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Can Merchant Interconnectors Deliver Lower and More Stable Prices? The Case of NorNed

EPRG Working Paper 0926

Cambridge Working Paper in Economics 0947

Vladimir Parail

The drive to reduce carbon dioxide emissions has led many countries to invest heavily in wind turbines. At the currently low level of penetration, fluctuations in wind power output that result from changing weather conditions can easily be managed using existing arrangements. However, as the share of wind power in the overall generation mix increases, variations in output of wind turbine generators are likely to cause large fluctuations in electricity prices and may compromise system stability.

One commonly suggested solution is to strengthen electrical connections between neighbouring regions, so that uncorrelated shocks in those regions can at least partly offset one another. The recently completed 700MW merchant interconnector between South Norway and the Netherlands, known as NorNed, is a particularly interesting case study in this regard. It connects a market characterised by price shocks due to changing demand and fuel prices to one which is dominated by reservoir generation, where generators arbitrage away significant price fluctuations. In theory, a reservoir system can act as a battery when connected to a system with a fluctuating electricity price, importing and storing electricity when the electricity price in the neighbouring system is low and running down its stocks when the price in the neighbouring system is high.

Much of the existing work on this topic seems to suggest that private investment in interconnector capacity is likely to be below the socially optimal level because of economies of scale in building transmission cables. It is claimed that the marginal investment decision is distorted by the effect of additional investment on profits from existing transmission capacity. The argument is equivalent to the explanation of why monopoly output is below the competitive level. Increasing transmission capacity reduces price differences between markets, driving down the profits of existing transmission capacity.

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Since economies of scale in transmission investment mean that it cannot be provided competitively, i.e. in small increments by different parties, the actual capacity built is likely to be below the socially optimum level.

This paper takes an empirical approach to examining the economic effects of NorNed. It concludes that arbitrage over the interconnector has had a low effect on prices in the Netherlands and South Norway. This implies that the majority of welfare gains resulting from trade across the interconnector are likely to be accrued to its owners, undermining the practical validity of the theoretical argument that economies of scale in transmission investment lead to a divergence between social and private benefits of transmission investment. On the scale of NorNed, there is little evidence to suggest that transmission capacity between different markets cannot be provided competitively.

The paper also estimates the effect of arbitrage over NorNed on price volatility in the Dutch day-ahead electricity market. It finds little support for the proposition that merchant interconnectors with capacity similar to that of NorNed can achieve a substantial reduction of price volatility in the connected markets. Given that NorNed connects the Dutch market to a reservoir system characterised by stable prices, NorNed represents an upper bound on such capability for interconnectors of its size. This suggests that the effectiveness of interconnectors in reducing price fluctuations caused by changing wind power output in a system otherwise dominated by thermal power generators may have been overstated and capacity considerably greater than that of NorNed may be required to achieve the desired effect.

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Abstract

This paper estimates the effect of the merchant interconnector between Norway and the Netherlands on the level and residual volatility of hourly day-ahead electricity prices in the two connected markets. The price effects are estimated using single equation ARMA models and the volatility effects are estimated using EGARCH models with multiplicative heteroskdasticity. Both the level and volatility effects on prices are found to be modest. This result implies that the majority of welfare gains resulting from trade across the interconnector are likely to be accrued to its owners, undermining the practical validity of the theoretical argument that lumpiness in transmission investment leads to a divergence between social and private benefits of transmission investment. This paper finds that, on the scale of NorNed, there is little evidence to suggest that transmission capacity between different markets cannot be provided competitively.

Keywords merchant interconnectors, electricity prices, price volatility, time series, egarch

JEL Classification C22, G10, L9, L94

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Can Merchant Interconnectors Deliver Lower and More Stable Prices? The Case of NorNed

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1 Introduction

The drive to reduce carbon dioxide emissions has led many countries to invest heavily in wind turbines. Whilst the share of wind power in total world generation is only around 1.5% as of 2008, this share had doubled between 2005 and 2008[1]. At the currently low level of penetration, fluctuations in wind power output that result from changing weather conditions can easily be managed using existing arrangements. However, as the share of wind power in the overall generation mix increases, variations in output of wind turbine generators are likely to cause large fluctuations in electricity prices and may compromise system stability.

One commonly suggested solution is to strengthen electrical connections between neighbouring regions, so that uncorrelated shocks in those regions can at least partly offset one another. The recently completed 700MW merchant[2] interconnector between South Norway and the Netherlands, known as NorNed, is a particularly interesting case study in this regard. It connects a market characterised by price shocks due to changing demand and fuel prices to one which is dominated by reservoir generation, where generators arbitrage away significant price fluctuations.

*I would first of all like to thank my supervisor, David Newbery, for providing the inspiration for this paper and for reading and discussing the numerous drafts that landed on his desk. I would also like to thank Arina Nikandrova for helping me to get to grips with some of the econometric models used in the paper and for coming up with suggestions that made the progress of my work so much smoother. Finally, I would like to thank Nicholas Vasilakos, Michael Pollitt, Steve Satchell and the anonymous referee for commenting on and helping to improve this paper at the various stages of its development.

[1] "World Wind Energy Report 2008," World Wind Energy Association (Feb. 2009)

[2] The capacity to transmit power over NorNed is auctioned in the day-ahead market

In theory, a reservoir system can act as a battery when connected to a system with a fluctuating electricity price, importing and storing electricity when the electricity price in the neighbouring system is low and running down its stocks when the price in the neighbouring system is high.

The resulting gains from trade would likely be even greater when a power system with a significant proportion of wind generation is connected to a reservoir system. Because output from wind turbines is highly variable, the benefits from storing surplus wind energy when it is abundant and drawing on reserves when it is scarce are likely to be very high. Whilst a similar effect can be achieved by relying on reserves of thermal generation capacity in periods when wind energy is scarce, this may be a lot more expensive than building additional transmission capacity.

Generally, economic gains from connections between neighbouring electricity markets can come from two sources. Firstly, there could be a consistent difference between prices in the two connected markets. Secondly, since electricity prices in day ahead markets are generally volatile, economic gains can be realised without a consistent difference in prices. If price shocks in the two connected markets are not perfectly correlated, an interconnector can be a substitute for peaking generation capacity in both markets. Since interconnector capacity can be used to arbitrage price differences between connected markets, private investors should be able to recoup their investment through price arbitrage. However, much of the existing work on this topic seems to suggest that private investment in interconnector capacity is likely to be below the socially optimal level because of economies of scale in building transmission cables. This is discussed in more detail below.

The most often cited papers that deal with the economic effects of connecting different electricity markets via high capacity cables have been theoretical rather than empirical. They tend to treat the formation of prices as a deterministic process and derive static oligopoly equilibrium outcomes in the presence on an interconnector. This applies to Joskow and Tirole (2000), who show that allowing generators to hold physical rights to transmission capacity may give them the incentive to create network congestion. It is also true of Borenstein et al. (2000), who model the effects of connecting two identical monopolistic electricity markets with deterministic demand and constant marginal cost on the behaviour of incumbent monopolists. Their model predicts that when the capacity of the transmission line is above a certain threshold, the two firms act as a duopoly and prices in both markets are lower than the monopoly price. This happens without any power flowing through the interconnector, which is a direct consequence of perfect symmetry between the two markets. From this result, the authors conclude that the social value of transmission capacity may not be closely related to the actual flows of electricity across the interconnector.

One theoretical paper that is closer in spirit to this one is Joskow and Tirole (2005). It studies interconnectors in a dynamic setting by examining the decision to invest in transmission capacity. The authors argue that private investment in transmission capacity is likely to be below the socially optimal level due to lumpiness in transmission investment. The marginal investment decision is distorted by the effect of additional investment on profits from existing transmission capacity. The argument is equivalent to the explanation of why monopoly output is below the competitive level. Increasing transmission capacity reduces price differences between markets, driving down the profits of existing transmission capacity. Since lumpiness in transmission investment means that it cannot be provided competitively, i.e. in small increments by different parties, the actual capacity built is likely to be below the socially optimum level.

The same argument is also employed in papers that straddle the line between theoretical and empirical work on the economics of interconnectors. De Jong and Hakvoort (2006) use a simple calibrated supply and demand model to predict that socially optimal transmission capacity is likely to be double the capacity that would maximise profits for a merchant transmission investor. Brunekreeft (2003) also makes the argument that, because of economies of scale in transmission investment, private provision of transmission capacity would be below first-best. However, quoting statistics on the relationship between total transmission capacity and average cost, Brunekreeft notes that, for interconnectors with capacity upwards of 750MW, economies of scale are likely to be minor. Finally, Newbery (2006) deals directly with the issue of the impact of interconnectors on price levels and volatility with respect to the 1,000MW interconnector between the UK and the Netherlands, which is under construction at the time of writing. There, the estimated profits from the proposed interconnector are halved after accounting for its effect on price levels and volatility in the connected markets.

This paper takes an empirical approach to examining the economic effects of NorNed. By estimating its effect on the level of day-ahead electricity prices in the Netherlands and South Norway, it helps to characterise the economic gains attributable to the interconnector. It concludes that arbitrage has had a low effect on prices in the Netherlands and a slightly greater effect on prices in South Norway. This result is surprising in two respects. Firstly, NorNed could be expected to have a significant effect on prices in the Netherlands given that short-run price elasticity of demand for electricity tends to be low and the capacity of NorNed is equal to approximately 5% of average total available generation capacity in the Netherlands. Secondly, electricity is a storable commodity in a reservoir system and flows over NorNed would not be expected to impact South Norway prices immediately. Instead, that effect would be expected to be spread across a large number of hours. Hence the effect of exports from South Norway on the price in that market would be expected to at least partly offset the effect of imports into South Norway in other hours. Since this kind of dynamic is not possible in a market characterised exclusively by thermal generation and both the Netherlands and South Norway electricity markets are similar in size, the effect of arbitrage over NorNed on South Norway prices could be expected to be considerably lower than on prices in the Netherlands.

These results imply that the majority of welfare gains resulting from trade across the interconnector are likely to be accrued to its owners, undermining the practical validity of the theoretical argument that lumpiness in transmission investment leads to a divergence between social and private benefits of transmission investment. On the scale of NorNed, there is little evidence to suggest that transmission capacity between different markets cannot be provided competitively. The question of whether this result is at least partly due to the failure to implement market coupling with respect to NorNed or the response of incumbent generators and any resulting implications for market power in the Dutch electricity market are left for future research.

This paper also estimates the effect of arbitrage over NorNed on price volatility in the Dutch day-ahead electricity market. It finds little support for the proposition that merchant interconnectors with capacity similar to that of NorNed can achieve a substantial reduction of price volatility in the connected markets. Given that NorNed connects the Dutch market to a reservoir system characterised by stable prices, NorNed represents an upper bound on such capability for interconnectors of its size. This suggests that the effectiveness of interconnectors in reducing price fluctuations caused by changing wind power output in a system otherwise dominated by thermal power generators may have been overstated and capacity considerably greater than that of NorNed may be required to achieve the desired effect.

The rest of the paper is organised as follows. Section 2 describes the data set. Section 3 goes through the methodology used in estimating the price level effect of NorNed. Section 4 sets out and interprets the results of this estimation exercise and extends that analysis to test how the price effect of NorNed varies with market conditions. In particular, it tests whether the price effect of NorNed is stronger during peak hours when spare generation capacity is scarce. Section 5 sets out a model of volatility in electricity markets and how this model is used to estimate the effect of NorNed on residual volatility. Section 6 presents and interprets the results of volatility analysis and Section 7 concludes.

2 Data

The span of the data set is between 01 January 2006 and 12 March 2009. This is chosen deliberately so as to include sufficient observations before and after 6 May 2008 when NorNed was activated and enable a fair before and after comparison. The analysis presented in this paper relies on high frequency hourly data wherever possible, resulting in 28,008 separate observations for every such variable. When hourly observations are not available, average daily or weekly values are entered for each hour of the corresponding day or week. A full list of variables and their descriptions is given in Appendix B.

Hourly log Amsterdam Power Exchange (APX) and log South Norway day ahead electricity prices are the dependent variables in the analysis presented here and their properties are described in detail at the end of this section. The South Norway nodal price is deemed to be more appropriate than the Nord Pool[3] system price because the former is the price at which any imports from the Netherlands would be sold and any exports to the Netherlands would be paid for. The Nord Pool system price and the South Norway nodal price are only equal when none of the transmission constraints within the Nord Pool area are binding[4]. Day ahead rather than spot prices are used because the vast majority of trades occur in the day ahead market. The auction for transmission rights over NorNed is likewise conducted one day ahead of those rights being exercised.

Log coal and gas prices represent the determinants of the cost of generating electricity from those fuels. The log EU Emission Trading Scheme (ETS) price also reflects part of the cost of generating electricity from fossil fuels. Natural logarithms of all sample price data, including electricity and fuel prices, are taken for the purposes of econometric analysis. This is done in order to linearise any non-linear relationships in the data and results in a distribution which resembles a normal more than a log normal. Histograms of the two log electricity price series may be seen in Appendix A.

Hourly and week-day dummies are introduced to account for regular variations in demand between different hours of the day and different days of the week. The dummy variable for public holidays accounts for lower demand during those days. Monthly dummies account for seasonal variations in demand, and in the case of South Norway, seasonal variations in reservoir levels, which determine generators' willingness to supply electricity. The latter effect is also accounted for directly by variables that capture the average historic reservoir levels in Norway for any given week[5] together with variables that capture the difference between average historic and actual reservoir levels.

Weather observations play a dual role. For the Netherlands, average wind speed observations account for the influence of wind generators on the system price and average daily temperature observations account for the components of electricity demand related to heating. For South Norway, temperature observations also play a similar role. However, both temperature and precipitation observations are instruments for reservoir levels, which determine the willingness of hydro generators to supply electricity. Thus daily weather observation may capture some information that is missed by average weekly reservoir level observations.

[3]Single power market for Norway, Denmark, Sweden and Finland

[4]In the 28 months prior to NorNed coming online, the South Norway nodal price was the same as the Nord Pool system price 18% of the time. In the 10 months after that date, this proportion was only 2.6%.

[5]Averaged for the period between 1990 and 2003

The variable that captures flows over the NorNed interconnector, measured in units of 100MW[6], is added to each regression together with a dummy variable that takes a value of 1 when NorNed is operational and 0 otherwise. This is done to make sure that the estimated effect of trading over NorNed on log APX and South Norway prices is not biased by changes to the log electricity price that are not directly attributable to NorNed during the period after its opening. The variable that takes a value of 1 when NorNed is operational and 0 otherwise captures the effect of NorNed on residual price volatility in the two regressions. This variable is employed in the models that specify multiplicative heteroskedasticity.

Whilst the degree of market power in the Dutch and Norwegian electricity markets is one of the key determinants of prices, there have been no significant changes in market structure in these markets in the last four years, which covers the length of the sample period. This means that the measured level of market power is likely to remain broadly the same for the duration of the sample period and adding a measure of market power into a time series regression would simply mean that it drops into the constant[7]. Measures of market power are therefore omitted from the analysis presented in this paper.

Figure 1 plots average weekly APX and South Norway prices for the entire sample period. A plot of the average weekly APX gas price is added as a benchmark for the APX electricity price. Like electricity prices, this is also quoted in €/MWh for comparability.

[6] The variable is not weighted by demand as this would make it endogenous to the price. Section 4.4 provides evidence to suggest that the effect of NorNed on the APX price is not significantly different in peak and off-peak hours.

[7] NorNed would add a competitive fringe to the importing market, thus reducing market power in that market. This effect could be expected to be captured by the variable representing flows over NorNed.

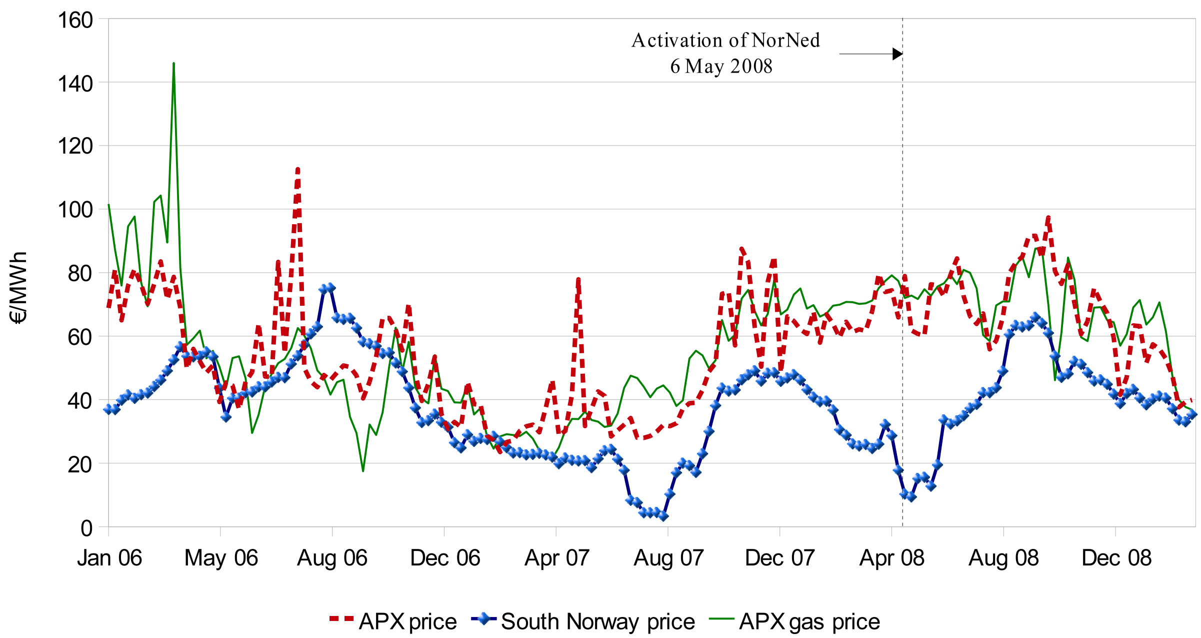

Figure 1: Average weekly prices

APX and South Norway prices can be seen to be following a broadly similar trend around 50% of the time, with significant deviations lasting several months at a time. APX prices are higher and more volatile than South Norway prices almost throughout the sample period. After the activation of NorNed, there appears to be some convergence between APX prices and South Norway prices. However, it does not occur immediately and, as can clearly be seen from the graph, APX and South Norway prices have tended to be close to one another more often than not. Hence the apparent convergence may be attributable to other factors. Given the prevalence of gas turbine generators in the Netherlands, one would expect a significant relationship between APX gas and electricity prices. They appear to be highly correlated in the long run. However, most of the short run volatility in average weekly APX prices seems to be explained by other factors.

Figure 2 characterises the average daily pattern of APX and South Norway prices throughout the sample period.

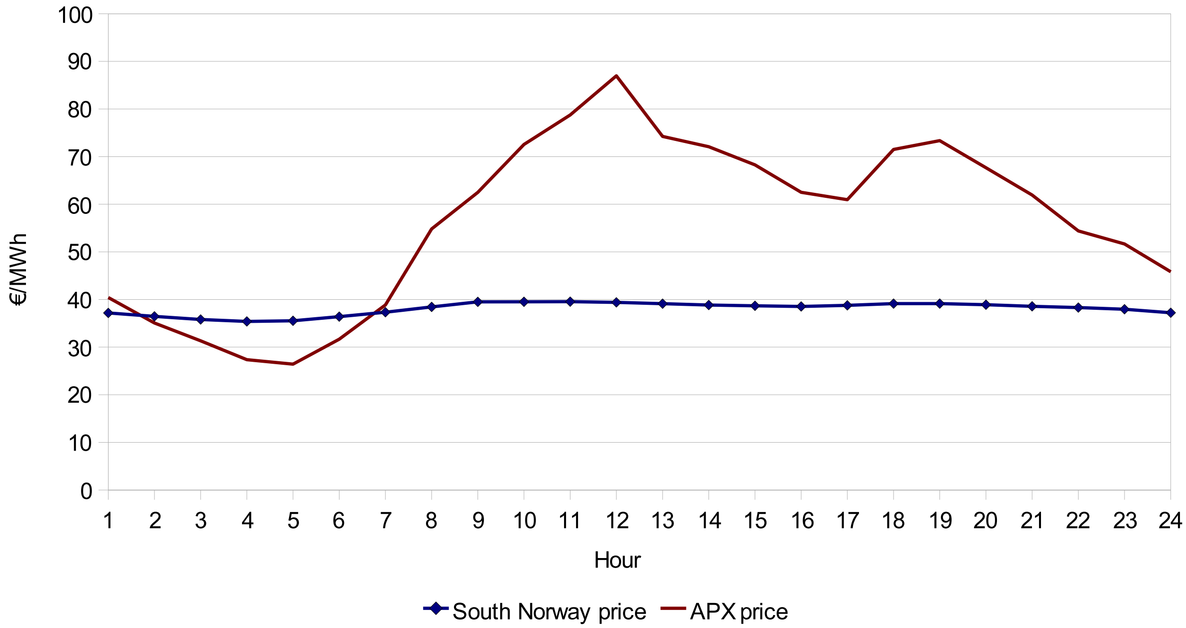

Figure 2: Daily pattern of electricity prices

The pattern of significantly higher prices during peak hours is considerably more pronounced in APX prices than in South Norway prices, where this pattern is barely visible. This is consistent with the effect of a high proportion of reservoir generation in Norway. Reservoir generators would be expected to arbitrage any consistent and significant intra-day variation in prices.

A simple visual test of the effect of NorNed on price differences between the two market is to plot the average hourly difference between the APX price and the South Norway price before and after NorNed coming online[8]. This is given in Figure 3 below. Two things become apparent by observation. The first is that the average price difference has increased since NorNed came online compared to the 26 months in the run-up to that date. The second is that the daily pattern of price differences has remained remarkably similar after the activation of NorNed.

[8] This is calculated by subtracting the South Norway price from the APX price.

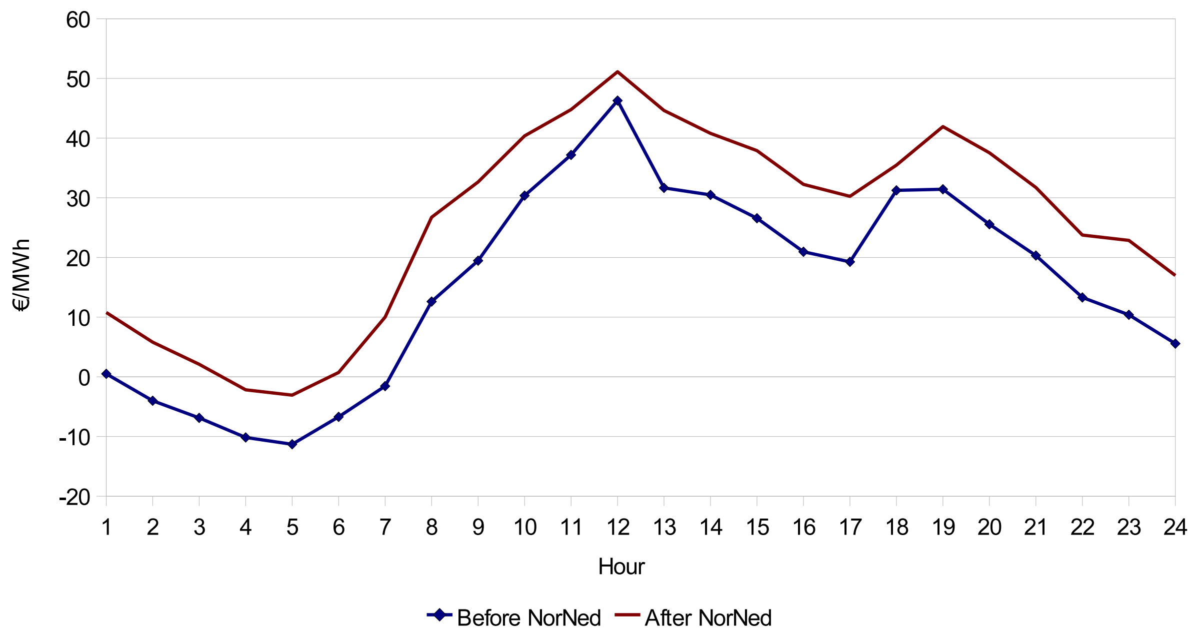

Figure 3: Average hourly price difference

3 Estimating the price level effects of NorNed

3.1 Methodology

The purpose of this section is to determine the best method for estimating the effect of NorNed on prices in the two connected regions and then to carry out that estimation. The analysis proceeds by adopting the simplest possible technique to begin with and then subsequently refining that technique if it is found to be inadequate. The first step is to fit two linear regressions to the data, with log APX and South Norway electricity prices as the dependent variables, and then examine the residuals from those regressions to see if they satisfy the Gauss-Markov conditions.

The condition of zero autocorrelation in the residuals is found to be violated with respect to both sets of residuals, though the null hypothesis of a unit root in log APX or South Norway price is also rejected. In order to deal with the specification error that produces this autocorrelation, a model with an autoregressive error structure is adopted. Finally, the variable that represents electricity flows across the NorNed interconnector is tested for potential simultaneity bias. Test results show that such bias is unlikely to be present in the coefficients estimated by the ARMA model.

3.2 Gauss-Markov conditions

If a time series regression equation is given by

$$y_t = \sum_{i=1}^{K} x_{it}\beta_i + \varepsilon_t ,$$

the Gauss-Markov assumptions in the context of this regression state that:

1. $\mathrm{E}(\varepsilon_t) = 0$,
2. $\mathrm{Cov}(\varepsilon_s, \varepsilon_t) = 0$, i.e. the residuals are not autocorrelated, and
3. $\mathrm{Var}(\varepsilon_t) = \sigma^2 < \infty$, i.e. the residuals are homoskedastic with a finite variance.

Assuming for the time being that the above conditions are satisfied, two linear regressions are fitted for log APX and log South Norway prices using the Newey-West estimator. This is an OLS estimator using a heteroskedasticity and autocorrelation consistent (HAC) covariance matrix[9], which means that the estimated standard errors are robust to the effects of heteroskedasticity and autocorrelation of lag up to 1,000 periods. In all other respects, it produces the same results as OLS. All relevant explanatory variables are included in each regression to start with[10], and any variables that are not significant at the 90% confidence level are eliminated from the regression equations. The R^2 values for both regressions are 0.60. Full results are reported in Appendix D.

3.3 Autocorrelation

Although the presence of autocorrelation in the regression residuals means that Gauss-Markov conditions are not satisfied, autocorrelation on its own does not make OLS estimates biased or inconsistent as long as lagged values of the dependent variable are not present on the right hand side of the regression equation. It merely makes OLS estimates inefficient, distorting their associated t-statistics[11]. However, significant autocorrelation in the residuals indicates that the model is incorrectly specified. With all significant explanatory variables included[12], the R^2 val-

[9] See Newey, W. K. and West, K. D., "A simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," Econometrica, Vol. 55 (1987), pp. 703-708

[10] The full list of explanatory variables is given in Appendix B

[11] See Greene, W.H. *Econometric Analysis*, 5th ed. Chapter 12

[12] Significance tests are based on a 90% confidence level.

ues for both regressions are 0.60, which means that a significant proportion of the variation in log electricity prices is unexplained. In combination with the presence of autocorrelation in the residuals, this could mean that the explanatory variables omitted from the regression are autocorrelated. These omitted variables may introduce substantial bias in the estimates of the OLS coefficients exogenous variables included in the regression[13].

The test of the Gauss-Markov assumption of zero autocorrelation in the regression residuals is carried out by implementing the LM test for the joint significance of N lags of the residuals in the regression of the least squares residuals on all independent explanatory variables and lagged least squares residuals. The result is a strong rejection of the null hypothesis of zero autocorrelation for N of anywhere between 1 and 100 for both regressions. Figures 4 and 5 below confirm that strong autocorrelation is present in the residuals from both regressions.

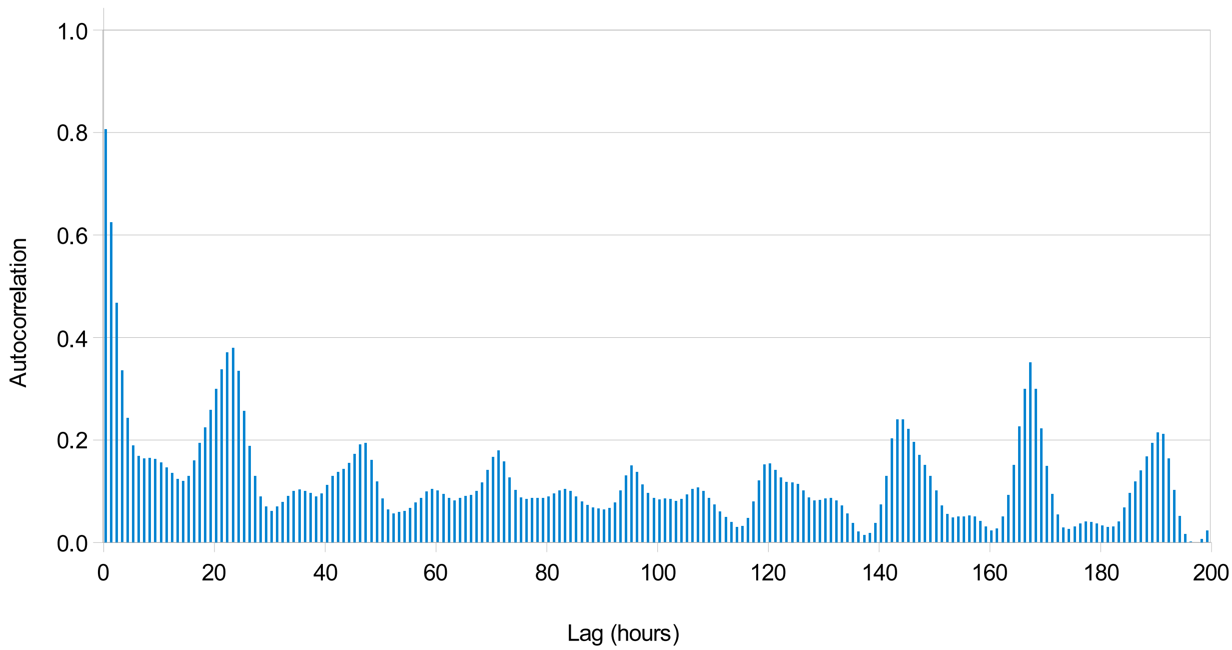

Figure 4: Autocorrelation function for log APX price OLS regression residuals

[13]See Greene, W.H. *Econometric Analysis*, 5th ed. pp148-149

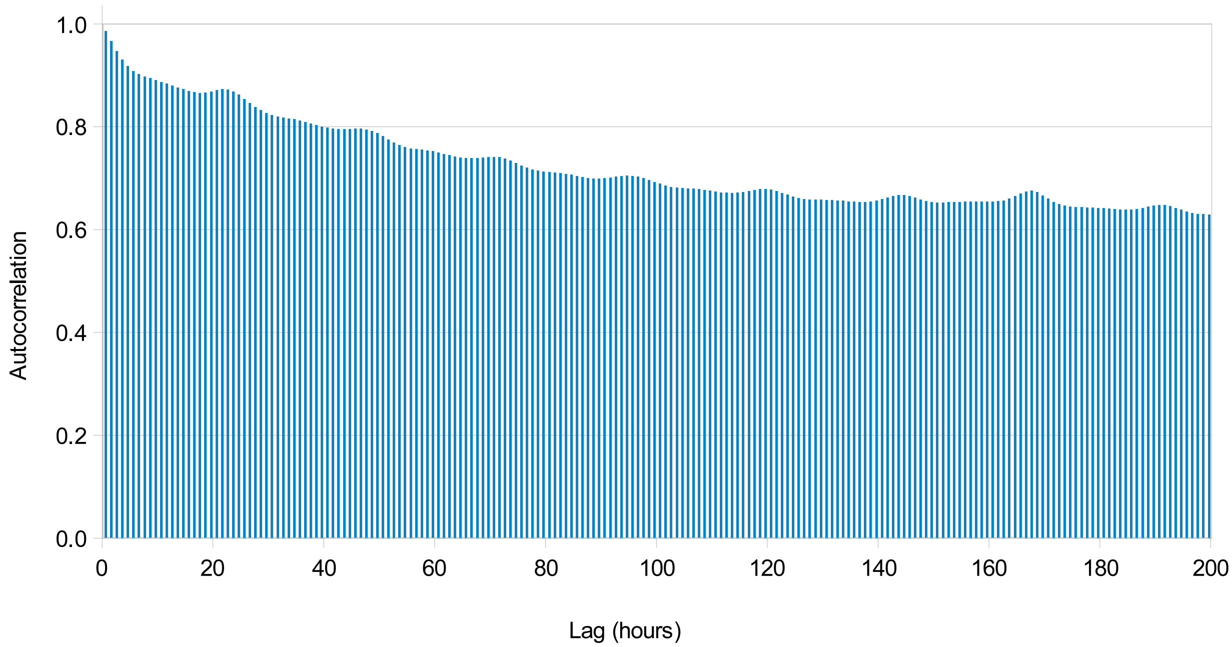

Figure 5: Autocorrelation function for log South Norway price OLS regression residuals

The extent of autocorrelation in regression residuals is clearly much greater in the case of South Norway. This is due to the fact that much of the electricity generation in Norway is reservoir based. A reservoir generator must make an optimal inter-temporal choice on when to produce energy as generation in one time period is a substitute for generation in another time period. This would mean dynamic optimisation of output decisions on an hourly basis. If there is a shock to the electricity price in any given hour, even if the shock is transient, it will induce generators to either reduce or increase reservoir levels compared to their expected levels. This change would in turn affect the willingness of generators to supply electricity in subsequent periods. The same would not be the case for a transient shock in a thermal system because there are no electricity reserves to draw on in a thermal system. However, a thermal system can be slow to respond to shocks because even if spare generation capacity is available, it may take some time to get a plant up and running. This could generate persistence in price shocks on an hourly basis.

Figure 4 also reveals that cyclical autocorrelation patterns with daily and weekly periodicity are present together with hourly autocorrelation in the residuals from the regression of log APX prices. This suggests that unexplained shocks to the electricity price level tend to be persistent on an hourly, daily and a weekly basis in a thermal system, with hourly persistence being the strongest factor. One example of a shock that is likely to display both hourly and daily persistence is a plant outage lasting several weeks. If the plant in question only comes into operation during peak hours, the shock to the price due to its outage is likely to persist only during the remaining peak hours of that day and to have a recurring effect during peak hours of subsequent days until it is brought back into operation. The ability of a thermal system to dampen such shocks may be limited because most plants can be expected to be operating at full capacity during peak hours.

The weekly pattern of autocorrelation in the residuals of log APX prices is more difficult to explain. It is likely to be due to contracting and electricity derivatives trading. Assume, for example, that a significant number of contracts are created, specifying delivery of electricity on a certain day of the week for a number of months. Assume further that all parties' positions are not perfectly hedged, meaning either that some of the parties with a long position do not require all the electricity they are contracted to buy or that some of the parties with a short position do not have all the electricity required to meet the terms of their contract. Any shock that affects a period under the contract is likely to display persistence with weekly periodicity.

Strong autocorrelation in the dependent variable could also indicate the presence of a unit root, meaning that the time series is not stationary, or in other words, not mean reverting. This could mean that the probability distribution of the dependent variable is not the same for all observations but changes over time. The consequence for regression results would be that standard errors of estimated coefficients would be distorted and inferences based on standard significance tests would become invalid[14]. A significant relationship between two or more variables could simply mean that they are following the same trend without any further underlying relationship between them, a phenomenon more commonly known as spurious correlation.

We test for the presence of a unit root using the Elliott-Rothenberg-Stock efficient test. This is similar to the Augmented Dickey-Fuller test but is adjusted for heteroskedastic errors. The null hypothesis of a unit root at lag one is rejected at the 99% confidence level for both log price series. However, keeping in mind the cyclical pattern of autocorrelation in hourly electricity price series, we also test for a unit root at longer lags. The maximum order of the lag for the purposes of this test is 49, chosen by using the Ng-Perron sequential t-test[15]. For log APX prices, the null hypothesis of a unit root is rejected at the 99% confidence level for all lag lengths up to 49. For log South Norway prices, the null hypothesis of a unit root is rejected at the 95% confidence level for all lag lengths except 19-23 and 46-47, for which it is rejected at the 90% confidence level, in some cases only marginally. This result suggests that log APX prices are stationary, but the stationarity of log South Norway prices cannot be completely ensured. This is the result we would expect after observing the frequency distributions of the two log price

[14]See Greene, W.H. *Econometric Analysis*, 5th ed. Ch. 20, pp632-635

[15]Knittel & Roberts (2005), who also use an hourly time series of electricity prices, only test for a unit root up to an order of 4

series in Figures 10 and 11 in Appendix A. The distribution of log APX prices looks a lot like a normal distribution with the same mean and variance parameters, whereas the distribution of log South Norway prices is characterised by significant skewedness and kurtosis.

3.4 ARMA

Econometric literature generally recommends specifying a model with autoregressive disturbances if the residuals from an OLS model are found to be serially correlated[16]. Therefore, in order to correct for this specification error, the estimation technique is refined to incorporate autocorrelation in the disturbances. This is formulated as follows

$$y_t = \sum_{i=1}^{K} x_{ti}\beta_i + \mu_t$$

$$\mu_t = \sum_{p=1}^{P} \phi_p \mu_{t-p} + \sum_{q=1}^{Q} \theta_q \varepsilon_{t-q} + \varepsilon_t.$$

The first equation is a structural equation and the second equation specifies the ARMA structure of the disturbances. The explanatory variables in the structural equation are as in the original linear regression with Newey-West standard errors. This model is estimated using conditional maximum likelihood, which, given the large number of observations, should yield the same results as unconditional maximum likelihood. The results may be seen in Appendix E.

Figures 12 and 13 in Appendix C plot the autocorrelation functions of residuals from the ARMA models of log APX and log South Norway prices. They demonstrate that, in both cases, model misspecification has been corrected and model residuals resemble white noise.

3.5 Endogeneity

The focus of this paper is on the effect of trading over the NorNed interconnector on prices in the two connected regions. However, putting flows over NorNed directly into a regression where the log electricity price is the dependent variable may result in inconsistent estimates. This is because the direction of electricity flows is determined by the price difference between the two

[16] See, for example, Godfrey (1987)

connected regions, making it likely that flows over NorNed are endogenous to the electricity price[17].

One simple test for endogeneity is the augmented Durbin-Wu-Hausman test[18]. This test is performed in three stages. Firstly, the potentially endogenous variable that represents flows over NorNed is regressed on all exogenous variables. Secondly, the residuals from that regression are saved as a new variable. Thirdly, the original regression with log APX or log South Norway prices as the dependent variable is carried out with the new variable added to the list of explanatory variables in that regression. If the coefficient of that new variable is significant, this is taken as an indication that simultaneity bias may be present.

The test is carried out with respect to both log South Norway and log APX prices. The null hypothesis that flows over NorNed are exogenous to log prices cannot be rejected at the 90% confidence level in either case[19]. This result suggests that simultaneity bias is unlikely to be a problem. The reason that flows over NorNed are not significantly endogenous to prices is because those flows are determined by the sign of the difference in prices between the two connected regions and not the magnitude of that difference. Electricity typically flows from the low price region to the high price region up to the full capacity of the interconnector. This means that most unexplained shocks to the electricity price either in South Norway or the Netherlands have no effect on flows over NorNed.

Note also that, because there is no single market mechanism that simultaneously determines day-ahead electricity prices and power flows over the interconnector, a process otherwise known as market coupling, electricity does not always flow from the region with lower day-ahead prices to the region with higher day-ahead prices. Between 6 May 2008, when NorNed became fully operational, and 12 March 2009, which is the last date on our data set, electricity actually flowed from the higher price market to the lower price market 12.7% of the time. This market imperfection is another reason why the case for electricity prices and flows over NorNed being simultaneously determined is weak.

[17]Other ways of entering flows over NorNed into the regression were attempted, such as entering one dummy variable for periods when electricity is being exported from Norway and another for when electricity is being imported into Norway. The estimated coefficients gave broadly the same results as the specification opted for here, except that the variable corresponding to imports into Norway was mostly insignificant.

[18]Davidson, R. and MacKinnon, J. G., *Estimation and Inference in Econometrics*, New York: Oxford University Press (1993)

[19]The test of significance is carried out on the basis of Newey-West standard errors, ensuring that the results of the test are not affected by heteroskedasticity or serial correlation in the residuals

4 Results: price effect of NorNed

4.1 ARMA estimates

The primary aim of this paper is to estimate the effect of electricity flows over NorNed on electricity prices in the Netherlands and South Norway. Separate regression models are estimated for each of the two markets. In order to test the robustness of the results, each model is estimated for two different data samples. They are firstly estimated for the entire sample period, which includes observations from before and after May 2008 when NorNed came online. Secondly, they are estimated for the sub-sample of observations beginning on 6 May 2008 when NorNed came online. Assuming that NorNed is used up to its full capacity, the estimated average effect of flows from Norway to the Netherlands is to reduce the APX electricity price by 2.6% and to increase the South Norway nodal price by 4.2%[20].

The ARMA regression estimates of the average effect of flows over NorNed on electricity prices in the Netherlands and South Norway are both significant at the 90% confidence level and consistent with respect to the sample used[21]. Re-estimating both regressions for the sub-sample of observations since NorNed came online produces very similar estimates of the price effect of NorNed.

4.2 Interpretation

These results suggest that, since NorNed was activated, the average sensitivity of APX prices to electricity flows across the interconnector has been low, and indeed lower than for South Norway prices. This result is surprising in two respects. Firstly, NorNed could be expected to have a significant effect on prices in the Netherlands given that the capacity of NorNed is equal to approximately 5% of average total available generation capacity in the Netherlands and that the short-run price elasticity of demand for electricity tends to be very low. If the supply of electricity is independent of flows over NorNed, the short-run price elasticity of demand implied

[20]The regression coefficient of $norned$ gives the estimated effect of 100MW of exports from Norway to the Netherlands on the log APX price. Translating from logarithms to actual prices, the absolute estimated effect of exports over NorNed on prices will differ depending on the starting price, but the estimated percentage change will always be the same. A coefficient -0.01 implies that exports from Norway to the Netherlands up to the full capacity of NorNed can be expected to reduce the APX price by 6.8%.

[21]In the EGARCH model with multiplicative heteroskedasticity, corresponding estimates of the price effect of NorNed on both sets of prices are significant at the 99% significance level.

by the estimated price effect of NorNed is around -2[22]. This is an order of magnitude higher than the short-run price elasticity of demand for electricity estimated in most empirical studies, which tends to be around -0.3[23]. Another way to look at it is that, if the average short-run price elasticity of demand for electricity in the Dutch market is -0.3, the implied average short-run price elasticity of supply in the Dutch electricity market is 2.2[24], which is reasonably high and suggests a relatively flat short run electricity supply curve.

Secondly, the effect of NorNed on the APX price could be expected to be greater than its effect on the South Norway price given that the two markets are of comparable size[25]. The Norwegian generation base is characterised by a large share of reservoirs in overall generation capacity. When electricity is imported or exported by a reservoir system, the impact of those flows on the system price is unlikely to be restricted to that hour because electricity is storable in a reservoir system. Generators are willing to supply electricity up to the point where their marginal cost is equal to their marginal revenue. The largest component of marginal cost for a reservoir generator is the shadow price of production, i.e. the ability to sell that electricity in another time period. Unless reservoirs are overflowing, this would be positive for any given period because production in the current period reduces the generator's ability to take advantage of higher prices in another period. In other words, the option value of unused reservoir capacity is generally positive. Hence imports into a reservoir system in a given time period are unlikely to cause a significant drop in the market price in that period because reservoir generators would be unwilling to supply electricity at a significantly lower price. The same would not be the case for the Dutch electricity market, which is dominated by thermal generation, because production in one hour is not a substitute for production in another hour for a thermal generator.

One possible explanation, which is tested in Section 4.4, is that the low price response of the Dutch electricity market is determined by the behaviour of generators. This section tests whether the system price is more responsive to flows over NorNed when the system is operating near full capacity. Another explanation is that the Dutch electricity market is closely integrated with its neighbouring markets and NorNed capacity is small relative to the total available generation capacity in those markets. This is explored in Section 4.3.

It is also worth remembering that market coupling has not been implemented between the

[22]Price elasticity $\epsilon_k(p)$ of Marshallian demand $x_k(p,m)$ for good k is given by $\epsilon_k(p) = \frac{\partial x_k(p,m)}{\partial p_k}\frac{p_k}{x_k(p,m)}$, where m denotes income

[23]See [3], [5], [8], and [26] among numerous other studies

[24]The total change in equilibrium quantity Q of good k is given by $dQ_k = dp_k\left(\frac{\partial x_k(p,m)}{\partial p_k}\frac{p_k}{x_k(p,m)} + \frac{\partial y_k(p)}{\partial p_k}\frac{p_k}{y_k(p)}\right)$, where the second term inside the brackets is the price elasticity of supply for good k

[25]Both markets also have links with neighbouring markets, which, depending on transmission constraints at any given time, can expand the definition of a domestic market. South Norway is directly connected with the rest of Norway, as well as Sweden and Denmark.The Netherlands is directly connected with Belgium and Germany.

Netherlands and Norway. As stated earlier, one result of the current market arrangements is that electricity does not always flow from the region with lower day-ahead prices to the region with higher day-ahead prices. It would be interesting to know what difference market coupling between Norway and the Netherlands would make to the effect of flows over NorNed on prices in the two markets. It is possible that the apparent lack of sensitivity of the APX price to flows over NorNed is due to imperfections in the market mechanism that is currently in place. Unfortunately, this counter-factual cannot be checked using existing data.

4.3 Market integration

All national electricity markets in Europe are connected to some extent, either directly or indirectly through other countries. Unless those links are permanently constrained, individual markets may effectively be merged with other neighbouring markets some of the time, with a single market price for electricity prevailing in both. Since imports into a large market can be expected to have less of an impact on the market price than exports into a similar but smaller market, the coupling of two or more markets may reduce the price impact of imports into any one of them. The low average sensitivity of electricity prices in the Netherlands to flows over NorNed may therefore be due to the fact that the Dutch electricity market is coupled with large neighbouring markets much of the time. The Dutch electricity market is connected to the Belgian and German markets, and also to the French market indirectly via the Belgian market. The interaction with French and German markets is of particular interest in this respect because they are large relative to the Dutch market.

By inserting an appropriate dummy variable into the regression equation, it should be possible to test this theory. This variable should be correlated with binding transmission constraints that separate the Dutch market from neighbouring markets. This exercise is much more easily carried out with respect to the French market because market coupling has been implemented between the French, Dutch and Belgian markets. This means that a single system price is calculated for all three markets, assuming that there are no transmission constraints, and if those constraints turn out to be binding for that price, those are priced explicitly so as to balance supply and demand in each zone. When markets are effectively merged, the electricity price in those markets will be the same. This is not the case for German and Dutch markets because the auctions for transmission capacity and electricity in the two countries are held separately and at different times, making it more difficult to tell when the transmission constraints between the two markets are binding.

The regression for the log APX price is run using the ARMA model as before. The results are checked for consistency by also running the regression using a sub-sample of observations for the period after NorNed was activated. The only difference is that one extra variable is added to this regression. The additional variable takes the following values

$$coup_t = \begin{cases} norned_t & if\ apx_t \neq powernext_t \\ 0 & otherwise \end{cases}.$$

This means that $coup$ equals the quantity of exports from Norway to the Netherlands in any period where the transmission constraints between the French and Dutch markets are binding (i.e. the APX price is different from the Powernext (French) price) and a value of 0 otherwise[26]. The regression then takes the following general form.

$$y_t = \alpha + \beta_1 norned_t + \beta_2 coup_t + \sum_{i=3}^{N} x_{it}\beta_i + \epsilon_t \ ,$$

where x_i are other explanatory variables. When electricity prices in the French and Dutch day ahead markets are different, the regression equation effectively becomes

$$y_t = \alpha + (\beta_1 + \beta_2) norned_t + \sum_{i=3}^{N} x_{it}\beta_i + \epsilon_t \ ,$$

and when the two markets are effectively merged, it becomes

$$y_t = \alpha + \beta_1 norned_t + \sum_{i=3}^{N} x_{it}\beta_i + \epsilon_t \ .$$

Thus if $norned$ and $coup$ are both significant, the effect of market coupling on the sensitivity of electricity prices to flows over NorNed is given by the ratio of β_1 to $\beta_1 + \beta_2$. If the value of that ratio in absolute terms is not significantly different from 1, this indicates that coupling between the French and the Dutch day ahead electricity prices makes no significant difference to the sensitivity of the APX price to flows over NorNed.

When the modified ARMA regression is run, $coup$ turns out not to be significant at the 90% confidence level. Its coefficient is also small relative to the coefficient of $norned$, such that that the ratio $\beta_1/(\beta_1 + \beta_2)$ is 1.04. This result is stable to running the regression for the sub-sample of observations beginning with NorNed coming online. The ratio $\beta_1/(\beta_1 + \beta_2)$ in this case is 1.01 and $coup$ is also not significant at the 90% confidence level.

Putting aside for a moment the result that $coup$ is not significant at any reasonable confidence level, a ratio $\beta_1/(\beta_1 + \beta_2)$ of 1.04 would indicate that, when the French and Dutch markets are effectively merged, the sensitivity of the APX price to flows over NorNed is actually slightly higher than when the prices prevailing in those markets are different. All this points to the conclusion that the effect of electricity flows over NorNed on the APX price is unlikely to depend on whether the connections between French and Dutch electricity markets are constrained.

[26] Exports in the opposite direction are represented by negative numbers as before

4.4 Price spikes

The ability of an interconnector to dampen significant price spikes determines its contribution to price stabilisation and ultimately to system stability. For this contribution to be significant, it would have to be the case that the effect of trading over NorNed in terms of the price movement it produces is considerably greater during a price spike than during a period of relative price stability. Otherwise, given the sensitivity of the APX price to flows over NorNed estimated in Section 4.1, NorNed is unlikely to make a significant contribution to electricity price stability in the Netherlands.

The reaction of a thermal system to imports over an interconnector may depend on how tight market conditions are in any given period. If most generators are not operating near full capacity, the merit order curve is likely to be flat locally because generators would be able to increase their output without bringing less efficient generation units into play. Unless the market price is significantly above marginal cost, imports are unlikely to push prices down under these conditions because domestic thermal generators would be unwilling to supply electricity at below marginal cost. Thus imports would simply crowd out domestic generation, leaving the market price virtually unchanged.

For similar reasons, exports out of this market would be unlikely to push domestic prices up under these conditions. Domestic generators would simply increase production without increasing their marginal cost. If, on the other hand, most generators are operating at or near full capacity, their marginal cost curve is likely to be very steep or even vertical locally. If marginal cost pricing prevails, imports into this market are likely to push the market price down significantly because some generators will have been supplying electricity at marginal cost which is very high and imports would push those generators out of the market by lowering the system marginal cost.

This theory can be tested by interacting an appropriately chosen dummy variable, which would be correlated with tight market conditions, with flows over NorNed and adding the resulting variable into the model. The methodology would be as in Section 4.3. The dummy variable must be exogenous to the regression residuals. If the dummy variable is correlated with the regression residuals, which would be the case if it was chosen on the basis of the price level in a given period, results are likely to be spurious. A simple way to get around this problem is to use a dummy variable which is exogenous to the regression residuals but is still positively correlated with tight market conditions and above-average prices. The variable chosen here is equal to flows over NorNed during peak hours, defined as all week-day hours excluding the period between 9pm and 7am, and equal to 0 otherwise[27].

[27] The Dutch, Belgian and French markets are marginally less likely to be coupled during peak hours than during off-peak hours as defined here, though the difference is very small.

The regression for the log APX price is run as before using the ARMA model. The only difference here is that one extra explanatory variable is added to the regression equation. This variable takes the following values

$$peak_t \quad = \quad \begin{cases} norned_t & if \sum_{\delta=8}^{21} H\delta_t \neq 0 \\ 0 & otherwise \end{cases},$$

where $H\delta_t$ is an hourly dummy variable that takes a value of 1 when t corresponds to hour δ and a value of 0 otherwise (e.g. $H23_t$ takes a value of 1 if t corresponds to the penultimate hour of a day and a value of 0 otherwise). This means that $peak_t$ is equal to $norned$ in any period defined as a peak hour, and equal to 0 otherwise. The regression then takes the following general form

$$y_t = \alpha + \beta_1 norned_t + \beta_2 peak_t + \sum_{i=3}^{N} x_{it}\beta_i + \epsilon_t \ ,$$

where x_i are other explanatory variables. For peak hours, the regression equation effectively becomes

$$y_t = \alpha + (\beta_1 + \beta_2) norned_t + \sum_{i=3}^{N} x_{it}\beta_i + \epsilon_t \ ,$$

and for off-peak hours, it becomes

$$y_t = \alpha + \beta_1 norned_t + \sum_{i=3}^{N} x_{it}\beta_i + \epsilon_t \ .$$

When the modified ARMA model is run, the coefficient of $peak$ is not significant at the 90% confidence level. The relevant coefficients of $norned$ and $peak$ are such that that the ratio $\beta_1/(\beta_1 + \beta_2)$ is 0.79. A qualitatively similar result is obtained after running the regression for the sub-sample of observations beginning with NorNed coming online. The ratio $\beta_1/(\beta_1 + \beta_2)$ in this case is 0.90 and $peak$ is also not significant at the 90% confidence level[28]. When the ARMA model is run excluding the $norned$ variable and including the $peak$ variable, the coefficient of $peak$ is likewise not significant at the 90% confidence level.

Overall, there is little evidence to suggest that the effect of flows over NorNed on the APX price may be greater for peak hours than for off-peak hours. Setting aside for the moment the lack of a statistically significant result, given the low estimated average sensitivity of the APX price to electricity flows across the interconnector, the corresponding effect in peak hours is still relatively small. If $\beta_1/(\beta_1 + \beta_2)$ is 0.79, this implies that the effect of trading over NorNed on the APX price is only 27% greater in peak hours than off-peak hours. This result would still imply that the

[28]Note that significance tests may be affected by the presence of heteroskedasticity. See Section 5.2 for more details

effectiveness of NorNed in terms of smoothing out electricity price spikes in the Netherlands is fairly limited.

This result could also have implications for the behaviour of generators in the Dutch market. In the standard Cournot model with N players[29], linear demand and constant marginal cost, total industry output is given by

$$\sum_{i=1}^{N} q_i = \frac{N(a-c)}{N+1}.$$

Any imports or exports over NorNed would be treated as a competitive fringe, expressed as a change in parameter a. It immediately follows from this formula that industry output is more responsive to flows over NorNed when N is large. Therefore the result that the APX price is slightly more sensitive to flows over NorNed in peak than off-peak hours could imply two things. Firstly, it could imply that generators' behaviour is slightly less competitive during peak hours than during off-peak hours. Secondly, it could imply that the merit order curve is upward sloping for peak hours.

Neither of these two implications would be surprising. One would expect both of them to hold. It is surprising that their cumulative effect appears to be fairly modest in quantitative terms and is not statistically significant. A more detailed study of the effect of NorNed on competitive behaviour of incumbent generators in the Netherlands is beyond the scope of this paper and is left for future study.

5 Estimating the effect of NorNed on residual volatility

5.1 Methodology

The estimation technique set out in Section 3 can help to measure the effect of flows over NorNed on the expected APX and South Norway prices. However, in order to test the hypothesis that NorNed has changed the volatility of prices in the Netherlands and South Norway since it has come into operation, it is also necessary to estimate the effect of NorNed on residual price volatility. The variance of residuals from the ARMA model of log APX prices makes up around

[29]The Cournot model is useful in this context because it behaves like a monopoly when $N = 1$ and like perfect competition as $N \to \infty$

60% of total variance of log APX prices and 62% of total variance of APX prices[30]. This suggests that residual volatility contains a slightly greater share of price spikes compared to its share of overall volatility.

This section sets out the framework for estimating the effect of NorNed on residual variance of electricity prices in the two connected regions. It supplements Sections 3 and 4 by calculating the dampening effect of NorNed on volatility that is not explained by the model. The first step is to test the assumption of homoskedastic errors in the ARMA models of log APX and South Norway prices, which is found to be violated in both cases. More detailed examination reveals that heteroskedasticity partly results from autocorrelation in the variance of residuals.

To model autocorrelation in the variance of regression residuals, an EGARCH model with multiplicative heteroskedasticity and an autoregressive error structure is proposed[31]. This involves modelling volatility of regression residuals with exogenous explanatory variables whilst also accounting for persistence in volatility. The coefficient of the variable in the volatility equation that indicates the availability of NorNed is used as an estimate of the effect of NorNed on residual volatility of electricity prices. In justifying the choice of methodology, this section reviews more traditional models of conditional heteroskedasticity as well as EGARCH and EARCH. A summary of their main properties for the purposes of this paper is given below.

[30]The residual variance as a proportion of total variance of log APX prices is calculate directly from the structural model. For APX prices, this proportion is calculated by generating predicted log APX prices from the structural model, converting them to predicted APX prices by taking the natural exponent and then calculating residuals as the difference between actual and predicted APX prices. The proportion of residual variation in total variation of APX prices is then calculated from this result directly.

[31]Volatility of log APX prices is modeled as an EARCH process given the lack of clear cyclicality in the autocorrelation function for square errors.

	ARCH	GARCH	EARCH	EGARCH
Multiplicative heteroskedasticity	Can be specified	Can be specified	Can be specified	Can be specified
MA terms in volatility equation	Yes	Yes	Yes	Yes
AR terms in volatility equation	No	Yes	No	Yes
Asymmetric shocks	Symmetric shocks only	Symmetric shocks only	Asymmetric shocks allowed	Asymmetric shocks allowed
Unrestricted coefficients	Coefficients may imply negative volatility	Coefficients may imply negative volatility	Unrestricted	Unrestricted

The advantage of being able to specify autoregressive (AR) as well as moving average (MA) terms in the volatility equation is that it allows the modelling of repeated patterns of autocorrelation in square returns. This is found to be relevant in the case of South Norway prices but not APX prices. Asymmetric shocks represent added model flexibility by which positive and negative shocks can persist in different ways. This is found to be relevant in the case of both APX and South Norway prices[32]. Finally, EARCH and EGARCH models, by specifying volatility in logarithmic form, avoid the possibility of volatility being negative for some periods depending on estimated model parameters. Since this is a real possibility for ARCH and GARCH models, this implies restrictions on parameters in those models that may be difficult to work out and implement.

5.2 Heteroskedasticity

The first step is to check if the Gauss-Markov condition of homoskedastic errors is satisfied. The most general test for heteroskedasticity is the White test. For the purposes of this test, no assumptions need to be made about the specific nature of the heteroskedasticity. The null hypothesis is that regression residuals are homoskedastic and the test statistic is asymptotically distributed as chi-squared. The test is carried out on the residuals from both ARMA regressions. The null hypothesis of homoskedastic errors is rejected for both with P values of 0 in each case.

[32] See Appendix F for details.

For the log South Norway price ARMA regression, the test statistic is 10,694 with 361 degrees of freedom, and for the log APX price ARMA regression, the test statistic is 9,626 with 748 degrees of freedom. This result suggests that heteroskedasticity in the residuals from both regressions is likely to be significant.

Heteroskedasticity does not cause coefficient estimates from an ARMA model to be biased. However, it does cause the estimates of the variance of those coefficients to be biased, meaning that those coefficient estimates are not efficient and their associated t-statistics are likely to be distorted. This means that selecting which variables to keep in a regression and which to eliminate on the basis of their associated t-statistics may lead to the elimination of some variables that are in fact significant and to retaining some that are insignificant. In order to obtain efficient estimates of the coefficients of all relevant explanatory variables, an adjustment to the estimation technique is required. This is discussed further in subsequent sections.

5.3 Persistence in volatility

All we know so far from carrying out the White test is Section 5.2 is that price volatility has not been constant in either of the connected markets throughout the span of our data set. The disadvantage of the White test for heteroskedastic errors is that it does not specify the exact form of heteroskedasticity found in the residuals. However, some information may be obtained by observation from a plot of regression residuals against time. The plots of residuals against time for the two ARMA regressions are as follows.

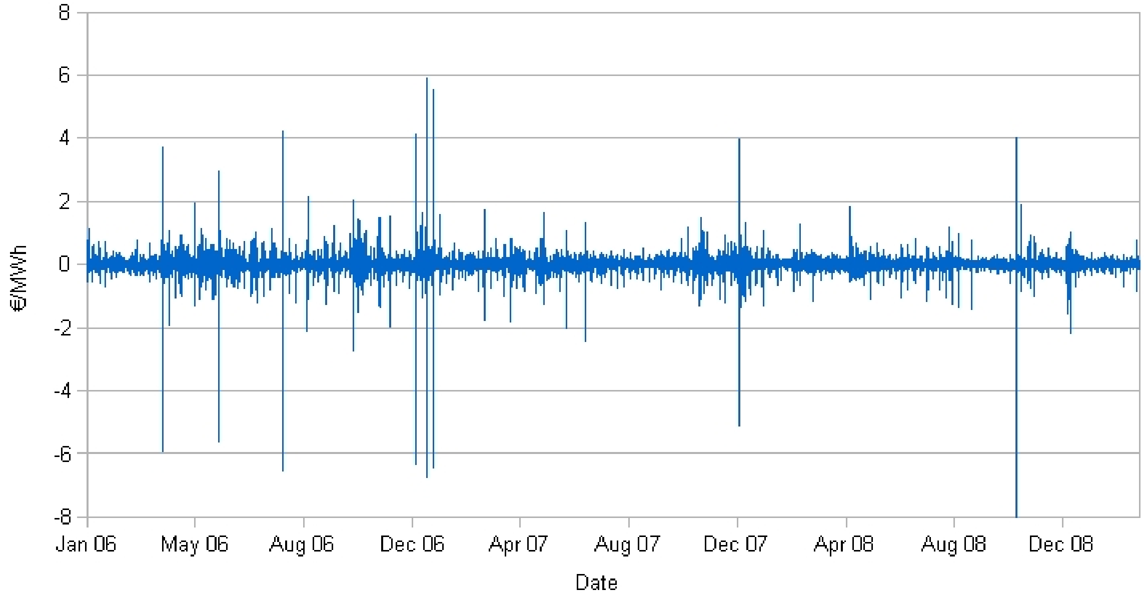

Figure 6: Residuals from ARMA regression of log APX price

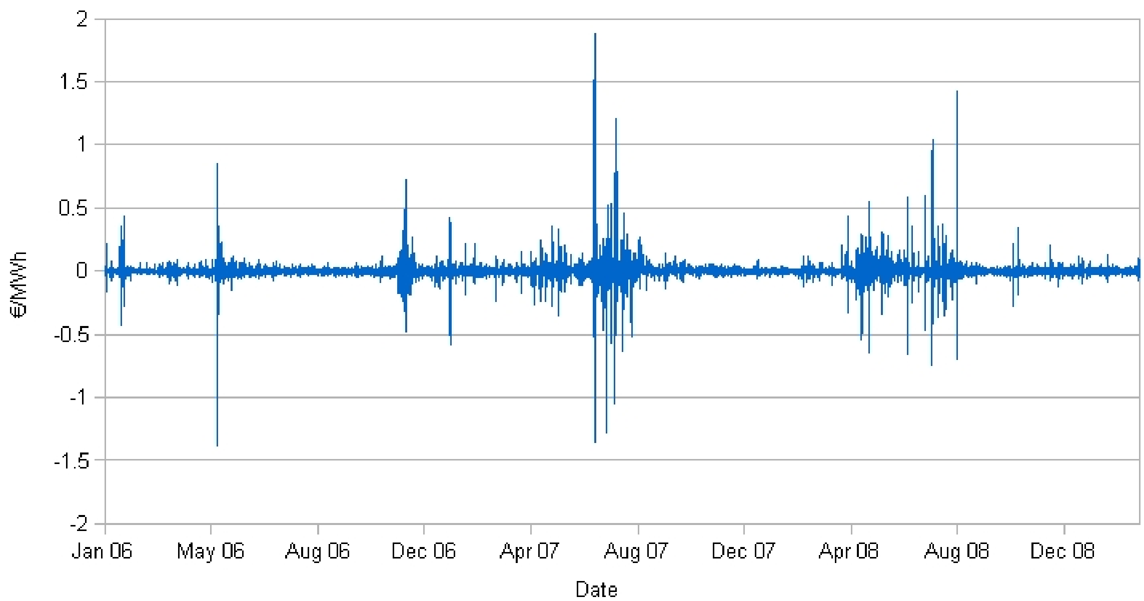

Figure 7: Residuals from ARMA regression of log South Norway price

A quick glance reveals that, particularly for the residuals from the ARMA model of log South Norway prices, periods of high volatility tend to be bunched together, as are periods of relative calm. This indicates that volatility may contain a strong element of persistence. In that case, squared errors from the ARMA model could be expected to display a significant degree of autocorrelation. It is possible to check for persistence in squared errors by examining their associated autocorrelation function. These are plotted below for both ARMA models.

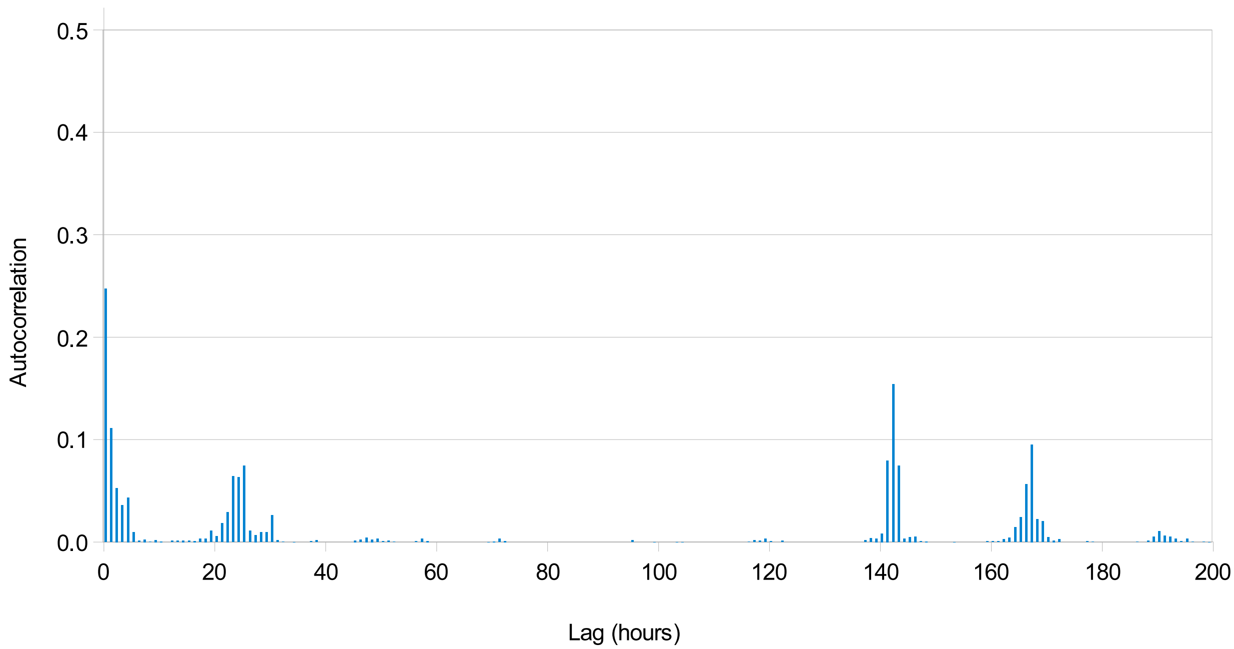

Figure 8: Autocorrelations of squared errors from log APX price ARMA model

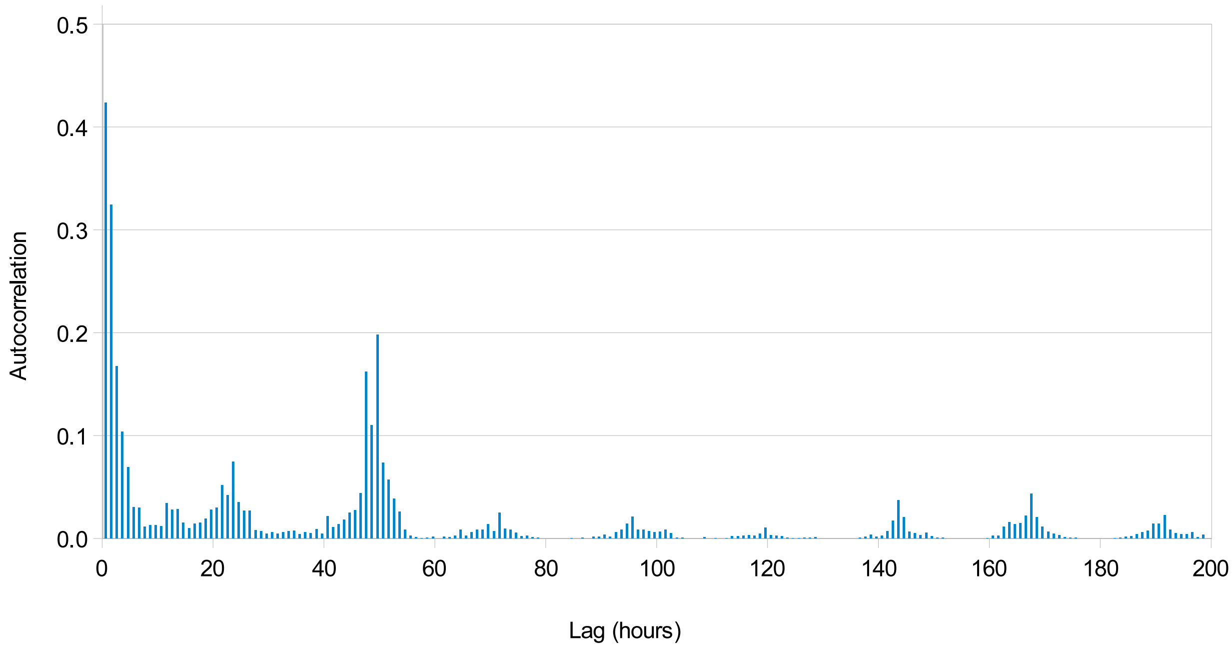

Figure 9: Autocorrelations of squared errors from log South Norway price ARMA model

It is possible to tell by observation that squared errors display a significant degree of persistence in the ARMA model of log South Norway prices, with hourly and daily patterns of autocorrelation. For log APX prices, there appear to be clusters of autocorrelation in square errors corresponding to hourly, daily and weekly persistence in volatility. A more formal test for serial correlation in squared errors is the LM test proposed in Engle (1982). The test involves regressing squared residuals on a constant and q lagged values. The null hypothesis is that there is no autocorrelation in squared errors. The alternative hypothesis is that at least one of the estimated coefficients of the lagged squared error terms is significant. For a sample of T residuals, the test statistic TR^2 follows chi-squared distribution with q degrees of freedom. Applying the test to the residuals from both ARMA models results in a strong rejection of the null hypothesis for both. This confirms what could be gathered from observing the plots of autocorrelations of squared errors.

Persistence in the volatility of electricity prices can occur for different reasons. In a reservoir system, when reservoir levels are low, the shadow price of generation in the current period is high because it removes the option to produce in another time period. Thus periods of volatility are likely to coincide with low reservoir levels when generators are less willing to arbitrage volatility in the electricity price. Since reservoirs cannot be replenished quickly, volatility is likely to be characterised by persistence. In a thermal system, a supply or a demand shock can be expected to have a greater effect on the price level when market conditions are tight. Since periods when market conditions are tight tend to be bunched together during peak hours and separated by periods of 24 hours or weekly intervals, persistence in volatility is likely to be characterised by the same pattern.

5.4 ARCH

A commonly observed property of many economic time series and especially high frequency financial time series is that the volatility of the time series is not constant through time. Rather, periods of low volatility and periods of high volatility tend to be grouped together. Autoregressive Conditional Heteroskedasticity (ARCH) models estimate time-dependent volatility as a function of observed prior volatility. The volatility model may also include regressors that account for a structural component of volatility. ARCH models were first introduced by Engle (1982). They model the variance of regression residuals as a linear function of past residuals. An ARCH(m) model can be written as

$$y_t = \sum_{i=1}^{K} x_{ti}\beta_i + \varepsilon_t$$

$$\sigma_t^2 = \gamma_0 + \gamma_1\varepsilon_{t-1}^2 + \ldots + \gamma_m\varepsilon_{t-m}^2$$

where

$$\varepsilon_t \sim N(0, \sigma_t^2)$$

ε_t^2 are the squared residuals for period t and γ_j are the ARCH parameters. The model specifies the conditional mean and the conditional variance, where variance is a function of the magnitude of past unanticipated shocks ε_t^2. This model was generalized in Bollerslev (1986) to include lagged values of the conditional variance. The GARCH(m,l) model can be written as

$$y_t = \sum_{i=1}^{K} x_{ti}\beta_i + \varepsilon_t$$

$$\sigma_t^2 = \gamma_0 + \gamma_1\varepsilon_{t-1}^2 + \ldots + \gamma_m\varepsilon_{t-m}^2 + \delta_1\sigma_{t-1}^2 + \ldots + \delta_l\sigma_{t-l}^2$$

where γ_j are the ARCH parameters and δ_j are the GARCH parameters. The GARCH model of conditional variance can be considered an ARMA process in the squared residuals. Both ARCH and GARCH models are calculated from the underlying data using conditional maximum likelihood, which means that the likelihood is calculated based on an estimated set of starting values for the squared residuals ε_t^2 and variances σ_t^2.

The GARCH model revolutionised the modelling of returns on financial instruments, which had previously assumed that those returns were normally distributed, and has since then found applications in other fields. It has been applied to the modelling of electricity prices in a number of papers, some of which are mentioned below. It's major advantage is that it enables the persistence in volatility, which we observe in the case of hourly log APX and log South Norway prices, to be modeled explicitly.

However, the GARCH model has a number of limitations which create difficulties with applying it to the modelling of volatility in electricity prices. These are described in Nelson (1991). The first such limitation is that both positive and negative shocks are assumed to affect the conditional variance of the residuals in exactly the same way. Knittel and Roberts (2005) find that the effect of shocks to hourly electricity prices on future volatility depends on the sign of those shocks as well as their magnitude for the price series that the examine. This paper also finds this to be the case for log South Norway and log APX prices.

Another limitation of the GARCH model lies in the non-negativity constraints on the GARCH terms, which are designed to ensure that σ^2 remains positive with probability 1. These constraints imply that increasing shocks will always increase σ^2 in future periods. This rules out oscillatory behaviour in the σ_t^2 process and creates problems for applied researchers, who often find that the parameters of their model that provide the best fit to their data actually violate those constraints. This has certainly been the case for modelling electricity prices, with Duffie et al. (1998) amongst others finding that the GARCH terms estimated for daily electricity prices violate the non-negativity constraints.

A third drawback of GARCH models is that the estimated process for conditional volatility is often non-stationary and indeed explosive. This is because in GARCH models, the conditional moments of GARCH may be explosive even when the underlying process is strictly stationary. Escribano et al. (2002) and Goto and Karolyi (2003) find this to be the case with GARCH models fitted to average daily electricity prices. They deal with this problem by introducing jump processes into the equation governing conditional volatility. We find that, in the case of log South Norway and APX prices, using a variation on the GARCH model can help to overcome this problem.

5.5 EGARCH

The Exponential Generalised Autoregressive Conditional Heteroskedastic (EGARCH) model, first proposed in Nelson (1991), addresses all three of the concerns about the GARCH model set out above. Conditional variance is modeled in logarithmic form as

$$\ln(\sigma_t^2) = \sum_{k=1}^{K} \beta_k z_{t-k} + \sum_{m=1}^{M} \gamma_m \mid z_{t-m} - \sqrt{2/\pi} \mid + \sum_{j=1}^{J} \delta_j \ln(\sigma_{t-j}^2)$$

$$z_t \sim N(0, \sigma_t^2).$$

Thus the logarithm of the conditional variance can be negative without the underlying conditional variance being negative. This means that the non-negativity restrictions on the coefficients in the above equation are not required. The model allows for positive and negative shocks to have differing effects on conditional variance, which are captured by the first term on the RHS of the above equation. The symmetric effect of shocks is captured by the second term. Finally, because now conditional variance is determined by a linear process, its stationarity can be checked in the same way as for a normal ARMA process. This is done by checking whether any of the roots of the characteristic polynomial lie outside of the unit circle[33].

5.6 Multiplicative heteroskedasticity

ARCH family models, including EGARCH, assume a form of path-dependence in volatility that does not rely on a particular explanation for volatility levels. Whilst they have been used successfully to model electricity prices, it is likely that modelling conditional volatility using exogenous determinants in addition to ARCH effects would yield more efficient estimates than a plain ARCH family model. Also, since the main aim of this paper is to test the effect of NorNed on the level and volatility of prices in the two connected markets, it is essential for us to be able to add an explanatory variable associated with NorNed into the equation governing conditional volatility.

The last refinement to the methodology adopted in this paper is to model the equation governing the conditional variance of log electricity prices as an Exponential Generalised Autoregressive Conditional Heteroskedastic process with additive exponential terms that model volatility using exogenous explanatory variables. It therefore extends the EGARCH modelling approach adopted by Knittel and Roberts (2005) by adding explanatory terms to the mean and conditional variance equations. Mean log electricity prices are modeled with an extensive set of exogenous explanatory variables and residuals that follow an ARMA process as before.

The general specification of the EGARCH models of log South Norway and log APX prices is as follows.

$$y_t = \sum_{i=1}^{K} x_{ti} \beta_i + \mu_t$$

[33] It can be easily checked that both EGARCH processes estimated in this paper are stationary

$$\mu_t = \sum_{p=1}^{P} \phi_p \mu_{t-p} + \sum_{q=1}^{Q} \theta_q \varepsilon_{t-q} + \varepsilon_t$$

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{q=1}^{Q} \alpha_q w_{qt} + \sum_{k=1}^{K} \beta_k z_{t-k} + \sum_{m=1}^{M} \gamma_m \mid z_{t-m} - \sqrt{2/\pi} \mid + \sum_{j=1}^{J} \delta_j \ln(\sigma_{t-j}^2)$$

$$z_t \sim N(0, \sigma_t^2),$$

where w_{qt} are exogenous explanatory variables and α_q are their corresponding coefficients. Because volatility is specified in logarithmic form, taking the exponent of both sides of the above equation results in the following specification of actual volatility of log prices.

$$\sigma_t^2 = e^{\alpha_0 + \sum_{q=1}^{Q} \alpha_q w_{qt} + \sum_{k=1}^{4} \beta_k z_{t-k} + \sum_{m=1}^{4} \gamma_m |z_{t-m} - \sqrt{2/\pi}| + \sum_{j=1}^{J} \delta_j \ln(\sigma_{t-j}^2)}.$$

Hence each explanatory variable has a multiplicative effect on variance.

The explanatory variables added into the mean equation as well as the specification of the residuals are as in the ARMA models presented in Section 3.4. The specification of EGARCH terms in the conditional volatility equation is derived from the corresponding autocorrelation function of squared residuals. This may be seen in Section 5.3. Any such terms that are not significant at the 90% confidence level are removed from the equation.

The EGARCH model with multiplicative heteroskedasticity makes it possible to check directly whether NorNed has made a difference to residual volatility, i.e. price shocks that cannot be explained by any exogenous explanatory variables. The effect of NorNed is incorporated in the volatility equation through a dummy variable that takes a value of 1 when NorNed is operational and a value of 0 otherwise. So that the estimate of the volatility effect of NorNed is not completely spurious and does not capture any differences that are attributable to other factors, week-day, monthly and time-of-day dummies are also added into the volatility equation together with a dummy variable that takes a value of 1 after NorNed came online. Different indicators of reservoir levels are also added into the volatility equation in the log South Norway price model.

The full estimation results for both models may be seen in Appendix F.

6 Results: residual volatility effect of NorNed

6.1 EGARCH estimates

Applying the definition of multiplicative heteroskedasticity from Section 5.6 to EGARCH regression results[34], NorNed is estimated to lower the residual variance of log APX prices by 17%. This estimate is obtained after accounting for any time of day, week-day or seasonal effects and also any unknown factors that would have affected residual volatility for the entire period after NorNed came online. To translate this into the estimated effect of NorNed on APX prices, some preliminaries are required. Note that the mean of a log-normally distributed variable is given by

$$E(X) = e^{\mu+\sigma^2/2}$$

and its variance is given by

$$Var(X) = \left(e^{\sigma^2} - 1\right) e^{2\mu+\sigma^2},$$

where μ and σ^2 are the mean and variance of that variable's natural logarithm. Given estimates of μ and σ^2, that is the mean and variance of log APX prices estimated from the subset of the data sample for the period since NorNed came online[35] and applying the above formulas, a 17% drop in the residual variance of the log APX price translates into a 20% drop in the residual variance of the APX price[36]. Since σ^2 also enters the expression for the mean APX price, a reduction in the variance of the log APX price will also affect the mean of the APX price. However, given the values of μ and σ^2 estimated from the data sample and the fact that that residual variance makes up around 60% of total variance of log APX prices, this effect is found to be very small.

In the case of the log South Norway price, the estimated coefficient of the variable that represents the operating status of NorNed in the volatility equation is tiny and statistically insignificant at any reasonable level of confidence. It is therefore concluded that NorNed has had no effect on the residual variance of the log South Norway price.

6.2 Interpretation

In theory, a reservoir system should act as a battery when connected to a thermal system, importing electricity when the thermal system price is low and exporting when it is high. This

[34] See Appendix F. The estimated coefficient of the variable that represents the operating status of NorNed in the volatility equation is -0.1847.

[35] μ is estimated at 4.101 and σ^2 is estimated at 0.256

[36] In order to obtain this result, note that residual variance makes up around 60% of total variance of log APX prices

should dampen both positive and negative price shocks in the thermal system with one significant qualification. This would only occur if there is no permanent difference in prices between the two systems such that electricity only ever flows in one direction.

The pattern of electricity flows over NorNed has been fairly stable since it was activated, going from Norway to the Netherlands in all but a few night-time hours when electricity in the Netherlands tends to be very cheap. This means that, unless the effect of flows over NorNed is significantly greater during price spikes, NorNed is unlikely to make much difference to electricity price volatility in the Netherlands. Section 4.4 provides little evidence to support the theory that the effect of NorNed during peak hours is greater than during off-peak hours. Given this result, it is unlikely that NorNed is effective in eliminating significant price spikes.

The results set out in Section 6.1 suggest that, whilst NorNed has contributed to a reduction in volatility in the Dutch electricity price, this effect has not been dramatic. The estimated 20% reduction in residual volatility would translate into a 12% reduction in overall volatility of APX prices given the split between explained and unexplained variation in the ARMA model of APX prices. To put these numbers into perspective, given the properties of APX and South Norway prices, if the residual volatility in APX prices falls by 20%, this translates into a 5% drop in the average absolute price difference between the two markets[37]. This could be expected to be proportional to the drop in interconnector profits resulting from the effect of the interconnector on volatility.

Finally, the result that the operating status of NorNed has made no statistically significant difference to the volatility of the South Norway electricity price is not surprising. Since it is in the interest of domestic reservoir generators to arbitrage any significant price spikes, the addition of an interconnector is unlikely to either increase or decrease price volatility in that market.

7 Conclusion

This paper uses statistical inference to estimate the effect of the recently constructed interconnector between the Netherlands and South Norway on the level and volatility of electricity prices in those two markets. Its main purpose of is twofold. Firstly it is to check whether the incentives for private transmission operators to invest in transmission capacity are below the socially optimal level because additional transmission capacity by any player reduces the profits from existing transmission capacity belonging to that player. This argument relies on economies of scale in transmission investment. Secondly it is to check whether interconnectors can be an effective

[37] This figure is calculated using a simulation, which may be obtained from the author on request.

means of reducing electricity price volatility in the connected markets, something that is likely to be increasingly important as the proportion of wind capacity in the overall EU generation mix increases.

Whilst the focus of this paper is on the NorNed interconnector, the results are more widely applicable to the issue of connecting electricity markets by merchant interconnectors. On the first question, the results presented here suggest that lumpiness in transmission investment is unlikely to introduce any serious distortion into the investment decision of private transmission operators. Since NorNed consists of two 350MW cables, one such cable can be considered to be the smallest increment beyond which economies of scale can be expected to be small. Given the estimated average effect on the APX price of NorNed as a whole, the vast majority of the benefits from additional interconnector capacity is likely to be accrued to its owners. There is nothing to suggest that merchant interconnectors with capacity on the scale of NorNed cannot be provided competitively by private profit-maximising operators.

On the second question, the results presented here suggest that the effectiveness of merchant interconnectors on the scale of NorNed in reducing electricity price volatility is likely to be limited. Given that NorNed connects the Dutch market to a reservoir system characterised by stable prices, NorNed represents an upper bound on such capability for interconnectors of its size. It must therefore be concluded that interconnector capacity considerably greater than that of NorNed would be required to achieve significant electricity price stabilisation.

It is important to note that this paper measures the static effects of the interconnector on the two connected markets. It does not consider the dynamic effect on investment resulting from the change in the deterministic and stochastic properties of prices. Finally, it must be noted that these results are obtained under conditions where interconnector capacity is sold in an explicit auction and market coupling is not implemented between the two connected markets. It is possible that the results are driven partly by the market inefficiency resulting from failure to implement market coupling. Since it is impossible to check that counter-factual at this stage, the question of whether market coupling would make a difference to the results presented here is left for future research.

A Frequency distributions of log electricity prices

Figures 10 and 11 plot the frequency distributions of sample log APX and log South Norway prices. These distributions are compared against a plot of a normal distribution with mean and variance parameters calculated from the corresponding log sample price data.

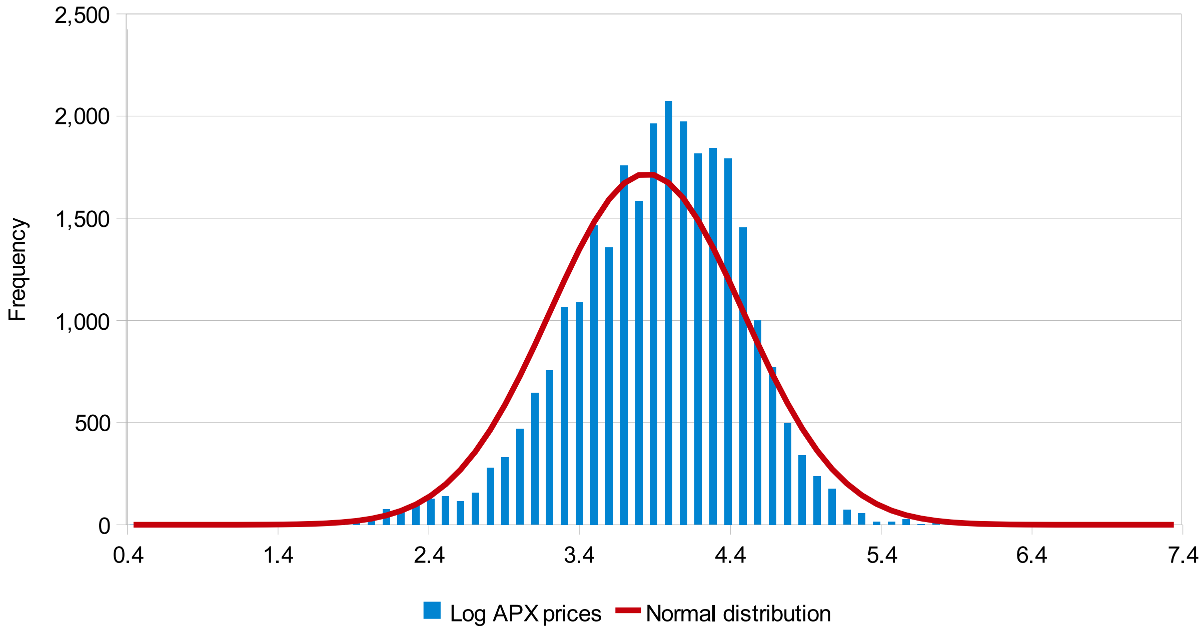

Figure 10: Frequency distribution of log APX prices

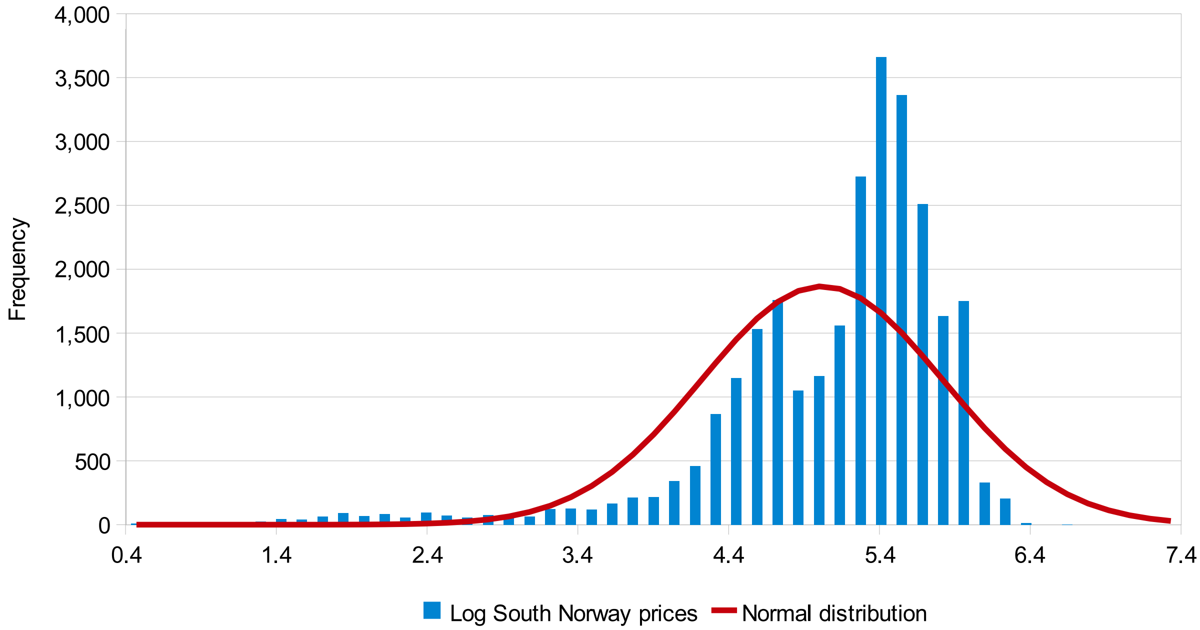

Figure 11: Frequency distribution of log South Norway prices

The distribution of log APX prices displays only a moderate amount of skewedness and kurtosis compared to a normal distribution with identical mean and variance parameters. The distribution of the log South Norway price is skewed and displays a more significant amount of kurtosis. It is also not characterised by a single peak in frequency around the mean.

B List of variables

Variable name	Description	Type	Source
lapx	Log APX electricity price (EUR)	Hourly	Bloomberg
lnwp	Log South Norway nodal price (EUR)	Hourly	Nord Pool
powernext	Log French electricity price (EUR)	Hourly	Bloomberg
lgas	Log APX gas NL price (EUR per MWh)	Daily	APX
lcoal	Log coal 3 month future price (EUR per ton)	Daily	EEX
lets	EU ETS log cabon price (EUR)	Daily	Bloomberg
nlcap	Planned available generation capacity in the Netherlands	Hourly	Tennet
norned	Power flows from NO to NL (MW)	Hourly	Statnett
op	Dummy variable indicating the availability of NorNed	N/a	N/a
break	Dummy variable indicating the construction of NorNed	N/a	N/a
coup	Instrumented power flows from NO to NL when lapx powernext (MW)	N/a	N/a
peak	Instrumented power flows from NO to NL in peak hours (MW)	N/a	N/a
H1 - H23	Hourly dummy variables	N/a	N/a
mon-sat	Week day dummy variables	N/a	N/a
hol	Dummy variable for public holidays in the Netherlands (non-weekend)	N/a	N/a
jan - nov	Monthly dummy variables	N/a	N/a
nnw1 - nnw34	Regional temperature and wind observations for the Netherlands	Daily	KNMI
nww1 - nww36	Regional temperature and precipitation observations for Norway	Daily	eKlima
hres1 - hres3	Average historical regional reservoir levels in Norway (%)	Weekly	NVE
dres1 - dres3	% deviation in Norway's regional reservoir levels from historical average	Weekly	NVE

C Autocorrelations of ARMA residuals

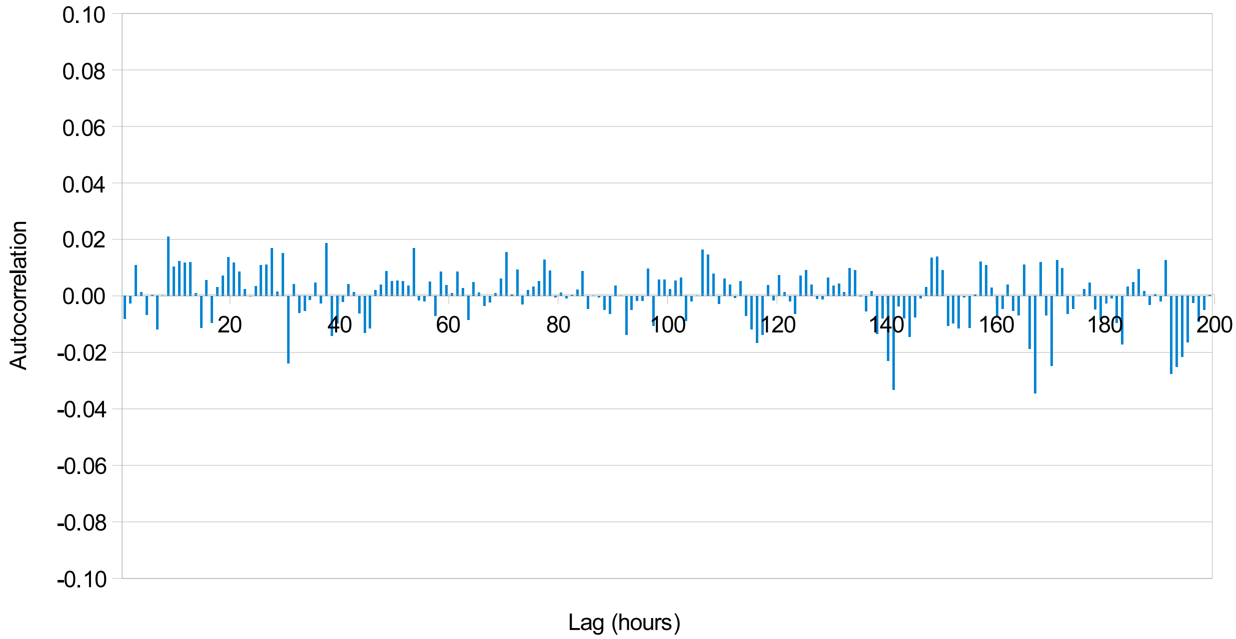

Figure 12: Autocorrelations of residuals from log APX price ARMA model

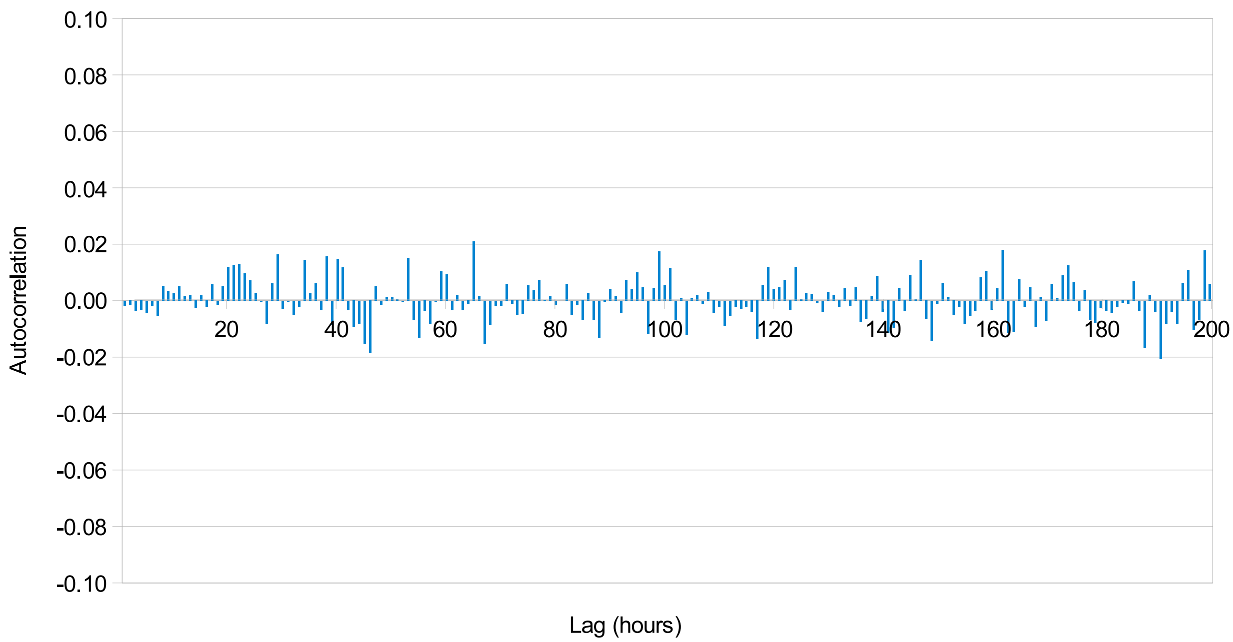

Figure 13: Autocorrelations of residuals from log South Norway price ARMA model

D Newey-West regression outputs

Regression with Newey-West standard errors — Number of obs = 28008
maximum lag: **1000** — F(48, 27959) = 297.44
Prob > F = 0.0000

lapx	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
H1	-.1434873	.0109667	-13.08	0.000	-.1649826	-.121992
H2	-.3104861	.0210163	-14.77	0.000	-.351679	-.2692932
H3	-.4667947	.0321484	-14.52	0.000	-.5298071	-.4037822
H4	-.6388303	.0403788	-15.82	0.000	-.7179748	-.5596859
H5	-.6778276	.0398182	-17.02	0.000	-.7558731	-.599782
H6	-.4740845	.0329796	-14.38	0.000	-.538726	-.409443
H7	-.300603	.0345816	-8.69	0.000	-.3683847	-.2328214
H8	.0616014	.031241	1.97	0.049	.0003675	.1228352
H9	.2320033	.0256358	9.05	0.000	.181756	.2822507
H10	.395783	.0234387	16.89	0.000	.349842	.441724
H11	.4793297	.0262737	18.24	0.000	.4278321	.5308274
H12	.5612929	.0335724	16.72	0.000	.4954894	.6270963
H13	.4479082	.0233527	19.18	0.000	.4021357	.4936807
H14	.4017055	.0248205	16.18	0.000	.3530561	.4503548
H15	.3305881	.0239433	13.81	0.000	.2836581	.3775182
H16	.2420131	.0232677	10.40	0.000	.1964072	.287619
H17	.2200674	.0272491	8.08	0.000	.1666578	.273477
H18	.340879	.0531703	6.41	0.000	.2366627	.4450953
H19	.397191	.054988	7.22	0.000	.2894119	.5049702
H20	.3520708	.0454414	7.75	0.000	.2630034	.4411381
H21	.2909399	.0314407	9.25	0.000	.2293146	.3525652
H22	.1670318	.0194154	8.60	0.000	.1289766	.2050869
H23	.1254234	.0109981	11.40	0.000	.1038666	.1469801
jan	.1032524	.0469896	2.20	0.028	.0111506	.1953543
feb	.1111076	.0471048	2.36	0.018	.01878	.2034353
may	-.1500304	.0454006	-3.30	0.001	-.2390179	-.0610429
aug	-.1281545	.0744399	-1.72	0.085	-.2740603	.0177513
oct	.2220203	.075483	2.94	0.003	.0740699	.3699707
nov	.1755718	.050324	3.49	0.000	.0769342	.2742094
mon	.1549904	.0285989	5.42	0.000	.0989351	.2110456
tue	.1463913	.0307799	4.76	0.000	.0860612	.2067214
wed	.1454671	.0269786	5.39	0.000	.0925878	.1983464
thu	.1053906	.0279103	3.78	0.000	.0506852	.1600961
fri	-.0557504	.0291742	-1.91	0.056	-.1129332	.0014324
sat	-.3690219	.0254375	-14.51	0.000	-.4188807	-.3191631
hol	-.1582435	.0489919	-3.23	0.001	-.25427	-.0622169
lgas	.4411542	.072844	6.06	0.000	.2983765	.583932
lets	.4708047	.0871805	5.40	0.000	.2999267	.6416827
norned	-.0110671	.0053178	-2.08	0.037	-.0214902	-.0006439
break	.2417231	.0574644	4.21	0.000	.1290901	.354356
nnw3	-.0075188	.0026964	-2.79	0.005	-.0128039	-.0022338
nnw5	.0044179	.0023708	1.86	0.062	-.000229	.0090649
nnw7	.0066478	.0022843	2.91	0.004	.0021705	.011125
nnw11	-.0035067	.0013158	-2.67	0.008	-.0060857	-.0009277
nnw15	-.0065158	.0024274	-2.68	0.007	-.0112736	-.001758
nnw20	.0048165	.0018807	2.56	0.010	.0011302	.0085027
nnw22	-.0059753	.0017775	-3.36	0.001	-.0094593	-.0024913
nnw23	.0053953	.0014453	3.73	0.000	.0025625	.0082281
_cons	.5879848	.2492301	2.36	0.018	.0994817	1.076488

Regression with Newey-West standard errors
maximum lag: **1000**

Number of obs = **28008**
F(34, 27973) = **20.44**
Prob > F = **0.0000**

lnwp	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
H2	-.0102536	.0060224	-1.70	0.089	-.0220579	.0015507
H3	-.0255269	.0127777	-2.00	0.046	-.0505718	-.0004821
H4	-.0388766	.0172753	-2.25	0.024	-.0727369	-.0050162
H5	-.0368279	.0180999	-2.03	0.042	-.0723047	-.0013512
H8	.0373931	.0057801	6.47	0.000	.0260638	.0487224
H9	.068911	.007925	8.70	0.000	.0533777	.0844444
H10	.0717208	.0097694	7.34	0.000	.0525723	.0908692
H11	.0730911	.0115184	6.35	0.000	.0505146	.0956677
H12	.0679947	.0120206	5.66	0.000	.0444337	.0915557
H13	.0610269	.0117249	5.20	0.000	.0380455	.0840082
H14	.0523627	.0108552	4.82	0.000	.0310859	.0736394
H15	.0481589	.0099618	4.83	0.000	.0286333	.0676844
H16	.0443392	.0094974	4.67	0.000	.0257239	.0629546
H17	.0494499	.01035	4.78	0.000	.0291634	.0697363
H18	.0576692	.011581	4.98	0.000	.0349698	.0803685
H19	.05731	.0112761	5.08	0.000	.0352084	.0794117
H20	.0512281	.0107365	4.77	0.000	.030184	.0722722
H21	.0427772	.0105422	4.06	0.000	.022114	.0634404
H22	.0379856	.010901	3.48	0.000	.0166191	.0593521
H23	.0264952	.0107678	2.46	0.014	.0053899	.0476006
mar	-.2132309	.0755206	-2.82	0.005	-.3612549	-.065207
mon	.0513905	.020635	2.49	0.013	.0109449	.0918362
tue	.05784	.019003	3.04	0.002	.0205933	.0950867
wed	.0590277	.0205265	2.88	0.004	.0187947	.0992607
thu	.0478315	.0155014	3.09	0.002	.0174479	.0782151
fri	.0343143	.0127782	2.69	0.007	.0092684	.0593602
lcoal	.3821909	.1761054	2.17	0.030	.0370158	.727366
lets	.6332518	.1630449	3.88	0.000	.3136758	.9528277
norned	.0142272	.0102771	1.38	0.166	-.0059164	.0343709
dres1	-.0519236	.0079099	-6.56	0.000	-.0674274	-.0364199
nww2	-.0087061	.0041827	-2.08	0.037	-.0169044	-.0005078
nww3	-.0491981	.0110219	-4.46	0.000	-.0708015	-.0275947
nww20	-.0077049	.0045882	-1.68	0.093	-.0166981	.0012882
nww22	.0119666	.0040978	2.92	0.004	.0039346	.0199985
_cons	-.0086557	.993611	-0.01	0.993	-1.956182	1.93887

E ARMA regression outputs

Time-series regression -- AR disturbances

Sample: **1 - 28008** Number of obs = **28008**
Distribution: **Gaussian** Wald chi2(73) = **3.16e+06**
Log likelihood = **2277.032** Prob > chi2 = **0.0000**

	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
lapx						
H1	-.14057	.0226851	-6.20	0.000	-.185032	-.096108
H2	-.3016611	.038931	-7.75	0.000	-.3779645	-.2253576
H3	-.451289	.0502008	-8.99	0.000	-.5496808	-.3528971
H4	-.6191768	.0602084	-10.28	0.000	-.7371831	-.5011706
H5	-.6577377	.0669082	-9.83	0.000	-.7888753	-.5266001
H6	-.4591571	.0702776	-6.53	0.000	-.5968986	-.3214155
H7	-.2921045	.0708847	-4.12	0.000	-.4310361	-.153173
H8	.0664975	.0722388	0.92	0.357	-.0750879	.208083
H9	.2362202	.0758429	3.11	0.002	.0875707	.3848696
H10	.3996527	.0787025	5.08	0.000	.2453986	.5539068
H11	.4829154	.0832099	5.80	0.000	.319827	.6460039
H12	.5648077	.0858993	6.58	0.000	.396448	.7331673
H13	.4523831	.0901281	5.02	0.000	.2757353	.6290309
H14	.4079276	.0920792	4.43	0.000	.2274557	.5883994
H15	.3395405	.0925137	3.67	0.000	.1582171	.520864
H16	.2549315	.0935987	2.72	0.006	.0714814	.4383816
H17	.2377066	.0884099	2.69	0.007	.0644263	.4109868
H18	.3619253	.0792561	4.57	0.000	.2065862	.5172643
H19	.4167199	.0713455	5.84	0.000	.2768854	.5565545
H20	.3670568	.0633669	5.79	0.000	.24286	.4912536
H21	.3008843	.0551289	5.46	0.000	.1928338	.4089349
H22	.1726123	.0441467	3.91	0.000	.0860863	.2591382
H23	.1275206	.0281506	4.53	0.000	.0723464	.1826947
jan	.1592088	.0615777	2.59	0.010	.0385188	.2798989
feb	.0255352	.067315	0.38	0.704	-.1063997	.1574701
may	-.0904668	.0530558	-1.71	0.088	-.1944543	.0135206
aug	-.0800055	.0506727	-1.58	0.114	-.1793221	.0193112
oct	-.0169002	.0654476	-0.26	0.796	-.145175	.1113747
nov	.034356	.0609943	0.56	0.573	-.0851906	.1539026
mon	.0414354	.0232978	1.78	0.075	-.0042274	.0870982
tue	.0056673	.0334275	0.17	0.865	-.0598493	.071184
wed	.0112902	.03744	0.30	0.763	-.0620909	.0846713
thu	.0211612	.0356689	0.59	0.553	-.0487485	.0910709
fri	.0285257	.0271477	1.05	0.293	-.0246827	.0817341
sat	-.1236594	.0172373	-7.17	0.000	-.1574438	-.0898749
hol	-.0904641	.0287092	-3.15	0.002	-.1467331	-.034195
lgas	.0903701	.0268604	3.36	0.001	.0377246	.1430155
lets	.0067089	.1580589	0.04	0.966	-.3030808	.3164987
norned	-.0038151	.0020384	-1.87	0.061	-.0078103	.0001801
break	-.0698533	.1350253	-0.52	0.605	-.334498	.1947914
nnw3	-.0024186	.0012625	-1.92	0.055	-.004893	.0000559
nnw5	.0016416	.0012397	1.32	0.185	-.0007881	.0040713
nnw7	.001909	.0014918	1.28	0.201	-.0010148	.0048329
nnw11	-.0011875	.0009024	-1.32	0.188	-.0029562	.0005812
nnw15	-.0010927	.0014641	-0.75	0.455	-.0039624	.001777
nnw20	-.000456	.0012867	-0.35	0.723	-.0029778	.0020658
nnw22	-.0015085	.0010024	-1.50	0.132	-.0034732	.0004561
nnw23	.0008307	.0008683	0.96	0.339	-.0008711	.0025325
_cons	3.421311	.5479989	6.24	0.000	2.347253	4.495369
ARMA						
ar						
L1.	.7985796	.0012149	657.32	0.000	.7961984	.8009608
L2.	-.0044763	.0014904	-3.00	0.003	-.0073974	-.0015552
L4.	-.040793	.0017983	-22.68	0.000	-.0443177	-.0372684
L7.	.0396479	.0034125	11.62	0.000	.0329595	.0463364
L16.	-.0211283	.005534	-3.82	0.000	-.0319747	-.010282
L17.	.0398489	.0052102	7.65	0.000	.0296371	.0500607
L21.	.0234084	.0033392	7.01	0.000	.0168637	.0299531
L23.	.0407517	.0027904	14.60	0.000	.0352827	.0462207
L24.	.0630636	.002587	24.38	0.000	.0579931	.0681341
L26.	-.0563146	.0024473	-23.01	0.000	-.0611112	-.0515179
L27.	.0152342	.0042291	3.60	0.000	.0069452	.0235232
L28.	-.0192585	.0035264	-5.46	0.000	-.02617	-.0123469
L48.	.0418015	.0041459	10.08	0.000	.0336756	.0499274
L49.	-.0506005	.0040244	-12.57	0.000	-.0584882	-.0427128
L72.	.0432312	.0047497	9.10	0.000	.0339218	.0525405
L73.	-.0307434	.0054064	-5.69	0.000	-.0413397	-.0201471
L96.	.0322983	.00506	6.38	0.000	.0223808	.0422158
L97.	-.034763	.0050078	-6.94	0.000	-.0445782	-.0249478
L120.	.0238396	.0051685	4.61	0.000	.0137095	.0339697
L121.	-.018183	.004954	-3.67	0.000	-.0278927	-.0084734
L143.	.0610365	.0013001	46.95	0.000	.0584883	.0635846
L144.	-.0135448	.001759	-7.70	0.000	-.0169924	-.0100972
L167.	.0314328	.0021719	14.47	0.000	.0271759	.0356896
L168.	.1786239	.0015194	117.56	0.000	.175646	.1816019
L169.	-.1503968	.0017873	-84.15	0.000	-.1538999	-.1468938
/SIGMA2	.0497635	.0000679	733.08	0.000	.0496305	.0498966

Time-series regression -- ARMA disturbances

Sample:	**1 - 28008**	Number of obs	=	28008
Distribution:	**Gaussian**	Wald chi2(78)	=	3.25e+07
Log likelihood =	**44518.21**	Prob > chi2	=	0.0000

	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
lnwp						
H2	-.0149293	.0021796	-6.85	0.000	-.0192013	-.0106573
H3	-.0225264	.0029912	-7.53	0.000	-.028389	-.0166638
H4	-.0275073	.00303	-9.08	0.000	-.0334459	-.0215686
H5	-.0203784	.0018937	-10.76	0.000	-.0240901	-.0166668
H8	.0229439	.0021804	10.52	0.000	.0186705	.0272174
H9	.0473598	.0041961	11.29	0.000	.0391357	.055584
H10	.0492249	.0068072	7.23	0.000	.0358831	.0625667
H11	.0559562	.0104498	5.35	0.000	.0354749	.0764375
H12	.0586228	.0143481	4.09	0.000	.030501	.0867445
H13	.059196	.0168529	3.51	0.000	.0261649	.092227
H14	.0557329	.0167698	3.32	0.001	.0228647	.0886011
H15	.053975	.0153661	3.51	0.000	.023858	.084092
H16	.0500543	.0133504	3.75	0.000	.023888	.0762206
H17	.0562081	.0120959	4.65	0.000	.0325005	.0799157
H18	.0660052	.0119209	5.54	0.000	.0426407	.0893698
H19	.0666431	.0114718	5.81	0.000	.0441588	.0891273
H20	.0605996	.0110277	5.50	0.000	.0389857	.0822135
H21	.0503526	.009181	5.48	0.000	.0323581	.0683471
H22	.0412339	.0065023	6.34	0.000	.0284896	.0539781
H23	.0258939	.0033632	7.70	0.000	.0193022	.0324855
mar	-.0052373	.0355192	-0.15	0.883	-.0748536	.064379
mon	.0088676	.0033166	2.67	0.008	.0023673	.015368
tue	.014583	.0041458	3.52	0.000	.0064573	.0227087
wed	.0186849	.0041839	4.47	0.000	.0104846	.0268852
thu	.0040071	.0039168	1.02	0.306	-.0036697	.0116838
fri	-.0054917	.0030656	-1.79	0.073	-.0115002	.0005169
lcoal	.1132169	.1175978	0.96	0.336	-.1172705	.3437043
lets	-.0149462	.062516	-0.24	0.811	-.1374754	.1075829
norned	.0058419	.0003	19.47	0.000	.0052539	.0064299
dres1	-.0036941	.001011	-3.65	0.000	-.0056755	-.0017127
nww2	.0000103	.0003357	0.03	0.976	-.0006477	.0006682
nww3	.0001918	.000738	0.26	0.795	-.0012546	.0016383
nww20	-.0004411	.0002995	-1.47	0.141	-.0010281	.0001459
nww22	.0007175	.0002145	3.34	0.001	.0002971	.0011378
_cons	3.127905	.5062023	6.18	0.000	2.135766	4.120043
ARMA						
ar						
L1.	1.135519	.0011478	989.26	0.000	1.133269	1.137769
L2.	-.2492302	.0019131	-130.28	0.000	-.2529798	-.2454806
L3.	-.0218083	.0026857	-8.12	0.000	-.0270721	-.0165444
L4.	.0092512	.0025729	3.60	0.000	.0042083	.014294
L6.	-.0132792	.0032266	-4.12	0.000	-.0196033	-.0069552
L7.	.0405308	.0033409	12.13	0.000	.0339828	.0470789
L9.	.0290628	.0039605	7.34	0.000	.0213004	.0368252
L10.	-.0310717	.0046398	-6.70	0.000	-.0401655	-.0219779
L11.	.0192955	.0050977	3.79	0.000	.0093041	.0292869
L12.	.0092688	.0049669	1.87	0.062	-.0004662	.0190038
L13.	-.0095705	.0033678	-2.84	0.004	-.0161712	-.0029698
L14.	.0238346	.0037297	6.39	0.000	.0165246	.0311446
L16.	-.0113141	.0043084	-2.63	0.009	-.0197584	-.0028699
L17.	.0060982	.0041869	1.46	0.145	-.0021081	.0143045
L20.	.0104243	.0026406	3.95	0.000	.0052488	.0155999
L21.	.050073	.0035548	14.09	0.000	.0431056	.0570403
L22.	.0286209	.0041199	6.95	0.000	.020546	.0366957
L23.	-.059522	.0031371	-18.97	0.000	-.0656706	-.0533733
L24.	.1294614	.0030067	43.06	0.000	.1235683	.1353546
L25.	-.1143585	.0029043	-39.38	0.000	-.1200508	-.1086662
L26.	.0259225	.0042796	6.06	0.000	.0175347	.0343103
L27.	-.0145487	.0051141	-2.84	0.004	-.024572	-.0045253
L28.	-.0028322	.0039147	-0.72	0.469	-.0105049	.0048405
L47.	.0151683	.001989	7.63	0.000	.0112698	.0190667
L48.	-.0018514	.0023315	-0.79	0.427	-.0064211	.0027183
L49.	-.0201223	.0025572	-7.87	0.000	-.0251343	-.0151102
L72.	.0286075	.0031092	9.20	0.000	.0225136	.0347014
L73.	-.0266981	.0028013	-9.53	0.000	-.0321885	-.0212077
L95.	.0095718	.0031865	3.00	0.003	.0033265	.0158172
L96.	.0088469	.0046128	1.92	0.055	-.0001941	.0178879
L97.	-.0098324	.0032639	-3.01	0.003	-.0162295	-.0034353
L119.	-.0092612	.0047424	-1.95	0.051	-.0185561	.0000337
L120.	.0320616	.00652	4.92	0.000	.0192826	.0448406
L121.	-.0309179	.0039123	-7.90	0.000	-.0385859	-.0232499
L144.	.0363512	.0026089	13.93	0.000	.0312378	.0414647
L145.	-.0283358	.002642	-10.73	0.000	-.033514	-.0231577
L167.	.0350895	.0025514	13.75	0.000	.0300889	.0400901
L168.	.0813132	.0031838	25.54	0.000	.075073	.0875533
L169.	-.1110054	.002061	-53.86	0.000	-.1150449	-.1069659
ma						
L49.	.0015173	.0023747	0.64	0.523	-.0031371	.0061716
L50.	.0602873	.002349	25.66	0.000	.0556832	.0648913
L51.	.0491843	.0029772	16.52	0.000	.0433491	.0550195
L52.	-.0087905	.0036005	-2.44	0.015	-.0158474	-.0017337
L169.	.0411122	.0027431	14.99	0.000	.0357359	.0464885
/SIGMA2	.0024374	3.47e-06	702.06	0.000	.0024306	.0024442

F EGARCH regression outputs

ARCH family regression -- ARMA disturbances and mult. heteroskedasticity

Sample: **1 - 28008** Number of obs = **28008**
Distribution: **Gaussian** Wald chi2(73) = **1.26e+06**
Log likelihood = **20647.92** Prob > chi2 = **0.0000**

	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
lapx						
H1	-.0448146	.0086926	-5.16	0.000	-.0618519	-.0277774
H2	-.1467855	.0122786	-11.95	0.000	-.170851	-.1227199
H3	-.2313309	.0163241	-14.17	0.000	-.2633255	-.1993363
H4	-.3097662	.0196383	-15.77	0.000	-.3482565	-.2712759
H5	-.3145269	.0215734	-14.58	0.000	-.35681	-.2722439
H6	-.12084	.0237419	-5.09	0.000	-.1673733	-.0743067
H7	.09773	.0276882	3.53	0.000	.0434622	.1519978
H8	.3639005	.0285003	12.77	0.000	.3080409	.4197602
H9	.3845485	.0267542	14.37	0.000	.3321113	.4369858
H10	.4059841	.0247393	16.41	0.000	.3574961	.4544722
H11	.4140768	.0231233	17.91	0.000	.3687561	.4593976
H12	.4507867	.0219758	20.51	0.000	.4077149	.4938585
H13	.393296	.0206967	19.00	0.000	.3527312	.4338607
H14	.3831801	.0197034	19.45	0.000	.3445622	.4217979
H15	.3597197	.0189115	19.02	0.000	.3226539	.3967855
H16	.3026834	.0179799	16.83	0.000	.2674434	.3379234
H17	.2567557	.0171521	14.97	0.000	.2231383	.2903732
H18	.2557374	.0168202	15.20	0.000	.2227703	.2887044
H19	.2648132	.016361	16.19	0.000	.2327463	.2968801
H20	.2109485	.015245	13.84	0.000	.1810689	.2408281
H21	.1651447	.0130604	12.64	0.000	.1395468	.1907426
H22	.0711862	.0102802	6.92	0.000	.0510373	.0913351
H23	.0808339	.0063546	12.72	0.000	.0683792	.0932886
jan	.0131491	.0205882	0.64	0.523	-.0272032	.0535013
feb	-.0619743	.0185971	-3.33	0.001	-.098424	-.0255246
may	-.0792023	.0231077	-3.43	0.001	-.1244926	-.033912
aug	-.0513624	.0186182	-2.76	0.006	-.0878533	-.0148714
oct	.0250814	.0306516	0.82	0.413	-.0349946	.0851575
nov	.123797	.0291384	4.25	0.000	.0666868	.1809071
mon	-.0206403	.0073665	-2.80	0.005	-.0350784	-.0062022
tue	-.0518114	.0098223	-5.27	0.000	-.0710626	-.0325601
wed	-.0817717	.0122141	-6.69	0.000	-.1057108	-.0578325
thu	-.1162267	.0137976	-8.42	0.000	-.1432696	-.0891838
fri	-.0808263	.0133856	-6.04	0.000	-.1070616	-.054591
sat	-.0331336	.0084281	-3.93	0.000	-.0496523	-.0166149
hol	-.051797	.015613	-3.32	0.001	-.082398	-.021196
lgas	.0743295	.0113944	6.52	0.000	.0519968	.0966621
lets	.1034052	.0546995	1.89	0.059	-.003804	.2106143
norned	-.0042343	.0006237	-6.79	0.000	-.0054567	-.0030119
break	.2078894	.0286407	7.26	0.000	.1517546	.2640242
nnw3	-.0010695	.0004265	-2.51	0.012	-.0019054	-.0002336
nnw5	.0010784	.0004881	2.21	0.027	.0001219	.002035
nnw7	.0017535	.0004783	3.67	0.000	.0008161	.0026908
nnw11	.0002178	.0003228	0.67	0.500	-.0004148	.0008505
nnw15	-.000241	.0004911	-0.49	0.624	-.0012035	.0007216
nnw20	-.001616	.0004314	-3.75	0.000	-.0024616	-.0007705
nnw22	.0006849	.0003566	1.92	0.055	-.000014	.0013837
nnw23	-.0012487	.000314	-3.98	0.000	-.0018641	-.0006333
_cons	3.506912	.1844448	19.01	0.000	3.145407	3.868417
ARMA						
ar						
L1.	.8503405	.0046732	181.96	0.000	.8411813	.8594998
L2.	-.0448943	.005026	-8.93	0.000	-.0547451	-.0350434
L4.	.0121266	.0023864	5.08	0.000	.0074494	.0168038
L7.	.0233438	.0014415	16.19	0.000	.0205186	.026169
L16.	-.0153911	.0024743	-6.22	0.000	-.0202406	-.0105416
L17.	.0294692	.0024575	11.99	0.000	.0246527	.0342858
L21.	.0007047	.0016039	0.44	0.660	-.0024389	.0038483
L23.	.0510528	.002455	20.80	0.000	.0462411	.0558645
L24.	.1109124	.0036787	30.15	0.000	.1037021	.1181226
L26.	-.1180425	.0038699	-30.50	0.000	-.1256274	-.1104575
L27.	.0064879	.0032782	1.98	0.048	.0000626	.0129131
L28.	-.0079893	.0020623	-3.87	0.000	-.0120312	-.0039473
L48.	.0547443	.0018442	29.68	0.000	.0511297	.0583589
L49.	-.0483011	.0019963	-24.20	0.000	-.0522137	-.0443885
L72.	.0325545	.0022379	14.55	0.000	.0281682	.0369407
L73.	-.0271205	.002306	-11.76	0.000	-.0316402	-.0226008
L96.	.0315075	.0017579	17.92	0.000	.028062	.034953
L97.	-.0303072	.0019169	-15.81	0.000	-.0340642	-.0265501
L120.	.043625	.0019991	21.82	0.000	.0397068	.0475432
L121.	-.0421003	.0020603	-20.43	0.000	-.0461385	-.0380622
L143.	.0143442	.0032096	4.47	0.000	.0080536	.0206349
L144.	.0253864	.003135	8.10	0.000	.019242	.0315308
L167.	.0413836	.0031558	13.11	0.000	.0351984	.0475688
L168.	.1705794	.0043073	39.60	0.000	.1621372	.1790216
L169.	-.172587	.0030934	-55.79	0.000	-.1786498	-.1665241

HET						
H1	.9697771	.0421088	23.03	0.000	.8872455	1.052309
H2	.0926414	.0451414	2.05	0.040	.0041658	.181117
H3	.8879847	.0497406	17.85	0.000	.790495	.9854744
H4	.8079264	.0519861	15.54	0.000	.7060356	.9098172
H5	.8912517	.0500042	17.82	0.000	.7932453	.9892581
H6	1.022719	.0512663	19.95	0.000	.9222385	1.123199
H7	1.537589	.0510289	30.13	0.000	1.437574	1.637603
H8	.8899183	.0589282	15.10	0.000	.7744212	1.005415
H9	.3429129	.0545951	6.28	0.000	.2359084	.4499174
H10	.7561021	.0455688	16.59	0.000	.6667888	.8454153
H11	-.0227947	.047196	-0.48	0.629	-.1152972	.0697077
H12	-.0665767	.051032	-1.30	0.192	-.1665975	.0334441
H13	-.4520632	.0558523	-8.09	0.000	-.5615317	-.3425948
H14	-.4391465	.0491871	-8.93	0.000	-.5355515	-.3427415
H15	-.6879529	.0498271	-13.81	0.000	-.7856123	-.5902936
H16	-.7039774	.0541398	-13.00	0.000	-.8100894	-.5978654
H17	-.5426359	.0514371	-10.55	0.000	-.6434508	-.441821
H18	.1488849	.0511766	2.91	0.004	.0485806	.2491891
H19	.0307352	.0493395	0.62	0.533	-.0659684	.1274388
H20	-.215337	.0530599	-4.06	0.000	-.3193326	-.1113415
H21	-.3168314	.0553571	-5.72	0.000	-.4253293	-.2083334
H22	-.381633	.0453561	-8.41	0.000	-.4705294	-.2927367
H23	-.2236867	.041724	-5.36	0.000	-.3054642	-.1419091
jan	-.7156058	.0470142	-15.22	0.000	-.8077519	-.6234598
feb	-1.368698	.0528449	-25.90	0.000	-1.472272	-1.265124
mar	-.8434445	.0476391	-17.70	0.000	-.9368155	-.7500736
apr	-.5699341	.0488355	-11.67	0.000	-.6656499	-.4742184
may	-.1360254	.0467893	-2.91	0.004	-.2277308	-.04432
jun	-.7009785	.0531077	-13.20	0.000	-.8050676	-.5968894
jul	-1.116789	.0523281	-21.34	0.000	-1.21935	-1.014228
aug	-.9452643	.0499537	-18.92	0.000	-1.043172	-.847357
sep	-1.253467	.051081	-24.54	0.000	-1.353584	-1.15335
oct	-.3497979	.0489433	-7.15	0.000	-.4457251	-.2538707
nov	-.5035459	.0535394	-9.41	0.000	-.6084813	-.3986106
break	-.6296031	.0730296	-8.62	0.000	-.7727385	-.4864677
op	-.1847251	.0728136	-2.54	0.011	-.3274371	-.0420132
mon	-.9332996	.0261263	-35.72	0.000	-.9845063	-.882093
tue	-1.157021	.0307115	-37.67	0.000	-1.217215	-1.096828
wed	-1.183498	.0325725	-36.33	0.000	-1.247339	-1.119657
thu	-1.171341	.0313228	-37.40	0.000	-1.232733	-1.10995
fri	-.574919	.0304129	-18.90	0.000	-.6345272	-.5153107
sat	.5108861	.027043	18.89	0.000	.4578829	.5638894
hol	.4018784	.0488523	8.23	0.000	.3061296	.4976271
_cons	-2.582253	.0553265	-46.67	0.000	-2.69069	-2.473815
ARCH						
earch						
L1.	-.0057218	.0052398	-1.09	0.275	-.0159916	.0045481
L2.	-.0088207	.0054233	-1.63	0.104	-.0194501	.0018087
L3.	-.0306887	.0042116	-7.29	0.000	-.0389432	-.0224342
L24.	-.0092912	.0052269	-1.78	0.075	-.0195357	.0009533
L25.	.015392	.0049466	3.11	0.002	.0056969	.0250871
L26.	-.0241481	.0045778	-5.28	0.000	-.0331205	-.0151757
L142.	-.000969	.0052343	-0.19	0.853	-.011228	.0092899
L143.	-.0401949	.0053148	-7.56	0.000	-.0506118	-.029778
L144.	.0086788	.0051016	1.70	0.089	-.0013201	.0186777
L167.	.0440366	.005194	8.48	0.000	.0338566	.0542167
L168.	.0268828	.0050152	5.36	0.000	.0170532	.0367124
L311.	-.0558161	.0048385	-11.54	0.000	-.0652993	-.0463328
L312.	.0328725	.0050753	6.48	0.000	.022925	.0428199
L337.	-.0233243	.0052913	-4.41	0.000	-.0336951	-.0129535
L338.	.0013414	.0050219	0.27	0.789	-.0085014	.0111842
L454.	-.0149871	.004611	-3.25	0.001	-.0240244	-.0059498
L455.	-.0078735	.0053663	-1.47	0.142	-.0183912	.0026442
L479.	.0047323	.005145	0.92	0.358	-.0053516	.0148163
L480.	.0717326	.0052669	13.62	0.000	.0614097	.0820555
L481.	.0642565	.0052704	12.19	0.000	.0539268	.0745862
L505.	.0589837	.0052461	11.24	0.000	.0487016	.0692658
earch_a						
L1.	.5765197	.0068172	84.57	0.000	.5631582	.5898811
L2.	.4211307	.0068045	61.89	0.000	.4077941	.4344674
L3.	.2823122	.0046998	60.07	0.000	.2731007	.2915236
L24.	.3026805	.0073568	41.14	0.000	.2882615	.3170995
L25.	.1831548	.0067999	26.94	0.000	.1698273	.1964823
L26.	.1567501	.0059117	26.52	0.000	.1451634	.1683367
L142.	.056725	.0072548	7.82	0.000	.0425058	.0709442
L143.	.1875134	.0069718	26.90	0.000	.173849	.2011778
L144.	.1768896	.0067949	26.03	0.000	.1635719	.1902074
L167.	.0626352	.0061076	10.26	0.000	.0506645	.074606
L168.	.1838188	.0066907	27.47	0.000	.1707053	.1969322
L311.	.0792299	.0058894	13.45	0.000	.0676868	.0907729
L312.	.0422848	.0075071	5.63	0.000	.0275711	.0569985
L337.	.0737976	.0073087	10.10	0.000	.0594729	.0881223
L338.	.014963	.0062996	2.38	0.018	.0026159	.02731
L454.	.1067839	.0057709	18.50	0.000	.0954732	.1180947
L455.	.0538141	.0074469	7.23	0.000	.0392185	.0684097
L479.	-.0139014	.0069476	-2.00	0.045	-.0275183	-.0002844
L480.	.0236073	.0067295	3.51	0.000	.0104177	.0367968
L481.	.096153	.0079025	12.17	0.000	.0806644	.1116416
L505.	.1505826	.0063054	23.88	0.000	.1382242	.1629409

ARCH family regression -- ARMA disturbances and mult. heteroskedasticity

Sample: **1 - 28008** | Number of obs = **28008**
Distribution: **Gaussian** | Wald chi2(**78**) = **2.01e+08**
Log likelihood = **78682.6** | Prob > chi2 = **0.0000**

	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
lnwp						
H2	-.004623	.000438	-10.56	0.000	-.0054814	-.0037645
H3	-.0080389	.0007216	-11.14	0.000	-.0094533	-.0066245
H4	-.0082439	.0007424	-11.10	0.000	-.009699	-.0067887
H5	-.0063079	.0004709	-13.40	0.000	-.0072308	-.0053849
H8	.0027987	.0006905	4.05	0.000	.0014455	.004152
H9	.007844	.0013789	5.69	0.000	.0051414	.0105466
H10	.0084118	.0018397	4.57	0.000	.004806	.0120176
H11	.0105877	.0019634	5.39	0.000	.0067396	.0144359
H12	.0123539	.0018712	6.60	0.000	.0086864	.0160213
H13	.0141921	.001714	8.28	0.000	.0108327	.0175515
H14	.0147344	.0015726	9.37	0.000	.0116521	.0178167
H15	.0146468	.0014844	9.87	0.000	.0117374	.0175562
H16	.0131247	.001428	9.19	0.000	.0103259	.0159235
H17	.0128503	.0014011	9.17	0.000	.0101041	.0155965
H18	.0136252	.0013961	9.76	0.000	.0108889	.0163614
H19	.0142555	.0013439	10.61	0.000	.0116214	.0168895
H20	.0144384	.0012306	11.73	0.000	.0120265	.0168504
H21	.01374	.0010084	13.63	0.000	.0117637	.0157164
H22	.0143076	.0007464	19.17	0.000	.0128446	.0157706
H23	.0112297	.0004325	25.97	0.000	.0103821	.0120774
mar	.0032293	.0057561	0.56	0.575	-.0080525	.0145112
mon	-.0056312	.0007918	-7.11	0.000	-.0071832	-.0040793
tue	-.0028355	.0010232	-2.77	0.006	-.004841	-.0008301
wed	-.0036211	.0011023	-3.28	0.001	-.0057817	-.0014606
thu	-.0042124	.0010554	-3.99	0.000	-.006281	-.0021438
fri	-.0082067	.0008435	-9.73	0.000	-.0098598	-.0065535
lcoal	-.0518884	.0173023	-3.00	0.003	-.0858002	-.0179765
lets	-.0271845	.0139763	-1.95	0.052	-.0545775	.0002086
norned	.0019782	.0000554	35.74	0.000	.0018697	.0020867
dres1	-.0008335	.0003064	-2.72	0.007	-.001434	-.000233
nww2	.0003055	.0000872	3.50	0.000	.0001345	.0004764
nww3	-.0003232	.0001584	-2.04	0.041	-.0006337	-.0000127
nww20	-.0004229	.0000641	-6.60	0.000	-.0005485	-.0002974
nww22	.0002235	.00005	4.47	0.000	.0001255	.0003215
_cons	3.804509	.0882971	43.09	0.000	3.63145	3.977568
ARMA						
ar						
L1.	1.23615	.0046269	267.17	0.000	1.227081	1.245218
L2.	-.348974	.0067984	-51.33	0.000	-.3622986	-.3356495
L3.	.0298517	.005901	5.06	0.000	.018286	.0414175
L4.	.0312298	.0040041	7.80	0.000	.023382	.0390776
L6.	.0036052	.0023038	1.56	0.118	-.0009101	.0081206
L7.	.0078232	.0020172	3.88	0.000	.0038695	.0117769
L9.	.0031436	.0020212	1.56	0.120	-.0008178	.0071051
L10.	-.0020726	.0024131	-0.86	0.390	-.0068021	.0026569
L11.	.0031639	.0020139	1.57	0.116	-.0007833	.007111
L12.	-.0008248	.0017605	-0.47	0.639	-.0042754	.0026257
L13.	-.0029427	.0015218	-1.93	0.053	-.0059254	.00004
L14.	.0006472	.0010175	0.64	0.525	-.0013472	.0026415
L16.	.0063865	.0015303	4.17	0.000	.0033872	.0093858
L17.	-.0018237	.0015065	-1.21	0.226	-.0047764	.001129
L20.	.0271312	.0011603	23.38	0.000	.024857	.0294053
L21.	-.0420889	.001896	-22.20	0.000	-.0458049	-.0383728
L22.	.043675	.0022838	19.12	0.000	.0391989	.0481512
L23.	.0316144	.0032354	9.77	0.000	.0252731	.0379556
L24.	.1696947	.0045586	37.23	0.000	.1607601	.1786294
L25.	-.2044835	.005743	-35.61	0.000	-.2157396	-.1932274
L26.	.0305574	.0048325	6.32	0.000	.0210858	.0400289
L27.	-.0138694	.004163	-3.33	0.001	-.0220287	-.0057102
L28.	-.0088278	.0025383	-3.48	0.001	-.0138027	-.0038529
L47.	.0058609	.0017292	3.39	0.001	.0024717	.00925
L48.	.0339363	.0035046	9.68	0.000	.0270673	.0408052
L49.	-.0396435	.002781	-14.25	0.000	-.0450943	-.0341928
L72.	.0119419	.0017223	6.93	0.000	.0085663	.0153175
L73.	-.0130936	.0017007	-7.70	0.000	-.0164268	-.0097603
L95.	-.0039179	.0014744	-2.66	0.008	-.0068077	-.0010281
L96.	.0256482	.0024584	10.43	0.000	.0208298	.0304665
L97.	-.0233622	.0018712	-12.49	0.000	-.0270296	-.0196947
L119.	.0061532	.0012831	4.80	0.000	.0036385	.008668
L120.	.0079564	.0025123	3.17	0.002	.0030324	.0128804
L121.	-.0072016	.0017904	-4.02	0.000	-.0107108	-.0036925
L144.	.0592269	.0013849	42.76	0.000	.0565125	.0619414
L145.	-.0573531	.00154	-37.24	0.000	-.0603714	-.0543349
L167.	.0413491	.0013865	29.82	0.000	.0386316	.0440667
L168.	.0647772	.0027866	23.25	0.000	.0593155	.0702389
L169.	-.1118012	.0022112	-50.56	0.000	-.1161352	-.1074673
ma						
L49.	-.0178834	.0027537	-6.49	0.000	-.0232806	-.0124862
L50.	.004504	.0022708	1.98	0.047	.0000532	.0089547
L51.	.0010352	.0018901	0.55	0.584	-.0026694	.0047397
L52.	7.45e-06	.0016849	0.00	0.996	-.003295	.0033099
L169.	.0151606	.0023518	6.45	0.000	.0105511	.01977

HET						
H1	.9182751	.050168	18.30	0.000	.8199477	1.016602
H2	-1.463747	.0382128	-38.31	0.000	-1.538643	-1.388852
H3	-.7583035	.0385253	-19.68	0.000	-.8338117	-.6827953
H4	-.3841132	.039759	-9.66	0.000	-.4620395	-.306187
H5	-.6571745	.0448337	-14.66	0.000	-.7450469	-.5693022
H6	.1184758	.0502829	2.36	0.018	.0199231	.2170285
H7	-.0374941	.0463839	-0.81	0.419	-.128405	.0534167
H8	.0149947	.0416706	0.36	0.719	-.0666782	.0966677
H9	-.4675711	.0382363	-12.23	0.000	-.5425128	-.3926293
H10	-1.356499	.0425818	-31.86	0.000	-1.439958	-1.27304
H11	-1.500065	.0412972	-36.32	0.000	-1.581006	-1.419124
H12	-.938187	.0412833	-22.73	0.000	-1.019101	-.8572731
H13	-.6994703	.0434891	-16.08	0.000	-.7847073	-.6142332
H14	-.7205256	.0431294	-16.71	0.000	-.8050577	-.6359936
H15	-.5762135	.0413081	-13.95	0.000	-.6571759	-.4952511
H16	-.2037913	.0439984	-4.63	0.000	-.2900265	-.1175561
H17	-.6127668	.0433417	-14.14	0.000	-.697715	-.5278185
H18	-.1866552	.0442869	-4.21	0.000	-.273456	-.0998544
H19	-.8717293	.0450865	-19.33	0.000	-.9600972	-.7833614
H20	-.7214125	.0439607	-16.41	0.000	-.807574	-.6352511
H21	-.4321235	.0450999	-9.58	0.000	-.5205178	-.3437293
H22	-.5787302	.0429169	-13.48	0.000	-.6628458	-.4946147
H23	-.5544028	.0504146	-11.00	0.000	-.6532136	-.4555921
jan	-.1016881	.0113261	-8.98	0.000	-.1238868	-.0794893
feb	-.1867235	.0126649	-14.74	0.000	-.2115462	-.1619007
mar	-.1358728	.0115948	-11.72	0.000	-.1585982	-.1131474
apr	.0178559	.0111375	1.60	0.109	-.0039733	.0396851
may	.2218335	.0120409	18.42	0.000	.1982337	.2454333
jun	.0692196	.0110934	6.24	0.000	.047477	.0909622
jul	-.0189336	.0116917	-1.62	0.105	-.0418488	.0039817
aug	.0089929	.0118336	0.76	0.447	-.0142004	.0321863
sep	-.2109143	.0122833	-17.17	0.000	-.2349891	-.1868394
oct	-.1510533	.0107764	-14.02	0.000	-.1721747	-.1299319
nov	-.0848349	.0107999	-7.86	0.000	-.1060024	-.0636674
break	-.0299741	.0230614	-1.30	0.194	-.0751737	.0152254
op	-.0006259	.0235367	-0.03	0.979	-.046757	.0455053
mon	-.0185216	.0061698	-3.00	0.003	-.0306142	-.006429
tue	-.1259691	.0068526	-18.38	0.000	-.1394	-.1125382
wed	-.1028786	.0070164	-14.66	0.000	-.1166305	-.0891267
thu	-.1193587	.0070904	-16.83	0.000	-.1332556	-.1054618
fri	-.1500726	.0066096	-22.71	0.000	-.1630271	-.137118
sat	-.1284006	.0061307	-20.94	0.000	-.1404166	-.1163846
_cons	-.3189115	.0344616	-9.25	0.000	-.386455	-.251368
ARCH						
earch						
L1.	-.0196578	.0035956	-5.47	0.000	-.026705	-.0126105
L24.	.0376554	.0033774	11.15	0.000	.0310358	.044275
L48.	-.0166575	.0043948	-3.79	0.000	-.0252712	-.0080439
L49.	.0380908	.0048982	7.78	0.000	.0284906	.047691
L50.	-.0331692	.0043108	-7.69	0.000	-.0416183	-.0247201
earch_a						
L1.	.7251709	.0047217	153.58	0.000	.7159165	.7344254
L24.	.3770019	.0046579	80.94	0.000	.3678725	.3861312
L48.	.1832618	.0059236	30.94	0.000	.1716518	.1948719
L49.	.0561297	.0068618	8.18	0.000	.0426808	.0695785
L50.	.0319923	.0055688	5.74	0.000	.0210778	.0429069
egarch						
L1.	.8602609	.0015514	554.51	0.000	.8572203	.8633016

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