monotone or inverse-U shape (U shape) is present versus the alternative that a U shape (inverse-U shape) is present. We refer to their paper for the details of the test procedure.

Cluster-robust standard errors are computed because the autocorrelation test as proposed by Wooldridge (2010) indicates the presence of autocorrelation. In addition, from residual plots, it appears as if the predicted values become less accurate when the predicted value becomes larger, i.e. the models seem to suffer from heteroskedasticity. The standard errors are clustered at the level of the sub-sector based on the ICB classification (104 clusters).

3.5 Results and discussion

3.5.1 Results

Table 3.3 reports the estimation results. The estimated coefficient for renewable energy use is interpreted as the change in profit in US$ per MWh-change in renewable energy use. The first two columns report the results of a reduced model with only renewable energy as independent variable. The estimated coefficients for renewable energy use are negative, but not statistically significant.

The third and fourth column report our main results based on estimating Eq. (3.3) with a within-estimation and random-effects estimation procedure, respectively. By controlling for the other key variables, the interpretation of the estimated coefficient for renewable energy moves in the direction of a causal effect.[20] The estimated coefficient for renewable energy use in both models are negative and highly non-significant (p-values of 0.554 and 0.938 in the fixed-effects and random-effects model, respectively). The key point estimates for the coefficient of renewable energy use are -10.78 from the fixed-effects model, and -0.77 from the random-effects model. Taken at face value, the first coefficient suggests a negative effect on profit of €11 per MWh increase in *RE* use within a firm, and the second coefficient sug-

[20] In our discussion of potential caveats in the conclusion, we particularly consider the threat that reverse causality poses to interpreting the coefficient of renewable energy as causal effect.

gest an effect on profit of almost zero per MWh increase in RE use.[21] However, considering the respective 95% confidence intervals of [-46.67, 25.21] and [-20.32, 18.77], these key coefficients are not estimated with a high degree of precision. Unfortunately, with the sample at hand, the true effect is too small to detect.

In comparison with the meta-analytic results of e.g. Margolis et al. (2009) and Dixon-Fowler et al. (2013), the negative and non-significant coefficients do not provide support for the positive relationship between profit and renewable energy use. Instead, the absence of a statistically significant effect of renewable energy use on profit and the point estimate from the random-effects model provide support for a non-existent impact of renewable energy use on profit. This is in line with the predicted relationship based on the adopted product-differentiation framework with profit-maximizing firms. We do not find evidence for a 'win-win' in the form of a better environment and higher firm profit. The negative coefficient from the fixed-effects estimation could be interpreted as support for the notion that firms are sacrificing profit in favor of renewable energy use, although it is not statistically significantly different from zero. In addition, the lower coefficient estimated with the fixed-effects estimator, as compared to the random-effects estimator, may be partly explained by the existence of lagged positive effects of renewable energy use on revenues.

Columns five and six of Table 3.3 report the estimation results for the quadratic model in Eq. (3.4) using a fixed-effects and random-effects estimator, respectively. In the fixed-effects model, the estimated coefficients for renewable energy and its square have the required signs for a U-shaped relationship with profit, but are not statistically significant. In addition, the formal test for a U shape fails to reject the null-hypothesis at conventional significance thresholds (p-value 0.151). In contrast, in the random-effects model, the estimated coefficients point to a potential inverse-U-shaped relationship. However, both the statistical non-significance of the coefficients as well rejection by the formal test (p-value 0.376) do not provide evidence for the presence of an inverse-U shape. These results do not corroborate the U-shaped relationship between CSR and profit that Barnett and Salomon (2012) find.

With respect to the other variables, conform expectation, the coefficients for assets, labor and total energy use are positive and significant in the random-effects

[21] It depends on the perspective whether €11 sacrifice in profit per MWh should be considered as substantial. Compared to the wholesale price of electricity (approximately €45/MWh in the past decade in Europe) or the certificate price (ranging from €2–€8 in Europe in 2018), this appears substantial. Considering the mean firm in the sample, however, this result translates to a decrease in profit of €11/MWh×1432GWh=€15.5 mln on a total profit of €1,132 mln.

model. In the fixed-effects model, the coefficient for assets is conform expectation. However, the coefficient for labor is negative and not statistically significant and the coefficient for total energy use is positive and not statistically significant. While we expect positive coefficients for all three productive inputs, we may not be able to statistically detect these simultaneously in the fixed-effects model when the usage of the three productive inputs within a firm is strongly correlated over time. This is less problematic in the random-effects model because there is considerably more variation in the three productive inputs between firms than within firms (see Table 3.2). The estimated coefficients for the firm and year-sector fixed effects are not reported to facilitate readability and because they are of limited interest.

	Key var. only		Linear specification		Quadratic specification	
	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects
RE (GWh)	-12.90	-8.20	-10.78	-0.77	-100.75	9.55
	(0.373)	(0.323)	(0.554)	(0.938)	(0.287)	(0.751)
RE^2					0.001	-0.0001
					(0.294)	(0.620)
K (mln US$)			15.45*	6.05***	15.57*	6.05***
			(0.089)	(0.000)	(0.088)	(0.000)
L (fte)			-4.51	10.74***	-4.26	10.72***
			(0.625)	(0.000)	(0.644)	(0.000)
TE (GWh)			0.58	3.92*	2.45	3.69
			(0.953)	(0.076)	(0.808)	(0.119)
Constant	1,293,553***	1,187,219***	737,110	935,284***	184,756	939,322***
	(0.000)	(0.000)	(0.276)	(0.000)	(0.785)	(0.000)
Pseudo R^2	0.0001	0.0002	0.23	0.32	0.23	0.32
No. of obs.	2700	2700	2,554	2,554	2,554	2,554
No. of firms	972	972	911	911	911	911
Year-sector dummies$^+$	No	No	Yes	Yes	Yes	Yes

P-value in parentheses.
* $p < 0.1$, *** $p < 0.001$.
$^+$ year-sector dummies are equal to one for firm i in year t if the firm belongs to sector s and zero otherwise.

Table 3.3. Estimation results. Dependent variable: net income (x1000 US$)

3.6 Conclusion

Firms buy renewable energy at premiums and typically report environmental concern as motivation to do so. The empirical environmental CSR literature suggests that there even exists a 'win-win' from this type of firm behavior: more environmental CSR is associated with higher profit levels.

From a microeconomic perspective, however, higher profit from renewable energy use in particular, and environmental CSR in general, is typically not expected. On the one hand, firms may be able to differentiate themselves from competitors by using renewable energy and thereby charge higher prices. On the other hand, competition for those high-WTP consumers drives down prices towards the level of marginal costs. In addition, if we assume that the objective of the firm is to maximize profit, there is no scope for renewable energy use at the expense of profit. Therefore, in this profit-maximization framework, we expect that there is no effect from renewable energy use on profit.

This paper has analyzed the relationship between renewable energy use and firm profit. In particular, we have tested the prediction that there is no impact of renewable energy use on firm profit, using panel data for 920 firms from various regions and sectors over the period 2014–2018. In this panel, also firms that use no or hardly any renewable energy are strongly represented.

The results suggest that there is no impact from renewable energy use on profit. The interpretation of this results is twofold. Firstly, our results do not imply that a 'win-win' relationship between renewable energy use and profit exists. In other words, promoting social goals (a better environment) does not appear to be associated with higher profit. This is different from the meta-analytic results of the environmental CSR literature, which have established such a 'win-win' relationship. Secondly, the results also appear to imply that firms are not sacrificing profit when they use renewable energy, which could have been an indication for a positive willingness to pay for the environment by firms. These findings are in line with the expected relationship between renewable energy use and profit from the adopted framework of product-differentiation by profit-maximizing firms. However, in one model, we estimate a coefficient that is statistically not significant but, in terms of effect size, relatively close to the price of (European) RECs. Therefore, we recommend further research to verify this paper's findings.

The results appear to indicate that firms do not have objectives beyond maximizing profit, and that firms are only willing to contribute to climate change mitigation through the purchase of renewable energy when this contributes to the profit-maximization objective as well. For government policy, this would imply that policies should affect firms' financial incentives in order to induce changes in behavior. This can be done, for instance, by affecting revenues (e.g. reducing information asymmetry in markets for green types which may raise consumer WTP) or costs (e.g. by introducing taxes on polluting inputs or subsidies for non-polluting alternatives).

This paper's main contribution is that it is the first to explicitly study the relationship between renewable energy use and profit. In addition, in relation to the broader environmental CSR literature, this paper uses a specific and concrete measure of environmental CSR in the form of renewable energy use, rather than an indicator variable of which it is not clear to what extent it represents actual environmental performance.

Several caveats of the current study need to be mentioned. First, on the basis of foundations of the microeconomic theory of the firm, such as profit maximization and product differentiation, this paper theorizes and empirically postulates that causality runs from renewable energy use to profit. We have not controlled for a potentially reverse relationship in which profit causes changes in renewable energy use, as this is highly complicated by the unavailability of data for truly exogenous instruments for renewable energy use. A reverse causal relationship might result from adopting other theoretical perspectives (e.g. agency theory). While the existing empirical evidence currently does not appear to support a causal relationship from CSR to profit (Kang et al., 2016; Scholtens, 2008), if the true relationship is of this kind, this paper's estimation results may suffer from an endogeneity bias. Secondly, considering the considerable standard errors, the key regression coefficients are not highly precise. As a result, we cannot conclusively distinguish between an effect of renewable energy use on profit that is zero or relatively small. Thirdly, the empirical analysis uses net income as measure for profit. This is a measure of accounting profit, whereas the theory concerns the relationship between economic profit and renewable energy use. To verify the findings of this paper and because firms increasingly play an important contribution in societies' efforts to mitigate climate change, further research regarding the link between firms' environmental contributions and financial objectives is required.

3.A Appendix: Robustness estimation results

	Model incl. R&D exp.		Model incl. debt	
	Fixed effects	Random effects	Fixed effects	Random effects
RE	-14.83	0.52	-10.39	-0.81
	(0.468)	(0.949)	(0.877)	(0.935)
K	56.79**	16.95*	20.03**	6.13***
	(0.048)	(0.088)	(0.03)	(0.000)
L	-15.30	1.90	-4.01	10.74***
	(0.193)	(0.505)	(0.955)	(0.000)
TE	2.58	1.15	0.23	3.94*
	(0.653)	(0.751)	(0.981)	(0.079)
R&D	-55.92	995.05***		
	(0.907)	(0.001)		
Debt			-22.17*	-0.35
			(0.081)	(0.951)
Constant	790,027.3	705,224.6***	871,787.2	936,025.5***
	(0.172)	(0.000)	(0.208)	(0.000)
Pseudo R^2	0.28	0.41	0.24	0.32
No. of obs.	2,098	2,098	2,554	2,554
No. of firms	765	765	911	911
Year-sector dummies$^+$	Yes	Yes	Yes	Yes

P-value in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
$^+$ year-sector dummies are equal to one for firm i in year t if the firm belongs to sector s and zero otherwise.

Table 3.A.1. Estimation results of alternative specifications including R&D expenditure (first two columns) and debt (last two columns) as control variables.

3.B Appendix: Kernel density plot of renewable energy use by firms in the sample

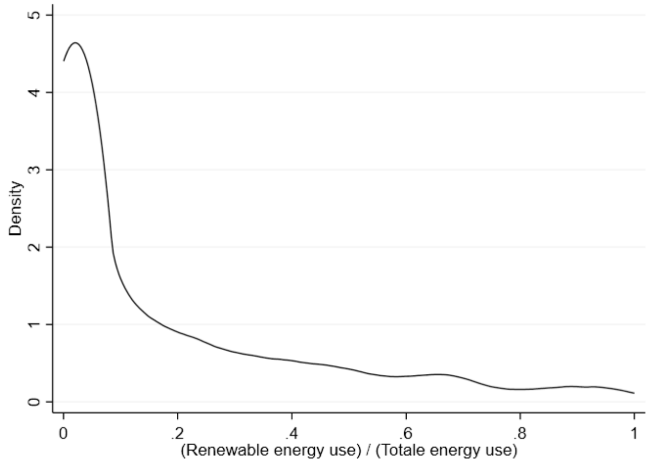


Figure 3.B.1. Kernel density plot of the share of renewable energy use in total energy use of the firm-years in the sample

Chapter 4

Performance of markets for European renewable energy certificates

4.1 Introduction

The emission of greenhouse gases by humans is associated with significant economic and social damages (e.g. IPCC, 2014; Nordhaus, 2006; Stern, 2007). Many governments around the world are therefore attempting to reduce their economy's greenhouse gas emissions. One of the typical aims of these governments is to facilitate the change from a non-renewable to a renewable-based energy system. For example, the EU aims to produce 32% of total energy consumption in 2030 from renewable sources, coming from 17% in 2016 (Commission, 2017). In addition to traditional policy tools such as taxes and subsidies, governments have implemented certification schemes to promote the use of renewable energy.

Certificates have been introduced to address the problem of information asymmetry in energy markets. Information asymmetry is typically present in energy markets because consumers cannot credibly distinguish between renewable and non-renewable energy. As a consequence, adverse selection may arise: consumers with a preference for renewables may end up buying less or none at all (Akerlof, 1970). Information asymmetry arises in energy markets because consumers do not

This chapter is based on Hulshof et al. (2019). I thank the editor and an anonymous referee of Energy Policy for very valuable comments and suggestions, and Phil Moody from the Association of Issuing Bodies (AIB) for data support.

experience differences between consuming renewable and non-renewable energy and production tends to occur elsewhere. The presence of networks in some important energy markets (e.g. electricity and gas) further complicates distinguishing between renewables and non-renewables because all energy in the network mingles. The purpose of certification is to bridge this informational gap. By providing consumers with information about unobservable characteristics (e.g. the production method), they are enabled to make better decisions.

In Europe, several certificate systems have been introduced for energy goods. EU directives 2009/28/EC (2009) and 2001/77/EC (2001) require member states to implement certificate systems for renewable electricity, called Guarantees of Origin (GO). GO certificates appear to be quite successful with approximately 35% of renewable electricity production receiving certification in 2015 in the EU28 countries (plus Switzerland and Norway) (AIB, 2017). The directives lay out a common framework for the design of GO certificate systems but differences between countries remain in the adopted designs. For example, differences exist in whether the certifier is a public or private organization. At the same time, unlike in Europe, certification of renewable electricity in the United States is not organized by the government at all but completely entrusted to private organizations.

The main question we address in this paper is twofold: (i) how do European markets for energy certificates perform, and (ii) how do design features of certificate systems relate to the performance of certificate markets. More specific, does it matter for the performance of a certificate market if the certifier is a public or private institution and if the certificate adheres to a common international standard. This paper contributes to the literature by providing an empirical assessment of the performance of certificates for energy goods in government-created markets. While other papers have generally focussed on a single country (e.g. Roe et al., 2001; Fuerst and McAllister, 2011), we analyse GO certificate markets in twenty European countries, which are comparable but differ in some critical design aspects, such as the public/private nature of the certifier.

This paper analyses the performance of GO certificate markets and the relationship between two design characteristics of certificate systems and market performance in twenty European countries over 2001-2016. We apply our analysis to the market for GOs because, unlike certificate markets for other energy carriers, relatively detailed data is available regarding quantities, prices and trade. Moreover, the electricity GO system is the largest and most ambitious certification scheme for energy goods in Europe. To investigate market performance, we analyse four market indicators: the churn rate, price volatility, the share of renewable electricity which is certified and the share of certificates that expires (i.e. is never used to claim consumption). We apply a panel data regression to a reduced-form supply and demand model to investigate the relationship between market performance and the public/private nature and presence of an international certificate standard.

Our results confirm that increasing amounts of renewable electricity receive certification. However, GO markets suffer from very poor liquidity, as measured by the churn rate, and volatile prices. While the churn rate is slowly improving in the EU and most individual countries, we do not observe improvements in volatility over time. Furthermore, GO certificate markets have been in a relatively stable state of oversupply. Overall, certification has become increasingly important as a trade mechanism for renewable electricity but the performance of certificate markets remains poor. With respect to the design characteristics, we find that the presence of an international standard significantly contributes to the market volume while we also find some evidence for a positive effect of public ownership over the certifier on market volumes.

The remainder of this paper is organised as follows. Section 4.2 provides an overview of the literature. Section 4.3 discusses the methods. Section 4.4 describes the data. Sections 4.5 provides the results. Finally, section 4.6 discusses the conclusions and policy recommendations.

4.2 Literature

4.2.1 Information asymmetry and certificates

Several theoretical papers discuss how providing information on the basis of certificates reduce information asymmetry. In a seminal paper, Akerlof (1970) describes how information asymmetry can result in adverse selection: consumers may have a willingness-to-pay for a good with certain quality aspects (e.g. renewable electricity) but if these quality aspects are unobserved, consumers will not express their (full) willingness-to-pay in the market. Certification aims to provide consumers with information about these unobserved aspects such that consumers can confidently express their willingness-to-pay in the market. Applied to environmental goods, Dosi and Moretto (2001) show theoretically that certification may have a positive effect on the supply of an environmental-friendly type of a good.

With respect to the design of certificate systems, several papers question the reliability of the certifier. Mahenc (2017) and Feddersen and Gilligan (2001) discuss how the incentive of certifiers is related to providing honest information. In particular, when a certifier's goal deviates from maximizing social welfare, such as maximizing profit (Mahenc) or maximizing environmental quality (Feddersen and Gilligan), the certifier has an incentive to provide dishonest information. When certifiers are profit-maximizing firms, Lizzeri (1999) shows that competition between certifiers can results in honest certification.

Also related to this paper is the literature that assesses the valuation of unobservable attributes of energy goods by consumers. A first group of studies within this literature applies stated-preference methods to assess preferences for different energy goods and their (unobservable) attributes in a hypothetical buying situation. Particularly for the electricity market, there is evidence that consumers prefer renewable over non-renewable electricity (e.g. Sundt and Rehdanz, 2015).

A second group of studies applies revealed-preference methods to investigate the willingness-to-pay for certified goods. For example, using hedonic-pricing techniques, Roe et al. (2001) show that the premium for renewable electricity in the US significantly increases with Green-E certification. More examples of revealed-preference analyses showing that consumers value environmental certification include Fuerst and McAllister (2011) for the US real-estate market and Elofsson et al. (2016) for the Swedish milk market. However, there exists also empirical evidence of environmental certification schemes that leave consumer demand unaffected. Park (2017) finds that the presence of a Korean energy-efficiency certificate does not influence the price of the certified goods. Similarly, Hornibrook et al. (2015) report that an ecolabel of the largest supermarket in the UK containing carbon information does not affect consumer choices.

A last related branch of literature discusses the physical design of certificates and the effect on consumer choice. Newell and Siikamäki (2014) find that, in addition to factual information in energy-efficiency certificates, the presence of logos (e.g. the US Energy Star or EU letter grade logo) significantly increases the willingness-to-pay of consumers for energy intensive household appliances.

4.2.2 European GO certificates

Several scientific papers specifically analyse various facets of the GO system. In a qualitative study, Aasen et al. (2010) conduct interviews amongst Norwegian firms to assess their perception of the informational content of GOs and find that companies have a large degree of distrust in GOs and do not believe that GOs result in any environmental effect. They propose as explanations that Norwegians perceive their electricity system as completely renewable because practically all domestic generation is renewable and that buying GOs does not affect the generation mix. In line with this, Winther and Ericson (2013), using a field experiment, found that a large group of Norwegian electricity consumers virtually did not respond to an offer from their supplier to buy GOs. From subsequent focus group sessions, the authors conclude that the Norwegians predominantly rejected the offer because they perceived their electricity as already being green. In a study on European level, Lise et al. (2007) discuss the key elements related to operating GO systems in Europe and conclude that the functioning of GOs depends on the presence of other support schemes (e.g. feed-in tariffs) as well as electricity market fundamentals such as the level of competition and level of domestic and international trade. In addition, the authors suggest that trading GOs separately from associated electricity flows is preferred over linked trading as the former minimizes the impact on the existing electricity market while also being accurate and inexpensive. In a study on the Dutch retail electricity market, Mulder and Zomer (2016) conclude that GOs are not very effective as a policy instrument to foster investments in renewable electricity generation. The GO system has also been discussed as potential international tradable green certificate system for compliance with (national) renewable energy targets. Specifically, Ragwitz et al. (2009) find that government-based trading in GOs is preferred over company-based trading for the purpose of target compliance because, amongst other advantages, the former is more compatible with existing support schemes. In addition, Nilsson et al. (2009) investigate the political and legislative processes over time surrounding the proposition and rejection of GOs as instrument for target compliance. They find that opponents of GO trading for target compliance had stronger incentives, better coordination and a clearer position and message than proponents.

European GO markets emerged in 2001 following EU legislation which mandates each member state to set up a certification scheme for renewable electricity. The rest of this section outlines the appropriate aspects of the GO system for our paper and draws heavily on the relevant legal documentation, in particular the EU directives 2009/28/EC (EU, 2009) and 2001/77/EC (EU, 2001). European GOs (interchangeably used with certificates from here on) explicitly target reducing information asymmetry between producers and consumers of renewable electricity. GO certificates are valid for one year and expire if they are not consumed (referred to as cancelled) within this period.

While running a certification scheme is mandatory, countries have considerable freedom in choosing their own certificate system design. This has led to differences between countries with respect to quality assurance and market organization.

Each country is required to appoint a certifier which is responsible for issuing and cancelling certificates and facilitating trade. More than one certifier may be appointed but each certifier is responsible for a non-overlapping geographical area. As a result, only one monopolistic certifier is active in most countries, except for Greece and Belgium where multiple regional monopolists are active.

Countries may freely decide to appoint a public or private certifier. France, Czech Republic and Portugal are the only countries with a currently or previously active private certifier.

A number of countries have adopted a common international standard for their GO certificates. This EECS-standard standardizes the information provided in the certificate and rules regarding issuance, cancellation and trade. EECS certificates are traded through a central electronic hub which is operated by the Association of Issuing Bodies (AIB), an association representing the GO certifiers. The presence of a standard facilitates international trade through regular advantages of standardization: it establishes a quality level of certificates and eases comparison of certificates from different origins. The presence of a central trading hub reduces transaction costs further because, absent a central hub, each country may set their own import and export procedures.

With respect to market organization, the EU rules try to foster an integrated European market for certificates. Countries are obliged to accept the import of GO certificates from other countries.[1] However, countries are free to set export restriction, which is done in practice by two countries: Austria does not allow the export of certificates obtained by a generator that has received state support and Spain requires any revenue from exporting certificates to be transferred to the government, which functions as an export ban.

Several countries exclude producers from obtaining certificates at all when they received state support. This concerns Croatia, France, Germany, Ireland and Luxembourg. The typical rationale for this policy is that, as the state support intends to provide a regular profit for the producers, additional revenues from certification would be windfall profits.

Table 4.1 summarizes the design choices of the analysed countries. In addition to the presence of the international standard and the certifier's public/private character, this table reports if a country has export or certification restrictions in place.

[1] Expected fraud or 'system weakness' is a valid reason to deny imports of certificates from a country.

	Implementation of international standard	Public/private certifier	Export restrictions	Certification restrictions
Austria	2004	Public	Yes	No
Belgium	2006	Public	No	No
Cyprus	2014	Public	No	No
Croatia	2014	Public	No	Yes
Czech Republic	2013	Private (2013-now)	No	No
Denmark	2004	Public	No	No
Estonia	2010	Public	No	No
Finland	2001	Public	No	No
France	2013	Private (2013-current)	No	Yes
Germany	2013	Public	No	Yes
Iceland	2011	Public	No	No
Ireland	2015	Public	No	Yes
Italy	2013	Public	No	No
Luxembourg	2009	Public	No	Yes
Netherlands	2004	Public	No	No
Norway	2006	Public	No	No
Portugal	No	Private (2013-2015)	No	No
Spain	2016	Public	Yes	No
Sweden	2006	Public	No	No
Switzerland	2009	Public	No	No

Table 4.1. Design characteristics of national GO certification schemes in EU countries

4.3 Method

We assess the performance of certificate markets by constructing four markets indicators (Section 4.3.1): the share of renewable electricity with a certificate (the certification rate), the churn rate, price volatility and the share of certificates that expires (the expiration rate). We relate design features of certification schemes to market performance by estimating a reduced-form supply and demand model based on quantities and market fundamentals (Section 4.3.2).

Our four performance indicators relate to primary market outcomes, such as quantities, prices and trade. Firstly, we assess the certification rate, a measure of market output. Generally, maturing markets are associated with increasing output volumes. As the amount of certification is related to the amount of renewable electricity (which has recently been increasing in many countries) we analyse the share of certified renewable electricity instead of the absolute volume. The certification rate (cr) is calculated as:

$$cr_{ti} = \frac{Q_{ti}}{RE_{ti}} \tag{4.1}$$

where Q refers to the volume of issued certificates, RE to the output of renewable electricity (both in MWh) and t and i to year and country, respectively.

Secondly, we assess market liquidity by evaluating the churn rate. The churn rate is frequently used as an indicator for liquidity in physical and financial markets (e.g. Heather, 2016; ACER/CEER, 2017). It indicates how often a product is traded before it is consumed. The churn rate may be defined as the ratio of traded volume to final consumption. A higher churn rate indicates a higher level of market liquidity. For commodity markets, a threshold above which a market is generally considered as being liquid and mature is 10 (Ofgem, 2009).

We construct three different churn rates in order to cope with the unavailability of individual transaction data. Our dataset includes aggregated data for the number of issued, cancelled, domestically traded, imported and exported certificates per calendar year. As certificates expire after one year, certificates issued in a given calendar year may have been cancelled in the same or next calendar year.[2] The same goes for imports. Imports in one year may have been cancelled in the same or next calendar year. Similarly, transactions and cancellations in one year can relate to certificates issued in the previous or same year. To overcome this difficulty, we constructed three churn rates that differ in the approach to calculate final demand for consumption.

The first churn rate (x^1) is based on the domestically traded volume and the number of issued and imported certificates in the same calendar year. The number of issued and imported certificates jointly determine the tradable volume in a market. For individual countries, the first churn rate is given by:

$$x^1_{ti} = \frac{T_{ti}}{Q_{ti} + IM_{ti}} \tag{4.2}$$

where T is domestic transfers and IM imported certificates.

[2] The AIB provides certification data twice: (i) by the time of production and (ii) by the time of transaction. Data provided by the time of production (i) refers to when the electricity related to the certificate was produced, while (ii) refers to when the certificate transaction took place (e.g. the year a certificate was issued). Discrepancies arise due to the administrative processing time of certifiers. As a result, renewable electricity produced in year t may receive a certificate in year t+1. Availability of data differs between the two statistics. E.g. data for issuance and expiration of certificates by time of transaction does not exist prior to 2009 while it is available for all years by time of production.

The second churn rate (x^2) is based on current year's traded volume and the number of issued and imported certificates in the previous year:

$$x_{ti}^2 = \frac{T_{ti}}{Q_{(t-1)i} + IM_{(t-1)i}} \tag{4.3}$$

The third churn rate (x^3) is based on the current year's traded volume and number of cancelled certificates (C):

$$x_{ti}^3 = \frac{T_{ti}}{Q_{ti} + C_{ti}} \tag{4.4}$$

The first churn rate relates current trade to current production, the second relates current trade to previous production and the third relates current trade to current consumption. There appears to be no good reason to prefer one over the others with our dataset. Therefore, for individual countries, we will report on the basis of the simple average of these three churn rates (xr):

$$xr_{ti} = \frac{x_{ti}^1 + x_{ti}^2 + x_{ti}^3}{3} \tag{4.5}$$

For the whole region (the international GO market), we cannot use Equations 4.2, 4.3 and 4.4 to calculate the churn rate because, for all countries combined, imports/exports are equal to zero since all registered imports and exports are between countries within the GO scheme. Therefore, when considering the whole region, imports/exports should be regarded as transactions. The available volume for final consumption is simply aggregated issued or cancelled volume. To take this into account, we calculate slight variations on Equations 4.2, 4.3 and 4.4 for the whole region (indicated by the prime superscripts):

$$x_t^{1'} = \frac{\sum_{i=1}^n T_{ti} + \sum_{i=1}^n IM_{ti}}{\sum_{i=1}^n Q_{ti}} \tag{4.2'}$$

$$x_t^{2'} = \frac{\sum_{i=1}^n T_{ti} + \sum_{i=1}^n IM_{ti}}{\sum_{i=1}^n Q_{(t-1)i}} \tag{4.3'}$$

and

$$x_t^{3'} = \frac{\sum_{i=1}^n T_{ti} + \sum_{i=1}^n IM_{ti}}{\sum_{i=1}^n C_{ti}} \tag{4.4'}$$

where n refers to country. We report again on the basis of the simple average:

$$xr_t^{'} = \frac{x_t^{1'} + x_t^{2'} + x_t^{3'}}{3} \tag{4.5'}$$

We cannot compare this churn rate to the churn rate of individual countries because Eq. 4.5′ will always tend to be higher than Eq. 4.5. This is inherent to increasing the geographical span of the market such that imports/exports become part of traded volume instead of the available volume for consumption (increasing the churn rate's numerator and decreasing its denominator). To calculate a churn rate for the whole region which is comparable to the churn rate for individual countries, we may take the cancelled-volume-weighted average of Eq. 4.5:

$$xr_t^{''} = \frac{\sum_{i=1}^{n} xr_{ti} * C_{ti}}{\sum_{i=1}^{n} C_{ti}} \tag{4.6}$$

Thirdly, we assess the development in certificate price volatility. Price volatility is an indicator for fluctuations in the price, i.e. price uncertainty. Generally, improvements in market maturity and liquidity are associated with decreasing price volatility (ACM, 2014). In mature, liquid markets, single events that affect supply or demand (e.g. a power plant outage) are absorbed by the market with less profound price effects as compared to illiquid markets. A common measure of price volatility is the standard deviation of price changes (e.g. Regnier, 2007). Here, we calculate annual price volatility as the standard deviation of monthly relative price changes.

Fourthly, we assess the expiration rate. If certificates are not used within one year, they expire and are not used to prove the consumption of renewable electricity. A high expiration rate is an indicator for a situation of relative oversupply. We calculate the expiration rate (er) by dividing the volume of expired certificates (E) by the volume of issued certificates:

$$er_{ti} = \frac{E_{ti}}{Q_{ti}} \tag{4.7}$$

Larger values for this indicator are associated with higher levels of excess supply.

4.3.1 Relating certificate system design features to market performance

To relate the two design features to market performance, we estimate a reduced-form supply and demand model of the quantity of issued certificates on the wholesale market. The intuition behind the model is that changes in the certified volume are caused by changes in fundamental demand and supply factors. The observed quantities reflect equilibrium prices, i.e. points where the demand and supply curves intersect. Our model is not able to isolate the effect of the design features on supply or demand, but enables testing whether these features have an effect on the market outcome, which is our main interest. We estimate the model $Q_{ti} = \Phi(\mathbf{X}_{ti}, \mathbf{Y}_{ti}, \mathbf{Z}_{ti})$ where $\mathbf{X}$ contains the design characteristics, and $\mathbf{Y}$ and $\mathbf{Z}$ the fundamental supply and demand variables, respectively. We will now first elaborate on these characteristics and fundamentals and then discuss the empirical specification.

Design characteristics and market fundamentals

The public/private nature of a certifier may be related to market performance through the reliability of certification and the certification fee. Assuming that governments are more inclined to maximize social welfare than firms, private certifiers have a greater incentive to provide dishonest certification than public certifiers by certifying grey electricity as green in an attempt to increase revenues (Mahenc, 2017). This type of behaviour by a private certifier would put upward pressure on the supply of certificates. However, as Mahenc points out, consumers may reasonably expect this type of behaviour from a profit-maximizing certifier. As a result, consumers may trust a private certifier less, putting downward pressure on demand. Also when certification is perfectly honest, monopolistic profit-maximizing certifiers may affect market outcomes by exercising market power and selecting a higher certification fee when left unregulated. A higher certification fee, which is the price in the wholesale market for certificates, is associated with a lower market quantity.

An important factor affecting the demand for certification is the output of renewable electricity, which in turn largely depends on meteorological factors. The output of these generators is typically eligible for certification such that increases in renewable electricity production directly increase the potentially certified volume. The installed capacity of renewable electricity generators determines the maximum output of renewable electricity. Meteorological conditions such as the wind speed, rainfall and solar radiation determine the actual output at a given moment.

Restriction policies on certification and exports affect the demand for certificates on a wholesale level. Governments that limit certification to non-supported generators put downward pressure on the demand since certification becomes uninteresting to generators when subsidies exceed certificate prices. Export restrictions limit the possibilities to market the certificate for a generator, putting downward pressure on expected benefits from certification and therefore demand for certificates.

The price of electricity is expected to be relevant for the certified volume through the demand for certificates. The final price of (certified) renewable electricity depends on both the certificate price and the electricity wholesale price (Mulder and Zomer, 2016). The certificate price represents the green premium in retail contracts for renewable electricity as certificates and 'physical' electricity (as in the actual electric flow) are traded separately. Retailers of renewable electricity need to procure both 'physical' electricity and certificates. Therefore, increases in the price of electricity raise the final costs of renewable electricity for end-users, putting downward pressure on the demand for renewable electricity and, in turn, for certificates.

Another important demand side variable is the level of income. As income rises, both residential and industrial end-users increase their demand for electricity (Kamerschen and Porter, 2004). Increases in the use of electricity put upward pressure on the demand for certificates as more certificates are required for end-users with certificate-based renewable electricity contracts.

The supply curve on the certificate wholesale market is somewhat peculiar. The marginal cost of certification by certifiers is nearly zero as certification is largely an automatised process and requires almost no variable inputs besides digital storage space. In a competitive market, the (short-run) supply curve would therefore be a flat line at a price of zero. However, by EU rules, GO certifiers are national/regional monopolists giving these firms market power. As these firms tend to be regulated companies, the extent to which market power can be exerted depends on the regulatory framework. In contrast to private certifiers, public certifiers have few incentives to exert market power. But other forms of regulation than public ownership can limit the exertion of market power as well, such as appointment of the certifier by tendering. Apart from the public/private nature of certifiers, we have no information about the type of regulation in individual countries.

Empirical model

We estimate a panel data model of the quantity of issued certificates Q in year t and country i, as a function of supply and demand fundamentals and the two design characteristics. The design characteristics are represented by two dummy variables indicating whether the international standard is present (ST, equal to 1 if present) and the certifier is public or private ($priv$, equal to 1 if private). The demand and supply fundamentals we control for are total renewable electricity generation (QRE), the consumer electricity price (PE) and a real GDP index (Y). Finally, we include two certification-policy dummy variables: export restrictions (exr; equal to 1 if present) and certification restrictions (cer; equal to 1 if present). The equation we estimate is:

$$Q_{ti} = \alpha_1 + \alpha_2 ST_{ti} + \alpha_3 priv_{ti} + \alpha_4 QRE_{ti} + \alpha_5 Y_{ti} + \alpha_6 PE_{ti} + \alpha_7 exr_{ti} + \alpha_8 cer_{ti} + c_i + u_{ti} \tag{4.8}$$

where c is an unobserved, time-invariant individual effect. Here, this may capture differences between countries in preferences for renewable electricity (Sundt and Rehdanz, 2015). The (endogenously determined) certification fee (the price in the wholesale market) is not included in the empirical model as information for individual countries is largely unavailable. Considering that private monopolistic certifiers may be more inclined to exert market power, omitting the certification fee as regressor implies that α_3 may capture the potential effect of a higher certification fee as well as the potential effect of the reliability of the certifier on market quantities.

We also estimate an alternative specification based on Eq. (4.8) where we consider a potential effect of the 2009 EU renewable energy directive on certificate market volumes. As this directive mandates countries to make individual plans to foster renewable energy, we add to the model a set of country-period dummies D that are equal to 1 in country i after the reform (2009-2015) and zero otherwise. This captures, for example, differences in renewable-energy policy situations before and after the reform within countries, taking into account that countries may have reacted differently and consequently experienced different developments. Because of the dummy structure, these variables may also capture other non-included factors that vary between the two periods, such as an increase in the willingness-to-pay for renewable electricity in country i. The second model we estimate is:

$$Q_{ti} = \alpha_1 + \alpha_2 ST_{ti} + \alpha_3 priv_{ti} + \alpha_4 QRE_{ti} + \alpha_5 Y_{ti} + \alpha_6 PE_{ti} + \alpha_7 exr_{ti} + \alpha_8 cer_{ti} + \boldsymbol{\beta}\mathbf{D}_{ti} + c_i + u_{ti} \tag{4.9}$$

4.4 Data

GO markets are not very transparent. While quantity data for European certificate markets is publicly available through the AIB, price data is not publicly available, partly because trade in GOs occurs only bilaterally or via brokers. Market players appear to corroborate this lack of transparency in GO markets (Greenfact, 2018b). Nevertheless, we were able to obtain a comprehensive dataset to analyse the functioning of GO markets.

We obtain data from various sources for 20 European countries: Austria, Belgium, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden and Switzerland. We include this set of countries as they have implemented the EU GO regulations while certification data is available for them in the AIB database.[3] Certification data is available from 2001-2016, while availability for other variables is sometimes limited.

We made three initial adaptations to the AIB database. First, we remove Slovenia from the database because data is not reported out of fears of exposing the trading position of a market participant. Second, the UK is removed from the database since, according to the AIB, the reported activity in their database concerns RECS certificates instead of GOs. Third, we aggregate the data of the four regional Belgian certifiers to obtain a single observation of each variable for Belgium.

Our GO price data comes from Greenfact. Greenfact is a market-monitoring firm which obtains prices by consulting market participants. The dataset includes monthly volume-weighted average prices for certificates. It further specifies the production year, certificate origin (country/region, e.g. Nordic), production technology and trade volume. Observations range from 2011-2017 but periods are substantially shorter for most of the products. In order to determine which prices are comparable to each other, we first distinguish between spot and forward contracts. A spot contract is defined as contract with a production year equal to or one year prior to the contract's transaction year. This seems logical considering that certifi-

[3] Non-EU member states Norway and Switzerland have also implemented the EU GO legislation.

cates expire after one year. Most of the trades in the database are spot contracts. We further distinguish products by country/region of origin and production technology.

From Eurostat, we extract the real annual GDP index and the electricity price for all countries, except for Switzerland, which is not reported. We use the bi-annual household electricity price and take the simple average to estimate the annual average electricity price. Some years are missing for Croatia, Estonia and Iceland. For Switzerland, we use the average annual end-user price, as reported by the Swiss Federal Office of Energy until 2015. All prices expressed in Swiss Francs are converted into Euros using the annual average Euro–Swiss Franc exchange rate according to Eurostat.

We obtain annual data on the production of renewable electricity for EU-countries and Norway from Eurostat (available until 2015). For Switzerland, we obtain this data from the IEA.

Information about implementation of the international standard is taken from Fact Sheet 17 on the website of the AIB. We inspect the websites of the (former) national certifiers to determine whether they are public or private institutions.

Table 4.A.1 in Appendix 4.A reports all descriptive statistics, except for certificate prices, which are reported in Table 4.A.2.

4.5 Results and discussion

This section first discusses the results of the four market performance indicators (Sections 4.5.1–4.5.4) and consequently the results for the relationship between the design features and market performance (Section 4.5.5).

4.5.1 Certification rate

GO certification of renewable electricity has become increasingly important in the EU since the start of operation in 2001. Figure 4.1 shows the development of the certification rate of renewable electricity, fossil electricity and total electricity in all countries combined. The certification rate of renewable electricity increased from 0.2% to 35.5% from 2001-2015. Certification of fossil electricity is much less important, as indicated by the low certification rate of 1.7% in 2015.

There are significant differences between countries in the relative importance of certification. Figure 4.2 shows the development of the certification rate in individual countries by comparing the average certification rate between four periods:

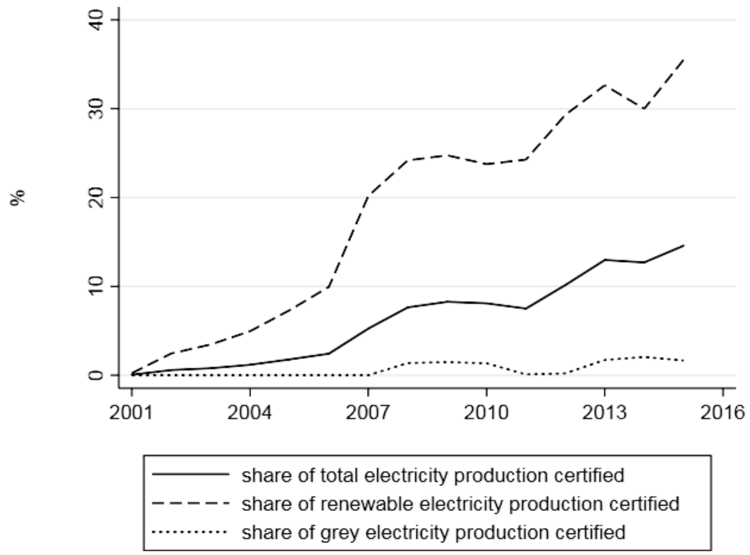


Figure 4.1. Certification rates for electricity in Europe, 2001-2015. Sources: AIB, Eurostat, IEA.

2001-2004 with 2005-2008 (panel a), 2005-2008 with 2009-2012 (panel b) and 2009-2012 with 2013-2015 (panel c). Years without an active certifier are excluded when calculating averages. Country names are represented by two-letter abbreviations. In these planes, countries on the diagonal lines reflect equal observations for the two considered periods, hence no change in the relative amount of certification.

In most countries, the amount of certified renewable electricity either increases or remains stagnant between two periods. In all periods, several countries are located above and quite distant from the diagonal line, indicating a considerable increase in the certification rate. Certification has become particularly important (>70%) in Denmark, Finland, the Netherlands, Norway and Switzerland. Most other countries have experienced increases as well.

Only one observation lies considerably far below the diagonal: Sweden in panel c, which is due to a data issue. Due to a legislative change, part of Swedish certificates became ineligible for export in 2010 and these certificates are not included in the database. The rest of the observations that lie below the diagonal (4 out of 52) are countries with very low certification rates (<2.5%).

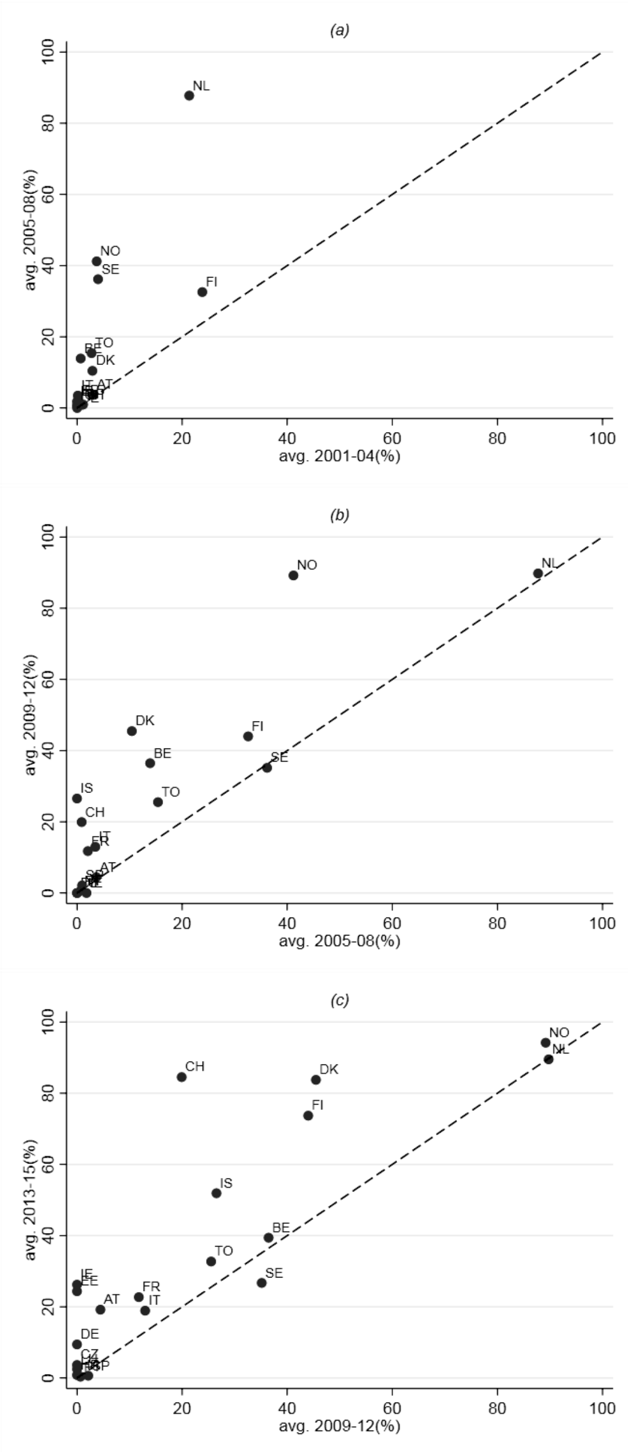


Figure 4.2. The certification rate by country, 2001-2015. Note: Each plot compares the 4-year average with the preceding 4-year average from 2001-2015 (one 3-year period: 2012-2015). Source: own calculations, AIB, Eurostat, IEA.

	x^1	x^2	x^3
Mean	0.21	0.36	0.46
Standard deviation	0.50	0.85	0.85
Minimum	0.00	0.00	0.00
Maximum	5.69	7.22	6.71

Table 4.2. Summary statistics of three churn rates for individual countries. x^1 approximates final demand for consumption by the number of issued certificates, x^2 by the number of issued certificates in the previous year and x^3 by the number of cancelled certificates. Source: own calculations based on AIB data.

4.5.2 Churn rate

Table 4.2 provides summary statistics of the three different churn rates for individual countries (corresponding to Eqs. 4.2, 4.3 and 4.4).[4] The three churn rates all have very low averages but are somewhat different from each other. The mean of the churn rate based on cancellations (0.46) is more than double the mean of the churn rate based on current year's issuance (0.21). The churn rates based on previous year's issuance and cancellations are more similar, both in terms of the means and standard deviations. This also holds for most individual years (not reported here). This suggests that cancellations tend to follow previous year's issuance closer than current year's issuance.

The churn rate remains low in each country. Figure 4.3 compares the simple average of the three churn rates between four time periods: 2001-2004 with 2005-2008 (panel a), 2005-2008 with 2009-2012 (panel b) and 2009-2012 with 2013-2016 (panel c). To facilitate readability, observations in the origin, reflecting zero domestic trade in both periods, are omitted. In the period 2009-2012, Austria is the first country where the churn rate exceeds 1 (1.4). The highest churn rates are observed in Estonia (2.2) and Italy (2.5), both in the most recent period. Other countries do not experience churn rates above 1.5 in any of the periods.

Figure 4.3 reveals mixed growth experiences over time between countries. Several countries have experienced steady increases in the churn rates since the beginning, such as Norway and Denmark. A few countries have experienced decreases, particularly in the period 2009-2012, such as Italy and France. In the most recent period, the churn rate has been increasing in almost all countries. Nevertheless, the levels remain very far below 10 in each country.

[4] After calculating the churn rates, 6 curious observations in 5 countries were deleted (Czech Republic, Finland, Germany, Italy, and Iceland). See Appendix 4.B for clarification.

For all countries combined, the churn rate displays an increasing trend over time (Figure 4.4). From 2002-2016, the churn rate and country-weighted average churn rate increased on average 14.5% and 16.7% per year, respectively. However, the levels of 1.65 (whole area) and 0.56 (country-weighted average) in 2016 are very poor and far from levels generally considered as liquid.

4.5.3 Price volatility

Figure 4.5 shows the development of spot prices for products for which we have most observations: Nordic hydro, Italian hydro and EU (i.e. unspecified) hydro (panel a), and EU biomass, EU solar and EU wind (panel b). At first glance, there appears a considerable amount of co-movement but, at times, movements and peaks in some price series are hardly reflected in the other price series. Correlation coefficients of the spot prices (see Table 4.C.1 in Appendix 4.C) suggest that, to some extent, certificates from different countries and technologies have their own price dynamics. Some products are strongly correlated but other products are uncorrelated or negatively correlated. This confirms that a product division for GO certificates on the basis of region and technology is appropriate.

The volatility in certificate prices is relatively high. Table 4.3 reports the volatility in monthly spot prices. Volatility differs by product but is quite high for all products. In 2017, volatility ranged from 3.4% for Dutch wind certificates (effectively based on only two price-change observations) to 105.6% for Belgian wind certificates. The volatility in Nordic hydro certificates, one of the most liquid products, was 14.3% in 2017. Over time, volatility has been fluctuating but the patterns do not appear to suggest a consistent improvement.

4.5.4 Expiration rate

Figure 4.6 depicts the expiration rate per year from 2001-2016 in the whole region. The amount of expired certificates ranged between 5% and 25% from 2001-2003. From 2004-2016, the expiration rate appears more stable, being on average 6.5% and ranging from 2.4%-10.4%. This indicates that, while most certificates are cancelled, a non-negligible amount of certificates expires and therefore remains unused for proving the consumption of renewable electricity.

Figure 4.7 compares the expiration rate in individual countries between four periods: 2001-2004 with 2005-2008 (panel a), 2005-2008 with 2009-2012 (panel b) and 2009-2012 with 2013-2016 (panel c). We exclude the expiration rate in Luxembourg

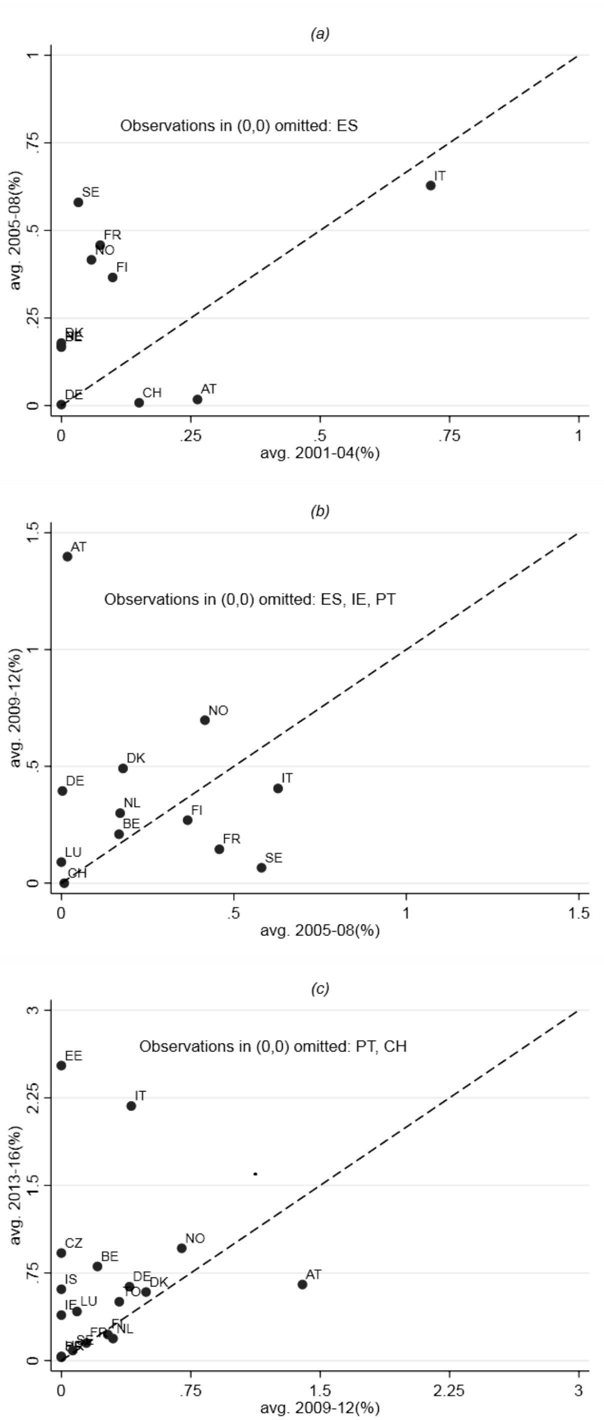


Figure 4.3. Churn rate by country, 2001-2016. Each plot compares the 4-year average with the preceding 4-year average from 2001-2016. Countries in (0,0) have active certification schemes. Differences in scaling are chosen to enable identification of individual countries in graphs. Source: own calculations, AIB.

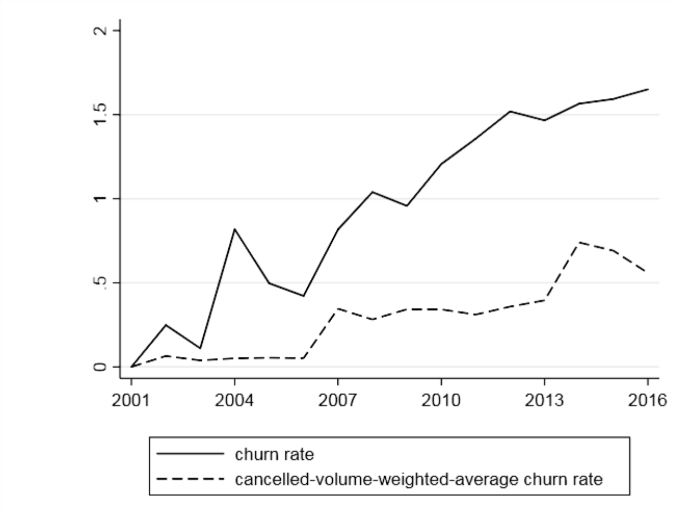


Figure 4.4. Churn rate in all countries combined, 2 types, 2001-2016. Source: own calculations, AIB.

Origin	Techno–logy	2011	2012	2013	2014	2015	2016	2017
Nordic	Hydro	66.6%	13.4%	31.2%	22.2%	19.0%	34.5%	14.3%
Belgium	Biomass							63.9%
	Solar							84.8%
	Wind							105.6%
EU (unspeci–fied)	Biomass		22.2%		54.4%	8.9%	41.7%	33.3%
	Hydro					33.6%	40.7%	34.4%
	Solar					23.1%	10.4%	78.1%
	Wind	16.0%	69.0%	32.6%	198.0%	54.7%	30.0%	34.3%
Italy	Hydro					15.7%	47.9%	59.8%
The Nether–lands	Biomass							30.9%
	Wind							3.4%
Switzerland	Hydro							21.8%

Table 4.3. Volatility in monthly spot prices (annual averages). Volatility is measured as the standard deviation of monthly relative price changes.

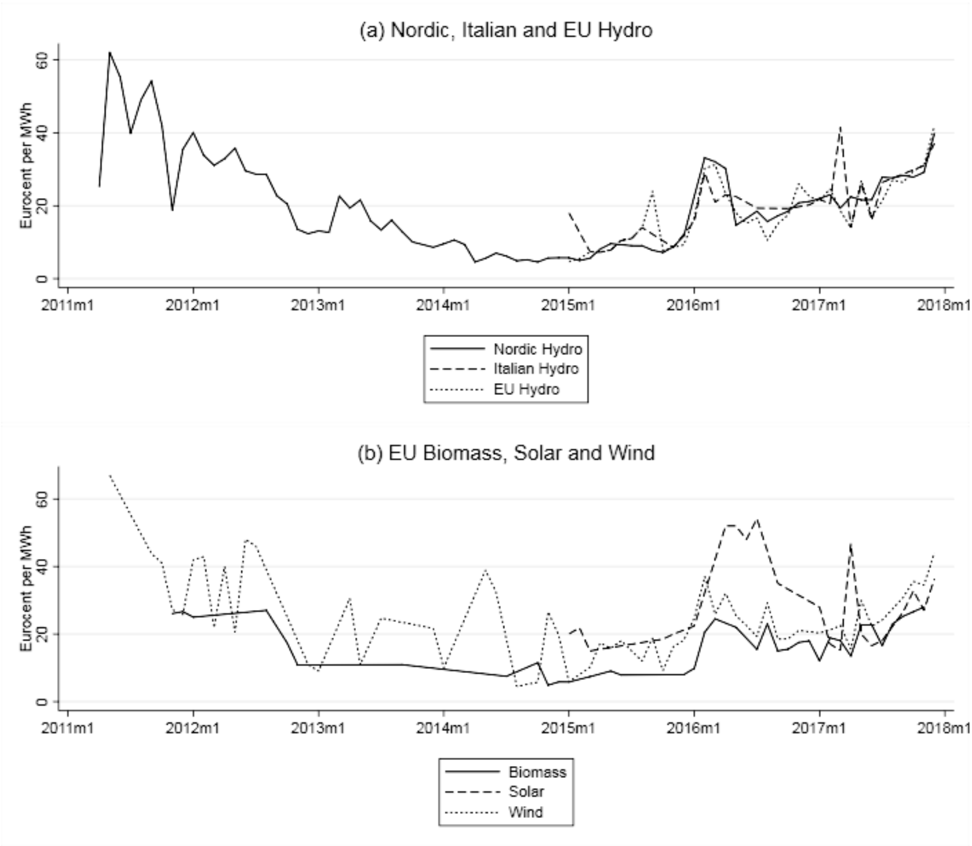


Figure 4.5. Spot prices for hydro GO certificates in three countries (panel a) and for GO certificates in the EU (i.e. not specified by country) for three different technologies (panel b). Source: Greenfact.

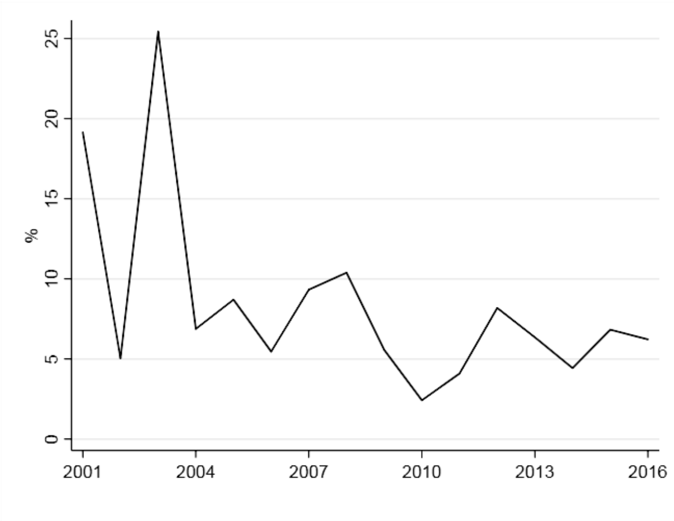


Figure 4.6. Expiration rate, all countries combined, 2001-2016. Source: own calculations, AIB.

in 2011, 2012 and 2014 because they exceed 100%, which should be impossible. We suspect this is caused by inaccuracies in the database. Notably, the number of countries without expirations decreases from 9 in the first period (Austria, Belgium, France, Germany, Italy, Netherlands, Spain and Switzerland) to 2 in the last period (Austria and Portugal). Denmark and Norway have very high expiration rates (>38%) in the initial years, but these decrease to less than 5% in the most recent period. From 2009-2012, the expiration rate decreases to levels below 8% in all countries except for Denmark. However, in the most recent period, expirations increase again in the majority of countries. The expiration rate appears especially high in major importing countries such as Germany and the Netherlands.

4.5.5 Certificate design features and market performance

The panel, consisting of 20 countries with data from 2001-2015, is unbalanced due to the fact that some countries start operating a certification scheme after 2001. There are also several years missing for the electricity price in Croatia, Estonia and Iceland.

We apply a within-estimation procedure to estimate the coefficients of Eqs. (4.8) and (4.9) because the time-invariant individual effects may be correlated with some of our regressors. For example, one could well imagine that differences in preferences for renewable electricity between countries are correlated with income (Mozumder

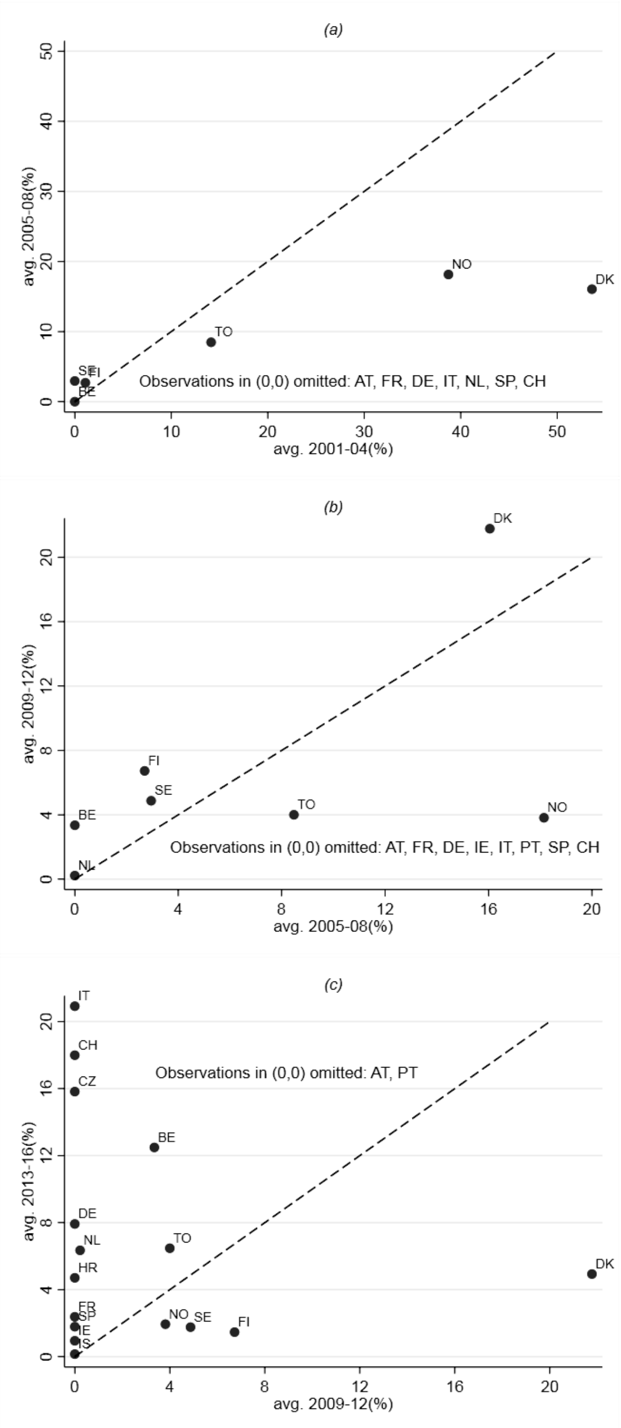


Figure 4.7. Expiration rate by country, 2001-2016. Each plot compares the 4-year average with the preceding 4-year average from 2001-2016. Countries in (0,0) have active certification schemes. Differences in scaling are chosen to enable identification of individual countries in graphs. Source: own calculations, AIB.

et al., 2011) or renewable electricity generation. As a consequence, we do not obtain estimates for the certification and export restriction variables because these did not vary over time in practice.

Statistical tests suggest that the assumption of white-noise errors is not satisfied. Autocorrelation tests as proposed by Wooldridge (2010) do not suggest that autocorrelation is present. However, likelihood-ratio tests suggest that the errors are heteroskedastic. Therefore, we compute White robust standard errors. We opt for this solution rather than computing cluster-robust standard errors because our sample consists of 20 clusters, much lower than the threshold for reliable inference on the basis of cluster-robust standard errors of approximately 50 according to Cameron et al. (2008).

Table 4.4 reports the estimation results, where Model A reports the results of the model in Eq. (4.8) (Columns 2,3 and 4) and Model B reports the results of the extended model in Eq. (4.9) (Columns 5, 6 and 7). Note that Model B has a considerably higher explanatory power (within R-squared of 0.710 vs. 0.223 in Model A) while the signs, sizes and significance levels of our estimates are largely consistent between the two models.

The estimates imply that the presence of the international standard positively influences the market volume. The estimated coefficients are 14.07 and 8.95 respectively for Model A and B which both are significant at a 0.01 confidence level. This effect is substantial: on average, the presence of the international standard positively affects the volume of issued certificates by 9–14TWh. The increase in volume is approximately equal to 57%-90% of the median volume of issued certificates in 2016.

The estimated effect of having a private instead of a public certifier is negative in both specifications and marginally significant (p-values of 0.07 and 0.12 in models A and B, respectively). The estimated coefficients of -5.88 and -4.51 are considerable in size in both models. Although these estimates are less statistically significant, this may point to a negative effect of private certifiers on market volumes. A possible explanation for this negative effect may be that, despite regulatory measures in some countries, private certifiers are able to exert market power, resulting in higher certification fees and lower market volumes. Supportive to this explanation, it appears from AIB statistics that, in 2015, the three private certifiers charged three out of the four highest variable certification fees (AIB, 2015). Another reason could be that end-users regard signals from private certifiers as less trustworthy, as noted by Mahenc (2017).

	Model A			Model B		
	Coeffi–cient	St. error	P-value	Coeffi–cient	St. error	P-value
International standard	14.07***	2.955	0.000	8.95***	2.955	0.003
Private certifier	-5.88*	3.181	0.066	-4.51	2.888	0.120
Renewable electricity generation (TWh)	0.167**	0.08	0.039	0.233***	0.094	0.013
GDP index	0.249*	0.148	0.093	0.139	0.084	0.102
Electricity price (€ / kWh)	-38.48	37.94	0.311	5.417	31.55	0.864
Constant	-33.86***	12.55	0.007	-28.71***	8.59	0.001
Country fixed effects	Yes			Yes		
Period-country fixed effects+	No			Yes		
Observations	284			284		
No. of countries	0.223			0.710		
Within R-squared	284			284		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
+ Period-country fixed effects refer to dummy variables for each country *i* that are equal to one for country *i* during the period 2009-2015 and zero otherwise.

Table 4.4. Fixed effects panel data estimation, 2001-2015. Dependent variable: Volume of issued certificates (TWh).

As expected, the generation of renewable electricity has a strongly significant positive effect on the market volume. The estimated coefficient for the GDP index is positive, conform expectation, and marginally significant. Our estimates for the coefficient of the electricity price have contrasting signs in the two models but are highly insignificant.

4.6 Conclusion and policy implications

Certification schemes have been introduced in renewable energy markets to address the problem of information asymmetry. Information asymmetry is an inherent market failure in energy markets because consumers cannot credibly distinguish between renewable and non-renewable energy. While certification is currently predominantly present in electricity markets, certification is expected to play an increasingly important role in other energy markets once renewable production comes off the ground in those markets (e.g. natural gas, hydrogen). Therefore, it is important to verify whether certification schemes prove an effective mechanism to facilitate trade in renewable energy and investigate how these schemes can be designed effectively.

The purpose of this paper is to investigate the performance of certificate markets and analyse the relationship between certificate system design and market performance. We apply our analysis to the market for electricity GO certification in twenty European countries. The analysis evaluates market performance by analysing (1) the share of certified renewable electricity, (2) the churn rate, (3) price volatility and (4) the share of expired certificates (a measure for 'excess' supply). This paper uses panel data to assess the effect on market performance of two critical design features of certificate systems: the public/private nature of certifiers and the presence of a common international standard.

Overall, the results suggest that markets for GOs remain in their infancy. The share of renewable electricity that receives certification has increased in the EU as a whole and in most individual countries since 2001. However, the other performance indicators yield a more pessimistic view. Market liquidity as measured by the churn rate is very poor and far below levels which are generally associated with a mature and liquid market, both in the region as a whole and in all individual countries. With respect to price volatility, GO certificate prices are very volatile and there are no clear signs of improvement over time. In addition to poor liquidity and high price volatility, the market appears to have been in a constant state of oversupply as a considerable amount of issued certificates is never used to claim the consumption of renewable electricity.

The analysis indicates that certification-scheme design choices affect market outcomes. The findings suggest that adopting a common international standard has a strong positive affect on market volumes. Moreover, we find some evidence that private certifiers could be associated with lower market volumes, which may be due to the higher certification fees that they seem to charge.

A number of data-related caveats of the analysis should be mentioned. First of all, the certification database is incomplete as observations for two countries were partly missing. Second, a few errors were discovered in the certification data. Although serious, we believe that we were able to handle these errors and obtained meaningful results. Thirdly, due to a lack of transparency in market prices, we rely on GO prices from a market monitoring firm. In case these prices are not representative for the market, some of our results may not be representative for the market.

Therefore, we recommend to improve the availability of data for certificate markets as this may facilitate both market liquidity and research on renewable energy markets.

Several policy implications can be drawn from this analysis. We found that European certificate markets are not yet functioning efficiently. With respect to certificate system design, international standardisation of certificates contributes to the efficiency of certificate markets. Public ownership over the certifier may also have a positive effect, although further research is required to corroborate this finding. In addition, policies that aim to improve market transparency may benefit the performance of certificate markets. The current lack of transparency, particularly regarding prices, may harm the confidence of market participants with respect to price formation and deter market entry.

4.A Appendix: Descriptive statistics

		2001–2004	2005–2008	2009–2012	2013–2016
Certification (TWh)					
Issued volume	min	0	0	0	0
	max	8.26	111.08	135.70	136.11
	mean	0.81	5.57	10.83	18.82
	SD	1.88	16.58	25.94	30.43
Cancelled volume	min	0	0	0	0
	max	7.55	28.75	43.81	87.59
	mean	0.38	3.06	9.86	15.85
	SD	1.23	6.34	13.22	19.70
Domestically trans–ferred volume	min	0	0	0	0
	max	0.54	39.58	43.76	88.99
	mean	0.03	1.00	4.67	11.98
	SD	0.10	4.71	9.18	20.57
Expired volume	min	0	0	0	0
	max	5.22	14.53	11.94	18.75
	mean	0.11	0.51	0.58	1.14
	SD	0.61	2.24	1.64	2.79
Imported volume	min	0	0	0	0
	max	8.35	28.14	52.89	80.31
	mean	0.21	2.15	8.22	14.31
	SD	1.23	4.97	13.12	20.50
Exported volume	min	0	0	0	0
	max	6.34	50.54	134.49	161.82
	mean	0.20	2.03	8.10	14.19
	SD	0.94	7.08	21.83	29.29
Renewable electricity production (TWh)	min	0.01	0.01	0.04	0.32
	max	131.39	142.97	159.98	203.70
	mean	31.05	35.21	42.21	50.75
	SD	34.20	38.61	44.16	54.07

Electricity price (€/kWh)	min	0.05	0.07	0.09	0.11
	max	0.23	0.27	0.30	0.31
	mean	0.13	0.15	0.18	0.19
	SD	0.04	0.05	0.05	0.05
GDP index	min	75.30	88.30	94.20	90.20
	max	100.60	121.20	112.20	149.70
	mean	88.02	99.90	100.36	105.71
	SD	5.84	5.68	2.72	9.60

Table 4.A.1. Descriptive statistics for all variables except for GO certificate prices. Sources: *Certification*: AIB; *Renewable electricity production, electricity price (both except for Switzerland) and GDP index*: Eurostat; *Swiss renewable electricity production*: IEA; *Swiss electricity price*: Swiss Federal Office of Energy.

Origin	Technology		2011	2012	2013	2014	2015	2016	2017
Belgium	Biomass	min						38.00	19.20
		max						38.00	54.37
		mean						38.00	36.40
		SD							8.71
	Solar	min							35.00
		max							84.71
		mean							58.28
		SD							23.31
	Wind	min							27.00
		max							103.24
		mean							56.19
		SD							28.67
EU (unspecified)	Biomass	min	26.07	10.85	10.93	4.88	5.81	9.85	12.07
		max	26.66	27.01	10.93	11.50	9.05	24.50	28.00
		mean	26.36	20.06	10.93	7.43	7.62	18.15	20.50
		SD	0.42	7.41		2.92	1.18	4.44	5.21
	Hydro	min					4.62	10.50	14.00
		max					24.00	31.25	41.84
		mean					9.80	20.28	24.97
		SD					5.13	6.43	7.43

	Solar	min					15.00	22.38	15.15
		max					21.86	54.15	46.71
		mean					19.08	43.92	25.84
		SD					2.57	12.61	9.86
	Wind	min	25.75	11.00	9.00	4.50	5.86	18.50	15.51
		max	66.93	48.00	30.55	38.93	18.87	37.05	44.00
		mean	40.94	34.05	19.36	19.71	14.17	24.58	27.36
		SD	16.61	14.01	9.19	13.54	4.53	5.79	8.37
Italy	Hydro	min					7.25	15.77	14.00
		max					18.00	29.00	41.67
		mean					10.57	21.26	26.06
		SD					3.77	3.85	9.26
Netherlands	Biomass	min						45.00	23.00
		max						45.00	66.50
		mean						45.00	36.26
		SD							13.18
	Solar	min							225.00
		max							365.00
		mean							280.00
		SD							74.67
	Wind	min							233.40
		max							451.50
		mean							315.73
		SD							73.22
Nordic	Hydro	min	18.83	12.33	8.60	4.56	4.97	4.66	19.40
		max	62.02	40.08	22.65	10.59	11.73	33.15	39.77
		mean	42.45	27.47	15.10	6.57	8.06	21.75	25.88
		SD	14.30	8.60	4.51	2.10	1.95	6.50	5.51
Switzerland	Hydro	min							70.38
		max							496.99
		mean							282.22
		SD							171.74

Table 4.A.2. Descriptive statistics of GO certificate spot prices (€ ct/MWh). Source: Greenfact.

4.B Appendix: Construction of churn rates and data issues

In the Czech Republic, Finland and Italy, the churn rates based on cancellations spike to unrealistically high levels in the very first year of operation (e.g. 30 in Finland). These rates all drop after the first year and both churn rates based on issuance do not spike. The majority of these certificates was most probably cancelled (or expired) in the next year, thereby inflating the churn rate based on cancellations in the first year of operation. For these three countries, we can be quite certain that the spikes are caused by the way we constructed the churn rates.

For Germany, both the churn rate based on issuance and previous year's issuance spike in 2002 to more than 1000 and 3000 respectively. These spikes are caused by an extremely high level of domestic transfers (more than 513,000) in 2002. In 2001 and 2002 combined, there were less than 600 certificates issued and no imports at all. Moreover, no transfers at all were conducted in Germany in any other year between 2001 until 2007. Also, no cancellations occurred until 2004. This gives sufficient reason to believe that the number of 513,000 transfers does not represent the actual traded volume in Germany in 2002.

In Iceland, the churn rate based on cancellations spikes to 243 in 2015 (coming from 0.37 in the previous year). This is caused by a concurrent decrease in cancelled volume of 89% and massive increase in transferred volume of 7410%. We cannot conclude that our calculation method causes the spike nor that it is caused by suspicious reporting. Two signals that the spike does not represent the actual state of liquidity in 2015 are: (i) the other two churn rates in that year take on plausible values and (ii) the churn rate based on cancellations drops again to 1.8 in 2016. Moreover, even in the most mature and liquid markets, churn rates of 243 are rarely observed. Therefore, we omit this observation.

4.C Appendix: Correlation coefficients between selected certificate spot price series

	Nordic Hydro	EU Biomass	EU Hydro	EU Solar	EU Wind	IT Hydro
Nordic Hydro						
EU Biomass	0.84					
EU Hydro	0.12	-0.03				
EU Solar	0.86	0.92	0.04			
EU Wind	0.57	0.58	-0.14	0.57		
IT Hydro	0.63	0.84	0.01	0.78	0.44	

Table 4.C.1. Correlation coefficients between certificate spot price series.

Chapter 5

Design of renewable support schemes and windfall profits: a Monte Carlo analysis for the Netherlands

5.1 Introduction

Many governments use subsidy schemes in order to increase the production of renewable electricity, and realize climate-policy objectives. Supporting renewable electricity with subsidy schemes involves sizeable government expenditures.[1] For example, in the EU in 2017, governments spent €78.4 billion, or 0.5% of GDP, on subsidies for renewable electricity (Taylor, 2020). These subsidies contributed to renewable electricity production of 1,003TWh or 30.4% of total electricity production (Eurostat, 2020a). Dividing total subsidy expenditures over total renewable-electricity production implies an average subsidy expenditure per kWh of €7.8 ct.[2] Compared to the average electricity wholesale price in the EU over 2015–2019 of

I thank Florian Egli, Marisa Korteland, Sander Lensink, and Sarah Vaessen for data support, and four anonymous reviewers for highly instructive comments and suggestions.

[1]Subsidies are defined here as payments from the government to renewable-electricity investors.

[2]This understates the actual expenditures per kWh since a portion of renewable electricity production is unsupported, such as hydro electricity from the Nordic countries. For reference, renewable electricity production in the EU in 1990 was 328TWh or 12.6% of total production (as in the main text, these figures are for the current EU28 countries) (Eurostat, 2020a). At the same time, as increasing renewable-electricity generation exerts downward pressure on electricity prices (i.e the merit-order effect), subsidy expenditures may exceed the additional cost of renewable electricity to society.

€ 4.1 ct/kWh, this is very substantial (Eurostat, 2020b). The financial burden that subsidy payments put on society is also reflected in the considerable renewable-electricity-specific taxes and levies that typically fund these schemes. For instance, in 2019, the average EU household faced a renewable-energy related tax on electricity consumption of € 2.6 ct/kWh (Eurostat, 2020c).

In light of the considerable expenditures associated with promoting renewable electricity, it is important to design subsidy schemes in a cost-efficient manner. From the perspective of the government budget, attaining cost-efficiency implies not only stimulating low-cost technologies but also not paying more than necessary for a certain project. This is particularly important as taxpayers or energy consumers typically fund the subsidy schemes, such that relatively generous schemes result in large welfare transfers from these groups to subsidized investors, who seek to gain private benefits (see also Borenstein, 2017).

This paper focuses on the degree to which subsidized renewable energy projects yield private benefits in excess of what is required for investors to be willing to undertake them. We refer to these "excessive" private benefits as windfall profits. Limiting windfall profits implies that compensation for a project should not exceed the project's levelised-cost-of-electricity (LCOE). A key challenge for achieving this is that, due to information asymmetry between governments and investors, it is prohibitively costly to observe both the true LCOE and revenues of individual renewable electricity projects. This hinders tailoring the subsidy at the minimally required level for each project. As a consequence, most governments provide a uniform feed-in subsidy for renewable electricity or a specific technique (e.g. on-shore wind). This means that projects with favourable characteristics will be remunerated in excess of their LCOE and, as a consequence, earn windfall profits, putting a financial burden on those who finance the scheme. In turn, this implies a typical trade-off between effectiveness and cost-efficiency (from the perspective of the government budget): a lower subsidy level will improve cost-efficiency and limit windfall profits, but will reduce the policy's effectiveness in triggering investments.

This paper empirically investigates to what extent the Dutch feed-in premium (FiP) scheme resulted in windfall profits.[3] Despite being a relative laggard in the European energy transition,[4] the Netherlands provides a relevant case to study as

[3]FiP is a type of feed-in subsidy where generators are required to sell the electricity on the market and additionally receive a per-unit subsidy, i.e. a premium. The other type of feed-in subsidy is a feed-in tariff (FiT), where generators solely receive a fixed subsidy payment per unit of generation, i.e. a tariff, and, hence, they are not exposed to price risk.

[4]In 2018, the Netherlands had a renewable electricity share of 14.8%, partly due to spending € 1 billion in renewable electricity subsidies in that year.

it has operated a FiP since 2003 and implemented a number of design adaptations specifically aimed at limiting windfall profits without reducing effectiveness. To learn from this experience, we investigate how windfall profits for on-shore wind projects have developed from 2003–2018. In addition, we analyse to what extent investors are able to seek out projects yielding the highest windfall profits, despite the scheme's adaptations.

The contribution of this paper is that, compared with the previous literature which is mainly focused on the efficiency (e.g. Schmalensee, 2012; Borenstein, 2012) and effectiveness (e.g. Nicolini and Tavoni, 2017; Haas et al., 2011) of renewable-energy promotion schemes, it focuses on the distributional effects. Specifically, the paper provides quantitative insight regarding the effect on windfall profits of not sufficiently accounting for heterogeneity in project characteristics in the subsidy scheme design. In addition, we learn whether policymakers can account for this heterogeneity by increasing the scheme's level of detail, thereby reducing the opportunities for firms to realize windfall profits.

Hence, to analyse the degree of windfall profits, we need to account for heterogeneity in project characteristics. We realize this by adding stochasticity in the key wind-project variables to the existing scheme's deterministic calculation of the required subsidy level, based on the characteristics of a reference project. Specifically, for the years 2003, 2009 and 2018, we estimate the distribution of the required subsidy of *potential* on-shore wind projects using Monte Carlo simulations in an investment model with stochastic inputs, reflecting the variability in the characteristics of on-shore wind projects (e.g. full-load hours). We then compare the estimated distributions with the actually granted subsidy. *Potential* investments here refers to the group of investments resulting from the observed spread in stochastic inputs, beyond the group of actually installed turbines. For example, we consider the spread in wind circumstances of practically all locations in the Netherlands. The selected years coincide with the three phases of the Dutch scheme between 2003–2018 (the MEP, SDE and SDE+), which had distinct characteristics. In addition, for 2018, the paper estimates the distribution of the required subsidy of *actual* investments. We compare these estimates with the results for *potential* investments to evaluate how successful investors are in seeking out projects that yield windfall profits.

We find that the windfall profits have decreased considerably in the period 2003–2018. Both the number of potential projects earning windfall profits (from 81% to 68%) as well as the average windfall profit per kWh (from €2.4 ct/kWh in 2003 to €0.9 ct/kWh in 2018) have decreased significantly. This decrease is the result of differentiating between projects as well as tighter assumptions on a project's cost by the government. Nevertheless, windfall profits remain present to a substantial extent and have as a percentage of the granted subsidy remained unchanged (31% in 2003 vs. 32% in 2018). Moreover, in actual practice, investors are highly successful in seeking out the investments that yield the highest windfall profits.

The remainder of this paper is organized as follows. Section 2 discusses the related literature. Section 3 expands on the characteristics and evolution of the Dutch scheme. Section 4 and 5 discuss the method and data, respectively. Section 6 provides the results and discussion. Section 7 concludes.

5.2 Related literature

There exists an extensive literature on the optimal design of climate policy, which is largely focused on the efficiency of policy measures and somewhat less on the distributional effects. This section reviews a number of key lessons from the literature. For a more broad discussion on the various policy options and their design, see for instance Meyer (2003), Haas et al. (2011), Green and Yatchew (2012), Gerlagh and Van der Zwaan (2006) and Schmalensee (2012).[5]

With climate change being a classical market failure in the form of a negative externality from CO_2 emissions, the two optimal policy responses, or first-best solutions, according to the economic literature are (e.g. Stavins, 2011): a carbon tax conform Pigou (1920), or a emission-rights trading scheme conform Coase (1960). When adequately designed, these policies result in exact internalization of the external costs associated with emitting CO_2 (e.g. producing/consuming electricity with fossil fuels) and, as a result, highest possible productive efficiency. Other, typically less efficient, available policy tools that may contribute to decarbonization target the electricity sector more directly, such as feed-in subsidies for renewables, a renewable portfolio standards (RPS) and command-and-control measures. These policy tools are sometimes referred to as second-best climate policies, given that they typically do not result in exact internalization of the external costs of fossil-fuelled generation, and therefore not in maximum productive efficiency (e.g. Borenstein, 2012; Schmalensee, 2012). A major reason for this is that second-best policies usually focus on a particular reduction option (e.g. renewable electricity) while other, potentially less costly, reduction options may be available.

[5]Readers interested in the effect of increasing renewable-electricity generation on electricity prices may consult e.g. Hirth (2013) and Gianfreda and Bunn (2018).

Despite being regarded as sub-optimal by most economists, second-best policies have become highly popular for addressing emissions in the electricity sector. This is particularly true for subsidies. In 2018, out of 135 countries with some form of regulatory policy for renewable electricity in place, 111 operated a feed-in subsidy (REN21, 2020). In support of their effectiveness, there is empirical evidence that subsidies result in increased investment in renewable electricity (Bolkesjø et al., 2014; Nicolini and Tavoni, 2017; Dijkgraaf et al., 2018). Regarding the popularity of second-best policies, Lyon and Yin (2010) empirically investigate the motivation of US states to implement an RPS and find that the main drivers appear to be political ideology and private interests.

In the literature on policy support for renewable electricity, subsidies have also been extensively compared to an RPS (e.g Schmalensee, 2012; Haas et al., 2011). The key difference is that, with subsidies one fixes the price/support and let the market determine the quantity of renewable electricity, whereas with an RPS one fixes the market quantity and let the market determine the price/support through trade in RPS certificates. Principally, subsidies and an RPS may achieve the same market outcome with the same burden for society.[6] Several scholars point out that subsidies provide more certainty to investors than an RPS, considering that the latter creates certificate-price risk, which puts upward pressure on the required return on equity (Lemming, 2003). This may result in subsidies providing more renewable generation per Euro of support (e.g Mitchell et al., 2006; Haas et al., 2011). Related to this, Jaraitė and Kažukauskas (2013) find empirical evidence that firms operating in a country with an RPS have higher levels of accounting profit.[7]

With respect to the design of subsidies in relation to windfall profits, Haas et al. (2011) propose that a support scheme should be technology specific. They argue that, due to the large differences in costs between renewable-electricity technologies, a uniform subsidy for all technologies could result in considerable windfall profits to the infra-marginal renewable electricity producers. They suggest this can be limited by differentiating in the level of the subsidy between technologies. A downside is that this may aggravate the above-mentioned productive-inefficiency drawback due to the support encompassing fewer reduction options.

[6]Provided that the subsidy is financed through a levy on electricity consumers. Otherwise, an RPS tends to increase the price of electricity, putting downward pressure on demand, whereas subsidies do not.

[7]The authors view the additional accounting profits as excess profits. In our view, this may not necessarily be the case because these additional accounting profits may reflect a normal compensation for the additional risk associated with investing under an RPS, as compared to investing under a feed-in subsidy.

From a public finance perspective, subsidies for renewable energy that result in windfall profits are not desirable for at least two reasons. Firstly, subsidies that result in windfall profits imply welfare transfers to renewable-electricity producers from other economic agents, such as electricity consumers or taxpayers. The latter groups may perceive this as unfair, potentially eroding their support to contribute to policies for climate-change mitigation (Verbruggen, 2008). Secondly, many governments, for instance in the OECD countries, are relatively limited in their capability to raise public spending, owing to limitations on raising additional taxes or public debt. Considering that renewable energy goals and associated subsidy expenditure "compete" with other governmental goals that require public expenditure (e.g. providing infrastructure, social security, healthcare etc.), minimizing expenditure on renewable energy subsidies contributes to simultaneously achieving as many of these goals as possible (Joumard et al., 2004).

From this review, we infer that the optimal subsidy level for renewable electricity meets two conditions: (i) subsidies are productively efficient, i.e. should trigger the low-cost reduction options; and (ii) subsidies should not result in windfall profits to investors. Point (ii), this paper's focus, translates to setting the subsidy equal to the minimally required level for investors to be willing to undertake the project. In turn, given the irreversible nature of investments in renewable electricity, this implies promising a subsidy such that the net present value of the project is exactly zero: $NPV = 0$.

5.3 The Dutch subsidy scheme for renewable electricity

This section discusses the Dutch subsidy scheme for renewable electricity and its development from 2003–2018. The scheme has been a FiP since the start and aims at remunerating the part of an investment in on-shore wind that cannot be earned back in the market. The design of the scheme has changed several times, which is reflected in the scheme's name changes in 2008 (from MEP to SDE) and 2011 (from SDE to SDE+). Table 5.1 provides an overview of the key aspects of the scheme.[8]

[8] With respect to the characteristics of investors, we note that, in the EU, as with projects in other industries, there are few restrictions on the eligibility to invest in renewable-electricity projects. Our analysis investigates windfall profits by comparing revenues and costs, including the opportunity cost of capital. When profits are nonnegative for a project, investing is attractive, no matter where the investor comes from. In practice, investors in renewable energy projects in the Netherlands are domestic as well as foreign.

Prior to discussing the adaptations to the design of the scheme, we first discuss the general rule that has been used to determine the subsidy level, which remained constant over the full period.

Name of scheme	MEP	SDE	SDE+
Period	2003-2006	2008-2010	2011-2018
Scheme type	Fixed FiP	Sliding FiP	Sliding FiP
Premium adjustment frequency	Never	Annually, based on average capture price	
Category differentiation within on-shore wind	1 category	1 category *(2008-09)* 2 categories *(2010)*: turbine<6000kW turbine>6000kW	2 categories *(2011-14)* 4 categories *(2015-18)*: 8≤wind speed[+](ws) 7.5≤ws<8 7≤ws<7.5 ws<7

Table 5.1. Key characteristics of subsidy scheme. [+] In meters per second.

5.3.1 The general rule determining the level of the Dutch subsidy

During the period 2003–2018, to determine the level of the subsidy, the government has applied the general principle of determining the minimally required subsidy for an equity investor to be willing to invest in the project. This calculation is based on an NPV model of the revenues and expenses of an on-shore wind project to an equity investor. Regarding debt financing, the Dutch support scheme makes assumptions about financial variables, such as the share of equity investment and interest rate, and these serve as inputs in the NPV model.

To calculate the minimally required subsidy per kWh (S), the point of departure is realizing that equity investors are willing to invest as long as the NPV of the project's revenues (NPV_R; including subsidy payments) exceeds the NPV of the project's expenditures (NPV_C): $NPV_R - NPV_C \geq 0$. The optimal (i.e. minimally required) subsidy is where $NPV_R - NPV_C = 0$. This does not imply that the support scheme tries to prevent investors from earning a positive accounting profit. After all, the rate at which future cost and benefit cash flows are discounted represents the return on equity (r_e) and, when all other inputs (and the model itself) are assumed precisely correct, the return on equity determines to which extent the investor earns accounting profit. If the return on equity equals a normal return for the associated risk (i.e. is also assumed precisely correct), investors earn positive accounting profit and zero economic profit.

In a given year, the support scheme identifies as revenues to the equity investor the market value of electricity, nominally equal to the production (Q, in kWh) times the electricity price (P^e, in € ct/kWh), and the subsidy revenue, nominally equal to Q times the per-unit subsidy (S, in € ct/kWh). The initial support scheme provided a fixed feed-in premium, such that the subsidy S remained fixed over the lifetime of the project. As a result, the NPV of revenue (in € ct) equalled:

$$NPV_R = \sum_{t=1}^{T} \frac{(1-\tau)Q_t(P_t^e + S)}{(1+r_e)^t} \tag{5.1}$$

where t refers to year, T to the lifetime of the project in years and τ to the corporate tax rate.

The costs to an equity investor consist of three main components: the initial equity investment, the operating costs of the wind turbine, and the costs associated with debt financing. The support scheme assumes that the annual operating costs are composed of a fixed component and variable per-unit costs of production. Further, it is assumed that the loan is an annuity loan. The NPV of the total costs becomes (in € ct):

$$NPV_C = eX + \sum_{t=1}^{T} \frac{(1-\tau)(1+\pi)^t[Q_t VC_t + FC_t] - \tau[D + I_t] + A}{(1+r_e)^t} \tag{5.2}$$

where e is equal to the share of equity in total investment, X to the total one-time upfront investment (in € ct), VC to the variable costs of production (in € ct), FC to the fixed operating costs (in € ct), D to depreciation (in € ct), and A to the fixed annual annuity (in € ct; which is equal to the loan instalment R plus interest payment I, both in € ct).

Using (1) and (2) in $NPV_R - NPV_C = 0$ and solving for S gives the minimally required subsidy (in € ct per kWh):

$$S = \frac{eX + \sum_{t=1}^{T} \frac{(1-\tau)(1+\pi)^t[Q_t VC_t + FC_t] - \tau[D+I_t] + A}{(1+r_e)^t}}{\sum_{t=1}^{T} \frac{(1-\tau)Q_t}{(1+r_e)^t}} - \frac{\sum_{t=1}^{T} \frac{(1-\tau)Q_t P_t^e}{(1+r_e)^t}}{\sum_{t=1}^{T} \frac{(1-\tau)Q_t}{(1+r_e)^t}} \tag{5.3}$$

This expression says that the subsidy per kWh is equal to the NPV of total expenditures per kWh minus the NPV of revenues in the electricity market per kWh. We refer to the first term on the right-hand side as the base subsidy (B, in € ct/kWh). B is equal to the minimally required subsidy per kWh when the electricity price is equal to zero and, therefore, an estimate of the LCOE. Denoting the second term on the right-hand side as the discounted volume-weighted average electricity price ($\bar{P}^e$, in €ct/kWh), (3) becomes:

$$S = B - \bar{P}^e \tag{5.4}$$

The support scheme uses the following assumptions and definitions on the elements of (3):

- $Q_t = F_t U = FU$, where F and U are the annual number of full-load hours and turbine capacity (in kW), respectively. The full-load hours F are assumed to be constant over time;
- $X = c_i^{kW} U$, where c_i^{kW} equals the investment costs per kW of turbine capacity;
- $VC_t = c_q^{kWh} Q_t = c_q^{kWh} FU$ and $FC_t = c_f^{kW} U$, where c_q^{kWh} and c_f^{kW} are parameters equal to the variable operating costs per generated kWh and fixed operating costs per kW of capacity, respectively;[9]
- $D = X/T$. Depreciation occurs linearly over the life time;
- $A = \frac{r}{1-(1+r)^{-T}}(1-e)X$, where r is the interest rate on the loan. This is the general expression for an annuity loan of $(1-e)X$, i.e. the debt requirement;
- $I_t = A - R_t = A - R_1(1+r)^{t-1} = A - [A - (1-e)X(1+r)](1+r)^{t-1}$. This follows from general principles of annuities.

A consequence of these assumptions and definitions is that the estimates of S and B do not depend on U because all components on the right-hand side of (3) are proportional to U.[10]

Based on Equation (3) and the additional assumptions, the key unknown parameters that need to be determined to estimate B are:

- F, the number of full-load hours per year;
- c_i^{kW}, c_q^{kWh} and c_f^{kW}, the cost parameters;
- T, the lifetime of the project;
- r_e and r, the required return on equity and interest rate, respectively;

[9]This implies that the scheme assumes that the fixed and variable operating costs remain constant over time. In reality, these costs appear to have decreased (Wiser et al., 2020). While this is not necessarily a source of heterogeneity, and thus does not necessarily affect the estimated spread in windfall profits across projects, it may impact the accuracy of our estimates of the level of windfall profits.

[10]I.e. the scheme assumes that there are no economies of scale and constant returns to scale.

- e, the share of equity in the total investment;
- π, an inflation parameter pertaining specifically to the cost parameters.

When the electricity price can be perfectly forecasted, the subsidy rule with a fixed per-unit subsidy in Eq. (3) would result in an NPV of zero, both in expectation and realization. In practice, however, electricity prices are uncertain and cannot be forecasted perfectly, such that, while the subsidy rule in Eq. (3) may result in an *expected* NPV of zero (such that investors are willing to undertake the project), the *realized* NPV may be different.[11] In 2006, the scheme introduced a sliding-premium, with annual updates of the (estimated) realized average electricity price during the lifetime of the project. In this new setting, prior to granting the subsidy, the government estimates B and promises to pay a subsidy S_t, equal to B minus the realized electricity price in each year:

$$S_t = B - P_t^e \tag{5.5}$$

Assuming a constant annual production level of Q, this implies that producers receive $Q \times B$ each year, regardless of the realized electricity price.[12] Notice that, ex-ante to granting the subsidy, this also follows from Eqs. (3) and (4). Hence, this subsidy rule corresponds to the subsidy rule that would follow from (3) with perfect information about the investor's expected electricity prices.

Table 5.2 lists the assumptions for the key parameters of the NPV model in 2003, 2009 and 2018. As will be further discussed in the next subsection, there were four on-shore wind subsidy categories in 2018, with distinct assumptions regarding the full-load hours.

5.3.2 Adaptations to the subsidy scheme

Table 5.1 displays the evolution of two key features of the scheme's design that were adapted: (i) the introduction of category differentiation for on-shore wind projects in 2010 and subsequent expansion of the degree of differentiation from 2011–2015;

[11] For this reason, the scheme until 2006 (the MEP) still classifies as a FiP rather than a FiT since producers were themselves responsible for selling the electricity on the market and were therefore exposed to price risk.

[12] The government maintains a price floor on the electricity price, which the next subsection discusses. If the electricity price would decrease below the price floor, revenues would actually be lower than $Q \times B$.

and (ii) the introduction of a sliding premium in 2008.[13]

Prior to 2010, there existed a single on-shore wind category with a uniform subsidy level. From 2010 onward, with the specific aim to limit windfall profits, the government introduced subsidy categories with respective subsidy levels. The intention was to differentiate in the required subsidy of projects on the basis of observable characteristics. In 2018, four on-shore wind subsidy categories existed, differentiated by the long-term average wind speed in the project's municipality. Table 5.1 lists the various subsidy categories and Figure 5.A.1 in Appendix 5.A displays category differentiation geographically. The subsidy level within a category is set equal to the estimated required subsidy of a reference project, based on Equation (3). In the NPV model, this translates to different assumptions for the number of full-load hours in each subsidy category (see Table 5.2 for the assumptions by category). For example, in 2018, the assumed number of full-load hours in the category wind speed$<$7m/s is 2350 whereas in the category wind speed$\geq$8m/s it is 3500. As a result, the base subsidy (and hence actual subsidy) is lower for the latter category.

[13] In 2011, another adaptation that was introduced was category phasing, applying simultaneously to all renewable-electricity technologies. Phasing entailed offering a subsidy in phases to the various subsidy technologies and categories, which had a distinct subsidy level (based on the estimated required subsidy). Categories with a relatively high subsidy were not eligible for subsidy in the first phase. With each phase, more costly categories became eligible. Phasing, however, was not relevant for on-shore wind subsidies in 2018 because all four on-shore wind categories were eligible for subsidy in the first phase.

Project characteristic	2003 (MEP)	2009 (SDE)	2018 (SDE+) $8 \leq ws$	$7.5 \leq ws < 8$	$7 \leq ws < 7.5$	$ws < 7$
Economic lifetime/ subsidy lifetime[1] (years)	15/10	15/15	15/15	15/15	15/15	15/15
Full-load hours	1800	2200[2]	3500	3100	2750	2350
Cost parameters						
c_i^{kW} (€ /kW)	1150	1250	1200	1200	1200	1200
c_q^{kWh} (€ /kWh)	0.018	0.01	0.0141	0.0141	0.0141	0.0141
c_f^{kW} (€ /kW)	0	24	12	12	12	12
Equity share	20%	20%	20%	20%	20%	20%
Return on equity	15%	15%	14.5%	14.5%	14.5%	14.5%
Interest rate	5%	5%	2%	2%	2%	2%
Inflation rate	0%	2%	1.5%	1.5%	1.5%	1.5%
Electricity price (P^e; € ct/kWh)	2.11	Annually adjusted				
Base subsidy (€ ct/kWh)	10.3	8.6[2]	5.4	5.9	6.4	7.3
Actual subsidy (€ ct/kWh)	7.8	Depends on P^e				
At $P^e = 4$	7.8	4.6	1.4	1.9	2.4	3.3
Electricity price floor (€ ct/kWh)	-	3.92	2.2	2.2	2.2	2.2

[1] Under the MEP, subsidies were paid during the first 10 years (subsidy lifetime) whereas the assumed lifetime of the project was 15 years (economic lifetime).
[2] In 2009, the government estimated the base subsidy using the parameter values in the table. However, for the actual payments, the government multiplied the base subsidy with $\frac{1}{80\%}$ which was paid out over 80% of the assumed full-load hours. This has no impact on the generosity of the subsidy but it guarantees that investors receive the estimated subsidy requirement in each year, including years with below-average wind speeds, because production in excess of the assumed full-load hours in windy years was not eligible for subsidy. In the SDE+, this was replaced by a system of banking in which under or overproduction was retained over time.

Table 5.2. Government assumptions for the key parameters in the subsidy calculation

Prior to 2008, the scheme contained a fixed feed-in premium, such that the electricity price was treated as an input that needed to be estimated for the entire lifetime of the project. Since 2008, the scheme contains a sliding premium, such that the government adjusts the actual subsidy per kWh annually, based on the realized (i.e. 'captured') electricity prices.[14] A single, nationwide estimate of the captured electricity price for wind turbines is calculated each year, applying to all subsidized turbines. As the capture price may differ across turbines due to differences in local weather conditions, the underlying temporal distribution of power production may create a location-specific source of price risk (Grothe and Müsgens, 2013). This paper does not consider this type of price uncertainty and its impact on windfall profits, as the Netherlands is a small country with relatively small differences in weather conditions between locations, such that capture prices are similar across locations.[15] With respect to the estimated capture price, the government maintains a floor on this price such that the actual subsidy is capped at the level of the base subsidy minus the floor on the capture price (P^e_{floor}). Therefore, the following condition applies to Equation (5): $S_t \geq B - P^e_{floor}$.

5.4 Method

5.4.1 Analytical framework

In practice, projects differ in a wide number of characteristics, such as the average wind speed, the generation profile, restrictions from land-use regulations (e.g. on the maximum height) etc. This results in a different required subsidy for each project. Optimally, the government would tailor the subsidy level to the characteristics of each individual project such that $NPV = 0$. However, this is impossible (or prohibitively costly) in practice due to information asymmetry between investors and the government: investors have better information than the government about the costs and benefits of their projects and, therefore, the required subsidy. For

[14]In a given year, the government now estimates the realized electricity price by taking the hourly unweighted-average day-ahead electricity wholesale price and multiplying by a correction factor to account for profile and imbalance costs. Profile costs emerge from the negative correlation between wind-electricity production and electricity prices. This implies that the unweighted-average electricity price tends to overestimate the average price received by wind producers. Imbalance costs emerge from differences in predicted and realized production levels. The correction factor is estimated annually on the basis of data from wind turbine operators and is constant across subsidy categories. For reference, in 2009 and 2018, the correction factor was set equal to 0.89 and 0.88, respectively.

[15]We have estimated the capture prices of hypothetical wind turbines at the following four geographically spread locations, of which two are coastal and two in the country's interior: Lauwersoog in the North, Hoogeveen in the East, IJmond in the West and Eindhoven in the South. We estimate the capture price by first estimating the hourly capacity factor at each location of a hypothetical turbine with a rated and cut-in wind speed of 12.5 m/s and 3 m/s, respectively, using hourly wind speed data from KNMI. Consequently, we estimate the capture price as the capacity-factor-weighted-average price at the four locations using hourly electricity day-ahead prices in 2018, obtained from Bloomberg. The respective capture prices (in €ct/kWh) equal 5.29, 5.28, 5.36 and 5.28 for Lauwersoog, Hoogeveen, IJmond and Eindhoven. Hence, these tend to be highly similar.

governments, it is not possible to rely on information from investors given the incentives of the latter to overstate the costs and understate the benefits.

As a consequence of this information asymmetry, the government offered the same subsidy to all on-shore wind projects prior to 2010, and to all projects within a subsidy category since then. Given that on-shore wind projects may differ considerably from each other, even within subsidy categories, the minimally required subsidy also varies between projects. As a result, for some projects, the minimally required subsidy will deviate from the actually granted subsidy. The government's deterministic estimate of the required subsidy will be too low for some projects and too high for other projects. Projects for which the estimate is too low will generally not be undertaken. Projects for which the estimate is too high will receive a higher subsidy than what was required for investors to be willing to undertake the project. Consequently, for realized projects, one may expect that the break-even constraint ($NPV \geq 0$) is satisfied.

Projects that receive a higher subsidy than their minimally required subsidy are deemed to enjoy windfall profits. The level of profit on these projects exceeds a normal profit level, given the risk associated with the project. Windfall profits arise when the actually granted subsidy (i.e. the government's estimate of the minimally required subsidy) deviates from a project's minimally required subsidy. We focus on the key source of windfall profits in the Netherlands, which is that the government's estimate of the base subsidy B may differ from a project's actually required base subsidy.[16] We define windfall profits per unit as B minus a project's actual LCOE (i.e. as the government's estimate of the minimally required subsidy minus the actual minimally required subsidy).

In the scheme, windfall profits arise when the assumptions about B in the NPV model in (3) for the reference project result in overestimating a project's LCOE. For example, the amount of full-load hours is assumed to be constant within a category. In reality this differs for each project. Consider two turbines located in municipalities with an average wind speed between 7m/s and 7.5m/s. If one turbine faces a wind speed of 7.1m/s and the other turbine a wind speed of 7.4m/s, the latter turbine has (ceteris paribus) a lower LCOE. However, in 2018, the subsidy for these two projects is identical (both are located in the green area on the map in Figure 5.A.1 in Appendix 5.A). Prior to the introduction of category differentiation, the subsidy was even fully independent of the expected wind speed/full-load hours.

[16]The other potential source of windfall profits is differences between the government's estimate of the capture price and the realized capture price. As argued in the previous footnote, this source is not very relevant in the Netherlands.

Ideally, to assess the degree of windfall profits, we would estimate the required subsidy for each individual project using project-level data and compare it with the granted subsidy. However, it is practically not possible to obtain the required micro-level data for this type of analysis. To overcome this, the analysis approaches the individual situation by (i) using other data that is available and enables estimating distributions for the key stochastic parameters of on-shore wind projects (e.g. wind speeds), and (ii) using these distributions as inputs in Monte Carlo simulations to estimate the distribution of the required subsidy.

5.4.2 Monte Carlo simulations

In order to estimate the windfall profits, we use the same NPV-based approach to calculate the required subsidy as the Dutch support scheme, i.e. Equation (3). Instead of the scheme's deterministic approach, however, this paper applies a stochastic approach. This way, the analysis explicitly considers that several key inputs of (3) differ among projects. NPV models are widely used for investment appraisal, including for investments in wind turbines (e.g. Schmidt et al., 2013; May, 2017). Using the same NPV-based approach as the official scheme, instead of another approach (e.g. real-options valuation), enables focusing on the effect on windfall profits of accounting for stochasticity.

The analysis introduces stochastic elements by taking into account that several key inputs of (3) vary between projects according to a certain distribution. We consider that the following inputs are stochastic: the number of full-load hours, the economic lifetime, the required return on equity and the share of equity (Table 5.2 lists the scheme's official assumptions for these inputs). The analysis replaces these deterministic values by a fitted distribution, based upon gathered data and information. The Data section below expands on the approach of fitting appropriate distributions.

After assuming a distribution for the stochastic inputs, we apply Monte Carlo simulations to estimate the required subsidy with Eq. (3) 2000 times.[17] In each simulation, an estimate is obtained of a project's minimally required subsidy. Based on these estimates, we are able to construct cumulative density functions (CDF) of the required subsidy. Consequently, we compare the CDF with the actually granted subsidy, which is based on the deterministic model with the scheme's official as-

[17]Using more simulations has a small effect on the key estimates and does not affect the conclusions. For instance, the difference between using 10,000 and 2,000 simulations in the estimates of the percentage of projects requiring less than the actual subsidy is, on average for the years and categories, 0.35 percentage points, and never more than 0.8 percentage points .

sumptions. To assess the extent of windfall profits, we inspect three key criteria: (i) the share of investments in on-shore wind that receives 'too much' subsidy, (ii) the average windfall profits per kWh enjoyed by profitable investments, and (iii) the average economic loss per kWh, which we refer to as "missing money", of unprofitable investments.

We perform this exercise for 2003 (the MEP scheme), 2009 (the SDE scheme) and 2018 (the SDE+ scheme). Given that there existed a single category for on-shore wind in 2003 and 2009, we perform the analysis once for these years. For 2018, we perform the simulation analysis for each of the four subsidy categories. This implies that the estimates of the distribution of the required subsidy for 2003 and 2009 are on a country-level, whereas for 2018, the estimates are for four separate regions that correspond to the four subsidy categories in that year (see Fig. 5.A.1).

5.5 Data

The analysis uses data from various sources. The goal is to obtain data and information about the stochastic variables that can be transformed into a probability distribution for the simulation exercise.

Data on the project level is unfortunately largely unavailable. To cope with this, the analysis uses other data sources to estimate or assume a distribution for the stochastic inputs. Specifically, the analysis (i) combines annual-average wind speed data for at approximately all locations and heights with hourly wind speed data of four weather stations to estimate distributions of the amount of full-load hours, (ii) fits a distribution to the observed lifetime of turbines constructed before 2003, for which we typically can observe the lifetime, (iii) assumes a distribution for the share of equity financing based on data for Germany from Egli et al. (2018), and (iv) assumes a distribution for the required return on equity also on the basis of data from Egli et al. (2018). The input distributions are not limited to the group of installed turbines but extend to all locations and heights. In turn, the estimated CDFs include all potential combinations of the input parameters. Therefore, they pertain to all *potential* investments, and have a theoretical nature.

5.5.1 Full-load hours

Transforming wind speed in to full-load hours

To estimate the distribution of full-load hours, we depart from the formula for power output (P) of a wind turbine at a given time:

$$P = 1/2\rho A v^3 c_p \eta_g \eta_b \tag{5.6}$$

where ρ represents the air density, A represents the swept area of the rotor, v equals the wind speed (in m/s), c_p is the power coefficient, and η_g and η_b represent the generator and gearbox efficiencies, respectively (Manwell et al., 2010). Assuming that the wind speed is constant during a year, the number of full-load hours (F^{avg}) of project i is given by the power output that the turbine generates at the location's average wind speed (P^{avg}), divided by the turbine's maximum output (P^{max}), multiplied by the (average) number of hours in a year of 8766 ($= \frac{3*8760+8784}{4}$; accounting for leap years):

$$F_i^{avg} = \frac{P_i^{avg}}{P_i^{max}} 8766 = \frac{1/2\rho_i A_i (v_i^{avg})^3 c_{p,i}\eta_{g,i}\eta_{b,i}}{1/2\rho_i A_i (v_i^{max})^3 c_{p,i}\eta_{g,i}\eta_{b,i}} 8766 = (\frac{v_i^{avg}}{v_i^{max}})^3 8766 \tag{5.7}$$

where v^{avg} is the long-term average wind speed, and v^{max} the rated wind speed (i.e. the minimum wind speed at which the turbine delivers its maximum output). We assume that the rated wind speed is 12.5 m/s for all turbines.[18] While Equation (7) is an imprecise measure of the full-load hours because the wind speed is not constant in reality (which will be addressed below in this section), it importantly reflects the fact that wind speed is a critical determinant of full-load hours. Therefore, to estimate the distribution of full-load hours, we require information on the distribution of the wind speed.

We extract data for the long-term average wind speed at a large amount of locations using the 'Windviewer SDE+'. The Windviewer SDE+ contains the long-term average wind speed at every location in the Netherlands at every height between

[18] In reality, the design of wind-turbines is optimized for the local conditions at a turbine's location. This may result in systematic differences in the rated wind speed across location-height combinations. In particular relevant for our analysis is that the rated wind speed tends to be somewhat higher at favourable wind locations. Our generic assumption of 12.5 m/s for all turbines, which is based on the observation that many of the commonly installed turbines have a rated wind speed of 12 or 13 m/s (see e.g. https://en.wind-turbine-models.com/turbines), may therefore overstate the rated wind speed at locations with a low average wind speed, and understate the rated wind speed at locations with a high average wind speed. In turn, this may result in an underestimation of the full-load hours of the former, and overestimation of the full-load hours of the latter.

20m and 260m (based on meteorological data from the KNMI). To pick the locations, we select a number of random coordinates within the borders of each municipality (n=380) using GIS. The number of coordinates per municipality is chosen proportionally to the municipality's surface size, with the largest number of coordinates being 100 for Southwest-Frisia (Súdwest-Fryslân), the largest municipality.[19] This yields a total of 4583 coordinates. Next, for each coordinate, we select 5 heights which represent the hub heights of theoretical wind turbines at that coordinate. This gives a total number of $4583 \times 5 = 22,915$ coordinate-hub height combinations.[20]

The choices of the hub heights have a strong impact on the distribution of full-load hours because the wind speed is higher at greater altitudes. In this analysis, it is particularly important to take into account that turbines have become increasingly high in the past two decades. To select appropriate heights, we look at the actual hub heights of newly installed (on-shore) turbines in the subsidy year and the subsequent year.[21] The historical data for hub heights is provided by Bosch & van Rijn / Windstats.[22] Based on this data we assign each turbine to a hub-height category of 10m: 31-40m, 41-50m etc. This yields a discrete probability distribution for the hub-height categories of newly installed turbines for the three years. Figure 5.B.1 in Appendix 5.B displays the result of this exercise for 2003. Consequently, we randomly select five heights per coordinate with the following rule: the height falls within a hub-height category with a probability equal to the share of new turbines in that hub-height category for the given year. Finally, the exact height is a random number from the range of heights within that category (only whole integers are considered).[23] For example, in 2003, the selected height falls in the hub-height category 61-70m with a probability of 0.37 (see Figure 5.B.1 in Appendix 5.B). Given that this height category is selected, each particular height within this category has a probability of 0.1 of being selected. This implies that, with this procedure, each of the integers ranging from 61-70 has a 3.7% chance ($0.37 \times 0.10 \times 100\%$) of being selected.

[19]The coordinates are based on the RD (Rijks-Driehoek) coordinate system. We used the municipal situation of 2018. For municipality size, we used data from Statistics Netherlands (CBS).

[20]In other words, these coordinate-height combinations are approximately randomly distributed in a 3D shape of the Netherlands.

[21]Considering that (a) there is usually a time lag between the moment the subsidy is granted and the commissioning of the wind turbine longer than a year (e.g. under the SDE+, subsidy receivers have to commission the turbine within 4 years), and (b) that the hub heights of newly installed turbines has been increasing yearly, our choices for the heights of the turbines can be considered relatively conservative.

[22]See https://windstats.nl/. This historical database includes characteristics of almost all Dutch wind turbines.

[23]This means that we assume that, within a height category, heights are uniformly distributed.

To transform the wind speed observations in to full-load hours, we use a modified version of Equation (7). Eq. (7) tends to underestimate the actual full-load hours (F) because the wind speed is not constant during a year and wind speed enters the power equation with a third power. In other words, the difference between power output at the average wind speed and power output at a wind speed of 1 m/s *above* the average is bigger than the difference between power output at the average wind speed and power output at a wind speed of 1 m/s *below* the average. Therefore the variation in wind speed at a location is an important determinant of F. As location-specific data regarding within-year variation in the wind speed is not available to us, we estimate a wind-profile correction factor (f^{cor}). This correction factor is specific to the turbine's location l (interior vs. coastal) and average wind-speed range w, and is based on hourly wind-speed observations at four Dutch weather stations. Appendix 5.C provides the details on the construction of the correction factors.

Considering that wind turbines occasionally fail or require maintenance, we assume that wind turbines are not producing 2% of the time, i.e. the downtime $d = 0.02$ (Echavarria et al., 2008).[24]

Our translation of the average wind speed at the location-height point of project i becomes:

$$F_{i,l,w} = (1-d) \times f^{cor}_{l,w} \times F^{avg}_i = 0.98 \times f^{cor}_{l,w} \times \left(\frac{v^{avg}_i}{12.5}\right)^3 \times 8766 \tag{5.8}$$

Fitting distributions to the full-load hours data

To fit a distribution to the full-load hour observations, we first inspect a histogram of the data. Appendix 5.D displays the histograms for 2003, 2009 and, by category, for 2018. The histograms show that the location of the peak and the length of the tails in the distribution differs by year and subsidy category. In 2003, there appears to a somewhat longer tail on the right-hand side. In 2009, there also appears to be more mass in the left side of the distribution. For the four categories in 2018, the distributions have relatively longer tails on the left-hand side. Based on a visual inspection and the literature (see e.g. Gianfreda and Bunn, 2018), we select a wide range of theoretical distributions as appropriate candidates, including the lognormal, inverse Gaussian, gamma, inverse gamma, beta, minimum extreme value type 1, Rayleigh and Weibull distributions.

[24] We are implicitly assuming that the downtime is randomly distributed over time. In practice, operators may try to schedule predictable downtime at hours with a low wind speed, such as downtime for maintenance.

To fit the distributions to the data, we use maximum-likelihood to estimate the distribution parameters. Consequently, we calculate the Akaike information criterion (AIC) for the fitted distributions and use the distribution with the lowest AIC value in the simulations.

For the full-load hours in 2003 and 2009, we assume a gamma distribution. For 2018, we assume minimum extreme value type 1 distributions for the three subsidy categories with the lowest wind speeds, and a Weibull distribution for the subsidy category with the highest wind speed. Table 5.F.1 in Appendix 5.F displays the fitted distributions.[25]

5.5.2 Economic lifetime

To estimate the distribution of the economic lifetime of turbines, we use historical data on the commissioning and decommissioning of Dutch turbines. This data is also provided by Bosch & van Rijn / Windstats. Figure 5.E.1 in Appendix 5.E shows a histogram of the observations.

A difficulty for estimating the distribution of the lifetime is that we only observe the decommissioning date of decommissioned turbines, but not the decommissioning date of active turbines. This results in an over-representation of turbines with a short lifetime and a form of non-survivor bias in estimating the distribution of the economic lifetime. This problem is aggravated by the fact that the amount of newly installed turbines has grown significantly in more recent periods. The large majority of these turbines has not reached a conventionally assumed economic lifetime of about 15 (assumed by Dutch government) or 20 years (Fraunhofer, 2018). To partly overcome this problem, the analysis only considers turbines installed before 2003 for estimating the distribution of the lifetime (n=806), as we know the decommissioning date for the majority of those turbines.[26]

Since the economic lifetime is an inherently stochastic factor (and individual project risk cannot be perfectly observed), insurance policies exist against prema-

[25]Because of the limited number of observations, particularly for the tails of the distributions, the fitted CDFs are approximations of the true distributions and include values outside the range of observed full-load hours. This results in some draws in the simulations that are outside of the range of observed values. However, we are not highly worried about the impact on the results, as 96% of the fitted joint cumulative density overlaps with the observed range of full-load hours.

[26]A more conventional solution for analysing survival data and lifetimes would be to use the Kaplan-Meier estimator. However, for some (old) decommissioned turbines, which cannot be identified, the database does not report the decommissioning date and the Kaplan-Meier estimator regards these turbines as not-decommissioned i.e. very old but still active turbines. This type of data inaccuracy results in an overestimation of the turbine lifetime with the Kaplan-Meier estimator. Given our preference to underestimate rather than overestimate windfall profits, we opt for the chosen solution.

ture turbine failure (like for most stochastic factors). This type of insurance policy protects an individual project from the risks of premature failure and the associated costs. However, insurance does not eliminate or reduce the risks on premature breakdown itself, i.e. does not affect the distribution of the economic lifetime. Insurance merely affects whether the risks and associated costs are borne by the individual project or the insurer (i.e. all insured parties). The current analysis does not consider insurance against premature breakdown, but estimates the 'true' distribution of project costs and associated required subsidy, independent of which party is the residual-risk owner. Hence, the paper focuses on windfall profits of projects, not of investors.

With respect to the fitted distribution, a logistic distribution yields the lowest AIC value. Table 5.F.1 lists the parameter values of this distribution.

5.5.3 Share of equity

The share of equity in financing on-shore wind projects can vary considerably between projects. This variability stems from a number of project characteristics, including the relative bargaining power of the equity and debt investor(s) and the project-specific costs.

Project-specific data about the share of equity for Dutch projects is unavailable as this resides largely in the private domain. However, Egli et al. (2018) investigates financing conditions for (subsidized) German on-shore wind electricity projects during 2004–2017. We use their compiled database to estimate a distribution for the share of equity in the Netherlands. This database includes the share of equity financing for 36 representative utility-scale on-shore wind projects, provided by actual investors who represent 80% of the installed German on-shore wind capacity over 2004–2017.[27] While including highly valuable, difficult-to-find information, a downside is that the database includes relatively few observations, particularly for earlier years. This limits the degree of precision with which the distributions are estimated.

To estimate a distribution for the three years of our analysis, we split the database in three periods; 2004–2006 (n=3), 2007–2012 (n=9), and 2013–2017 (n=24); and use the observations in these periods to fit a distribution for the share of equity in 2003, 2009, and 2018, respectively. Given the low number of observations in the earliest

[27] The investors providing the data tend to be large players who may be more focused on somewhat larger projects. This may imply that smaller projects are under-represented in their database. Nevertheless, covering 80% of the installed capacity, their database reflects the large majority of the market.

period, which complicates fitting an accurate distribution, we assume a deterministic distribution for 2003, using the average of the observed equity share in that period. For, respectively, 2009 and 2018 we find that a Rayleigh and minimum extreme value type 1 distribution provide the best fit.

5.5.4 Required return on equity

The required rate of return on equity for a project depends on the project-specific risks and returns, and perceived general (systematic) risks and returns. The project specific risks and returns of investments in wind turbines are related to the specific circumstances regarding wind speed, construction costs, technical risks and transaction costs, such as regarding environmental licenses (Egli, 2020). In addition, the required rate of return varies among projects as the compensation required for the systematic, non-diversifiable risks is a stochastic variable subject to changing perceptions of changing macro-economic circumstances.

Like with the share of equity, this data resides largely in the private domain for Dutch projects. However, the database from Egli et al. (2018) also reports the required return of equity for German projects over 2004–2017. For fitting distributions to this data, we use the same period split as before: 2004–2006 (n=3), 2007–2012 (n=7), and 2013–2017 (n=23). Due to the low number of observations in the first period, we assume a deterministic distribution with the average of the observations here as well. For, respectively, 2009, and 2018 we find that a Gamma and Weibull provide the best fit.

5.6 Results and discussion

This section first presents the simulation results for the distribution of the required subsidy of the *potential* investments in 2003, 2009 and 2018. Next, the section focuses on 2018 and estimates the required subsidy of the 187 *actual* projects that were granted subsidy in that year.

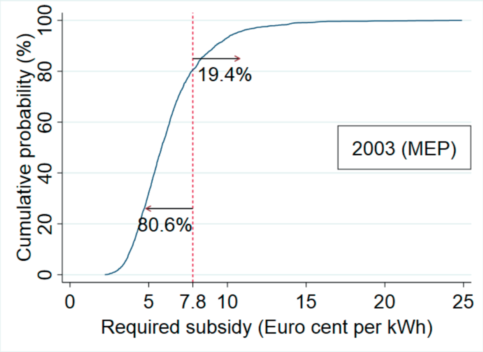
5.6.1 Monte Carlo simulations for *potential* investments

Figure 5.1 presents the main results. It displays the estimated cumulative density functions of the required subsidy for on-shore wind projects. In each graph, the vertical dotted lines represent the actually granted subsidy in the associated year and category, corresponding to the scheme's estimate of the required subsidy for a reference project. In addition to summarizing the key results of Figure 5.1, Table 5.3 provides the estimates of the windfall profits and missing money measures.

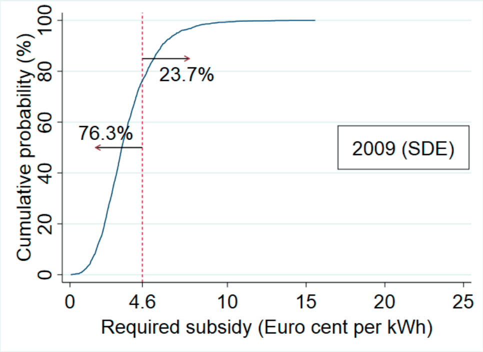
Figure 5.1a displays the results for 2003. We estimate that 81% of all potential projects requires a lower subsidy than the actual amount of €7.8 ct/kWh. This concerns the projects on the CDF that are located down-left of the intersection with the vertical dotted line. Only 19% of the potential projects requires a higher subsidy. These are the projects on the CDF located top-right of the intersection with the vertical line. The interpretation of this intersection is that it determines the probabilities that a randomly drawn investment from the pool of potential investments has a higher or lower required subsidy than the actual subsidy.

The average windfall profit of profitable projects (i.e. projects on the CDF located down-left of the intersection with the vertical line) equals €2.42 ct/kWh, or 31% of the actual subsidy amount. The average economic loss of projects located top-right of the intersection equals €2.23 ct/kWh.

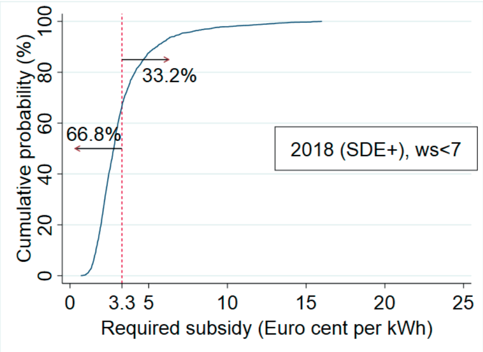
Figure 5.1b displays the result for 2009. The main result is that the share of projects requiring a subsidy below the granted amount decreased to 76%. On the basis of an unpooled z-test for two proportions (which we use for all percentage comparisons in this section), this is statistically significantly lower than in 2003 ($p < 0.001$). The windfall profit statistic also decreased in absolute terms, to €1.76 ct/kWh. On the basis of an unpaired two-sample t-test (which we use for all number comparisons in this section), this decrease is statistically significant ($p < 0.001$). In relative terms, however, the windfall profit measure increased to 38% of the actual subsidy. This increase is statistically significant ($p < 0.001$). The missing money statistic decreased in absolute terms to €1.47 ct/kWh, and increased in relative terms to 32% of the actual subsidy. Both these changes are statistically significant ($p = 0.049$ and $p < 0.001$, respectively).



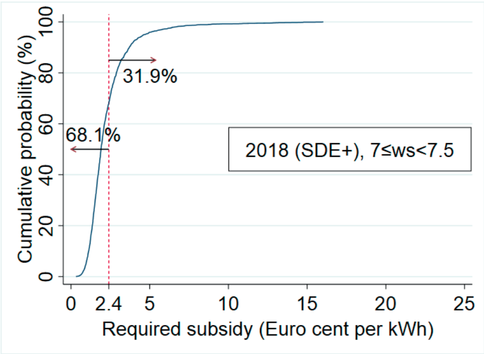
(a) 2003 (MEP)



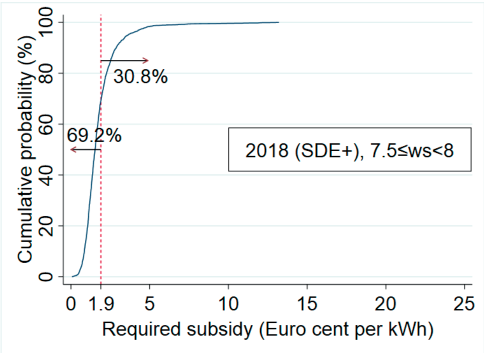
(b) 2009 (SDE)



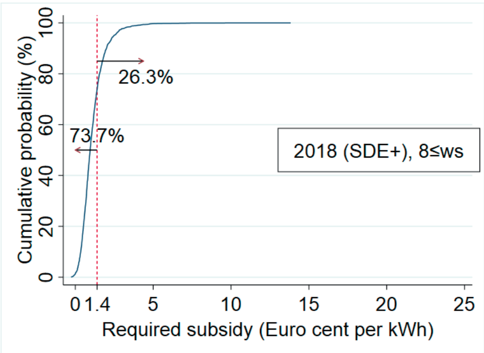
(c) 2018 (SDE+), ws<7



(d) 2018 (SDE+), 7 ≤ws< 7.5



(e) 2018 (SDE+), 7.5 ≤ws< 8



(f) 2018 (SDE+), 8≤ws

Figure 5.1. Cumulative distribution function of the required subsidy per kWh in 2003 (panel a), 2009 (panel b) and 2018 (panels c–f). The vertical dotted lines equal the actual subsidy under the respective regimes. Arrows to the right (left) indicate the share of projects with a required subsidy above (below) the actual subsidy. Note: for 2009 and 2018, the actual subsidy changes annually due to changes in the capture price. However, this does not affect the relative position of the CDF to the vertical dotted line. This only changes the position of the two graphs relative to the x-axis. In the graph, we assume a capture price of €4 ct/kWh.

Subsidy scheme	Share of projects requiring less than actual subsidy	Avg. windfall profits in €ct/kWh (% of actual subsidy)	Avg. missing money in €ct/kWh (% of actual subsidy)
2003 (MEP)	80.6%***	2.42*** (31.0%)	2.23*** (28.6%**)
2009 (SDE)	76.3%***	1.76*** (38.3%***)	1.47 (32.0%**)
2018 (SDE+) All categories+	68.1%***	0.852*** (32.2%)	1.548 (58.6%***)
2018 ws<7	66.8%***	1.005*** (30.5%)	2.008*** (60.8%***)
2018 7≤ws<7.5	68.1%***	0.801*** (33.4%)	1.361 (56.7%***)
2018 7.5≤ws<8	69.2%***	0.615*** (32.9%)	1.034*** (55.4%***)
2018 8≤ws	73.7%	0.642*** (45.9%)	0.694*** (49.6%***)

Table 5.3. Three profitability statistics for potential projects in 2003, 2009 and 2018. + Weighted by the surface of dry land without buildings. *,**,*** Statistically significantly different than the corresponding parameters of *both* other two subsidy regimes at a 10%, 5% and 1% confidence level, respectively. 2003, and 2009 are only compared to 2018 (SDE+) All categories, and not to the 2018 subcategories.

Panels c–f of Fig. 5.1 show the results for 2018. From lowest to highest wind-speed category, the share of projects down-left of the actual subsidy equals 67%, 68%, 69% and 74%, respectively. The average, weighted by surface of dry land without buildings of the respective categories, equals 68%. These values are all statistically significantly lower than in 2003 and 2009 ($p < 0.001$), except for the category $8 \leq ws$ compared with 2009 ($p = 0.16$). The weighted-average windfall profit statistic also decreased in absolute terms compared with both previous periods ($p < 0.001$). In relative terms, the average windfall profit decreased again compared with 2009 ($p = 0.002$), but was not statistically significantly different from 2003 levels ($p = 0.28$). The missing money statistic increased slightly in absolute terms and increased strongly in relative terms versus 2009.

The results indicate that the degree of windfall profits decreased over time. Both the probability that a randomly drawn project from the pool of potential investments enjoys windfall profits as well as the average windfall profit per kWh of profitable projects decreased during 2003-2018. The quantified changes from 2003 to 2009 solely relate to tighter assumptions in the scheme regarding characteristics of the reference project. The quantified changes to 2018 relate to both tighter assumptions for the reference project's characteristics, as well as to the introduction of category differentiation. Nevertheless, even after the alterations, the scheme provides substantial windfall profits in 2018. For the profitable potential projects, this amounts to a weighted-average windfall profit of €0.852 ct/kWh, or 32% of the actual subsidy. Given the incentive for investors to seek out projects with the lowest possible costs, i.e. projects located as far down-left as possible on the CDFs in Figure 5.1, one may expect that the windfall profits of the actually undertaken investments are above these levels. The next subsection analyses this in more detail. Furthermore, given that the scheme in 2018 provides more windfall profits in some subsidy categories, and thus geographical areas, than others, one may expect that these categories attract more actual investments. Appendix 5.G assesses whether this is the case.

5.6.2 Analysis of *actual* projects that received subsidy in 2018

To gain further insight into renewable-energy investor behaviour in response to the subsidy scheme, this subsection analyses the required subsidy of the 187 actual projects that were granted subsidy in 2018. In contrast to the information-constrained government, investors have much better information about the project's required subsidy. They will search for projects with favourable characteristics, which are ideally located as far left as possible on the CDF of potential projects (Figure 5.1), but at least to the left of the vertical line (for otherwise they will make a loss). Therefore, we expect that investors will (a) only undertake investments that are profitable and (b) seek investment opportunities that yield the highest returns. Based on these two expectations, we hypothesize that (a1), in terms of Figure 5.1, actual investments are located to the left of the vertical line; and that (b1) the average windfall profits per kWh is higher for actual investments than for potential investments.

For the actual investments in 2018, we observe the (expected) amount of full-load hours from publicly available information on the website of the government agency administering the subsidy (RVO).[28] For these projects, we estimate the required subsidy with Equation (3), using the observed project-specific full-load hours. This amount of full-load hours is the amount reported to RVO by the project prior to granting the subsidy.[29] Unfortunately, we do not observe other project-specific characteristics (e.g. required return on equity, equity share etc.). We deal with this

[28]Unfortunately, this data is not available before 2011. This is a key reason why we analyse potential investments and rely on wind-speed data to determine the full-load hours in the first part of the analysis.

[29]This amount is based on an expert report, stating the median expected amount of full-load hours.

by assuming that these characteristics are equal to the assumptions from the official scheme.[30] Based on the estimates of the minimally required subsidy, we construct the CDFs of the required subsidy of actual investments for the four categories in 2018. We mention that, whereas the total number of 187 subsidy grants in 2018 was quite substantial, the distribution of projects over the categories was unequal. This results in some categories having a relatively low number of observations (e.g. the highest wind-speed category only has 12 observations, see Figure 5.2 for n by category) which in turn causes individual projects to potentially have a considerable impact on some of the results in this subsection.

Panels a–d of Figure 5.2 show the estimated CDFs of the required subsidy for actual investments in 2018. In constructing the CDFs of Figure 5.2, we have standardized the project size to 1000kW, such that 20% of the cumulative probability of the actual investments is equal to 20% of the actually installed cumulative capacity.[31] Table 5.4 provides the windfall profit and missing money measures for the actual investments.

The estimated CDFs of actual investments tend to be in line with Hypothesis a1. For the lowest, second-lowest and highest wind-speed categories, the share of actual investments that requires a lower subsidy than the actually granted amount ranges from 88–100%. An unpooled two-proportions Z-test suggests that these shares are statistically significantly higher than the associated share of the same subsidy category for the potential investments ($p < 0.001$ in all cases). For the second-highest wind-speed category (panel c of Figure 5.2), the share of projects located down-left of the actually granted subsidy is at 42% considerably lower. However, inspecting the missing money statistic, we see that the average economic loss per kWh in this category is very close to zero, and even the lowest of the four categories. This signals that almost all projects that are located to the right of the vertical line in this category have an estimated required subsidy that is a tiny amount higher than the actual subsidy. In Figure 5.2c, this is reflected by the near-vertical portion of the CDF which is located approximately on top of the vertical line that

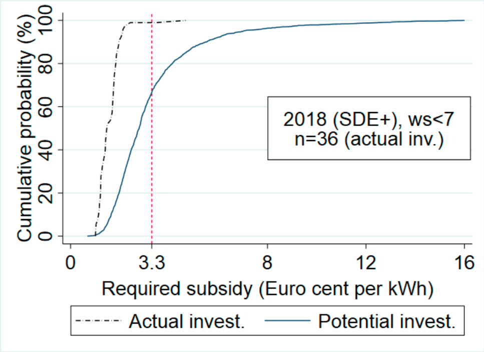
[30] Note that these assumptions tend to be in the conservative range of the distributions that we estimated in Section 5 (from the perspective of the required subsidy).

[31] This is to correct for the fact that some subsidy grants are for a single small turbine (e.g. with a capacity of 10kW) whereas other subsidy grants comprise a very large number of turbines (e.g. with a total capacity of more than 60000kW).

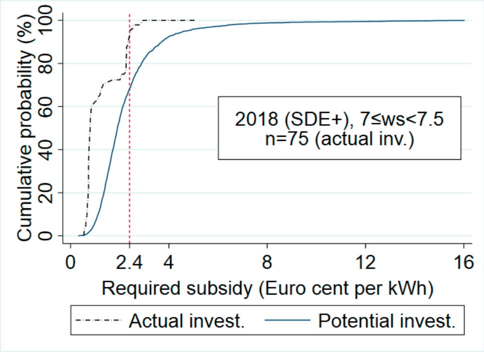
reflects the actual subsidy.[32]

The windfall profit measures are considerably higher for actual investments than for potential investments in all categories, except for the highest wind speed category. For these three categories, the profit measures are statistically significantly higher ($p < 0.001$ for the categories ws$<$7 and 7 $\leq$ws$<$ 7.5, and $p = 0.025$ for 7.5 $\leq$ws$<$ 8). On average, the amount of windfall profits per kWh is 50% higher compared with the potential projects, and this difference is statistically significant ($p < 0.001$). These results provide support for Hypothesis b1: actual projects realize considerably higher windfall profits than the average potential project. Arguably, this is because firms have more information about the characteristics of specific projects (as opposed to the government) and seek out the most profitable projects.

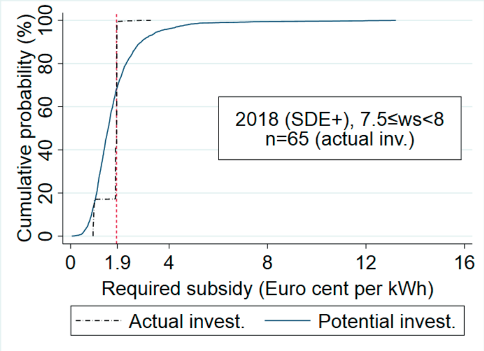
[32]There are several reasons why actual projects are located to the right of the vertical line, i.e. have a higher estimated required subsidy than the actual amount. One reason is the possibility that we underestimate the costs of projects due to inaccuracies in the assumptions for the project parameters. This may be due to adopting the government assumptions for the non-observed parameters of the actual projects, which are in the conservative range of our estimated distributions for potential investments. As a consequence, the degree to which actual projects yield more windfall profits relative to the potential projects may be somewhat larger than reported here. In addition, some subsidized investments are not by private firms, but by government-owned institutions. As a result, these investments may be (partially) driven by other motivations than profit. For example, in the lowest wind-speed category, over 99% of the installed capacity for which the estimated required subsidy exceeds the actual subsidy belongs to HVC, an energy and waste company owned by local public authorities.



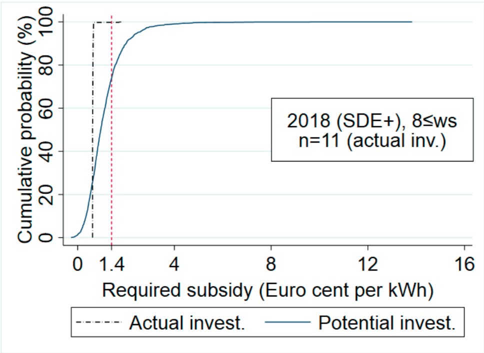
(a) 2018 (SDE+), ws<7



(b) 2018 (SDE+), 7 $\leq$ws< 7.5



(c) 2018 (SDE+), 7.5 $\leq$ws< 8



(d) 2018 (SDE+), 8≤ws

Figure 5.2. Cumulative distribution functions (CDF) of the required subsidy per kWh of actual and potential investments in 2018. The vertical dotted lines equal the actual subsidy. Note: the actual subsidy the actual subsidy changes annually due to changes in the capture price. However, this does not affect the relative position of the CDF to the vertical dotted line. This only changes the position of the two graphs relative to the x-axis. In the graph, we assume a capture price of €4 ct/kWh.

Subsidy category	Share of projects requiring less than actual subsidy	Avg. windfall profits in € ct/kWh (% of actual subsidy)	Avg. economic loss in € ct/kWh (% of actual subsidy)
2018 (SDE+) All categories+	84.6%***	1.277*** (49.7%***)	0.471*** (16.0%***)
2018 ws<7	99.0%***	1.745*** (52.9%***)	1.365 (41.4%***)
2018 7≤ws<7.5	87.8%***	1.333*** (55.5%***)	0.15* (6.3%***)
2018 7.5≤ws<8	41.6%***	0.398** (21.3%**)	0.017*** (0.9%***)
2018 8≤ws	99.8%***	0.773 (55.2%)	0.347*** (24.8%**)

Table 5.4. Three profitability statistics for actual investments in 2018. +Weighted by installed capacity. *,**,*** Statistically significantly different than the same parameter for the same subsidy category for potential investments in Table 3, at a 10%, 5% and 1% confidence level, respectively.

5.7 Conclusion

Because of information asymmetry, it is prohibitively costly for governments to design subsidy schemes such that each individual project receives precisely what is needs. Therefore, they typically set a uniform subsidy for renewable energy or a specific technology (e.g. on-shore wind). The consequence is that projects with a minimally required subsidy below the granted subsidy earn windfall profits at the expense of those who finance the scheme, such as electricity consumers or taxpayers. Relatively generous subsidy schemes thus imply large welfare transfers from the latter group towards the group of subsidized investors, whose primary concern is realizing private gains.

This paper analyses the degree of windfall profits to on-shore wind electricity projects in the Netherlands receiving a feed-in premium at three points in time: 2003, 2009 and 2018. We focus on windfall profits resulting from the heterogeneity in the characteristics of on-shore wind projects that is ignored by the schemes. During 2003–2018, several design changes to the scheme were implemented that specifically aim at reducing windfall projects, such as differentiating in the subsidy between on-shore wind projects. For each of the three years, which correspond to distinct scheme designs, the analysis uses Monte Carlo simulations to estimate the distribution of the required subsidy of all randomly-drawn investments in on-shore wind that are available in the Netherlands (the *potential* investments), and compares this with the granted subsidy. In addition, for 2018, we estimate the distribution of the required subsidy of *actual* projects and compare it with the results for *potential* investments. The first part answers the question to what extent support schemes result in windfall profits due to ignoring project heterogeneity. The second part answers the question to what extent investors are successful in seeking out projects that yield high windfall profits.

We find that the degree of windfall profits has decreased considerably over time. Specifically, the share of potential investments with a required subsidy below the actual subsidy decreased from 81% in 2003 to 68% in 2018. At the same time, the average windfall profits decreased from € 2.42 ct/kWh to € 0.85 ct/kWh. These decreases followed from two adaptations in the scheme: differentiating subsidy levels between on-shore wind projects on the basis of the turbine location as well as tighter estimates by the government of the required subsidy for a reference project. In relative terms, however, average windfall profits were at 32% of the actual subsidy in 2018 not lower than the 31% in 2003. Hence, despite that windfall profits have decreased in absolute terms, they have not disappeared, and remained constant in relative terms.

Analysing *actual* investments in 2018, it appears that investors successfully seek out the most profitable investments. 85% of the actually subsidized investments generates windfall profits, and, at €1.28 ct/kWh, the average windfall profits of actual investments are 50% higher than the average of the profitable *potential* investments. This is likely due to investors having better information about individual characteristics of on-shore wind projects than the government, enabling them to seek out the most profitable investments.

An important caveat of this study relates to the availability of data. The simulation analysis aimed at approaching reality by taking into account the heterogeneity in project characteristics, but data for most project-specific characteristics is not publicly available. As a result, the input distributions for the simulations rely on other data sources and data transformations (e.g. conversion of wind-speed observations into full-load hours). Despite using objective, technical or empirical-based sources, these input distributions remain approximations. Also, the analysis focuses on the key sources of heterogeneity, but does not include *all* sources of heterogeneity.

Given this paper's focus, the policy implications are directed at the distributional effects of subsidies for renewable electricity. We disregard the economic inefficiency caused by these subsidies (Borenstein, 2012). Naturally, an assessment of the suitability and desirability of climate policies should always regard both distributional impacts as well as effects on efficiency.

Regarding policy lessons, our findings indicate that the measures that were implemented to limit the degree of windfall profits in the Netherlands were relatively successful. In particular, the introduction of differentiation between projects on the basis of observable project characteristics has resulted in lower windfall profits. Differentiation in the subsidy level is increasingly becoming a standard feature of feed-in subsidy schemes (e.g. countries like Switzerland and Denmark have also implemented types of differentiation (IEA, 2021)). Nevertheless, given that differentiation still occurs relatively rudimentary, policies aimed at further increasing the level of differentiation in the subsidy level may further reduce the degree of windfall profits. For example, when wind-speed data is available, governments may let the subsidy level depend on the exact wind speed at the turbine's location and hub height, as opposed to the average wind speed in the whole municipality at a given height. Furthermore, investors do not pick on-shore wind projects randomly but successfully seek out projects that have the lowest costs (and therefore yield the highest windfall profits). Therefore, for determining the subsidy level, policy makers may want to estimate the number of projects or amount of capacity that needs to be subsidized to achieve an underlying goal. If the required amount of projects, for instance, is lower than half of the available projects, the government can infer that a subsidy equal to the LCOE of the average project (as the Dutch scheme explicitly aims for) is too high. Improving the design of the subsidy scheme in such a way helps to make renewable-energy policy more cost efficient.

5.A Appendix: Map with subsidy areas

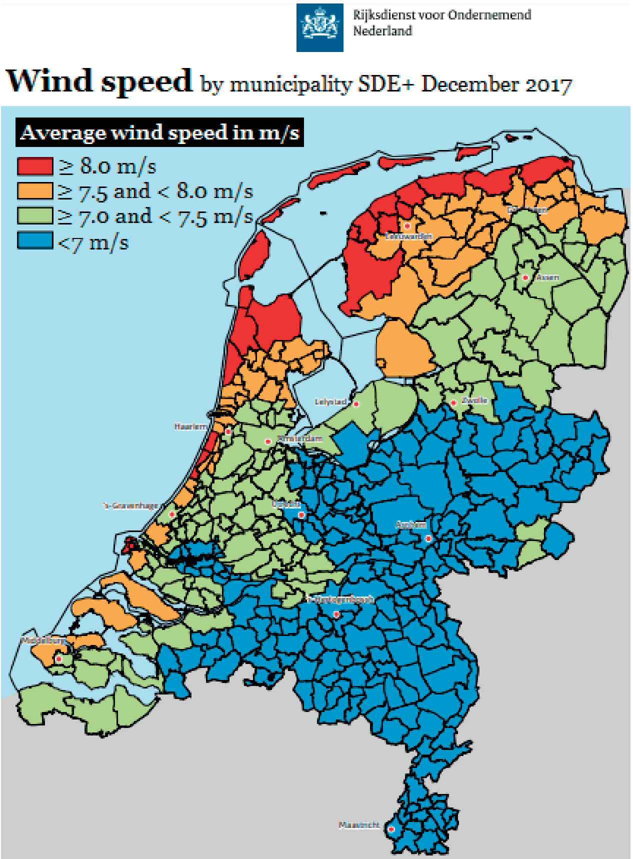


Figure 5.A.1. Map of the Netherlands by subsidy category in 2018. Each municipality is associated with one of the four subsidy categories on the basis of the local average wind speed. Source: adapted/translated from RVO.

5.B Appendix: Share of newly installed turbines by hub height, 2003–2004.

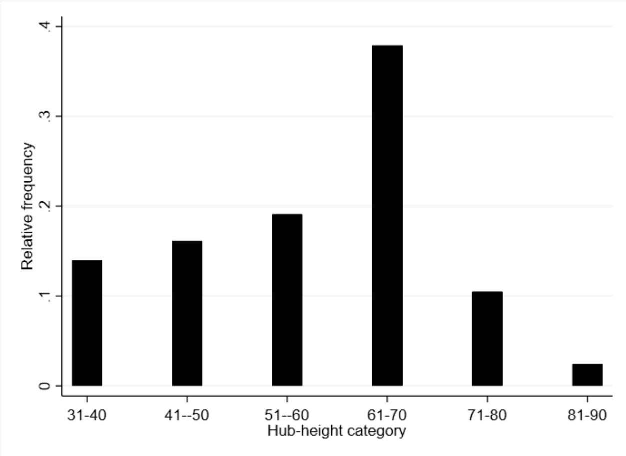


Figure 5.B.1. Relative frequency of newly installed turbines in 2003 and 2004, by hub-height category. This is used as approximation of the discrete probability function for the hub height of potential turbines that received subsidy in 2003.

5.C Appendix: Construction of the wind-profile correction factor

We overcome the unavailability of data for variability in wind speed within a year by estimating a wind-profile correction factor (f^{cor}). The correction factor links the full-load hours calculation of equation (7) to a more precise measure of full-load hours that takes into account the wind-speed variability at a location within a year. At four Dutch weather stations (Lauwersoog, IJmond, Hoogeveen and Eindhoven), for which hourly wind-speed data is available, we calculate in relatively precise manner the amount of full-load hours (approach 1). In addition we calculate the full-load hours at these weather stations using equation (7) (approach 2). The ratio of these two is our wind-profile correction factor (i.e. the full-load hours of approach 1 divided by the full-load hours of approach 2). This correction factor corrects the full-load hour calculations for all the coordinate-hub height combinations on the basis of (7) to better reflect the true number of full-load hours.

Approach 1, the more precise approach, is the following: for each hour h separately, we calculate the relative power output (i.e. the capacity factor) in that hour, using that hour's wind speed (v_h): $\frac{P_h}{P^{max}}$. We assume a cut-in wind speed of 3 m/s (i.e. power output below 3m/s is zero) and rated wind speed of 12.5 m/s in these calculations. The number of full-load hours is then found by aggregating over the capacity factors of all hours. Approach (2) is given by equation (7).

The wind-profile correction factor as calculated as the ratio between the full-load hours based on the hourly approach (approach 1), to the full-load hours based on equation (7) (approach 2). Because this correction factor is sensitive to the level of the average wind speed, we calculate it at various average wind speeds. To that end, for each station, based on the actually observed hourly wind speeds, we create six new series of hourly wind speed observations by scaling the actual observations with a constant factor. This factor is chosen such the average wind speed of the scaled series are equal to 4.5, 5.5, 6.5, 7.5, 8.5 or 9.5, which represent the following wind-speed ranges (w):[33] 4–5m/s, 5–6m/s, 6–7m/s, 7–8m/s, 8–9m/s, 9–10m/s (wind-speed averages above 10m/s are not observed). These scaled series

[33] The wind-speed range w solely refers to the wind speed categories of the wind-profile correction factor and should not be confused with the official wind-speed areas from the subsidy scheme in 2018. For example, consider two theoretical turbines at a certain location in the municipality of Eindhoven, one with a hub-height of 60m and corresponding average wind speed of 5.33, and one with a hub-height of 150m and corresponding average wind speed of 7.19. For the subsidy scheme, both turbines fall in the category 'wind speed $<$ 7m/s'. However, for the wind-profile correction factor, they fall in different categories, corresponding to their actual average wind speed.

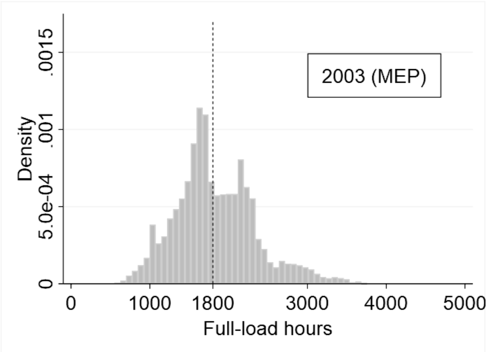
are deemed to represent wind speeds patterns at that location when the average wind speed would fall in these wind-speed ranges.[34] Consequently, we use the scaled observations at each of the four stations to calculate six wind-profile correction factors that represent different average wind speeds. Finally, we average the results of Lauwersoog and IJmond, two coastal weather stations, and use the resulting six wind speed correction factors for turbines located near the coast. Turbines are considered near the coast when they fall in the highest or second-highest wind speed category (this corresponds to the red and orange areas on the map in Figure 4 in Appendix A). We also average the results of the Hoogeveen and Eindhoven stations, which are in the interior of the country, and use the resulting six wind-speed correction factors for inland turbines. Turbines are considered inland when they fall in the lowest and second-lowest wind speed category (this corresponds to the blue and green areas in Figure 4. For example, for a turbine at a certain location near Eindhoven with a hub-height of 60m, the average wind-speed is 5.33m/s and we therefore apply the correction factor for interior locations with a wind speed between 5–6m/s (equal to 1.836). For a turbine on the exact same location near Eindhoven but with a hub-height of 150m, the average wind-speed is 7.19m/s and we therefore apply the correction factor for interior locations with a wind speed between 7–8m/s (equal to 1.400). Table 5 lists the correction factors.

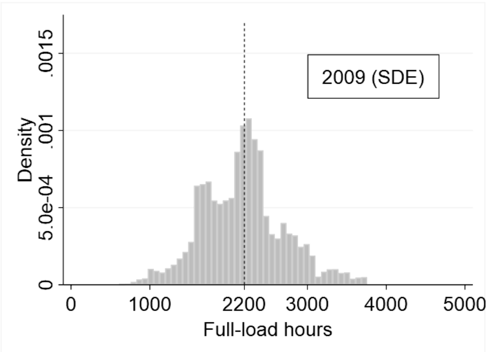
Wind-speed	Coastal			Interior		
range	Lauwers–oog	IJmond	Average	Hooge–veen	Eindhoven	Average
4–5m/s	1.730	1.712	1.721	1.904	1.971	1.938
5–6m/s	1.694	1.692	1.693	1.768	1.903	1.836
6–7m/s	1.544	1.553	1.548	1.622	1.636	1.629
7–8m/s	1.361	1.387	1.374	1.403	1.398	1.400
8–9m/s	1.158	1.185	1.172	1.173	1.201	1.187
9–10m/s	0.986	1.005	0.996	0.981	0.975	0.978

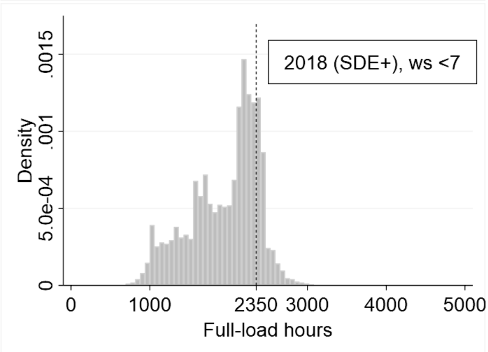
Table 5.C.1. Wind-profile correction factors by wind-speed range

[34]This procedure maintains deviations from the mean in absolute terms. For example, the difference between the minimum or maximum and the mean is the same for the six average wind speeds.

5.D Appendix: Histograms of full-load hours







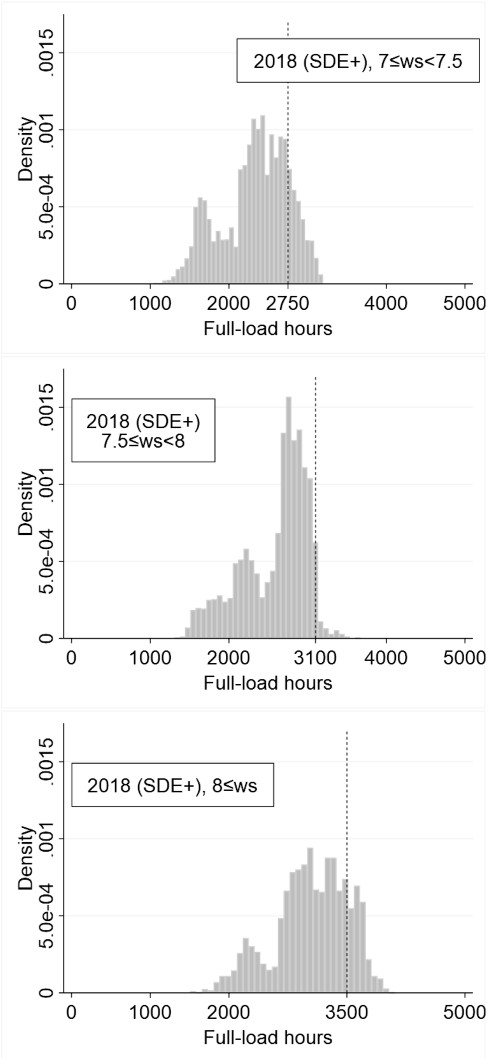


Figure 5.D.1. Histogram of full-load hours of potential projects in 2003, 2009 and in 2018 by category. The vertical dotted lines represent the assumption of the government for the number of full-load hours.

5.D.1 Actual investments

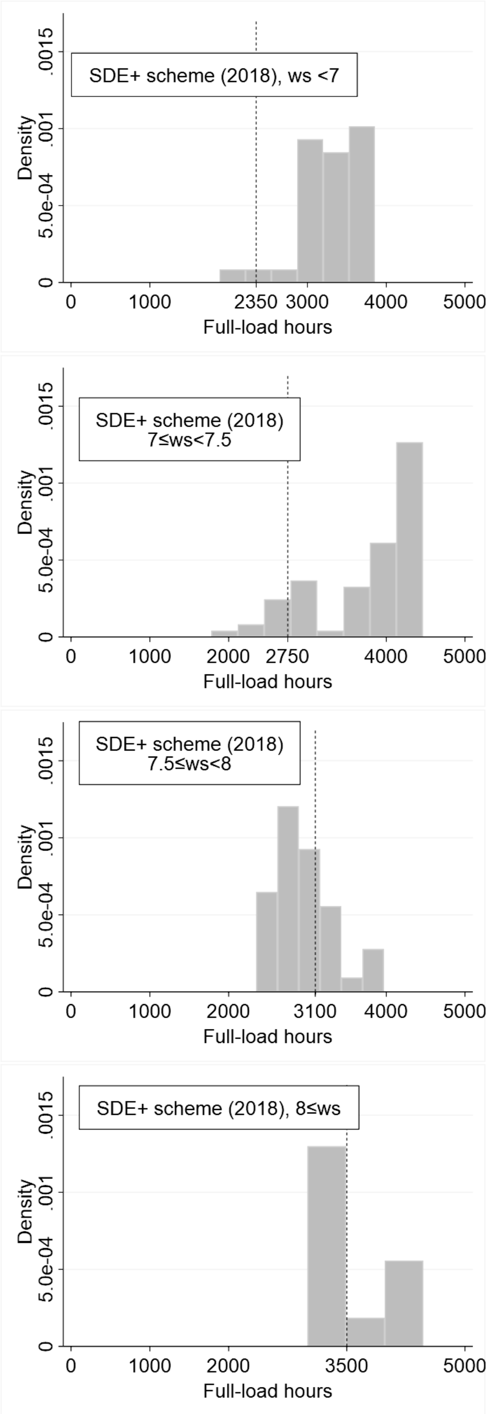


Figure 5.D.2. Histogram of full-load hours of actual projects in 2018. The vertical dotted lines represent the assumption of the government for the number of full-load hours.

5.E Appendix: Histogram of economic lifetime

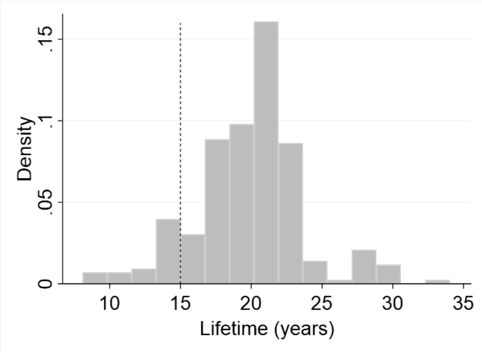


Figure 5.E.1. Histogram of economic lifetime of turbines in the Netherlands built before 2003 for which we observe the decommissioning time. The vertical dotted lines represent the assumption of the government for the economic lifetime.

5.F Appendix: Distribution fitting results

	2003 (MEP)	2009 (SDE)	2018 (SDE+) ws<7.0	2018 (SDE+) 7.0≤ws<7.5	2018 (SDE+) 7.5≤ws<8.0	2018 (SDE+) 8.0≤ws
Full-load hours						
Distribution	Gamma	Gamma	Min. extr. value type 1	Min. extr. value type 1	Min. extr. value type 1	Weibull
Parameters						
Mean	1830	2181	1952	2334	2586	3046
Location			2149.66	2526.90	2775.00	
Scale	144.52	130.71	341.26	334.11	327.12	3241.34
Shape	12.67	16.68				7.85
Economic lifetime						
Distribution	Logistic	Logistic	Logistic	Logistic	Logistic	Logistic
Parameters						
Mean	19.88	19.88	19.88	19.88	19.88	19.88
Scale	2.09	2.09	2.09	2.09	2.09	2.09
Share of equity						
Distribution	Determi–nistic	Rayleigh	Min. extr. value type 1	Min. extr. value type 1	Min. extr. value type 1	Min. extr. value type 1
Parameters						
Mean	0.225	0.191	0.221	0.221	0.221	0.221
Location			0.248	0.248	0.248	0.248
Scale		0.153	0.481	0.481	0.481	0.481
Required return on equity						
Distribution	Determi–nistic	Gamma	Weibull	Weibull	Weibull	Weibull
Parameters						
Mean	0.1	0.094	0.063	0.063	0.063	0.063
Scale		0.0007	0.069	0.069	0.069	0.069
Shape		135.26	4.19	4.19	4.19	4.19

Table 5.F.1. Fitted distributions for the stochastic inputs

5.G Appendix: Investments by subsidy category, 2018

The results from Section 6.1 show that the scheme provides windfall profits to relatively more potential investments in some categories, and thus geographical zones, than in other categories.[35] One may expect the former categories/zones to attract relatively more actual investments, simply because more profitable investments are available. To verify whether this is the case in actual practice, we inspect how much investment in on-shore wind each subsidy category has attracted in 2018.

Figure 8 provides a scatter plot of the installed capacity per acre of surface versus the share of potential projects with a required subsidy below the actual subsidy.[36] In the plane, each of the four data points corresponds to one of the subsidy categories, which in turn correspond to four geographical zones (cf. Fig. 4). Somewhat in contrast with our expectation, it appears from the plot that subsidy categories with a relatively high share of projects with a required subsidy below the actual subsidy do not appear to attain relatively more actual investments. Bearing in mind that we only have four data points, Bearing in mind that we only have four data points, a likely explanation for this result is that spatial planning and land-use regulations make that the locational choices of investors deviate from those which would be optimal from an unconstrained business-economic perspective.

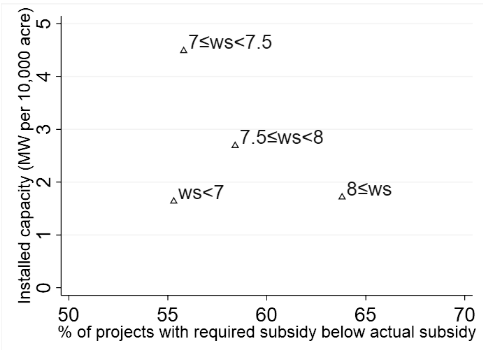


Figure 5.G.1. Plot of installed capacity per 10,000 acre of land and the windfall profit measure of potential and actual investments, 2018. Each observation is associated with a specific subsidy category and labeled accordingly.

[35]Specifically, the scheme is more generous in categories with higher assumed wind speeds, which geographically correspond to the areas in the West and North of the country. Considering that land prices typically differ by region (non-rented farmland prices are higher in the South and East of the Netherlands than in the North and West (Agrimatie, 2020), in contrast with urban land), one may be worried that this results in a systematic bias of our results. However, a governmental investigation suggests that the price of land in wind turbine projects is, while being related to the profitability of the project, not related to the fundamental regional land price (Ministerie van Financiën, 2018).

[36]Surface here is equal to dry land without buildings, based on data of Statistics Netherlands (CBS).

Chapter 6

Conclusion and discussion

6.1 Imperfect information and incentives for renewable energy

Energy markets can play a key role in realising the energy transition from non-renewable to renewable energy systems. A number of market failures, however, hamper the functioning of energy markets and the development of renewable energy. Primarily hampering the development of renewable energy is the negative externality associated with emissions from non-renewable energy. This market failure manifests itself in the form of overconsumption of non-renewable energy and underconsumption of alternatives such as renewable energy. Another market failure that hampers renewable energy markets, and which is the primary concern of this dissertation, is information asymmetry. A key source of information asymmetry between energy suppliers and consumers is the inability of end-users to distinguish between renewable and non-renewable energy. This may also result in underconsumption of renewable energy: When end-users prefer renewable energy but are not able to distinguish between renewables and non-renewables, they may opt for non-renewables because they cannot trust the suppliers' claims regarding the energy source.

To address the overconsumption of non-renewable energy, a large number of governments have chosen to provide subsidies for renewable energy. The associated expenditures are already relatively considerable while the share of renewable energy in total energy consumption remains relatively modest. At the same time, governments have set highly ambitious future targets to further reduce emissions and increase renewable consumption. In light of this, it is important to keep the costs of the energy transition under control.

This thesis aims to contribute to the discussion on organizing an efficient energy transition. The chapters do so through empirical research, based on a microeconomic perspective. In particular, this thesis investigates whether end-users prefer renewable energy to the extent that renewable energy can command a premium in renewable energy markets, which would curb the need for subsidies. Next, the thesis investigates whether the existing solution for addressing information asymmetry in energy markets, certification, is functioning properly. A well-functioning certificate market is required for end-users with preferences for renewables to express their willingness to pay a premium in the market, and, therefore, for producers of renewable energy to earn a premium. Lastly, the dissertation investigates design aspects of subsidy schemes that specifically aim to keep subsidy expenditures under control. The rest of this chapter will briefly summarize and discuss the key findings of the chapters, and discuss the policy implications of this dissertation in an integrated manner.

6.2 Summary and discussion of key findings

The findings from Chapter 2 suggest that a considerable portion of the Dutch consumers quite strongly prefers lower CO_2 emissions. Many consumers appear to derive utility from contributing to climate-change mitigation, despite not getting a material or financial benefit in return. The fact that individual contributions to CO_2 emission reductions have a virtually negligible effect on climate-change mitigation makes this particularly remarkable. These findings are broadly in line with the theoretical (Andreoni, 1990) and experimental (Crumpler and Grossman, 2008) evidence that some consumers derive utility purely from voluntarily contributing to a public good, regardless of the effect of the voluntary contribution on the provision of the public good (in terms of quality or quantity). It should be noted that Chapter 2 derived these results in a stated-preference setting under the assumption of perfect information, which is an assumption that is frequently not satisfied in practice. This latter point is precisely the reason that studies concerning consumer valuation of CO_2 emission reductions have mainly applied stated-preference techniques. Because of the well-known tendency of stated-preference research to overstate the true valuation, the “hypothetical bias” (despite this chapter’s efforts to mitigate this bias), it is of interest to investigate how Chapter 2’s results hold up in a revealed-preference setting where information asymmetry is not an issue. This is an interesting path for further research.

The findings from Chapter 3 suggest that firms only pay premiums for renewable energy when this contributes to their financial objective, for instance when consumers are willing to pay more for the firms' goods when these have renewable energy characteristics. This evidence does not corroborate firms' typical claims that environmental concern, as opposed to financial concern, is the driver for procuring renewable energy. Hence, we do not find evidence that firms are motivated by altruistic concerns, at least when it comes to the environment. This chapter's results are supportive to the microeconomic assumption that firms behave environmentally in order to maximise profit. While this concept of the firm as purely profit-maximising economic agent is very fundamental in microeconomics, it has hardly been explicitly empirically tested. When firms act purely in their own interest it is not highly difficult for the rest of society to motivate firms to behave (environmentally) in the interest of the rest of society. Consumers can do this by preferring (and paying for) products with characteristics that do little harm to others. And governments can very much rely on traditional policy tools, such as taxation and subsidisation, to be highly effective in altering the decisions of firms.

The findings from Chapter 4 show that, while certification has been embraced as a tracking and trading mechanism for renewable energy, at least in the EU, existing markets for certificates cannot be characterised as well-functioning. Judging by characteristics such as liquidity and price volatility, these markets do not come close to conforming to the benchmark of a perfectly competitive market. Proxying the degree of success in reducing information asymmetry by the functioning of the certificate market, this appears to imply that information asymmetry is not yet appropriately addressed by existing certification schemes. Further research in this area could focus on the appropriate design of certificate and labelling schemes such that information asymmetry is reduced more successfully. For instance, the current situation of trading in renewable energy as a bundle of power and a renewable energy certificate may be compared to other types of market design, such as trade in (renewable) energy in distinct and dedicated commodity markets where energy and energy characteristics are inseparable. It may also be interesting to investigate the optimal design and functioning of certificate markets for other energy commodities, such as hydrogen or methane.

The findings from chapter 5 show that windfall profits from renewable energy subsidies in the Netherlands, despite having decreased considerably over time, remain quite substantial. The decrease in windfall profits appears to a large extent attributable to changing the design of the scheme, specifically the introduction of differentiating in the subsidy between projects on the basis of observable project characteristics. Furthermore, the results showed that investors in practice are highly successful in seeking out the projects that yield the highest windfall profits.

6.3 Policy implications

The findings of this dissertation imply that adverse selection as a result of information asymmetry is likely to manifest itself, resulting in market inefficiencies characterised by underconsumption of renewable energy. This in turn means that governments need to spend less on renewable energy subsidies than what would be required when energy markets would not suffer from information asymmetry. The more information asymmetry is reduced, the lower the required amount of subsidy expenditures, up until the point where information asymmetry is fully reduced such that renewable energy commands its maximum potential market premium. In order to lower subsidy expenditures in practice, policy makers occupied with subsidy scheme design should recognise the premium that renewable energy commands, which is typically reflected in the price of renewable energy certificates. Many existing schemes neglect this premium that renewable energy earns in the market by assuming that renewable energy producers receive the undifferentiated wholesale energy price when they sell their energy.

The existing solution for information asymmetry in energy markets, certification–which has been present mainly in electricity markets but is expected to become more important in the near future in other energy markets, such as the markets for methane and hydrogen–does not yet appear to function properly. This suggests that information asymmetry is not reduced very successfully. Improving the functioning of this policy measure, for instance by facilitating transparency and liquid markets, may contribute to further reducing information asymmetry in energy markets, thereby reducing adverse selection. As this tends to increase the premium that renewable energy producers earn in the market, this may contribute to a lower need for subsidy expenditures.

It is evident that solving information asymmetry between producers and consumers of renewable energy does not alter the costs of providing renewable energy to society (apart from possible taxation or regulatory costs). However, by solving information asymmetry, society can harness the WTP for renewable energy that is ‘available’. In turn, as this reduces the required amount of subsidy expenditure, solving information asymmetry reduces the financial burden on those less willing to contribute to climate-change mitigation. As a consequence, this may have a positive effect on public support for climate policy.

Realising that solving information asymmetry will probably not eliminate the need for renewable energy subsidies in the short and medium turn, it is also important to spend subsidy budgets cost-efficiently, both from the perspectives of allocative-efficiency and minimising windfall profits. In relation to the latter perspective, the findings of this thesis suggest that differentiating in the level of the subsidy among projects on the basis of observable characteristics can be desirable. For the optimal degree of differentiation, the marginal costs and benefits of the degree of differentiation may be considered. On the cost side of this policy tool, increasing the degree of differentiation may involve regulatory costs. On the benefit side, increasing the degree of differentiation may reduce the deadweight loss associated with taxation, which is an economic benefit, and welfare transfers (from renewable energy producers to other economic agents) which may be considered desirable, depending on the preferences of society. As long as the marginal regulatory costs are lower than the marginal reduction in deadweight loss from taxation, increasing the degree of differentiation is always optimal. Beyond that point, it is a normative matter whether it is desirable to increase the degree of differentiation, given that further increasing differentiation comes at a net economic costs, while the 'benefits' (which may not be perceived as benefits at all, depending on the society) constitute only welfare transfers.

Generally, this dissertation finds that, as many consumers are willing to contribute financially to emission reductions, embracing information-asymmetry reduction as a key policy tool for emission reductions, and improving the design of subsidy schemes, such as differentiating between projects or accounting for revenues from certificate markets, contributes to the cost-efficiency of renewable-energy policy.

Bibliography

Aasen, M., Westskog, H., Wilhite, H., and Lindberg, M., 2010. The EU electricity disclosure from the business perspective—A study from Norway. *Energy Policy*, 38(12):7921–7928.

ACEA. European automobile manufacturers association - Passenger car fleet by fuel type, 2018. URL http://www.acea.be/statistics/tag/category/passenger-car-fleet-by-fuel-type.

ACER/CEER. Annual report on the results of monitoring the internal electricity and gas markets in 2016. Electricity wholesale market volume, 2017.

Achtnicht, M., 2012. German car buyers' willingness to pay to reduce CO_2 emissions. *Climatic Change*, 113(3-4):679–697.

ACM. 2014 liquidity report. Wholesale markets for natural gas and electricity, 2014.

Agrimatie. Agricultural land price higher, mobility lower. https://www.agrimatie.nl/ThemaResultaat.aspx?subpubID=2232&themaID=3588&indicatorID=3589&sectorID=2243, 2020.

AIB. Aib-member tariffs 2015, 2015.

AIB. Annual statistics Q2 2017 [data base] . https://www.aib-net.org/aib_activity_statistics, 2017.

Akerlof, G., 1970. The market for lemons: Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 89:488–500.

Alberini, A., Bigano, A., Ščasnŷ, M., and Zvěřinová, I., 2018. Preferences for energy efficiency vs. renewables: What is the willingness to pay to reduce CO_2 emissions? *Ecological Economics*, 144:171–185.

Algemene Rekenkamer. Autobelastingen als beleidsinstrument: Effecten van elektrische auto's en bestelauto's voor belastingopbrengsten, luchtkwaliteit en klimaat, 2020.

Andor, M. A., Manuel, F., and Colin, V., 2017. Germany's Energiewende: A tale of increasing costs and decreasing willingness-to-pay. *The Energy Journal*, 38:858–865.

Andreoni, J., 1990. Impure altruism and donations to public goods: A theory of warm-glow giving. *The Economic Journal*, 100(401):464–477.

Apple. Apple now globally powered by 100 percent renewable energy. `https://www.apple.com/newsroom/2018/04/apple-now-globally-powered-by-100-percent-renewable-energy/`, 2018. Online; accessed 11 October 2018.

Archsmith, J., Gillingham, K., Knittel, C. R., and Rapson, D. S., 2017. Attribute substitution in household vehicle portfolios. *NBER Working Paper No. 23856*, pages 1–42.

Barnett, M. L. and Salomon, R. M., 2012. Does it pay to be really good? Addressing the shape of the relationship between social and financial performance. *Strategic Management Journal*, 33(11):1304–1320.

Bigerna, S., Bollino, C. A., Micheli, S., and Polinori, P., 2017. Revealed and stated preferences for CO2 emissions reduction: The missing link. *Renewable and Sustainable Energy Reviews*, 68:1213–1221.

Bjørner, T. B., Hansen, L. G., and Russell, C. S., 2004. Environmental labeling and consumers' choice—an empirical analysis of the effect of the Nordic Swan. *Journal of Environmental Economics and Management*, 47(3):411–434.

Bolkesjø, T. F., Eltvig, P. T., and Nygaard, E., 2014. An econometric analysis of support scheme effects on renewable energy investments in europe. *Energy Procedia*, 58:2–8.

Bollino, C. A., 2009. The willingness to pay for renewable energy sources: the case of Italy with socio-demographic determinants. *The Energy Journal*, 30(2):81–96.

Borenstein, S., 2012. The private and public economics of renewable electricity generation. *Journal of Economic Perspectives*, 26(1):67–92.

Borenstein, S., 2017. Private net benefits of residential solar PV: The role of electricity tariffs, tax incentives, and rebates. *Journal of the Association of Environmental and Resource Economists*, 4(S1):S85–S122.

Brouwer, R., Brander, L., and Van Beukering, P., 2008. "A convenient truth": air travel passengers' willingness to pay to offset their CO_2 emissions. *Climatic Change*, 90(3):299–313.

Brzeszczynski, J., Ghimire, B., Jamasb, T., and McIntosh, G., 2019. Socially responsible investment and market performance: The case of energy and resource companies. *The Energy Journal*, 40(5):17–72.

Cameron, A. C., Gelbach, J. B., and Miller, D. L., 2008. Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, 90(3):414–427.

Carroll, A. B. and Shabana, K. M., 2010. The business case for corporate social responsibility: A review of concepts, research and practice. *International Journal of Management Reviews*, 12(1):85–105.

Carson, R. T. and Groves, T., 2007. Incentive and informational properties of preference questions. *Environmental and Resource Economics*, 37(1):181–210.

Cason, T. N. and Gangadharan, L., 2002. Environmental labeling and incomplete consumer information in laboratory markets. *Journal of Environmental Economics and Management*, 43(1):113–134.

CBS. Nederlanders en hun auto. Een overzicht van de afgelopen 10 jaar. Centraal Bureau voor de Statistiek, 2017.

CEC. Commission of the European Communities Case No IV/M.1406. HYUNDAI / KIA, Regulation (EEC) No 4064/89. Merger Procedure, 1999.

CentERdata. The CentERpanel, 2018. URL `https://www.centerdata.nl/en/projects-by-centerdata/the-center-panel`.

Chatterji, A. K., Levine, D. I., and Toffel, M. W., 2009. How well do social ratings actually measure corporate social responsibility? *Journal of Economics & Management Strategy*, 18(1):125–169.

Coase, R. H., 1960. The problem of social cost. *Journal of Law and Economics*, 3:1–44.

Commission, E., 2017. Directive of the european parliament and of the council on the promotion of the use of energy from renewable sources (proposal). com/2016/0767.

Crumpler, H. and Grossman, P. J., 2008. An experimental test of warm glow giving. *Journal of Public Economics*, 92(5-6):1011–1021.

Davis, K., 1973. The case for and against business assumption of social responsibilities. *Academy of Management Journal*, 16(2):312–322.

Diederich, J. and Goeschl, T., 2014. Willingness to pay for voluntary climate action and its determinants: Field-experimental evidence. *Environmental and Resource Economics*, 57(3):405–429.

Dijkgraaf, E., van Dorp, T. P., and Maasland, E., 2018. On the effectiveness of feed-in tariffs in the development of solar photovoltaics. *The Energy Journal*, 39(1):81–99.

Dixon-Fowler, H. R., Slater, D. J., Johnson, J. L., Ellstrand, A. E., and Romi, A. M., 2013. Beyond "does it pay to be green?" A meta-analysis of moderators of the CEP–CFP relationship. *Journal of Business Ethics*, 112(2):353–366.

Dosi, C. and Moretto, M., 2001. Is ecolabelling a reliable environmental policy measure? *Environmental and Resource Economics*, 18(1):113–127.

Echavarria, E., Hahn, B., Van Bussel, G., and Tomiyama, T., 2008. Reliability of wind turbine technology through time. *Journal of Solar Energy Engineering*, 130 (3).

EEA. EEA greenhouse gas - data viewer, 2018. URL `http://www.eea.europa.eu/data-and-maps/data/data-viewers/greenhouse-gases-viewer`.

Egbue, O. and Long, S., 2012. Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy Policy*, 48:717–729.

Egli, F., 2020. Renewable energy investment risk: An investigation of changes over time and the underlying drivers. *Energy Policy*, 140:111428.

Egli, F., Steffen, B., and Schmidt, T. S., 2018. A dynamic analysis of financing conditions for renewable energy technologies. *Nature Energy*, 3(12):1084–1092.

Elofsson, K., Bengtsson, N., Matsdotter, E., and Arntyr, J., 2016. The impact of climate information on milk demand: Evidence from a field experiment. *Food Policy*, 58:14–23.

Emissions Analytics. Hybrids are 14 times better than battery electric vehicles at reducing real-world carbon dioxide emissions, 2019. URL `https://www.emissionsanalytics.com/news/hybrids-are-better`.

EPA. Green power partnership program success metrics. `https://www.epa.gov/greenpower/green-power-partnership-program-success-metrics`, 2019. Online; accessed 9 September 2019.

Espey, M. and Nair, S., 2005. Automobile fuel economy: What is it worth? *Contemporary Economic Policy*, 23(3):317–323.

EU, 2001. Directive 2001/77/EC of the European Parliament and of the Council of 27 September 2001 on the promotion of electricity produced from renewable energy sources in the internal electricity market. *Official Journal of the European Union*, 44:33–40.

EU, 2009. Directive 2009/28/ec of the european parliament and of the council of 23 april 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing directives 2001/77/ec and 2003/30/ec. *Official Journal of the European Union*, 52:16–62.

European Parliament, 2018. Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources. *Official Journal of the European Union*, 128:83–206.

Eurostat. Production of electricity and derived heat by type of fuel [data base], 2020a.

Eurostat. Electricity prices components for non-household consumers - annual data (from 2007 onwards) [data base], 2020b.

Eurostat. Electricity prices components for household consumers - annual data (from 2007 onwards) [data base], 2020c.

Eurostat. Complete energy balances [data base], 2020d.

Feddersen, T. J. and Gilligan, T. W., 2001. Saints and markets: Activists and the supply of credence goods. *Journal of Economics & Management Strategy*, 10(1):149–171.

Fontaras, G., Georgios Zacharof, N., and Ciuffo, B., 2017. Fuel consumption and CO_2 emissions from passenger cars in Europe–Laboratory versus real-world emissions. *Progress in Energy and Combustion Science*, 60:97–131.

Fraunhofer. Levelized cost of electricity renewable energy technologies. Fraunhofer Instıtute for Solar Energy System ISE, 2018.

Fuerst, F. and McAllister, P., 2011. Eco-labeling in commercial office markets: Do LEED and Energy Star offices obtain multiple premiums? *Ecological Economics*, 70(6):1220–1230.

Gerlagh, R. and Van der Zwaan, B., 2006. Options and instruments for a deep cut in CO2 emissions: Carbon dioxide capture or renewables, taxes or subsidies? *The Energy Journal*, 27(3).

Gianfreda, A. and Bunn, D., 2018. A stochastic latent moment model for electricity price formation. *Operations Research*, 66(5):1189–1203.

Golosov, M., Hassler, J., Krusell, P., and Tsyvinski, A., 2014. Optimal taxes on fossil fuel in general equilibrium. *Econometrica*, 82(1):41–88.

Green, R. and Yatchew, A., 2012. Support schemes for renewable energy: An economic analysis. *Economics of Energy & Environmental Policy*, 1(2):83–98.

Greene, D. L., Evans, D. H., and Hiestand, J., 2013. Survey evidence on the willingness of US consumers to pay for automotive fuel economy. *Energy Policy*, 61: 1539–1550.

Greenfact. Wholesale GO Prices. `https://greenfact.com/Data/Prices`, 2018a. Online; accessed 11 October 2018.

Greenfact. The Greenfact market survey 2018. The current status and environment within the GO market, 2018b. URL `https://greenfact.com/News/711/Greenfact-survey-results-available`.

Grothe, O. and Müsgens, F., 2013. The influence of spatial effects on wind power revenues under direct marketing rules. *Energy Policy*, 58:237–247.

Haas, R., Resch, G., Panzer, C., Busch, S., Ragwitz, M., and Held, A., 2011. Efficiency and effectiveness of promotion systems for electricity generation from renewable energy sources–Lessons from EU countries. *Energy*, 36(4):2186–2193.

Hackbarth, A. and Madlener, R., 2013. Consumer preferences for alternative fuel vehicles: A discrete choice analysis. *Transportation Research Part D: Transport and Environment*, 25:5–17.

Hackbarth, A. and Madlener, R., 2016. Willingness-to-pay for alternative fuel vehicle characteristics: A stated choice study for Germany. *Transportation Research Part A: Policy and Practice*, 85:89–111.

Haq, G. and Weiss, M., 2016. CO_2 labelling of passenger cars in Europe: Status, challenges, and future prospects. *Energy Policy*, 95:324–335.

Heather, P. The evolution of European traded gas hubs. OIES paper: NG104, 2016.

Hensher, D. A. and Greene, W. H., 2003. The mixed logit model: the state of practice. *Transportation*, 30(2):133–176.

Hidrue, M. K., Parsons, G. R., Kempton, W., and Gardner, M. P., 2011. Willingness to pay for electric vehicles and their attributes. *Resource and Energy Economics*, 33 (3):686–705.

Hirth, L., 2013. The market value of variable renewables: The effect of solar wind power variability on their relative price. *Energy Economics*, 38:218–236.

Hornibrook, S., May, C., and Fearne, A., 2015. Sustainable development and the consumer: Exploring the role of carbon labelling in retail supply chains. *Business Strategy and the Environment*, 24(4):266–276.

Hulshof, D. and Mulder, M., 2020a. Willingness to Pay for CO2 Emission Reductions in Passenger Car Transport. *Environmental and Resource Economics*, 75(4): 899–929.

Hulshof, D. and Mulder, M., 2020b. The impact of renewable energy use on firm profit. *Energy Economics*, 92:104957.

Hulshof, D., Jepma, C., and Mulder, M., 2019. Performance of markets for European renewable energy certificates. *Energy Policy*, 128:697–710.

ICCT. From laboratory to road: A 2018 update of official and "real-world" fuel consumption and CO_2 values for passenger cars in Europe. White paper, 2019.

IEA, 2019. *World Energy Statistics 2019*.

IEA. Policies database. `https://www.iea.org/policies/`, 2021.

IPCC, 2014. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]*. IPCC.

Ito, N., Takeuchi, K., and Managi, S., 2013. Willingness-to-pay for infrastructure investments for alternative fuel vehicles. *Transportation Research Part D: Transport and Environment*, 18:1–8.

Jaraitė, J. and Kažukauskas, A., 2013. The profitability of electricity generating firms and policies promoting renewable energy. *Energy Economics*, 40:858–865.

Joumard, I., Kongsrud, P. M., Nam, Y.-S., and Price, R., 2004. Enhancing the effectiveness of public spending: experience in OECD countries.

Kamerschen, D. R. and Porter, D. V., 2004. The demand for residential, industrial and total electricity, 1973–1998. *Energy Economics*, 26(1):87–100.

Kang, C., Germann, F., and Grewal, R., 2016. Washing away your sins? Corporate social responsibility, corporate social irresponsibility, and firm performance. *Journal of Marketing*, 80(2):59–79.

King, A. A. and Lenox, M. J., 2001. Does it really pay to be green? An empirical study of firm environmental and financial performance. *Journal of Industrial Ecology*, 5(1):105–116.

Konar, S. and Cohen, M. A., 2001. Does the market value environmental performance? *Review of Economics and Statistics*, 83(2):281–289.

Kronmal, R. A., 1993. Spurious correlation and the fallacy of the ratio standard revisited. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 156 (3):379–392.

Lancaster, K. J., 1966. A new approach to consumer theory. *Journal of Political Economy*, 74(2):132–157.

Lemming, J., 2003. Financial risks for green electricity investors and producers in a tradable green certificate market. *Energy Policy*, 31(1):21–32.

Lind, J. T. and Mehlum, H., 2010. With or without U? The appropriate test for a U-shaped relationship. *Oxford Bulletin of Economics and Statistics*, 72(1):109–118.

Lise, W., Timpe, C., Jansen, J. C., and ten Donkelaar, M., 2007. Tracking electricity generation attributes in europe. *Energy Policy*, 35(11):5855–5864.

List, J. A. and Gallet, C. A., 2001. What experimental protocol influence disparities between actual and hypothetical stated values? *Environmental and Resource Economics*, 20(3):241–254.

Lizzeri, A., 1999. Information revelation and certification intermediaries. *The RAND Journal of Economics*, pages 214–231.

Longo, A., Markandya, A., and Petrucci, M., 2008. The internalization of externalities in the production of electricity: willingness to pay for the attributes of a policy for renewable energy. *Ecological Economics*, 67(1):140–152.

Löschel, A., Sturm, B., and Vogt, C., 2013. The demand for climate protection–empirical evidence from Germany. *Economics Letters*, 118(3):415–418.

Lyon, T. P. and Yin, H., 2010. Why do states adopt renewable portfolio standards? An empirical investigation. *The Energy Journal*, 31(3).

MacKerron, G. J., Egerton, C., Gaskell, C., Parpia, A., and Mourato, S., 2009. Willingness to pay for carbon offset certification and co-benefits among (high-) flying young adults in the UK. *Energy Policy*, 37(4):1372–1381.

Mahenc, P., 2017. Honest versus misleading certification. *Journal of Economics & Management Strategy*, 26(2):454–483.

Manwell, J. F., McGowan, J. G., and Rogers, A. L., 2010. *Wind energy explained: theory, design and application*. John Wiley & Sons.

Margolis, J. D. and Walsh, J. P., 2001. *People and profits? The search for a link between a company's social and financial performance*. Lawrence Erlbaum: Mahwah, NJ.

Margolis, J. D., Elfenbein, H. A., and Walsh, J. P. Does it pay to be good... And does it matter? A meta-analysis of the relationship between corporate social and financial performance. Working paper, available at SSRN: https://ssrn.com/abstract=1866371, 2009.

May, N., 2017. The impact of wind power support schemes on technology choices. *Energy Economics*, 65:343–354.

McFadden, D. and Train, K. E., 2000. Mixed MNL models for discrete response. *Journal of Applied Econometrics*, 15(5):447–470.

McWilliams, A. and Siegel, D., 2000. Corporate social responsibility and financial performance: correlation or misspecification? *Strategic Management Journal*, 21 (5):603–609.

McWilliams, A. and Siegel, D., 2001. Corporate social responsibility: A theory of the firm perspective. *Academy of Management Review*, 26(1):117–127.

McWilliams, A. and Siegel, D. S., 2011. Creating and capturing value: Strategic corporate social responsibility, resource-based theory, and sustainable competitive advantage. *Journal of Management*, 37(5):1480–1495.

Meyer, N. I., 2003. European schemes for promoting renewables in liberalised markets. *Energy Policy*, 31(7):665–676.

Meznar, M. B., Nigh, D., and Kwok, C. C., 1994. Effect of announcements of withdrawal from South Africa on stockholder wealth. *Academy of Management Journal*, 37(6):1633–1648.

Ministerie van Financiën. IBO grondvergoeding energievoorzieningen, 2018.

Mitchell, C., Bauknecht, D., and Connor, P. M., 2006. Effectiveness through risk reduction: A comparison of the renewable obligation in England and Wales and the feed-in system in Germany. *Energy Policy*, 34(3):297–305.

Mozumder, P., Vásquez, W. F., and Marathe, A., 2011. Consumers' preference for renewable energy in the southwest USA. *Energy Economics*, 33(6):1119–1126.

Mulder, M. and Zomer, S. P., 2016. Contribution of green labels in electricity retail markets to fostering renewable energy. *Energy Policy*, 99:100–109.

Murdock, J., 2006. Handling unobserved site characteristics in random utility models of recreation demand. *Journal of Environmental Economics and Management*, 51 (1):1–25.

Myung, I. J., 2003. Tutorial on maximum likelihood estimation. *Journal of Mathematical Psychology*, 47(1):90–100.

Nemet, G. F., 2006. Beyond the learning curve: Factors influencing cost reductions in photovoltaics. *Energy Policy*, 34(17):3218–3232.

Nestle. New wind farm opens in Dumfries and Galloway to power Nestle in the UK & Ireland. `https://www.nestle.co.uk/media/newsfeatures/new-wind-farm-opens-in-dumfries-and-galloway-to-power-nestle-in-the-uk-and-ireland`, 2018. Online; accessed 11 October 2018.

Newell, R. G. and Siikamäki, J., 2014. Nudging energy efficiency behavior: The role of information labels. *Journal of the Association of Environmental and Resource Economists*, 1(4):555–598.

Ng, A. and Zheng, D., 2018. Let's agree to disagree! On payoffs and green tastes in green energy investments. *Energy Economics*, 69:155–169.

Nicolini, M. and Tavoni, M., 2017. Are renewable energy subsidies effective? Evidence from Europe. *Renewable and Sustainable Energy Reviews*, 74:412–423.

Nilsson, M., Nilsson, L. J., and Ericsson, K., 2009. The rise and fall of GO trading in European renewable energy policy: The role of advocacy and policy framing. *Energy Policy*, 37(11):4454–4462.

Nordhaus, W. D., 2006. Geography and macroeconomics: New data and new findings. *Proceedings of the National Academy of Sciences of the United States of America*, 103(10):3510–3517.

Oberndorfer, U., Schmidt, P., Wagner, M., and Ziegler, A., 2013. Does the stock market value the inclusion in a sustainability stock index? An event study analysis for German firms. *Journal of Environmental Economics and Management*, 66(3): 497–509.

Ofgem. Liquidity in the GB wholesale energy markets. Ref 62/09., 2009.

Orlitzky, M., Schmidt, F. L., and Rynes, S. L., 2003. Corporate social and financial performance: A meta-analysis. *Organization Studies*, 24(3):403–441.

Park, J. Y., 2017. Is there a price premium for energy efficiency labels? Evidence from the introduction of a label in Korea. *Energy Economics*, 62:240–247.

Paton, G., Nov 2015. Petrol vehicles are sucked into VW emissions scandal. *The Times*. URL `https://www.thetimes.co.uk/article/petrol-vehicles-are-sucked-into-vw-emissions-scandal-srf0xlx87wp`.

Petitjean, M., 2019. Eco-friendly policies and financial performance: Was the financial crisis a game changer for large US companies? *Energy Economics*, 80:502–511.

Pigou, A. C., 1920. *The economics of welfare*. Palgrave Macmillan, London.

Porter, M. E. and Van der Linde, C., 1995. Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives*, 9(4): 97–118.

PWC. Corporate renewable energy procurement survey insights, 2016.

Ragwitz, M., del Río González, P., and Resch, G., 2009. Assessing the advantages and drawbacks of government trading of guarantees of origin for renewable electricity in Europe. *Energy Policy*, 37(1):300–307.

RE100. Moving to truly global impact: Influencing renewable electricity markets. RE100 Progress and Insights Annual Report, 2018.

Regnier, E., 2007. Oil and energy price volatility. *Energy Economics*, 29(3):405–427.

REN21. Renewables 2019: Global status report, 2020.

Revelt, D. and Train, K. E., 2000. Customer-specific taste parameters and mixed logit: Households' choice of electricity supplier. *Working Paper No. E00-274*, Department of Economics, University of California, Berkeley.

Ricardo-AEA. Improvements to the definition of lifetime mileage of light duty vehicles. Report for European Commission – DG Climate Action, 2015.

Roe, B., Teisl, M. F., Levy, A., and Russell, M., 2001. US consumers' willingness to pay for green electricity. *Energy Policy*, 29(11):917–925.

Rosen, S., 1974. Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of Political Economy*, 82(1):34–55.

Russo, M. V. and Fouts, P. A., 1997. A resource-based perspective on corporate environmental performance and profitability. *Academy of Management Journal*, 40 (3):534–559.

Scarpa, R. and Willis, K., 2010. Willingness-to-pay for renewable energy: Primary and discretionary choice of British households' for micro-generation technologies. *Energy Economics*, 32(1):129–136.

Scarpa, R., Thiene, M., and Train, K. E., 2008. Utility in willingness to pay space: a tool to address confounding random scale effects in destination choice to the alps. *American Journal of Agricultural Economics*, 90(4):994–1010.

Schmalensee, R., 2012. Evaluating policies to increase electricity generation from renewable energy. *Review of Environmental Economics and Policy*, 6(1):45–64.

Schmidt, J., Lehecka, G., Gass, V., and Schmid, E., 2013. Where the wind blows: Assessing the effect of fixed and premium based feed-in tariffs on the spatial diversification of wind turbines. *Energy Economics*, 40:269–276.

Schneider, S. H. and Goulder, L. H., 1997. Achieving low-cost emissions targets. *Nature*, 389(6646):13–14.

Scholtens, B., 2008. A note on the interaction between corporate social responsibility and financial performance. *Ecological Economics*, 68(1-2):46–55.

Semenova, N. and Hassel, L. G., 2015. On the validity of environmental performance metrics. *Journal of Business Ethics*, 132(2):249–258.

Shaked, A. and Sutton, J., 1982. Relaxing price competition through product differentiation. *The Review of Economic Studies*, pages 3–13.

Shaked, A. and Sutton, J., 1987. Product differentiation and industrial structure. *The Journal of Industrial Economics*, pages 131–146.

Siegel, D. S. and Vitaliano, D. F., 2007. An empirical analysis of the strategic use of corporate social responsibility. *Journal of Economics & Management Strategy*, 16(3): 773–792.

Sillano, M. and de Dios Ortúzar, J., 2005. Willingness-to-pay estimation with mixed logit models: some new evidence. *Environment and Planning A*, 37(3):525–550.

Stavins, R. N., 2011. The problem of the commons: still unsettled after 100 years. *American Economic Review*, 101(1):81–108.

Stern, N., 2007. *The economics of climate change. The Stern review*. Cambridge University Press.

Sundt, S. and Rehdanz, K., 2015. Consumers' willingness to pay for green electricity: A meta-analysis of the literature. *Energy Economics*, 51:1–8.

Tanaka, M., Ida, T., Murakami, K., and Friedman, L., 2014. Consumers' willingness to pay for alternative fuel vehicles: A comparative discrete choice analysis between the US and Japan. *Transportation Research Part A: Policy and Practice*, 70: 194–209.

Taylor, M. Energy subsidies: Evolution in the global energy transformation to 2050. Technical report, International Renewable Energy Agency (IRENA), 2020.

Train, K. E., 1998. Recreation demand models with taste differences over people. *Land Economics*, 47(2):230–239.

Train, K. E., 2009. *Discrete choice methods with simulation*. Cambridge university press.

Train, K. E. and Weeks, M., 2005. *Discrete choice models in preference space and willingness-to-pay space*. Springer.

Train, K. E. and Winston, C., 2007. Vehicle choice behavior and the declining market share of US automakers. *International Economic Review*, 48(4):1469–1496.

United Nations. Paris agreement. Report, 2015.

Van der Ploeg, F. and Withagen, C., 2014. Growth, renewables, and the optimal carbon tax. *International Economic Review*, 55(1):283–311.

Verbeek, D. and Boelhouwer, J., 2010. Milieu van later, wiens zorg nu. *Wisseling van de Wacht: Generaties in Nederland. Sociaal en Cultureel Rapport; van den Broek, A., Bronneman-Helmers, R., Veldheer, V., Eds*.

Verbruggen, A., 2008. Windfalls and other profits. *Energy Policy*, 36(9):3249–3251.

Veum, K., Londo, M., and Jansen, J. A review of past and existing GoO systems, 2015.

Volkswagen. Volkswagen Sachsen reduces environmental footprint using Naturstrom hydropower. `https://www.volkswagen-newsroom.com/en/press-releases/volkswagen-sachsen-reduces-environmental-footprint-using-naturstrom-r-hydropower-667`, 2017. Online; accessed 11 October 2018.

Waddock, S. A. and Graves, S. B., 1997. The corporate social performance–financial performance link. *Strategic Management Journal*, 18(4):303–319.

Wang, X., Bennett, J., Xie, C., Zhang, Z., and Liang, D., 2007. Estimating non-market environmental benefits of the conversion of cropland to forest and grassland program: A choice modeling approach. *Ecological Economics*, 63(1):114–125.

Weitzman, M. L., 1974. Prices vs. quantities. *The review of Economic Studies*, 41(4): 477–491.

Winther, T. and Ericson, T., 2013. Matching policy and people? Household responses to the promotion of renewable electricity. *Energy Efficiency*, 6(2):369–385.

Wiser, R., Bolinger, M., Hoen, B., Millstein, D., Rand, J., Barbose, G., Darghouth, N., Gorman, W., Jeong, S., Mills, A., and Paulos, B. Wind Energy Technology Data Update: 2020 Edition. Lawrence Berkeley National Laboratory, 2020.

Wooldridge, J. M., 2010. *Econometric analysis of cross section and panel data*. MIT press.

Ziegler, A., 2012. Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: A discrete choice analysis for Germany. *Transportation Research Part A: Policy and Practice*, 46(8):1372–1385.

Ziegler, A., Busch, T., and Hoffmann, V. H., 2011. Disclosed corporate responses to climate change and stock performance: An international empirical analysis. *Energy Economics*, 33(6):1283–1294.

Nederlandse samenvatting

Energiemarkten kunnen een belangrijke rol spelen bij het realiseren van de transitie van fossiele naar hernieuwbare energie. Echter, deze markten worden gekenmerkt door marktfalens, die resulteren in onderconsumptie van hernieuwbare energie en overconsumptie van fossiele energie ten opzichte van het sociaal-optimale niveau. Het belangrijkste marktfalen is de negatieve externaliteit die voortkomt uit de uitstoot van CO_2 bij de verbranding van fossiele energiebronnen zoals olie en gas. Deze CO_2-uitstoot draagt bij aan ongewenste klimaatverandering, en de marginale kosten die hiermee gemoeid zijn vallen, zonder overheidsingrijpen, niet ten deel aan de energieproducenten of -consumenten. Dit resulteert in een te lage prijs voor fossiele energie, waardoor partijen er te veel van produceren en consumeren.

Een tweede marktfalen dat energiemarkten parten speelt, met potentieel dezelfde gevolgen voor de relatieve overconsumptie van fossiele energie, is informatie asymmetrie. Dit marktfalen doet zich in belangrijke mate voor tussen energieaanbieders en consumenten als het gaat om de herkomst van energie. Vanuit het perspectief van de consument heeft een gegeven energietype (bijvoorbeeld gas of stroom) identieke karakteristieken, ongeacht of de bron hernieuwbaar of fossiel is. Dit maakt dat, terwijl producenten perfecte informatie over de energiebron hebben, consumenten geen onderscheid kunnen maken tussen fossiele en hernieuwbare energie. Als consumenten een voorkeur hebben voor hernieuwbare energie en bereid zijn daar meer voor te betalen, dan heeft de aanbieder, die begrijpt dat de consument hem niet goed kan controleren, een prikkel om fossiele energie als hernieuwbare energie aan te bieden. Hierdoor kunnen consumenten aanbieders niet vertrouwen en zullen zij, hoewel ze het intrinsiek misschien wel zouden willen, niet of minder snel voor hernieuwbare energie kiezen. Dit resulteert, net als bij de negatieve externaliteit, in een te lage prijs ten opzichte van het sociale optimum, maar ditmaal voor hernieuwbare energie. De gevolgen voor de marktkwantiteit en daarmee emissies zijn hetzelfde, namelijk relatief te veel productie en consumptie van fossiele energie, en te weinig van hernieuwbare energie.

Om te pogen de overconsumptie van fossiele energie te reduceren kiezen overheden vaak voor het geven van subsidies aan producenten van hernieuwbare energie. De bijbehorende uitgaven zijn inmiddels substantieel. In de EU in 2017, bijvoorbeeld, gaven de nationale overheden hier gezamenlijk een slordige €80 miljard aan uit, wat neer komt op een 0.5% van het BBP. Mede als gevolg hiervan is voornamelijk het aandeel hernieuwbare stroom gestegen, van 12.6% in 1990 (toen er nauwelijks klimaatbeleid werd gevoerd) naar 30.4% in 2017. Het feit dat de stroomsector slechts zo'n 21% van de totale energievraag uitmaakt, en deze sector, in vergelijking met andere sectoren (zoals de industrie en gebouwde omgeving), tegen relatief lage kosten kan verduurzamen, illustreert dat de energietransitie hoge uitgaven met zich mee zal brengen. Dit laat ook zien dat het uitermate belangrijk is om deze transitie zo kosten-efficiënt mogelijk te laten verlopen.

Deze dissertatie richt zich, tegen de achtergrond van een gebrek aan voldoende prikkels voor hernieuwbare energie vanwege informatie asymmetrie en negatieve externaliteiten, op het zo goed mogelijk laten functioneren van energiemarkten. Een belangrijk doel hierbij is om het begrip te vergroten van de mogelijkheden voor het realiseren van een efficiënte energietransitie.

Het eerste deel van dit proefschrift, Hoofdstukken 2 en 3, richt zich op de preferenties van energiegebruikers voor hernieuwbare energie. Preferenties zijn namelijk van cruciaal belang voor de mate waarin informatie asymmetrie een probleem vormt. Als men niet meer wil betalen voor hernieuwbare energie, dan heeft het reduceren van die informatie asymmetrie geen effect op de keuze van gebruikers voor fossiele of hernieuwbare energie. Om te onderzoeken in welke mate informatie asymmetrie in die zin een relevant marktfalen is worden de preferenties, om precies te zijn de betalingsbereidheid, van respectievelijk consumenten en producenten onderzocht. Het onderscheidt tussen consumenten en producenten wordt gemaakt vanwege de aanname dat bij deze twee type 'economische agenten' een verschillende algemene motivering ten grondslag ligt aan het gedrag. Waar consumenten ernaar streven om hun nut te maximaliseren, streven bedrijven ernaar om hun winst te maximaliseren.

In Hoofdstuk 2 worden de preferenties van consumenten onderzocht voor de milieuvoordelen van het gebruik van hernieuwbare energie: CO_2-emissiereducties. In tegenstelling tot eerdere literatuur richt dit hoofdstuk zich op de betalingsbereidheid van consumenten voor CO_2-emissies, los van andere attributen van hernieuwbare energie die een rol kunnen spelen. Dit onderscheid is van belang omdat verschillende types hernieuwbare energie gemeen hebben dat ze CO_2-uitstoot verminderen, maar kunnen verschillen op andere, voor de consument relevante, gebieden (bijvoorbeeld elektrische versus moleculaire vorm van energie). In dit hoofdstuk wordt de betalingsbereidheid geschat met behulp van een discrete keuze-experiment onder een voor Nederland representatieve groep huishoudens, toegepast op de markt voor personenauto's. Het voordeel van een discrete keuze-experiment is dat hierbij geen gebruikt wordt gemaakt van data gebaseerd op echte transacties, die mogelijk niet de daadwerkelijke preferenties van consumenten reflecteren vanwege het informatie asymmetrie probleem. De markt voor personenauto's is een bij uitstek geschikte applicatie omdat consumenten in deze markt al voor de keuze staan om een auto te kiezen die varieert in het energietype (benzine, hybride, elektrisch, etc.). Daar komt bij dat, in veel grotere mate dan bijvoorbeeld bij het kiezen van een energiecontract voor thuis, de CO_2-uitstoot bij auto's relatief expliciet onderdeel is van het te kiezen product. Het belangrijkste resultaat is dat men, gemiddeld genomen, bereid is een aanzienlijk bedrag te betalen om CO_2-emissies te reduceren, namelijk in de orde van grote van € 200 per ton. De resultaten laten daarnaast zien dat er een hele grote mate van spreiding is in de betalingsbereidheid. Terwijl een deel van de consumenten bereid is fors meer te betalen, is ook een groot deel bereid een stuk minder te betalen. De conclusie die volgt uit dit hoofdstuk is dat een aanzienlijk potentieel is voor emissiereducties in de markt voor personenauto's. Vanuit het beleidsperspectief kunnen maatregelen die informatie asymmetrie reduceren een belangrijke bijdrage leveren aan het benutten van dit potentieel.

In Hoofdstuk 3 worden de preferenties van bedrijven onderzocht. In tegenstelling tot Hoofdstuk 2, wordt in Hoofdstuk 3 daadwerkelijk gedrag bestudeerd, om zo te analyseren of bedrijven, zoals zij vaak lijken te impliceren met hun claims in persberichten, bereid zijn winst in te leveren ten faveure van het gebruik van hernieuwbare energie. Dit hoofdstuk neemt een fundamenteel micro-economische raamwerk als uitgangspunt voor het analyseren van de daadwerkelijke keuzes die bedrijven maken om al dan niet hernieuwbare energie te gebruiken: bedrijven willen hun winst maximaliseren en kiezen voor (duurdere) hernieuwbare energie wanneer hen dat in staat stelt om hun product of bedrijf te differentiëren van concurrenten en hierdoor een hogere prijs te vragen. Dit raamwerk resulteert in de voorspelling dat bedrijven alleen hernieuwbare energie gebruiken als ze worden gecompenseerd voor de hogere kosten, en dat, bij voldoende concurrentie, deze compensatie niet groter is dan de stijging in de kosten. De empirische analyse in dit hoofdstuk test deze voorspelling aan de hand van bedrijfsinformatie (zoals winst en hernieuwbaar- en totaal energiegebruik) voor een groep van 911 bedrijven uit een groot aantal landen. Als uit de analyse zou blijken dat, in tegenstelling tot de voorspelling, bedrijven bereid zijn om winst in te leveren ten faveure van het gebruik van hernieuwbare energie, dan kan dit mogelijk geïnterpreteerd worden als een positieve betalingsbereidheid van bedrijven. De resultaten zijn, echter, in lijn met de voorspelling die voortkomt uit het micro-economische raamwerk: er lijkt geen effect te zijn van het gebruik van hernieuwbare energie op de bedrijfswinsten. Dit impliceert dat bedrijven geen positieve betalingsbereidheid hebben voor hernieuwbare energie als bijdrage aan het mitigeren van klimaatverandering, en dat bedrijven hier alleen toe bereid zijn wanneer dit bijdraagt aan het behalen van hun eigen winstdoelstelling.[1]

In het tweede deel van dit proefschrift wordt de aandacht verschoven naar beleidsmaatregelen. Omdat uit het eerste deel van dit proefschrift naar voren komt dat het wenselijk is om informatie asymmetrie te adresseren (omdat een aanzienlijk deel van de mensen een positieve betalingsbereidheid blijkt te hebben), wordt in Hoofdstuk 4 het functioneren van bestaande markten voor hernieuwbare energiecertificaten empirisch onderzocht. Deze certificaten worden vaak geïmplementeerd in energiemarkten met als doel om informatie asymmetrie te reduceren. Omdat certificaten worden verhandeld in afzonderlijke markten, neemt dit hoofdstuk als vertrekpunt dat de mate waarin een certificatensysteem succesvol is in het reduceren van informatie asymmetrie, sterk samenhangt met het goed functioneren van die certificatenmarkten. Hoofdstuk 5 gaat in op de vormgeving van subsidiesystemen en de rol die informatie asymmetrie tussen overheden en energieproducenten hierbij speelt. Bij subsidies relateert de informatie asymmetrie niet aan de karakteristieken van energie, maar aan de karakteristieken, en daarmee samenhangende kosten, van hernieuwbare-energieprojecten. Hier is het vertrekpunt dat, idealiter, de overheid de subsidie precies gelijkstelt aan het minimale benodigde subsidiebedrag van een specifiek project. In de praktijk is dit echter lastig omdat

[1] Dit impliceert overigens niet dat consumenten geen effect hebben op het milieu wanneer zij bereid zijn meer te betalen voor producten van bedrijven die hernieuwbare energie gebruiken. Immers, de hogere prijs die een consument betaalt voor dergelijke producten biedt bedrijven juist de benodigde financiële prikkel om deze, in plaats van meer milieubelastende, producten aan te bieden. Met andere woorden, bedrijven bieden de producten aan die de consumenten vragen, of dat nou goedkopere grijze, of duurdere groene producten zijn. Illustratief is de markt voor olie en afgeleide producten zoals autobrandstoffen. Zolang er vraag is van consumenten naar deze producten omdat deze groep, bijvoorbeeld, in brandstofauto's wil rijden zullen er bedrijven bereid zijn om deze producten te produceren. Wanneer consumenten voldoende extra bereid zijn te betalen voor duurzame alternatieven, zoals biobrandstoffen of auto's met een lage uitstoot, dan zullen bedrijven hun gedrag aanpassen. De andere optie om bedrijven een prikkel te geven hun gedrag aan te passen is door beleidsmaatregelen te treffen, zoals subsidies voor duurzame alternatieven of een belasting op CO_2.

de karakteristieken en kosten van een project niet perfect kunnen worden geobserveerd. Investeerders in projecten hebben namelijk een prikkel om hun kosten te overschatten, en opbrengsten te onderschatten.

In Hoofdstuk 4 wordt de gangbare beleidsmaatregel om informatie asymmetrie in energiemarkten te adresseren onderzocht. Hoewel certificaten inmiddels een belangrijke rol lijken te spelen bij de handel in hernieuwbare energie, zijn deze systemen en markten relatief jong. Daarom is het onduidelijk in welke mate certificatenmarkten goed functioneren, dat wil zeggen als een volwassen markt. Daar komt bij dat er tussen landen verschillen bestaan in de manier waarop het certificatensysteem is vormgegeven. Om te onderzoeken hoe goed die markten functioneren worden in dit hoofdstuk vier indicatoren gebruikt: de 'churn' ratio voor marktliquiditeit,[2] prijsvolatiliteit en de certificerings- en expiratieratio, waarbij de laatste twee een indicatie geven van de algehele interesse in certificaten. Deze indicatoren zijn geconstrueerd voor twintig EU-landen en geanalyseerd over de periode 2001–2016. Om te onderzoeken of de vormgeving van het systeem van belang is voor het functioneren van de markt is onderzocht of verschillen in vormgeving tussen landen gerelateerd zijn aan verschillen in de marktuitkomsten zoals het marktvolume. De vormgevingselementen waarop wordt gefocust zijn de (i) publieke vs. private natuur van de certificeerder, en (ii) de conformiteit aan de Europese standaard voor certificaten.

Een van de resultaten van dit hoofdstuk is dat certificatenmarkten nog niet functioneren als volwassen markten. Hoewel hernieuwbare energie in toenemende mate wordt gecertificeerd, zijn de markten waarop ze worden verhandeld illiquide en de prijzen zeer volatiel. Als het gaat om vormgeving van het systeem, laten de resultaten zien dat publiek eigendom over de certificeerder en het conformeren aan de Europese standaard, positief bijdragen aan de ontwikkeling van certificeringssystemen.

Vervolgens worden in Hoofdstuk 5 subsidiesystemen voor hernieuwbare energie onderzocht in relatie tot informatie asymmetrie. De focus ligt hierbij op de mate waarin subsidiesystemen resulteren in zogenaamde "overwinsten" voor gesubsidieerde investeerders in hernieuwbare energie en de manieren om hiermee om te gaan in de vormgeving van het systeem. Overwinsten komen voort uit subsidies die hoger ligger dan het minimale subsidiebedrag dat nodig was geweest voor het

[2] De churn ratio geeft de verhouding weer tussen het verhandelde en daadwerkelijk geleverde volume. In een liquide markt wordt een product meerdere keren verhandeld voordat het daadwerkelijk wordt geconsumeerd. Bijvoorbeeld, op de Nederlandse groothandelsmarkt voor aardgas (de TTF), een buitengewoon liquide en volwassen markt, was de churn ratio in 2019 bijna 100. Met andere woorden, een kuub gas werd zo'n 100 keer verhandeld voordat die kuub werdt geconsumeerd.

realiseren van een project. Dit is ongewenst vanwege de onnodig hoge inefficiënties uit belastingheffing die daaruit voortkomen, maar ook vanwege de geimpliceerde welvaartverschuivingen van belastingbetalers of energiegebruikers naar de gesubsidieerde investeerders, die op zoek zijn naar private rendementen. Een uitdaging bij het limiteren van overwinsten is dat overheden de projectkarakteristieken en dus de kosten niet goed kunnen observeren. Daarom wordt vaak een uniforme subsidie voor een techniek (bv. wind op land) gehanteerd, wat resulteert in overwinsten voor projecten met relatief lage kosten. Om die overwinsten te analyseren wordt in dit hoofdstuk de verdeling van de minimaal benodigde subsidie geschat voor wind-op-land projecten in Nederland, in 2003, 2009 en 2018. Deze drie jaren vertegenwoordigen verschillende ontwerpen van het systeem, waarbij specifieke aanpassingen zijn ingevoerd met als doel overwinsten te beperken, zoals het differentiëren in de subsidie tussen projecten op basis van de windsnelheid. De verdeling van het benodigde subsidiebedrag wordt geschat via het simuleren van een investeringsmodel waarin voor de belangrijkste projectkarakteristieken (die van invloed zijn op de winstgevendheid) wordt aangenomen dat ze verschillen tussen tussen projecten volgens een bepaalde verdeling. De verdeling voor ieder van de projectkarakteristieken wordt geschat met behulp van data, zoals windsnelheidobservaties van alle locaties en relevante hoogtes in Nederland.

De resultaten laten zien dat de overwinsten in zijn algemeenheid zijn verminderd tussen 2003 en 2018. Als we kijken naar de gemiddelde overwinst van een willekeurig getrokken project uit de groep van alle potentiële projecten, dan is de gemiddelde overwinst gedaald van € 2,42 ct/kWh in 2003 naar € 0,85 ct/kWh in 2018. Deze daling komt grotendeels voort uit de aanpassingen aan de subsidieregeling, zoals de invoering van categoriedifferentiatie. Echter, als percentage van het subsidiebedrag waren de overwinsten met 32% in 2018 niet lager dan de 31% in 2003. Overwinsten zijn dus niet verdwenen, en in relatieve termen zelfs gelijk gebleven. Vervolgens toont dit hoofdstuk aan dat het benodigde subsidiebedrag van de 187 *daadwerkelijke* ondernomen gesubsidieerde projecten in 2018 nog een stuk lager lag, en daarmee de gemiddelde overwinst, op € 1,28 ct/kWh, een stuk hoger. Hieruit blijkt dat investeerders succesvol zijn in het uitkiezen van de projecten die resulteren in de hoogste overwinsten. Het is aannemelijk dat zij hiertoe in staat zijn dankzij hun superieure informatie over de projectkarakteristieken ten opzichte van de overheid. Voor beleid impliceren deze resultaten dat differentiëren in het benodigde subsidiebedrag tussen projecten bijdraagt aan het limiteren van overwinsten. Ten opzichte van de bestaande praktijk lijkt er vaak nog relatief veel ruimte om deze mate van differentiatie te vergroten en zo overwinsten verder te beperken.

In zijn geheel beschouwd, laat dit proefschrift zien dat (i) een aanzienlijk deel van de energiegebruikers bereid is financieel bij te dragen een het reduceren van emissies, (ii) bedrijven hoofdzakelijk financiële prikkels nodig hebben voordat zij bereid zijn hun gedrag aan te passen, (iii) het verminderen van informatie asymmetrie een belangrijke rol kan vervullen bij het reduceren van emissies, en (iv) dat het verbeteren van de vormgeving van subsidiesystemen, zoals in grote mate differentiëren tussen projecten, kan bijdragen aan het realiseren van een kosten-efficiënte energietransitie.

Imperfect Information and Incentives for Renewable Energy

Daan Hulshof

To realise climate goals, many governments provide subsidies to renewable-energy investors. While these subsidy expenditures are already considerable, the share of renewable energy remains modest. Given that future targets are highly ambitious, realising the energy transition will only demand more policy interventions. What role can energy markets play in keeping the associated costs under control?

This thesis aims to contribute to the organization of an efficient energy transition, by analysing energy markets and the potential problem that information asymmetry plays in causing underconsumption of non-renewables. The thesis first investigates whether energy users, who are confronted with asymmetrical information, prefer renewable energy to the extent that renewables can command a premium, which would curb the need for subsidies. Next, the thesis investigates whether the existing solution for information asymmetry, green certificates, is functioning properly. Finally, the dissertation investigates subsidy-scheme designs in relation to the asymmetrical information of the government and investors about the minimally required subsidy that makes a renewable-energy project profitable. Overall, this thesis shows that (i) many individuals are willing to contribute financially to reducing emissions, (ii) firms require financial incentives for them to be willing to contribute to reducing emissions, (iii) reducing information asymmetry can play a key role in the reduction of emissions, and (iv) improving the design of subsidy schemes can contribute to realising a cost-efficient energy transition.

rug.nl/feb/research