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The impact of price and regulatory uncertainty in green certificate markets: Evidence from the Swedish-Norwegian market

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Master's Programme in Economics, thesis (15 credits), August 2019

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ABSTRACT

The European Commission favours market-based support policies, such as markets for tradable green certificates, to promote renewable energy. Meanwhile, these markets have received critique for exposing investors to large price risk as the level of support is determined by the market price of certificates. Unstable prices can also result from changes in regulation since the demand for certificates is politically determined. Using econometric techniques and a two-step procedure, this study examines the impact of price and regulatory uncertainty in the Swedish-Norwegian tradable green certificate market. It focuses in particular on how it affects investment decisions, based on a case study of wind power projects in Sweden undertaken between 2005 to 2018. The empirical results indicate that: (1) regulatory changes negatively impact certificate markets, resulting in more volatile prices. (2) this has a deterring effect on green investments; a one standard deviation increase in price volatility is estimated to reduce the probability of project development by 12%, consistent with the predictions of real options theory and findings in previous literature. Overall, these findings provide some valuable implications for European policy makers aiming to design efficient and cost-effective future green energy policies.

Keywords: tradable green certificates, price volatility, regulatory uncertainty, green investment, real options theory.

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1. Introduction

The European Commission (2013) advocates for market-based support policies for promoting renewable electricity projects. They reason that competitive energy markets should drive production and investment decisions in an efficient and cost-effective way. Meanwhile, most European countries have adopted price-based support systems in terms of feed-in tariffs to comply with the EU Renewable Energy Directive (2009/28/EC), which obligates member states to take on binding targets to increase their share of renewable energy. Sweden is one exception, being one of the first European countries to introduce a market for tradable green certificates in 2003. The later expansion of the market in 2012 to include Norway is also the only example of using a cross-country support policy (Schusser & Jaraité, 2018).

The problem with certificate markets is often pointed out as being the exposure of investors to great risk as the level of support is determined by the market price of certificates, in contrast to feed-in tariffs where the government ensures a certain amount of cash flow to investors by fixing the support level for a sufficient time period ahead (Fagiani & Hakvoort, 2014; Gross et al., 2010). Further insight on investment behaviour in these markets can therefore provide valuable implications for European policy makers in their task of designing efficient and cost-effective future support policies to promote investments in green technologies. This study contributes to the empirical research by examining the impact of price and regulatory uncertainty in the Swedish-Norwegian tradable green certificate market. It focuses in particular on how its presence affects investment decisions, based on a case study of onshore wind power in Sweden, the renewable technology considered to have the greatest potential in Scandinavia (Swedish Energy Agency, 2018).

Real options theory predicts that in an uncertain environment and when an investment is durable and irreversible, the option to delay an investment decision into the future when some uncertainties might be revealed has an economic value. If a real option exists, uncertainty over future certificate prices may delay or cancel renewable electricity projects as investors require a risk premium to be willing to proceed with the risky investment (Dixit and Pindyck, 1994). Price stability can therefore be crucial for reaching renewable targets on time in a market-based support system. However, volatile prices can result from regulatory changes since certificate markets are characterized by a politically driven demand, where the government sets the target of renewable energy to be reached by imposing quota obligations on some parties in the electricity market. The quota, corresponding to a certain share of the total electricity consumed or sold that must originate from renewable sources, is met by purchasing green certificates. Renewable energy producers with a licence to sell certificates, receive one such certificate per unit of electricity produced from the government, thus providing an additional source of revenue apart from the wholesale price of electricity (Fagiani & Hakvoort, 2014; Swedish Energy Agency & NVE, 2018).

According to International Energy Agency (2014), the expansion of renewable energy will slow down unless regulatory uncertainty is diminished. They argue that given the capital-intensive nature of renewables, a market context that assures a reasonable and predictable return for investors is vital, accentuating the relevance of addressing these questions. The Swedish-Norwegian agreement is the largest and only international tradable green certificate market in Europe (Schusser & Jaraité, 2018). Yet, few studies have empirically analysed the dynamics of this market; Although the link between price and regulatory uncertainty have already been addressed by Fagiani and Hakvoort (2014), who show that regulatory changes increase price volatility, they do not directly investigate the effect on green investments. Using a two-step procedure, this study is able to do so and thereby contribute with an extended analysis.

First, I examine how regulatory uncertainty is reflected through the certificate price by endogenously test for structural breaks in the unconditional variance of certificate returns, derived from a GARCH model. The identified break dates are thereafter compared to changes in regulation to see if there is any correspondence between them. Second, I apply a real options approach and estimate a hazard model to analyse how price uncertainty affects the timing of wind power investments in Sweden. The empirical analysis identifies three regimes of increased price volatility that can be connected to regulatory changes, and further shows that an increase in price volatility reduces the probability of immediate development of wind power projects. These findings show that regulatory uncertainty in green certificate markets reduces the efficiency of the support policy, as renewable energy investments are delayed or dismissed.

The remainder of the paper is organised as follows. Section 2 describes the function of the Swedish-Norwegian tradable green certificate market and identifies important political events and regulatory changes. Section 3 presents the main assumptions of real options theory in relation to investments in renewable energy, as well as a review of related research. Section 4 presents the empirical methodology, and section 5 describes the data sample used for this study.

The empirical results and robustness checks are presented in section 5 and 6, respectively. Finally, section 7 discusses the empirical findings and concludes with some policy implications.

2. The Swedish-Norwegian tradable green certificate market

2.1. Function and political events

The Swedish tradable green certificate market came into force on May 1st, 2003, thereby replacing earlier subsidies for renewable energy. It was later revised into its current form in January 2007, when the duration of the market was extended from 2010 to 2030 and the renewable electricity production target was increased from 10 to 17 terawatt hours (TWh) by 2016, compared to 2002. It was also decided that new plants (or larger capacity expansions) should be entitled to receive certificates for 15 years, whereas old plants that started operating before May 2003, initially included to ensure enough liquidity in the early market phase, should be phased out of the system in 2012 and 2014 (Bergek & Jacobsson, 2010).

Moreover, to comply with the EU Renewable Energy Directive adopted in 2008, the Swedish government decided in June 2009 to increase the target to 25 TWh by 2020. This followed by another major revision, aiming to find a strategy on how to extend the system. As a result, a government bill was announced on March 10th, 2010, suggesting an extension of the market to 2035 along with increased quotas (Swedish Energy Agency, 2009; Prop. 2009/10:133). In the same bill, it was also proposed that the market should be expanded to include Norway starting from January 1st, 2012. Accordingly, on December 8th, 2010 the Swedish and Norwegian governments signed a protocol aiming to create a common market lasting until 2035, and a final agreement was signed in June 2011 (Prop. 2010/11:155). The larger market was expected to improve competition, increase liquidity, and yield more stable prices. Furthermore, by enabling investments to take place where conditions are most profitable between the countries, it was expected that the renewable electricity target could be reached in a more cost-effective way (Swedish Energy Agency & NVE, 2018). A complete timeline over changes in the regulation governing the Swedish part of the scheme is presented in Figure 1[1].

[1] The joint market is governed by two national regulatory frameworks, although the regulatory foundation is the same in both countries. More than 90% of the installed plants within the Swedish-Norwegian agreement are placed in Sweden (Swedish Energy Agency & NVE, 2018, 2019). Hence, it is reasonable to assume that mainly changes in the Swedish regulation affects the market dynamics and motivate the delimitation of the analysis to this part of the scheme.

The certificate market is the primary policy instrument in Sweden and Norway to promote investments in renewable energy and functions as a voluntary financial support to producers of wind, solar, geothermal, hydro, and wave power, as well as biomass and peat. Each month, the state issues electronic certificates to licenced producers based on last months reported production, one per megawatt hour (MWh). These can be traded, either bilaterally between producers and quota obligated parties or through stock brokers, both within and across the countries on a specific market for green certificates. The brokered transactions are carried out through spot or forward contracts, where trading with spot contracts and forwards with delivery the following March are most liquid. The supply of certificates is determined by the aggregate production of renewable electricity whereas the demand is regulated by law, where quota obligations are primarily imposed on electricity suppliers and large energy intensive industries. Because electricity suppliers pass on the costs of certificates to consumers electricity bills, it is in principal private households that finance the Scandinavian expansion of renewable electricity (Swedish Energy Agency & NVE, 2018; Swedish Energy Agency, 2012).

By the end of March each year, obligated parties must hold enough certificates to meet the annual quota and hand them over to the state. If the quota is not reached, a penalty fee corresponding to 150% of the average certificate price in the previous year is imposed for each certificate they are short of (ibid.). Except for the first year, the quota obligations have been fulfilled to 99%, ensuring a constant demand and hence an additional revenue to green producers. Figure 2 illustrates the quota curves which determine the annual quota level, for Sweden and Norway, respectively. They are designed to stimulate the expansion of renewable electricity production in accordance with the postulated targets and are calibrated based on forecasts of future quota obligated electricity consumption. The quota increases until 2020 and is thereafter gradually reduced as green technologies become competitive with less support (Swedish Energy Agency, 2018). To balance supply and demand, certificates can be stored, where the difference between issued and cancelled certificates creates a reserve. The reserve is intended to function as a signal of the current supply and demand by pushing the price upwards in times of a temporary excess demand (hence a negative reserve), and vice versa in times of an excess supply (Swedish Energy Agency & NVE, 2018).

Figure 3 shows issued certificates for each technology and the number of total certificates issued annually, as well as cancelled certificates and the accumulated reserve between 2003 and 2018.

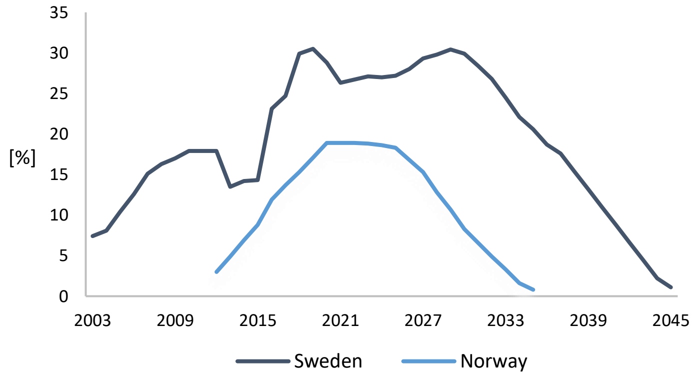

Figure 2. Quota levels within the Swedish-Norwegian tradable green certificate system. *Source*: Swedish Energy Agency and NVE (2018).

Apparently, the accumulated reserve has in general increased from year to year until 2015, implying that the surplus in the system has not only been temporary but persistent. It is also clear that the number of issued certificates has overall continuously increased since the system was first introduced in 2003, where wind power has accounted for the majority in recent years. Given the substantial installation costs of wind power turbines, market agents have claimed the certificate system to have been of crucial importance for the profitability of investments and for the decisions to invest in Sweden in past years (Bergek & Jacobsson, 2010). Hence, the support policy can be considered a success with regards to achieving the renewable electricity targets. In 2018, the joint market had contributed to 20,3 TWh new annual renewable production (compared to 2012) in a normal year (Swedish Energy Agency & NVE, 2018).

According to the Swedish-Norwegian agreement, the system should be reviewed at regular intervals in so called Checkpoints by the authorities in charge of management (Swedish Energy Agency and The Norwegian Water Resources and Energy Directorate (NVE)), determining if the quota level should be adjusted based on actual and forecasted electricity demand, production levels, and reserve of certificates. The first Checkpoint (Checkpoint 2015) was published in February 2014 and suggested an increase of the Swedish quota level from 2016 and onwards. In response to comments from market participants, a need of increased transparency in the system was also emphasised. These comments pointed out that uncertainties related to volatile and unpredictable prices, lack of liquidity and a shortage of information, could be so severe that many investments were at risk of being delayed or dismissed (Swedish Energy Agency, 2014). As a result, the Swedish government decided in May 2015 to increase the quota level from 2016 as well as increase the ambition of the common market from 26,4 TWh to 28,4 TWh

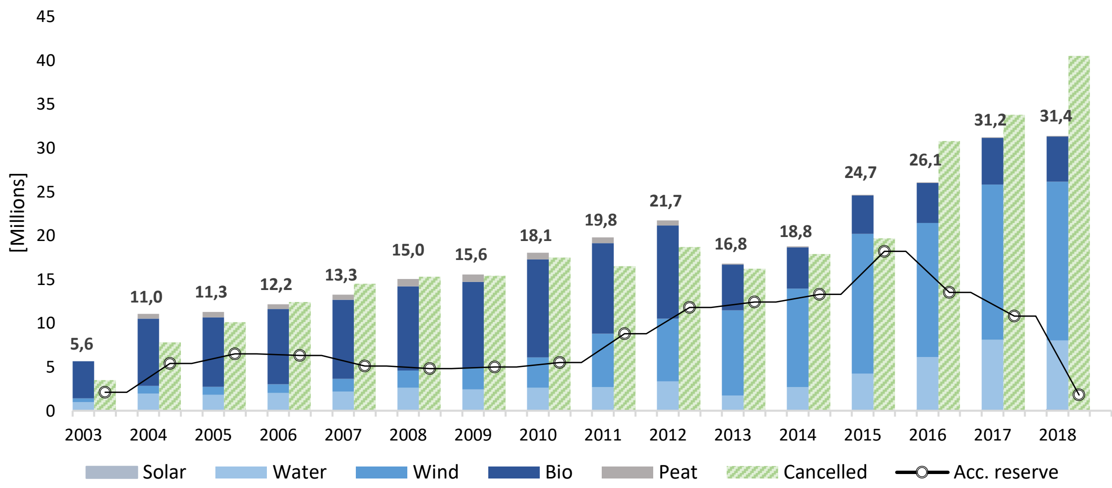

Figure 3. Annually issued certificates for each renewable technology are shown in different colors in the left bar together with the total number of issued certificates. Cancelled certificates are shown in dashed green in the right bar, whereas the accumulated reserve is marked by the black line. *Source*: Cesar (the Swedish database for green certificate accounts), and Swedish Energy Agency and NVE (2018, 2019).

production by 2020. Commitments to increase the information on current supply and demand within the system were also undertaken (Prop. 2014/15:123).

Moreover, already at the introduction of the market in Norway it was decided that Norwegian plants must start operating no later than December 31st, 2021 (originally 2020) to be entitled for certificates. No such stop-rule have been in place in Sweden where installation of new plants can take place at any time, although receive certificates at the latest until 2035 (later revised to 2045). In the first part of the second Checkpoint (Checkpoint 2017), published in June 2016, it was therefore suggested to set a Swedish stop-date coinciding with the Norwegian date, if no new target for the period after 2020 should be decided (Swedish Energy Agency, 2016a). However, later that same week, a new energy policy was signed by the Swedish parliament, aiming to reach a 100% renewable energy production by 2040. As a consequence, the duration of the certificate market in Sweden was extended to 2045, together with increased quotas and an additional production target of 18 TWh by 2030. The earlier suggested stop-date was thereby revoked in the second part of Checkpoint 2017, published in October 2016, and the decision was postponed to Checkpoint 2019 (Prop. 2016/17:179, Swedish Energy Agency, 2016b). When it was published in December 2018, Checkpoint 2019 suggested to put forward the stop-date to December 31st, 2030, but no political decision have yet been made (Swedish Energy Agency, 2018).

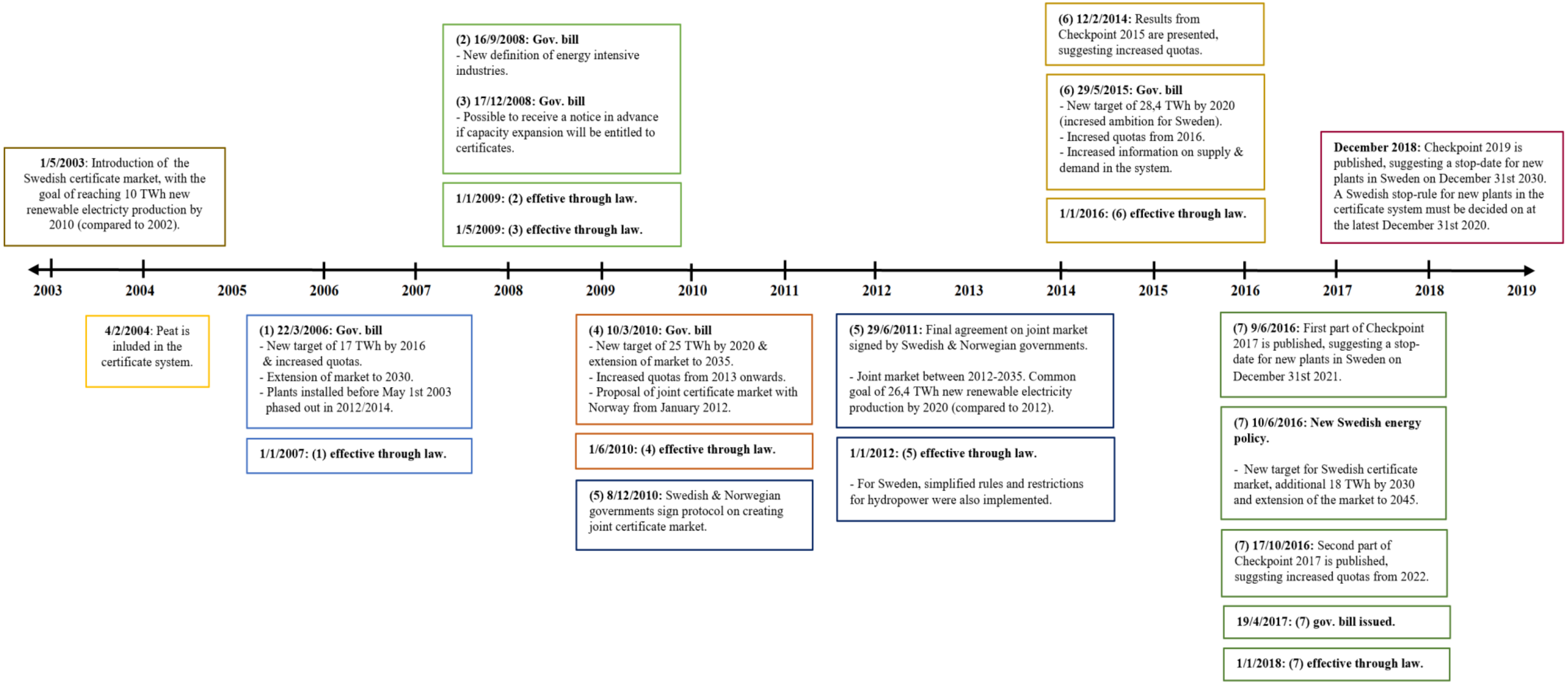

Figure 1. Timeline over policy events in the Swedish-Norwegian tradable green certificate market.

3. Theoretical framework and Literature review

3.1. Real options and renewable energy investments

Wind power is a highly capital-intensive technique where capital costs correspond to approximately 75% of total costs (Swedish Energy Agency, 2016a). This implies a large upfront cost that is more or less irreversible, i.e. a sunk cost. For instance, even if the plant would be sold, the costs of building permits and construction cannot be recovered. Meanwhile, future revenues can only be approximated based on available information and the overall profitability of the project is therefore always to some extent uncertain. Dixit and Pindyck (1994) reason that in the presence of irreversibility and uncertainty, the traditional net present value rule, stating that an investor should invest now if the discounted net value of expected future revenues (V) is larger than or equal to the investment cost (I), $V - I \geq 0$, is not consistent with optimal decision making. The rationale being that in an uncertain environment, firms might value the possibility to postpone the investment decision into the future and await more information that may reveal future conditions affecting the profitability of the project.

For example, consider a firm that is facing a decision to invest in a wind power project within a certain period of time. At any point in time within this period, the firm has an option, similar to a financial call-option, to either invest immediately (exercise the option) or delay the decision (hold the option). If the option is held and conditions develop in a favourable way, the option to invest will be exercised and a positive return is plausible. Conversely, if conditions do not turn out favourable, the option will not be exercised and no loss will be incurred. As such, the option to invest has an economic value in itself; once the irreversible investment is undertaken, that value is lost. Therefore, Dixit and Pindyck argue that the discounted net value of expected future revenues must not only cover the costs of the investment, but also the additional "real option" value (C):

$$V \geq I + C = V^*$$

where $V^*(P, I, C(\sigma))$ represents the value that must be reached to trigger an investment to take place immediately. In a certificate market, V^* should be strictly decreasing in the price of certificates and electricity (P), corresponding to the main sources of revenue for renewable electricity producers, and strictly increasing in investment costs (I) and uncertainty. The latter can be measured by the volatility in project values (σ). In the absence of uncertainty, $C(\sigma)$ reduces to zero and the optimal investment decision is derived from the net present value rule.

In the presence of uncertainty, $C(\sigma)$ functions as a risk premium that investors will require to be willing to proceed with the investment.

Thus, real options theory presumes that irreversible investments are highly sensitive to volatility in project values. When uncertainty increases, and it becomes more difficult to forecast future revenues, less investment will take place as $C(\sigma)$, and consequently V^*, increases (ibid.). Although the entire process from planning to realising a wind power project is lengthy, often spanning over several years, the construction time is short compared to conventional power plants (a number of months compared to a number of years). After receiving a building permit, that typically last 5 to 10 years with possible extension, investors may therefore postpone the investment and account for the value of waiting until conditions justify the irreversible investment (Boomsma et al., 2012; Swedish Energy Agency, 2019).

3.2. Literature on investment under uncertainty

Gross et al. (2010) provide an overview over the risks associated with investments in liberalized electricity markets, which they characterise as technical, financial and price risk. Technical risk refers to e.g. uncertainties over cost of capital and maintenance and lead times for construction, while financial and price risk include uncertainties over credits, contracts, interest rates and future prices of electricity, fuel, CO_2 and certificates. Although all these factors can affect the real option value, this study is delimited to focus on the uncertainty over future prices. On that account, the authors argue that it is crucial to consider the relationship between policy development and price risk; Incoming political parties may have different views on energy policy and change the 'rules' which can impact prices and price volatility, thereby obstructing the possibility to finance a project as lenders require higher interest rates when uncertainty over future benefits is large.

Moreover, several studies have shown that there is a correlation between energy markets and economic growth (e.g. Squalli, 2007; Fagiani & Hakvoort, 2014; Bredin & Muckley, 2011). For example, Bredin and Muckley (2011) find that increased economic activity leads to higher prices of European emission allowances, implying that economic growth should increase the incentive to invest in more carbon efficient technologies. Meanwhile, Fatás and Mihov (2013) show that fiscal policy volatility (measured by the variance of unforecastable changes in government consumption) lowers economic growth. They conclude that a plausible explanation is reduced incentives to invest as the uncertainty over future tax rates increases with volatile spending patterns. Thus, these findings further indicate the importance of regulatory stability to stimulate green investments. Similar conclusions are reached by International Energy Agency (2007) and Fagiani and Hakvoort (2014), who focus particularly on the link between regulatory uncertainty and price risk.

International Energy Agency (2007) formulate a model for quantifying investment risk created by climate policy uncertainty. They define climate policy as an effective CO_2 price such that all regulatory uncertainty is reflected through price uncertainty, which in turn is represented as an exogenous price shock or information event and modelled as a discreet jump in the CO_2 price. Using simulations, they find that regulatory uncertainty creates a risk premium by rising the trigger value of investment in the energy sector, consistent with the predictions of real options theory. They conclude that to reduce the impact of regulatory uncertainty on investment behaviour, the regulatory framework should be fixed for a sufficiently long time period ahead.

Fagiani and Hakvoort (2014) use a similar approach to empirically analyse how regulatory uncertainty is reflected through the certificate price in the Swedish-Norwegian market. It is one of the few existing empirical and econometric studies focusing on this particular market. They use data from January 2007 to March 2013 and estimate the variance of the certificate price series using a GARCH (1, 1) model and endogenously test for structural breaks in the unconditional variance. Their results show that regulatory changes strongly affect the market, resulting in periods of higher price volatility. Furthermore, contrary to policy makers expectations, they find that the creation of the joint market with Norway led to a period of higher volatility between 2010 and 2011. The authors reason that this could be explained by the fact that the market was still in an initial phase by that time and that prices may stabilize as the market matures. Nonetheless, they argue that the role of market power as a stabilizing factor should also be considered; Whereas the increased competition a larger market implies may reduce prices, it can also increase volatility. The role of market power, prior to the creation of the joint market, is addressed in Amandusen and Bergman (2012). Indeed, the authors find that Swedish green electricity producers can exercise market power on the Nordic electricity market by withholding certificates but argue that the problem could be resolved by market integration, which plausibly also would stabilize prices through diversification.

As such, it is relevant to extend Fagiani and Hakvoorts' (2014) study with more recent data, as the Swedish-Norwegian market at this point can be considered mature. By adding an analysis of investment timing, the effect of price and regulatory uncertainty on investments in green technologies can also be analysed empirically. For that purpose, several earlier studies have also applied a real options approach to investigate investment behaviour in commodity markets under uncertainty. Some use sophisticated dynamic optimization or contingent claim models to solve for the profit maximizing trigger value and optimal timing of investment (e.g. Boomsma et al., 2012; Linnerud et al., 2014; Kellogg, 2014; Fleten et al., 2016). Others use a similar approach to the one adopted here by estimating the likelihood of investment as a function of the determinants of the trigger value using hazard or logistic models (e.g. Cunningham, 2006; Bulan et al., 2009; Dunne & Mu, 2010; Kellogg, 2014; Linnerud & Simonsen, 2017).

Dunne and Mu (2010) and Kellogg (2014) use hazard-rates to model the timing of investments under price uncertainty in the US petroleum industry and both find evidence of the presence of a real option. Kellogg analyses the response of oil drilling activity and uses several measures of oil price uncertainty, including the conditional variance derived from a GARCH (1, 1) model. He finds that a one percentage point increase in volatility reduces the likelihood of drilling by 3.0%. Kellogg also continues to estimate a dynamic model of firms timing problem and finds that the cost of failing to respond to changes in volatility is substantial, reducing the value of a project by more than 25%. Bulan et al. (2009) and Cunningham (2006) are examples that test the presence of a real option in the housing market, both using proportional hazard models and GARCH-like uncertainty measures over housing prices. They find that a one standard deviation increase in volatility is associated with a 13%, respectively 11%, reduction in the likelihood of investment.

Linnerud et al. (2014) and Linnerud and Simonsen (2017) are examples that empirically analyse investment behaviour in the Swedish-Norwegian certificate market, but with a focus on the Norwegian part of the scheme. They use survey data to investigate the impact of regulatory uncertainty on investments in hydropower. Linnerud et al. focus on the years preceding the introduction of the joint market, particularly examining how uncertainty over the prospect of a future certificate market affected investment timing. Similar to International Energy Agency (2007) and the predictions of real options theory, they find that investments among professional corporations are less likely in years when a subsidy in a near future is considered probable, suggesting that decisions were delayed to utilize the increased future revenues of the subsidy. Conversely, non-professional investors are not found to incorporate timing in their investment decisions, but rather acted according to the net present value rule. However, Linnerud and

Simonsen, focusing on the years succeeding the market introduction, cannot find evidence of a difference between investor types.

4. Methodology

Based on the findings in previous literature, I expect to find that the presence of regulatory uncertainty in the Swedish-Norwegian market is reflected through the certificate price. Under this hypothesis, the effect of price and regulatory uncertainty on investments in wind power projects can be analysed by modelling the volatility of certificate prices. Assuming that the only source of uncertainty is the path of future asset prices, this should determine the option value, $C(\sigma)$, which in turn affect the trigger value where investment takes place, $V \geq V^*$. The first part of the study is therefore dedicated to testing this hypothesis.

4.1. Modelling the link between price and regulatory uncertainty

It is often presumed that asset prices evolve stochastically according to a Geometric Brownian motion:

$$dP_t/P_0 = \propto dt + \sigma dz \tag{1}$$

where $\propto$ is the drift term (expected price appreciation), σ is the volatility parameter, and *dz* is the increment of a Wiener process. However, this model assumes a constant drift and volatility parameter, whereas commodity prices often display short-run serial correlation and long-run mean reversion (Bulan et al., 2009; Dixit & Pindyck, 1994). I account for this by modelling the volatility of certificate prices in terms of the conditional variance derived from a generalized autoregressive conditional heteroskedasticity (GARCH) model. GARCH models allow for time-varying variance by measuring the conditional variance as a function of past realisations of the unconditional and conditional variance (Bollerslev, 1986). Thus, it assumes that large changes (of either sign) will be followed by large changes and vice versa for small changes, often called volatility clustering.

GARCH models are among the most widely used methods to measure volatility. It is preferable to use in this setting as well, given that financial traders often examine the observed volatility of the traded asset over the resent past when forming their expectations about future volatility (Fagiani & Hakvoort, 2014; Cunningham, 2006). In this setting, the standard GARCH (p, q) model (Bollerslev, 1986) can be defined as:

$$r_t = \sum_{i=1}^{p} \rho_i r_{t-i} + \varepsilon_t \qquad \varepsilon_t | I_{t-1} \sim N(0, h_t)$$

$$h_t = \propto_0 + \sum_{i=1}^{q} \propto_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{2}$$

and most often, the simplest form with $p = q = 1$, i.e. a GARCH (1, 1) model, is used in practice. The first equation of (2), called the mean equation, is defined as an autoregressive model of the logged returns, r_t, of the certificate price on lagged returns, $\sum_{i=1}^{p} r_{t-i}$, and ε_t is an innovation term. In the second equation, called the variance equation, the one-step-ahead conditional variance of the innovation term, h_t, is predicted as a function of a constant, $\propto_0$, and the sum of the p and q previous periods unconditional, ε_{t-i}^2, and conditional, h_{t-i}, variances. The sum $\sum_{i=1}^{p} r_{t-i}$ is defined as the number of lags required to rule out serial correlation in the innovations, such that the expectation of zero holds. It can be determined by a Ljung-Box Q-test over the standardized residuals. To further simplify the process of yielding white noise residuals, I estimate the mean and variance equation simultaneously using maximum likelihood.

The GARCH process requires stationarity and the following restriction must therefore be imposed to ensure a finite variance:

$$\sum_{i=1}^{q} \propto_i + \sum_{i=1}^{p} \beta_i < 1.$$

Given that the restriction holds, the unconditional, or long-run mean variance of ε_t is constant and equal to:

$$E[\varepsilon_t^2] = \sigma^2 = \frac{\propto_0}{(1 - \sum_{i=1}^{q} \propto_i - \sum_{i=1}^{p} \beta_i)}.$$

However, I want to test the hypothesis that regulatory uncertainty is reflected through the price by introducing discontinuous breaks in σ^2 in relation to a regulatory change in the certificate market, implying that the data generating process have changed over time such that the GARCH process may be unstable. To find the potential break points, I use an endogenous multiple structural break test procedure developed by Bai and Perron (1998). The procedure treats all dates of the breaks as unknown parameters to be estimated. This is preferable in this setting since the break dates are not known with certainty in advance. It also enables me to detect structural changes in the certificate price series not only caused by political events.

Bai and Perron (1998) suggest two ways to detect break points in a linear regression model estimated with ordinary least squares. Because I want to test the null hypothesis of a constant long-run variance against the alternative of a break, this regression is simply defined as the squared innovation term, derived from the mean equation in (2), regressed upon a constant:

$$\varepsilon_t^2 = \delta_j + u_t \qquad (t = T_{j-1} + 1, \ldots, T_j) \tag{3}$$

where the $j = 1, \ldots, m+1$ coefficients of δ_j are subject to $T_1, \ldots, T_m$ unknown breaks to be estimated using the full sample of T observations, and u_t is a disturbance term. The dates corresponding to the structural changes can thereafter be detected using a Double Maximum test which tests the null hypothesis of no breaks against the alternative of m breaks, where Bai and Perron recommend an upper bound of $m \leq 5$. The test is performed by repeated estimation of model (3) for every possible combination of break dates and thereafter select the combination that minimizes the sum of squared residuals. Alternatively, a sequential test can be performed, where the null hypothesis of l breaks against the alternative of $l+1$ breaks is tested. Initially, the null hypothesis of no breaks against the alternative of a single break is tested. If the null hypothesis is rejected, the presence of a single break against the alternative of two breaks is tested, and so forth. This process continues until the test fails to reject the null hypothesis of an additional break (Bai & Perron, 1998).

These tests enable me to endogenously determine the dates of the break points. Once these dates are detected, they can be included as dummy variables in the GARCH model, representing regimes where the unconditional variance is subject to change. The dummy variable, D_i, takes a value of 0 for all t up to the break date, and thereafter a value of 1 for all $t \geq t_{break}$:

$$\begin{gathered} r_t = \sum_{i=1}^{p} \rho_i r_{t-i} + \varepsilon_t \qquad \varepsilon_t | I_{t-1} \sim N(0, h_t) \\ h_t = \sum_{i=1}^{q} \propto_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{i=1}^{m} \gamma_i D_i \end{gathered} \tag{4}$$

4.2. Modelling the timing of investment decisions

Using the volatility derived from the GARCH model in equation (2) as a measure of investors expectation of future certificate price uncertainty, I continue to estimate a proportional hazard model to analyse the timing of investments. Proportional hazard models stem from survival analysis by modelling the duration time to some event (Jenkins, 2005). In this setting, an observation is defined as a specific site and I model the duration from an arbitrary starting point, set to January 2005, until the development of a wind farm (or single turbine) takes place on that site. If a real option exists, this occurs when the trigger value, V^*, is reached and the hazard rate of investment can therefore be defined as the probability of the investment decision being made at time *t*, conditioning on not having been made already:

$$\theta(t, X) = P\{V_t \geq V_t^* | V_x < V_x^*, \forall x < t\}$$

and the empirical model can be formulated as:

$$\theta(t, X_t) = \theta_t(t)\exp\{\beta' X_t\} \tag{5}$$

where $\theta_t(t)$ is a baseline hazard function that reflects the probability of investment as a function of time alone, whereas $\exp\{\beta' X_t\}$ describes the proportional increase or decrease in this probability associated with the determinants of V^* that are contained in the vector of covariates, X_t (Jenkins, 2005; Bulan et al., 2009).

In the baseline model, X_t is defined as:

$$\beta' X_t = \beta_1 P_t + \beta_2 \sigma_t^2 + \beta_3 \delta_t + \beta_4 I_t$$

where P_t is the current price of certificates, σ_t^2 is the volatility parameter of the certificate price series derived from the GARCH model, and δ_t is a discount rate. The expected price appreciation, i.e. the drift rate in equation (1), can be derived from the one-step-ahead forecast of an autoregressive model of returns, analogous the one in equation (2). However, presuming long-run mean reversion, the drift rate should oscillate around zero and it should be sufficient to model the volatility to measure the expected evolvement of prices (Boomsma et al., 2012). Assuming risk-neutral investors, δ_t is the risk-free rate of return, often defined as the interest on a long-term government bond. Although this model does not account for uncertainty over investment costs, I also include a variable to control for the fixed investment costs of wind power, I_t.

In the hazard model, the coefficients contained in X_t are presented in terms of hazard rates, i.e. e^{β}, meaning that the null hypothesis of $\beta = 0$ corresponds to a coefficient of 1. Thus, a coefficient larger than 1 indicates a positive effect on the baseline hazard and an increase in the probability of investment (and vice versa for a coefficient less than 1), whereas the size of the effect is interpreted as 1- e^{β}. For instance, a coefficient of 1.05 implies that a unit change in X_t increases the probability of investment by 5%.

Different hazard models can be obtained depending on what assumptions are made for the baseline hazard function and therefore about the hazard rates dependence on the duration time, *t*. In this setting, I use a Weibull distribution for t defined as: $\theta_t(t) = pt^{p-1}$. This distribution assumes that the hazard rate is either increasing, $p > 1$, or decreasing, $p < 1$, with time. An exception is when $p = 1$, in which case the baseline hazard is constant and independent of duration time, and the Weibull distribution reduces to an exponential distribution (Jenkins, 2005; Bulan et al., 2009). The Weibull distribution is preferable here since wind power is a new and advancing technology, only recently introduced to the market, and investments are thereby likely to have increased with time over the sample period.

4. Data

Summary statistics and sources for the data used in the study are presented in Table 1 and described in detail below.

4.1. Price data

I use weekly and monthly average spot prices of certificates collected from Svensk Kraftmäkling, which is one of the oldest and largest brokerage firms in the Nordic electricity market and have brokered certificates since the introduction of the market in 2003. Svensk Kraftmäkling keeps the only publicly available price recording of the spot and forward market for certificates. Prices prior to the year 2005 are unavailable, and for this reason the sample period is limited to the first week of January 2005 to the last week of December 2018. Because important volatility is lost when using aggregated data, which could limit the possibility to identify break points, I use weekly prices (daily prices being unavailable) in the first part of the analysis. Meanwhile, since I model investments at a monthly basis, monthly prices are used in the second part of the analysis, avoiding having to use fabricated scaled volatility measures. Further, because there are two major sources of revenue for wind power investors, i.e. the cash flows from selling certificates and electricity, I also collect day-ahead monthly electricity prices from Nord Pool to control for the impact of electricity price and volatility on the timing of investments as well.

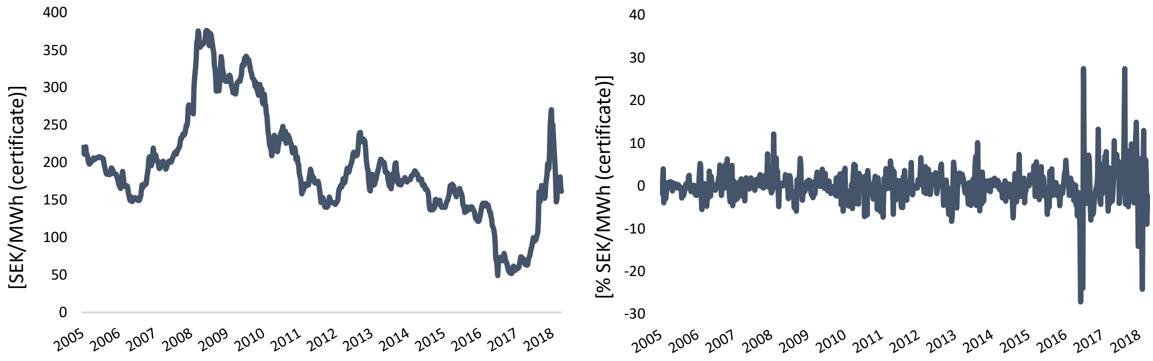

Figure 4. The graph to the left shows weekly average prices from January 2005 to December 2018 of certificate spot prices and the graph to the right shows the logged returns of the same series.

The left graph in Figure 4 displays the time series over weekly certificate prices and the right graph displays the first difference, i.e. returns, of the same series. Graphs over the monthly series for certificate and electricity prices can be found in Appendix A. Two price cycles in the certificate market during the sample period are readily apparent. The first is a peak, ranging from the first quarter of 2007 to the first quarter of 2010, approximately corresponding to the time of the first and second extension of the market duration. The second is a trough starting at the end of 2016, when prices dropped to a historical low level in the first quarter of 2017.

Between these spikes, prices have been meandering around a mean of 194 SEK/Certificate (see Table 1), although the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS)[2] test-statistics (see Appendix A, Table A1) indicate that the level of the sample series is non-stationary but that differencing once is sufficient to yield stationarity. Electricity prices have been more variable than certificate prices during the sample period. Volatility clustering in the return series is apparent and the degree of mean reversion also seems larger. The ADF statistic indicates that the level-series is stationary whereas the KPSS statistic does not, although both tests confirm that the first difference of the series is stationary.

4.2. Wind power investment data

I use data over installations of new onshore wind turbines in Sweden, for investment decisions made between 2005 to 2018, collected from Swedish Energy Agency. They keep a registry over all plants granted for certificates since the introduction of the market in 2003 ("Godkända anläggningar"). It contains information provided by the investor on for example technology

[2] Both the ADF and KPSS tests are used to test for stationarity of a time series. The former tests the null hypothesis of the presence of a unit root in the series, and the latter tests the null hypothesis that the series is stationarity.

type, installed capacity, municipality and name of the cooperation (or if the owner is a civilian). Importantly, it also contains the date when a turbine first started operating, making it possible to identify when an investment decision was undertaken.

Each observation in the data set generally corresponds to one wind turbine, I therefore aggregate the data such that all turbines installed at the same site (i.e. in the same wind farm), by the same firm and at a particular point in time, is defined as one investment[3]. Unfortunately, it is not possible to identify if several wind turbines have the same owner among civilians, and I therefore define each wind turbine as one investment in these cases. This approach is somewhat problematic since I could end up modelling a larger number of investment decisions than the actual number. I try to roughly approximate the size of this bias by identifying the location and project characteristics of turbines that started operating around the same time. Doing so, I find it possible that about 16 turbines could be owned by 8 civilians, hence this can be considered a minor bias given that a total of 119 turbines in the sample are owned by civilians.

I exclude wind turbines with a capacity less than 0.1 megawatt as these are considerably small and often do not require a building permit, why it is plausible that these investors use simpler decision rules than those investing in larger projects that require more comprehensive planning, permission application and funding. Moreover, I build my analysis on the assumption of single-agent decisions with price taking investors. However, it should be noted that the Swedish-Norwegian certificate system is a small market where wind power over the past six years have replaced bio-fuels as the leading electricity producer and supplier of certificates. I therefore exclude firms that own at least one substantially large wind farm with a capacity of 80 megawatt or more, as these firms plausibly can influence prices by holding large volumes of certificates. For similar reasons, I also exclude wind farms owned by the three largest electricity suppliers in Sweden (Vattenfall, Statkraft and Fortum) which together hold approximately 40% of the market share in the Nordic electricity market (Swedish Competition Authority, 2018)[4].

I end up with a sample of 763 projects, owned by 466 firms and economic cooperatives, and 119 civilians. The capacity installed per investment range from 0.105 to 79.35 megawatt with a mean of 6.5 and median of 2. The number of turbines installed per investment range from 1

[3] In the few cases when there is a time-gap of several months between the installation of one group of turbines until the next group of turbines at the same site, I define this as two different investments, presuming that an additional decision of expanding the initial investment was made at a later date.
[4] I also exclude turbines for which the start date of production is unclear, and one outlier in 2012 corresponding to the largest wind turbine in Sweden by that time (in Arnedal Gothenburg with a capacity of 4.1 megawatt).

to 30, with a mean of 3 and median of 1. Thus, the majority of investments in the sample can be characterized as having been undertaken by small firms and civilians.

One limitation with the data is that I do not observe the start date of construction, but for most investments only observe the date when the last turbine in a farm started producing electricity, i.e. the end of the construction period. Most real option studies address this issue by introducing a time lag to correct for the wedge between the decision to invest (option exercise) and the start of production (e.g. Bulan et al., 2009; Dunne & Mu, 2010; Kellogg, 2014). According to the European Energy Association (n.d.), a small wind farm of 10 megawatt can be built in two months and a larger farm of 50 megawatt can be built in six months. Numerous other sources confirm a minimum construction time of two months for one, or a couple of turbines, and six to twelve months for larger investments.

Because the range in size of projects in the sample is very large, using different lag-lengths is appropriate to adequately correct for the construction time. Hence, I divide the sample into small, medium and large projects and let the lag length be fixed within each group but vary across groups. To be specific, I define small projects as wind farms containing 1 to 4 turbines, medium as those containing 5 to 10 turbines, and large as those containing more than 10 turbines. Based on the information on construction time, I lag small investments by three months, medium investments by six months and large investments by twelve months[5]. Introducing a time lag can also further reduce or eliminate possible problems with simultaneity between new construction and prices.

4.3. Investment cost data

Data over investment costs for wind power between 2005 to 2016 is collected from Swedish Energy Agency (personal communication, 29 April 2019). It contains annual capacity weighted average investment costs expressed in SEK per kilowatt, defined as the cost of turbines, grid connection, financing, and other. The data is compiled from a study where accounting data from 250 wind farms were analysed. Because cost data is unavailable for 2017 and 2018, I use a linear extrapolation to generate cost estimates for these years. Moreover, since the data is annual, whereas I conduct the analysis at a monthly basis, prices are treated as constant within a year. Investment costs correspond to approximately 75% of the total costs of financing a wind

[5] Changing the lag length to four and nine months, respectively eight and fifteen months, for medium and large investments yields very similar results.

Table 1
Summary statistics and data sources for variables in the hazard model

Variable	Exp. sign	Obs.	Mean	Std.dev.	Min	Max	Source
Certificate price [SEK/MWh (certificate)] *Monthly (spot)*	+	168	193.85	70.26	56.62	372.05	Svensk Kraftmäkling
Certificate price uncertainty *Monthly volatility derived from GARCH (1, 1)* [%-squared]	−	168	67.44	86.09	18.12	606.79	
Discount rate [Δ %] *Monthly interest rate of 10-year government bond (one-year lag)*	−	167	−0.02	0.18	−0.68	0.40	The Riksbank
Annual investment cost of wind turbines [SEK/KW]	−	14	12 080.5	1883.90	8381	15 127	Swedish Energy Agency
Electricity price [SEK/MWh] *Monthly (spot) average of all Nordic bidding zones.*	+	168	341.03	118.59	89.49	740.02	Nord Pool
El. price uncertainty *Volatility derived from GARCH (1, 1) [%-squared]*	−	168	360.95	274.72	137.33	1805.85	

power project and the remaining 25% are variable costs including the cost of maintenance, land lease, insurance and taxes. However, the availability of estimates for these costs is limited in general (ibid.), and I lack accurate numbers for the sample period as well. Similar to Boomsma et al. (2012), I therefore assume that these costs can be considered as a negligible determinant for the investment decision, which seems reasonable given their small share of the total costs of investment.

Both prices and costs are expressed in nominal terms, treating inflation as an unobserved uncertainty that investors should consider when forming their price expectations, and as a measure of investors required rate of return, I collect data over monthly average interest rates on a 10-year government bond from the Riksbank. As evident from Figure A2 in Appendix A, the interest rate has been trending downwards, and this is confirmed by the ADF and KPSS statistics as well. For this reason, I use the differentiated series in the hazard model to avoid a spurious regression.

5. Empirical results

5.1. Structural break analysis

The estimates from four different low-order GARCH models of the weekly certificate price returns can be found in Appendix B, Table B1. As expected, the Bayesian Schwarz information criterion (BIC) indicates that a higher order process barely outperforms the simple GARCH (1, 1), and this more parsimonious model is therefore preferable to use. The mean equation is specified as an autoregressive process of order three as the Ljung-Box-Q statistic (see Appendix B, Table B2) implies that three lags are required to rule out serial correlation in the innovations. Moreover, the coefficients α_1 and β_1 in the GARCH (1, 1) model almost sum up to one, indicating that the GARCH process may be unstable and suffer from structural breaks.

The Sequential test finds one significant break in the unconditional variance of the certificate returns, corresponding to the third week of January 2017, and the same combination is found to maximize the F-statistic in the Double Maximum test. All suggested combinations of break dates by the endogenous break point tests are presented in Appendix B, Table B3. In Model 1 in Table 2, I include the break as a dummy variable in the variance equation of the GARCH (1, 1). The positive and statistically significant coefficient indicates an increase in the unconditional variance associated with the identified break date, which does not coincide with any regulatory change. However, several political events took place in the second half of 2016 that left unclear implications about the future regulatory framework after the joint target with Norway is met, due to the new energy policy that was adopted in between the first and second announcements of Checkpoint 2017. As shown in Figure 4, prices started to drop at the end of 2016 and became more volatile. The estimated increase in volatility in January 2017 is thus likely to be a consequence of the uncertain political environment in 2016.

One reason can be the indeterminate effect on the certificate price of an increase in the quota level, that followed by the new energy policy. Amundsen and Nese (2009) reason that because the quota is set as a percentage of total electricity consumption and not as a specific quantity, it is not necessarily true that the renewable electricity production will increase if there is an overall reduction in electricity consumption or conventional electricity production. This can result in unstable certificate prices, reducing the possibility to correctly forecast the future. The extension of the market duration and prospect of introducing a stop-date for new plants can also

Table 2
GARCH (1, 1) estimates of weekly certificate returns with dummy variables

	Model 1	Model 2	Model 3	Model 4	Model 5
ρ_1	0.33385***	0.33471***	0.34081***	0.34223***	0.33894***
	(0.04406)	(0.04354)	(0.04376)	(0.04391)	(0.04303)
ρ_2	-0.04835	-0.05553	-0.05861	-0.06335	-0.06397
	(0.05064)	(0.05048)	(0.05240)	(0.04982)	(0.05438)
ρ_3	0.06926*	0.07120*	0.06857*	0.07025*	0.06922*
	(0.03940)	(0.03889)	(0.03807)	(0.03707)	(0.040117)
α_0	0.00012***	0.00011***	0.00012***	0.00017***	0.00009***
	(0.00002)	(0.00002)	(0.00002)	(0.00003)	(0.00002)
α_1	0.22284***	0.20877***	0.21195***	0.22041***	0.18102***
	(0.03842)	(0.04175)	(0.04297)	(0.04735)	(0.03718)
β_1	0.59962***	0.54290***	0.51453***	0.39275***	0.61797***
	(0.06031)	(0.07673)	(0.07829)	(0.10621)	(0.07082)
γ_1 *(Jan-17)*	0.00098***	0.00119***	0.00133***	0.00180***	
	(0.00025)	(0.00030)	(0.00032)	(0.00045)	
γ_2 *(Mar-10)*		0.00007***	0.00025***	0.00034***	0.00018**
		(0.00002)	(0.00009)	(0.00012)	(0.00007)
γ_3 *(Sep-11)*			-0.00020**	-0.00034***	-0.00015**
			(0.00008)	(0.00013)	(0.00007)
γ_4 *(Jan-13)*				0.00028**	
				(0.00013)	
γ_5 *(Apr-14)*				-0.00023*	
				(0.00011)	
γ_6 *(Jun-16)*					-0.00001
					(0.00005)
γ_7 *(Oct-16)*					0.00083***
					(0.00024)
$\alpha_1 + \beta_1$	0.82246	0.75167	0.72648	0.61316	0.79899
BIC	-4.28208	-4.28361	-4.28727	-4.27957	-4.27529

Notes: standard errors in parenthesis.
* Denotes significance at 10% level.
** Denotes significance at 5% level.
*** Denotes significance at 1% level.

have an ambiguous effect on investment decisions. Linnerud and Simonsen (2017) point out the predictions of real options theory that investors should be eager to lock in future revenues early in a support system, but become less optimistic as the deadline approaches, unsure if they will be able to realize a project on time. Thus, one interpretation could be that whereas the proposed extension of the market to 2045 may have encouraged project development, the prospect of a stop-date already in 2021 would have the reverse effect. In Model 5, I also replace the dummy with one dummy for the second week of June 2016 and one for the third week of October 2016, i.e. the weeks when the results of Checkpoint 2017 and the new energy policy were announced. Although the BIC indicates a poorer fit to the data, the dummy for October

2016 is statistically significant and similar in size to γ_1, further evidence in favour of a connection between the break in January 2017 and the political debate.

In Model 2 and 3, I continue to include dummy variables for the second and third best combination of break dates found by the Double Maximum test, corresponding to the week between 15 to 21 March 2010 and 26 to 30 September 2011, respectively. The coefficient for the first dummy remains more or less robust in terms of magnitude and significance across all three specifications, and so does α_0, α_1 and β_1. The size of γ_2 increases when including the dummy variable for September 2011 in Model 3, and both dummy variables are statistically significant at a 1% and 5% level, respectively. The second break date directly coincides with the government proposal of extending the duration of the market to 2035 and the intention of creating a joint market with Norway, announced in the week prior. The third dummy does not coincide with any regulatory change but falls in between the months when Sweden and Norway signed the agreement of a joint market and the Swedish Parliament approved the bill (Fagiani & Hakvoort, 2014).

The second and third estimated break dates are the same as those found by Fagiani and Hakvoort (2014). Similar to the results here, they find that the coefficients for these breaks are more or less equal in absolute terms, although the Wald-test rejects the null hypothesis that they are equal in absolute size in this study[6]. The authors conclude that this implies that the market went through a temporary regime of higher volatility between 2010 and 2011, hampered by regulatory intervention, but that instability resolved in conjunction with the next break date, when volatility returned to previous levels.

Considering the unusually drastic change in the price and return series in 2017, I also split the sample period and re-estimate the break point tests using only observations for the years 2005 to 2016. The Double Maximum test now also suggests a combination of two additional breaks apart from March 2010 and September 2011, equivalent to the fourth week of January 2013 and the second week of April 2014 (see Appendix B, Table B3). In Model 4, they are included as dummy variables together with the first three dummies, and they are all found to be statistically significant at least at a 10% level. The dummy for January 2013 is not related to any regulatory change. The closest political event in relation to April 2014 is the publication of the first

[6] The p-value for testing the null hypothesis $|\gamma_2| = |\gamma_3|$ is equal to 0.0109.

Checkpoint in February 2014 that suggested increased quota levels, although the BIC indicates that Model 3 best fits the data and therefore should be preferred.

Nonetheless, interpreting the coefficients for the additional break dates included in Model 4 is relevant since they are located close in time after the creation of the joint market. The positive sign of the coefficient γ_4 implies an increase in the unconditional variance shortly after the market expansion in 2012, whereas the negative sign of the coefficient γ_5 indicates that prices partly stabilized again, approximately a year later. Yet, once again the Wald-test rejects the null hypothesis that the coefficients are equal in absolute terms[7]. These results suggest that the expansion of the domestic market to include Norway negatively affected investors as prices became more variable. This confirms and extends the empirical findings of Fagiani and Hakvoort (2014), by indicating that volatility did not only temporary increase in conjunction with the market integration but remained at a slightly higher level. Importantly, these results also contradict the conclusions of Amandusen and Bergman (2012) and the expectations of policy makers that the joint mechanism should stabilize prices.

In summation, although not all changes in volatility can be traced to changes in regulation, these findings overall support the hypothesis that uncertainty over the outcome of a regulatory change is reflected through the certificate price, creating regimes of increased variance. According to real options theory, increased volatility should deter investments. The reminder of the paper is therefore dedicated to examining the presence of a real option in the certificate market.

5.2. Timing of wind power investments under uncertainty

Table 3 presents the results for the hazard model in equation (5), estimated using maximum likelihood. For inference, I use the Huber-White variance-covariance matrix clustered on each individual site (wind farm) to allow for spatial and serial correlation in the hazard rates within each site (Kellogg, 2014; Bulan et al., 2009). Clustering at site-level is accurate since I in some cases observe that more than one firm operates at the same site, as well as additional turbines arriving at the site in the years succeeding the initial investment. These investment decisions are hence likely to be correlated.

[7] The p-value for testing the null hypothesis $|\gamma_4| = |\gamma_5|$ is equal to 0.0382.

Table 3
Baseline hazard model results for probability of wind power investment

Coefficient on covariate	Model 1	Model 2	Model 3	Model 4
Certificate price	1.0101*** (0.0005)	1.0095*** (0.0006)	1.0091*** (0.0006)	1.0077*** (0.0007)
GARCH-volatility certificate	0.9923*** (0.0014)	0.9915*** (0.0015)	0.9950*** (0.0015)	0.9942** (0.0015)
Investment cost	0.9998*** (0.0000)	0.9997*** (0.0000)	0.9997*** (0.0000)	0.9996*** (0.0000)
One-year lagged risk-free interest rate	0.7811 (0.1371)	0.6883* (0.1329)	0.7777 (0.1544)	0.6036** (0.1331)
Electricity price		1.0005** (0.0002)		1.0012*** (0.0003)
GARCH-volatility electricity		0.9998 (0.0001)		0.9996** (0.0001)
Baseline hazard	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0002*** (0.0003)	0.0004*** (0.0006)
Weibull parameter (p)	2.4069 (0.1410)	2.4045 (0.1433)	2.4065 (0.1392)	2.4140 (0.1401)
Log likelihood	-590.473	-587.763	-537.612	-528.826
Nr. of projects	*763*	*763*	*720*	*720*
Sample period	*2005–2018*	*2005–2018*	*2005–2015*	*2005–2015*

Notes: The hazard model is estimated using a Weibull distribution for the baseline hazard and coefficients are expressed in exponential form, e^{β}. Cluster-robust standard errors in parenthesis.
* Denotes significance at 10% level.
** Denotes significance at 5% level.
*** Denotes significance at 1% level.

To introduce further heterogeneity in the model, I also included dummy variables for electricity price area to account for possible differences in market characteristics between the four Swedish electricity areas (Linnerud & Simonsen, 2017). However, these turned out not to be statistically significant and were therefore excluded from the model. In Model 1 and 2, the full sample period is used for estimation, whereas only investment decisions undertaken between 2005 to 2015 are included in Model 3 and 4. This to test the possibility that a relationship between volatility and investments could solely be driven by the drastic drop in prices at the end of 2016.

As suspected, the Weibull parameter (p) is strictly larger than one in all model specifications, indicating that project development has increased with time over the sample period and that a Weibull distribution for the baseline hazard is appropriate. The coefficients in Model 1 have the signs predicted by real options theory and are robust in terms of size and significance for the inclusion of price and volatility of electricity in Model 2[8]. In all model specifications,

[8] The mean equation for the GARCH model of electricity returns is specified as an autoregressive process of order one, as the Ljung-Box-Q statistic (see Appendix B, Table B2) suggests that one lag is sufficient to rule out serial correlation in the innovations.

interest rates have been lagged one year as I found present values to be statistically insignificant, whereas the lagged values generally performed better. This is not so strange given the lengthy planning process for wind power projects. The interest rate can be considered as an opportunity cost for delaying construction and instead keeping the real option alive (Dixit & Pindyck, 1994). As such, higher interest rates should lower the hazard of development today. Although it is not statistically significant in the first model, the coefficient is substantially smaller than one in both models, in line with the expectations and findings in previous research (Bulan et al., 2009; Cunningham, 2006). In Model 2, a one percentage point increase in the risk-free interest rate lowers the monthly hazard rate of development by 31%.

Moreover, the coefficients for certificate and electricity prices are larger than one, suggesting that construction takes place faster when prices are high, whereas the cost of investment have the opposite effect. Importantly, the coefficient for volatility of certificate prices is less than unity and statistically significant at least at a 5% level in all four specifications, suggesting that investors delay investment decisions when volatility is large. In Model 2, a one standard deviation (35%) increase in the variance of certificate prices reduces the monthly probability of project development by 12%[9]. This is analogous to the point estimates in Bulan et al. (2009), Cunningham (2006) and Dunne and Mu (2010), indicating the validity of the results. Thus, the results are supportive of the presence of a real option in this market. Comprising these findings with those reported in section 5.1, this implies that the presence of regulatory uncertainty, reflected through unstable certificate prices, have hindered the intended stimulus of green investments by delaying or cancelling the development of new wind power projects.

Next, I also estimate the model splitting the sample into subgroups to check for differences across investments in small, medium and large projects, defined according to the description in section 4.2. The results are presented in Table 4 (Model 1, 2 and 3). The coefficient for certificate price volatility remains significant for all project sizes, and no difference between small and medium sized projects is apparent. Meanwhile, for large projects, the coefficient is unexpectedly significantly larger than unity. However, this group only contains 35 projects which is barely enough for statistical inference. It should also be noted that it contains projects ranging from 11 to as many as 30 turbines, and hence the fixed time lag for construction for this group may be problematic[10]. Another explanation could be that larger projects are less

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[9] The percentage change was calculated as $1 - [\,\hat{\beta}_2 \cdot \exp(0.35^2)]$.

[10] Re-estimating Model 3 using a construction lag of nine or fifteen months yields equivalent results.

Table 4
Hazard model results for probability of wind power investment, splitting sample into subgroups

Coefficient on covariate	Model 1 (small inv.)	Model 2 (medium inv.)	Model 3 (large inv.)	Model 4 (no civilians)	Model 5 (only civilians)
Certificate price	1.0086***	1.0155***	1.0286***	1.0105***	1.0056***
	(0.0007)	(0.0031)	(0.0057)	(0.0007)	(0.0020)
GARCH-volatility certificate	0.9902***	0.9901***	1.0044**	0.9929***	0.9831***
	(0.0018)	(0.0023)	(0.0017)	(0.0015)	(0.0047)
Investment cost	0.9997***	1.0001	1.0009*	0.9998*	0.9993***
	(0.0000)	(0.0001)	(0.0005)	(0.0000)	(0.0000)
One-year lagged risk-free interest rate	0.5837**	0.7518	1.4232	0.7521	0.1472***
	(0.1318)	(0.3241)	(1.5401)	(0.1407)	(0.0922)
Electricity price	1.0004	1.0013**	1.0046***	1.0007**	1.0006
	(0.0003)	(0.0006)	(0.0013)	(0.0003)	(0.0008)
GARCH-volatility electricity	0.9996**	1.0000	1.0031***	1.0000	0.9977***
	(0.0001)	(0.0002)	(0.0007)	(0.0001)	(0.0007)
Baseline hazard	0.0006***	0.0000***	0.0000***	0.0000***	0.9317
	(0.0007)	(0.0000)	(0.0000)	(0.0000)	(0.8798)
Weibull parameter (p)	2.2573	3.8660	11.5835	2.7509	2.0861
	(0.1305)	(0.8170)	(3.2613)	(0.2122)	(0.1668)
Log likelihood	-504.066	-38.276	27.427	-434.208	-90.914
Nr. of projects	*633*	*95*	*35*	*644*	*119*
Sample period	*2005–2018*	*2005–2018*	*2005–2018*	*2005–2018*	*2005–2018*

Notes: The hazard model is estimated using a Weibull distribution for the baseline hazard and coefficients are expressed in exponential form, e^{β}. Cluster-robust standard errors in parenthesis.
* Denotes significance at 10% level.
** Denotes significance at 5% level.
*** Denotes significance at 1% level.

dependent on revenues from certificates or that contractual terms make them less sensitive to short-term fluctuations in prices.

Also, the risk-free rate of interest only appears to affect the hazard of development for small projects. Perhaps this serves as a poor measure of investors required rate of return and that alternative, more sophisticated measures of the discounting factor should be considered. Nonetheless, Dixit and Pindyck (1994) argue that the value of waiting should be incorporated in the decision rule regardless of risk preferences, as this is simply consistent with optimal decision making. Lastly, taking into consideration the findings of Linnerud et al. (2014) and Linnerud and Simonsen (2017), in Model 4 and 5 I examine whether there is any difference between professional corporations (and economic cooperatives) and civilians. The figures are supportive of the findings in the more recent of the aforementioned studies, i.e. that professional corporations as well as civilians are able to respond optimally and value the option of waiting when uncertainty over future prices is large.

6. Robustness of hazard model results

In the first two models in Table 5 I test for robustness of the results of the estimated hazard model by specifying different distributions for the baseline hazard function. In Model 1, an exponential distribution for *t* is assumed, i.e. that the baseline hazard is constant over time, and in Model 2 a log-normal distribution is assumed. The latter is estimated in accelerated failure time, meaning that it relates a unit change in a covariate to a proportional change in survival time rather than in the hazard rate (Jenkins, 2005). In this model, coefficients are expressed in unexponential form and a positive coefficient indicates an increase in survival time, i.e. a decrease in the hazard rate (and vice versa for a negative coefficient). The coefficient for volatility of certificate returns is statistically significant at a 1% level and of the expected sign in both models. This holds for other coefficients as well, implying that the results are robust for alternative distributional assumptions, although the Weibull distribution is preferred according to the BIC.

Further, in Model 3, I use prices and investment costs expressed in real terms (based on actual inflation) instead of nominal, transformed into 2018 SEK using annual consumer price indices. The hazard ratio for the volatility of certificate prices remains significant but increases somewhat in size, suggesting that the proportional decrease in the monthly hazard of investment may be slightly lower if inflation is taken into consideration. As a last robustness check, I test for an alternative measure of price uncertainty. Dunne and Mu (2010) emphasise how research have shown that futures prices of oil are unbiased predictors of future spot prices and outperform time-series models. For this reason, the authors state that futures prices are generally considered as a benchmark price forecast among industry observers and used to hedge some of the price risk away. These arguments are also supported by Kellogg (2014).

Possibly this reasoning holds for certificate markets as well. In Model 4 I therefore replace the GARCH-volatility of certificate spot prices with the historical volatility (i.e. standard deviation) over the previous 12 months of forward contracts with one year to maturity, thereby using a similar uncertainty measure as Dunne and Mu (2010). Other covariates are kept unchanged. The coefficient for certificate volatility remains statistically significant. Now the reduction in the monthly hazard rate of a one standard deviation increase in volatility is estimated to 13.6%. Changing the price variable from spot prices to forward prices yields almost identical results, and the same holds for re-estimating the baseline hazard model using forward contracts for both

Table 5
Alternative specifications of the hazard model for probability of wind power investment

Coefficient on covariate	Model 1 (exponential distribution)	Model 2 (log-normal distribution)	Model 3[a] (real price)	Model 4 (hist. volatility forward certificate)
Certificate price	1.0038***	-0.0033***	1.0093***	1.0126***
	(0.0002)	(0.0003)	(0.0005)	(0.0008)
GARCH-volatility certificate	0.9947***	0.0058***	0.9934***	
	(0.0008)	(0.0008)	(0.0014)	
Std.dev. certificate[b]				0.8639***
				(0.0234)
Investment cost	0.9998***	0.0002***	0.9999**	1.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
One-year lagged risk-free interest rate	0.7023***	0.5172***	0.8774	1.0526
	(0.0757)	(0.1186)	(0.1451)	(0.1779)
Electricity price	1.0003*	-0.0003**	1.0093***	1.0006**
	(0.0001)	(0.0001)	(0.0005)	(0.0003)
GARCH-volatility electricity	0.9997***	0.0003***	0.9999	1.0001
	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Baseline hazard	0.0961***	0.8762***	0.0000***	0.0000***
	(0.0308)	(0.2723)	(0.0000)	(0.0000)
Weibull parameter (p)			2.5246	3.6216
			(0.1639)	(0.1979)
Log likelihood	-873.7374	-659.648	-583.279	-273.486
Nr. of projects	*763*	*763*	*763*	*715*
Sample period	*2005–2018*	*2005–2018*	*2005–2018*	*2006–2018*

Notes: Coefficients are expressed in exponential form, e^{β}, in all models except for Model 2, where the untransformed coefficients are presented. Cluster-robust standard errors in parenthesis.
* Denotes significance at 10% level.
** Denotes significance at 5% level.
*** Denotes significance at 1% level.
[a] Certificate prices, electricity prices and investment costs are expressed in real terms (2018 SEK), deflated using annual consumer price indices collected from Statistics Sweden.
[b] Standard deviation [%] of logged returns over the past 12 months, derived from forward contracts with one year to maturity.

the price variable and GARCH-volatility. Thus, using spot or forward contracts, a time-series model or historical volatility, does not appear to affect the results considerably.

7. Discussion and Conclusions

7.1. Discussion of the empirical findings

This study examines the impact of price and regulatory uncertainty in the Swedish-Norwegian market for tradable green certificates and how it affects investments in green technologies. Certificate markets are characterised by a politically driven demand and price volatility can therefore result from changes in regulation. By endogenously testing for structural breaks in the variance of certificate returns, the empirical analysis identifies three such periods of increased volatility that can be connected to regulatory changes, namely the extension of the domestic market to include Norway in 2012 and the political deliberations regarding the period after the joint target with Norway is met. The latter break point is close in time after the publications of the results from the second formal review of the system (Checkpoint 2017) and the adoption of a new political energy agreement, in June and October 2016. The two former break points relate to the period leading up to the creation of the joint market with Norway that resulted in a period of temporary increased volatility between 2010 and 2011, as well as the period succeeding the start of the joint mechanism where a period of increased volatility between 2013 and 2014 is apparent.

Interestingly, only one of the three identified periods occur after the start of a new policy period. International Energy Agency (2007) anticipate that regulatory uncertainty will be reflected though a one-time jump in prices at the introduction of a new policy period, which investors may value to await to see if prices stabilize in a way that justify the investment. Meanwhile, Dixit and Pindyck (1994, p.20) argue that “if governments wish to stimulate investment, perhaps the worst thing they can do is to spend a long time discussing the right way to do so”. Fleten et al. (2016) emphasise that the process leading up to the joint market went on for many years, during which the political discussion shifted several times. They argue that all these years of discussion on how and when to implement the support policy led to regulatory uncertainty for green investors. Similarly, the political discussion in 2016 sent asymmetric information on the design of future regulation. This because of the suggested stop-date for new plants in Sweden already in 2021 that was later revoked in conjunction with the new target for renewable energy and extension of the market duration, thereby postponing the decision on when new plants within the system should be stopped.

As such, these periods of increased volatility could plausibly be explained not only by an uncertainty over the outcome of a future change in regulation, but also about the future regulatory design in itself. This indicates that both a change in regulation, as well as the prospect of a future change in regulation, have a negative impact on certificate markets by making it more difficult to forecast future benefits of a project. Swedish authorities have several times received complaints from market participants on a shortage of information and lack of transparency within the system, threatening the credibility of the policy (Swedish Energy Agency, 2014, 2018). Indeed, this study continues to demonstrate that the presence of price and regulatory uncertainty deters investments in green technologies. More specifically, a one standard deviation increase in price volatility is estimated to reduce the monthly hazard rate of development of wind power projects in Sweden by approximately 12%. This is consistent with the predications of real options theory and findings in previous research.

For example, Gross et al. (2010) emphasise that policy makers must consider the option value for investments in new technologies, which may be large when information is poor or asymmetric, and Fatás and Mihov (2013) empirically show that policy volatility reduces economic growth as investments are dismissed. International Energy Agency (2007) further state that because of the high capital intensity of low-carbon technologies, regulatory uncertainty may induce suboptimal investment decisions, such as extending the life of an existing plant rather than investing in a new and more efficient plant. In the meantime, the EU Renewable Energy Directive (2009/28/EC) considers renewable energy as being of crucial importance not only to reduce greenhouse gas emissions, but also to improve energy security and promote technological and rural developments. In conclusion, taking these considerations into account, the empirical results of this study show that the presence of regulatory uncertainty in green certificate markets can slow down the transitioning towards a renewable energy sector, as these investments are delayed into the future or dismissed. This has negative consequences for the potential of green growth and important socio-economic developments.

7.2. Concluding remarks and policy implications

Among the few existing empirical and econometric studies that analyse the dynamics of this particular market, Fagiani and Hakvoort (2014) is the first to investigate the link between price and regulatory uncertainty. This study provides a more comprehensive analysis by including more resent data and directly address the question of how price and regulatory uncertainty impacts green investments. To my best knowledge, the latter question has only previously been addressed empirically with a focus on the Norwegian part of the scheme (Linnerud et al., 2014; Fleten et al., 2016; Linnerud & Simonsen, 2017). Meanwhile, the Swedish certificate system is the only example in Europe where a domestic market has been extended to an international market, thereby becoming the most extensive system in place (Schusser & Jaraité, 2018). Furthermore, the European Commission favours market-based support policies for renewables and has the ambition of connecting the electricity grid across the EU member states (Bergek & Jacobsson, 2010). The findings of this study can therefore provide some valuable implications for designing future energy policies.

Primarily, analogous to the findings in previous research, it is clear that regulatory stability and transparency is important for creating efficient support policies. Avoiding frequent changes in regulation or shifting the discussion on the prospect of regulatory changes, as observed in the Swedish-Norwegian market, will likely reduce the impact of regulatory uncertainty. International Energy Agency (2007) accentuate the need to consider the trade-off between regulatory certainty and flexibility, where a flexible regulation for instance is able to respond to political decisions and trends in other countries. This implies that it may be challenging to combine the interests of regulatory stability and developing a connected European electricity grid. Nonetheless, International Energy Agency argue that 5-15 years into the future is the critical period for investors building a new plant and that keeping clarity over the regulatory principles for this period is unlikely to considerably constrain governments abilities to respond to new information.

Moreover, Swedish policy makers expected that a larger market would lead to less volatile prices. Conversely, the empirical results indicate that volatility remained at a higher level after prices went through a more volatile regime at the beginning of the joint market in 2013 and 2014. Although additional analysis is needed to examine the long-term effects of market integration, as emphasised by Fagiani and Hakvoort (2014), these findings suggest that the increased competition a larger market brings may also offset some benefits in terms of price stability.

Future research could also extend the real options analysis of the Swedish-Norwegian green certificate market. While this study contributes with some new insight on how investors respond to uncertainty in this market, Kellogg (2014) point out that the empirical research on firms ability to optimally respond to price uncertainty of a magnitude that is consistent with real options theory have been lagging. His findings suggest that the cost of not responding to variation in price volatility can be substantial. Extending the analysis to solve for the profit maximizing timing of investment, can hence provide further indications on how severe the impact of price and regulatory uncertainty is on incentives to invest in green technologies.

Acknowledgments

I would like to express my gratitude to my supervisor, Assoc. Prof. Andreas Bergh, for the valuable inputs and comments throughout the progress of this thesis. I would also like to thank Prof. Joakim Westerlund, for the important econometric guidance.

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Appendices

Appendix A

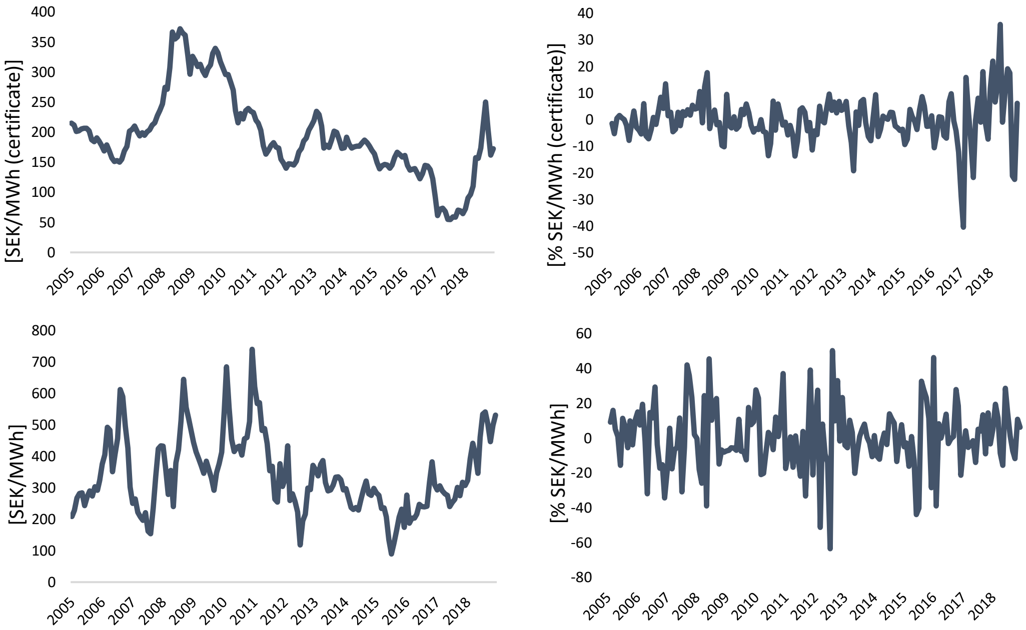

Figure A1. The upper graphs show monthly average prices (to the left) respectively logged returns (to the right) of certificate spot prices and the lower graphs show monthly average (to the left) respectively logged returns (to the right) of electricity spot prices. Both series span from January 2005 to December 2018.

Table A1

ADF and KPSS tests for stationarity.

Variable	ADF-statistic	KPSS-statistic
Certificate weekly prices		
Level	-1.702	5.12***
First difference	-10.047***	0.0727
Certificate monthly prices		
Level	-1.874	1.25***
First difference	-4.410***	0.0655
Electricity monthly prices		
Level	-2.953**	0.37*
First difference	-6.613***	0.0511
Interest rate gov. bond		
Level	-1.203	8.22***
First difference	-8.127***	0.041

Notes: In the ADF-test, H_0 = series contains a unit root, and in the KPSS-test, H_0 = series is stationary. All test-statistics are for a lag length of 5, except for the discount rate where the test-statistic is for a lag length of 1. An intercept term is included in the models.
* Denotes significance at 10% level.
** Denotes significance at 5% level.
*** Denotes significance at 1% level.

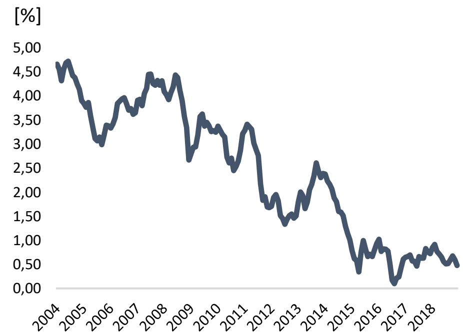

Figure A2. Monthly interest rate of a 10-year government bond for the years 2005 to 2018.

Appendix B

Table B1
GARCH (p, q) estimates of weekly certificate returns

	GARCH (1, 1)	GARCH (2, 1)	GARCH (3, 1)	GARCH (2, 2)
ρ_1	0.3403***	0.3259***	0.3143***	0.3172***
	(0.0432)	(0.0467)	(0.0462)	(0.0465)
ρ_2	-0.0603	-0.0447	-0.0236	-0.0310
	(0.0537)	(0.0485)	(0.0439)	(0.046)
ρ_3	0.0631	0.0592	0.0691*	0.0642*
	(0.0433)	(0.0377)	(0.0382)	(0.0378)
α_0	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1	0.2076***	0.35***	0.3497***	0.3631***
	(0.0179)	(0.045)	(0.0448)	(0.0466)
α_2		-0.1845***	-0.2498***	-0.1495**
		(0.0473)	(0.052)	(0.0685)
α_3			0.0859**	
			(0.0364)	
β_1	0.7917***	0.8325***	0.8086***	0.5713***
	(0.0123)	(0.0176)	(0.0198)	(0.1981)
β_2				0.2095
				(0.1535)
$\sum_{i=1}^{p,q} \alpha_i + \beta_i$	0.9993	0.998	0.9085	0.9944
BIC	-3101.064	-3102.695	-3098.909	-3097.913

Notes: standard errors in parenthesis.
* Denotes significance at 10% level.
** Denotes significance at 5% level.
*** Denotes significance at 1% level.

Table B2
Ljung-Box-Q test for serial correlation in standardized residuals of GARCH mean equation

	Weekly certificate prices						Monthly el. prices	
	AR(1)		*AR(2)*		*AR(3)*		*AR(1)*	
Lag	Q-stat	Pr.>Q	Q-stat	Pr.>Q	Q-stat	Pr.>Q	Q-stat	Pr.>Q
1	0.00455	0.9462	0.00176	0.9665	0.02403	0.8768	0.000022	0.9963
2	1.5826	0.4533	1.0942	0.5786	0.0504	0.9751	0.05113	0.9748
3	17.937	0.0005	17.839	0.0005	0.09852	0.9920	0.68931	0.8757
4	18.122	0.0012	18.026	0.0012	0.29954	0.9898	-2.9443	0.5672
5	20.121	0.0012	19.956	0.0013	2.1306	0.8308	4.5628	0.4715
6	20.599	0.0022	20.452	0.0023	2.1606	0.9044	5.8016	0.4458
7	21.248	0.0034	21.118	0.0036	3.4664	0.8388	6.0392	0.5352
8	21.327	0.0063	21.192	0.0067	3.5193	0.8977	6.1058	0.6354
9	21.522	0.0105	21.389	0.0110	4.0757	0.9064	6.1582	0.7240
10	21.525	0.0177	21.392	0.0185	4.0798	0.9437	7.1287	0.7132
11	21.875	0.0254	21.751	0.0264	4.6694	0.9461	7.1436	0.7873
12	21.974	0.0378	21.846	0.0393	4.7855	0.9648	7.5174	0.8216
13	25.406	0.0204	25.304	0.0211	8.7011	0.7951	7.5181	0.8735
14	25.42	0.0306	25.317	0.0316	8.8423	0.8410	8.5014	0.8616
15	25.679	0.0415	25.604	0.0424	8.9977	0.8776	9.5112	0.8493

Table B3

Estimated break dates (weeks) by the Double Maximum and Sequential tests (Bai-Perron tests) in the unconditional variance of weekly certificate returns

Estimated break dates significant at a 5% level	Scaled F-statistic	Weighted F-statistic	*l+1* selected comb.
Panel a: whole sample period			
W 3 January 2017	79.10071*	79.10071*	X
W 3 January 2017; W 3 March 2010	39.73690	45.65730	
W 3 January 2017; W 3 March 2010; W 4 September 2011	26.60387	35.39404	
W 3 January 2017; W 3 March 2010; W 4 September 2011; W 2 April 2014	19.95236	30.11053	
W 3 January 2017; W 3 March 2010; W 1 October 2011; W 2 July 2014; W 3 February 2013	15.96868	27.06053	
Panel b: sample period 2005-2016			
W 3 March 2010	10.83535	10.83535	
W 3 March 2010; W 4 September 2011	10.88412*	12.50574	X
W 3 March 2010; W 4 September 2011; W 2 April 2014	8.222805	10.93970	
W 3 March 2010; W 1 October 2011; W 2 April 2014; W 4 January 2013	8.302313	12.52920*	
W 3 March 2010; W 1 October 2011; W 2 April 2014; W 4 January 2013; W 39 September 2015	7.223686	12.24126	

Notes: The presented F-statistics are for the Double Maximum test and the asterisk (*) denotes the selected combination of break dates. The number of significant break dates found by the Sequential test is market in the fourth column.