Supplementary Information

Appendix 1: Estimating welfare gains

Two approaches have been used to estimate welfare gains. For historic interconnector performance, a series of metrics examining different aspects of welfare and trading efficiency have been developed, which are functions of market prices and interconnector flows (e.g. ACER, 2012; EU Commission, 2010-Q3). Since this approach cannot be used to estimate future welfare gains from interconnectors, the second approach is to use complex electricity system models to generate scenarios of flows and prices (e.g. Pöyry, 2012; Redpoint, 2013; ENTSO-E, 2014; EU Commission, 2015; and Aurora, 2016). Assumptions about the underlying electricity system vary widely between studies. Moreover, most models assume coupled markets, perfect foresight, and day-ahead plant dispatch, so account for neither demand uncertainty, trader behaviour, nor intra-day and balancing markets.

Appendix 2: Price-based metrics and flow-based metrics

2.1 Price-based metrics

Interconnectors promote price convergence as traders buy and sell electricity until expected prices equalise. Coupling markets and increasing interconnection capacity can increase price convergence (Zachmann, 2008). Price convergence can be measured by simply inspecting the mean (or median) price differential between zones.

Price differentials. In 2017, price convergence varied greatly across Europe. The average absolute day-ahead price differential ranged from less than 0.5 €/MWh on the borders between Estonia and Finland, Portugal and Spain, and between Latvia and Lithuania, to more than 10 €/MWh between the Germany/Austria/Luxembourg bidding zone and five of its neighbouring countries, and on all British borders (likely due to GB's Carbon Price Floor). Large price differentials indicate that increasing cross-zonal interconnection capacity would reduce overall electricity system costs (ACER, 2015; 2017). In the absence of interconnection transmission limits, one would expect prices in all zones to converge in a competitive single market (Castagneto Gissey *et al.*, 2014).

Various econometric methods have been used to analyse electricity spot price convergence (De Vany and Walls, 1999; Robinson, 2007; Zachmann, 2008). Using principal component analysis, Zachmann (2008) rejects the overall market integration hypothesis except for certain pairs of European markets. Robinson (2007) employs Β-convergence and co-integration tests, suggesting that convergence occurred for most European markets. Bunn and Gianfreda (2010) showed increased market integration for France, UK, Netherlands, Germany, and Spain. Integration was found not to increase with geographical proximity but with capacity of the interconnector. Kalantzis and Milonas (2010) found both interconnection and geographical distance playing a critical role in price dispersion.

Based on correlation and co-integration analyses, Boisseleau (2004) did not detect convergence among wholesale prices. Armstrong and Galli (2005) found convergence among wholesale price differentials in France, Germany, Netherlands and Spain from 2002 to 2004. Using fractional co-integration analysis, Houllier and de Menezes (2013) showed long memory for price shocks and co-integration to be present only for a few markets, including Germany, France and Netherlands. These studies considered integration between pairs of prices, whilst Castagneto Gissey *et al.* (2014) accounted for a whole system of prices, finding integration to be low but increasing over time and reflecting regulatory integration.

2.2 Flow-based metrics

Flow-based metrics are imperfect as they do not consider price differentials and hence the value of inefficient flows.

Indexed annual aggregation of hourly NTC values*.* Changes in cross-zonal Net Transfer Capacity (NTC) offered to the market for trade are analysed by ACER (2012) for the period 2008–2012, representing a very simple measure of interconnector use. They estimate it for 23 EU borders, finding a 9% increase to be a ‘modest [but] positive trend’. Despite this, the recorded values are meaningful only if extra capacities are not utilised inefficiently, so the measure fails to directly consider the efficiency of interconnector use.[1]

Capacity utilisation ratio*.*[2] The ratio of the number of hours when capacity was used to the number of hours when it was available. ACER (2012) compared the intra-day capacity utilisation to that in the day-ahead timeframe, concluding that intra-day capacity utilisation was relatively low.[3] In addition, the authors concluded that implicit allocation (as under market coupling) was less inefficient than explicit (or other) allocation methods.[4]

Absolute sum of net nominations per year*.* This measure indicates the level of available cross-zonal market capacity and is considered for *intra-day* markets by ACER (2018). They show that, in absolute terms, aggregated cross-zonal allocations nominated across the European network tripled between 2010 and 2017. While this metric is useful to understand the level of capacity nominated on the interconnector, it does not indicate whether this capacity is used inefficiently since it does not involve prices.

[1] See ACER (2012), Section 3.2.2.
[2] These are considered for price differentials greater than €1/MWh, which are viewed as significant by ACER (2016, 2017).
[3] For 2017, 50% utilisation rate in intra-day vs 86% utilisation rate in day-ahead.
[4] See ACER (2012), Section 5.2.

Appendix 3: Charts of Flow vs Price differential

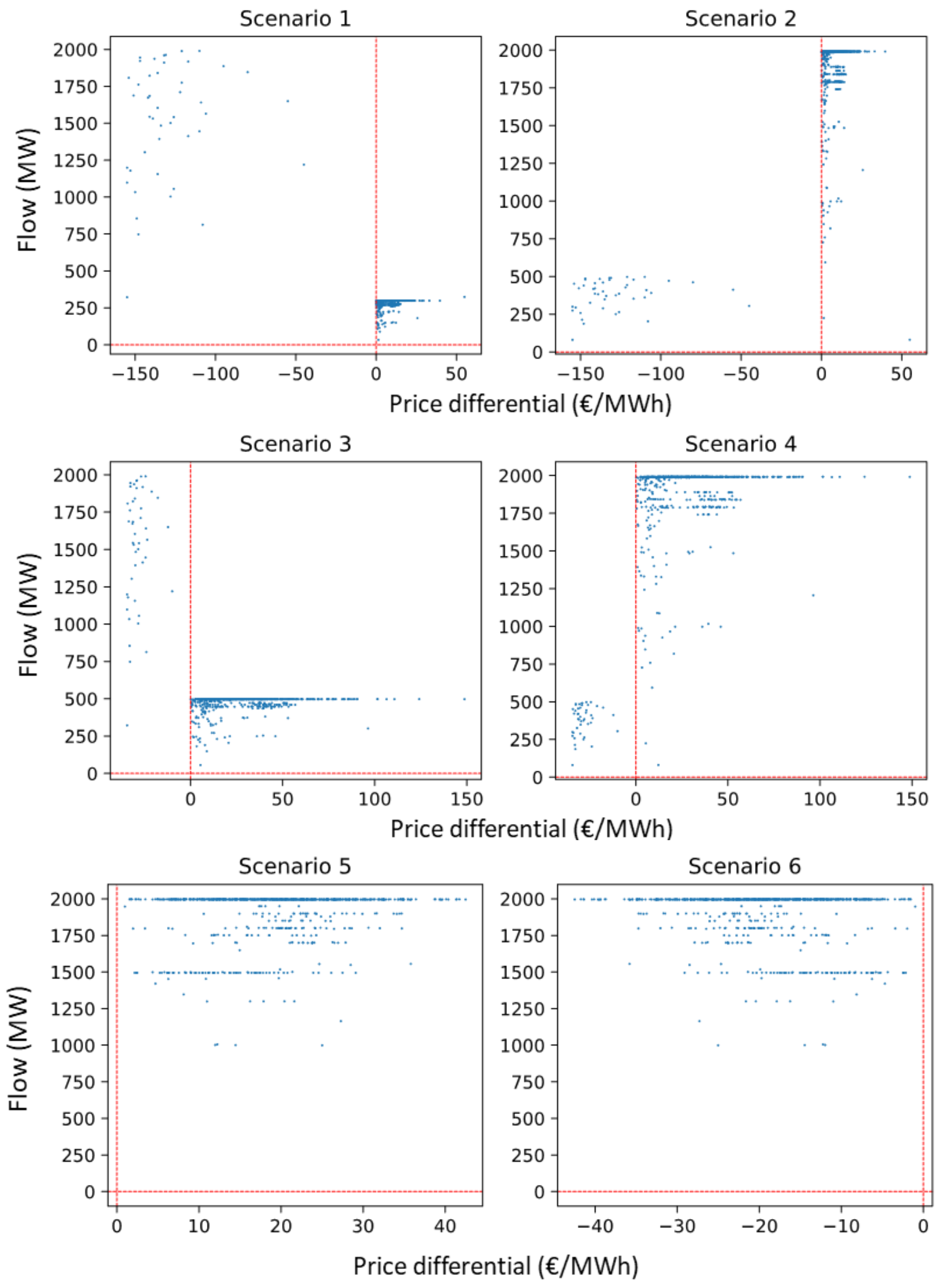

Figure A1(a). Scatterplots of the stress data for Scenarios 1–6.

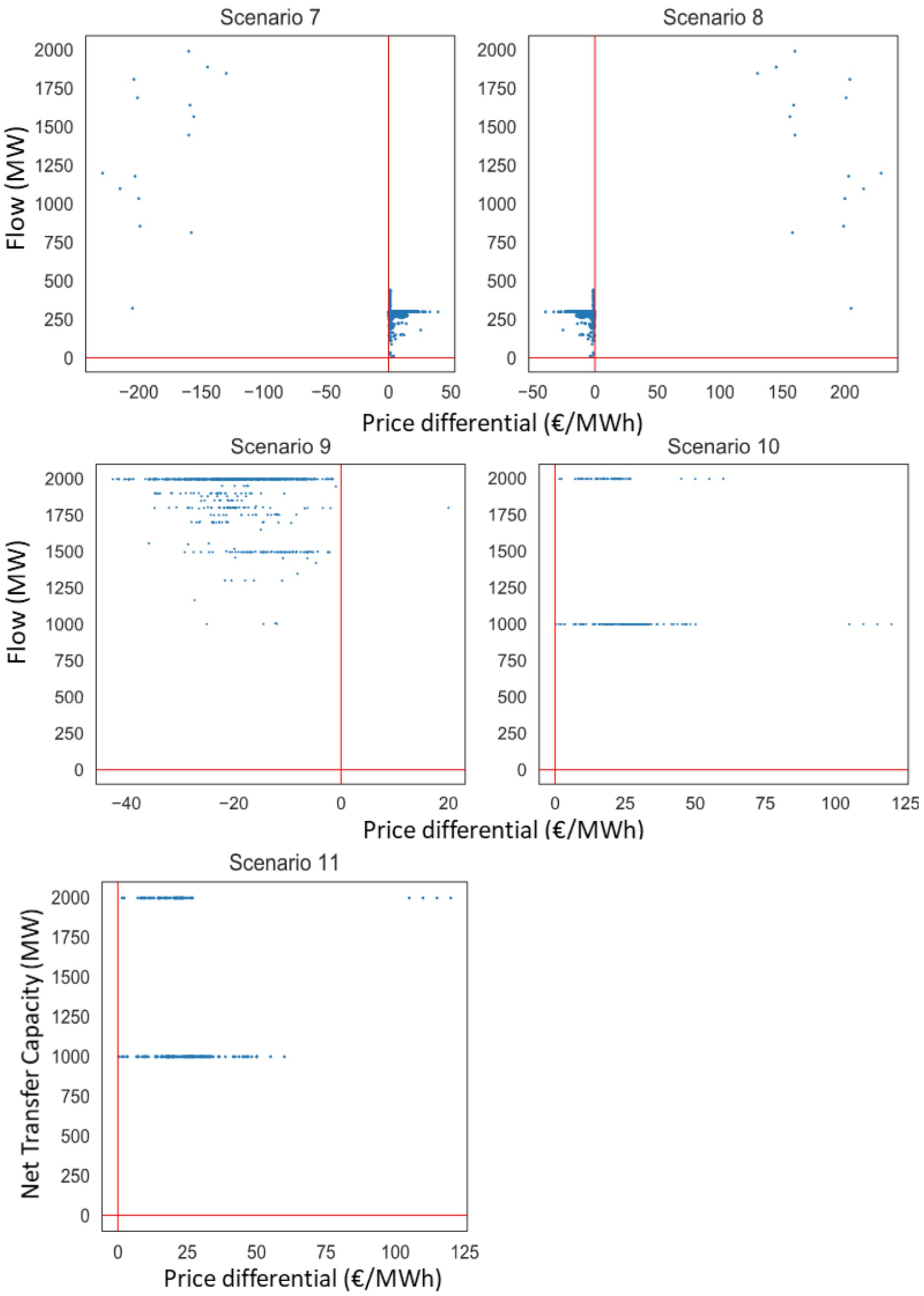

Figure A1(b). Scatterplots of the stress data for scenarios 7–11.

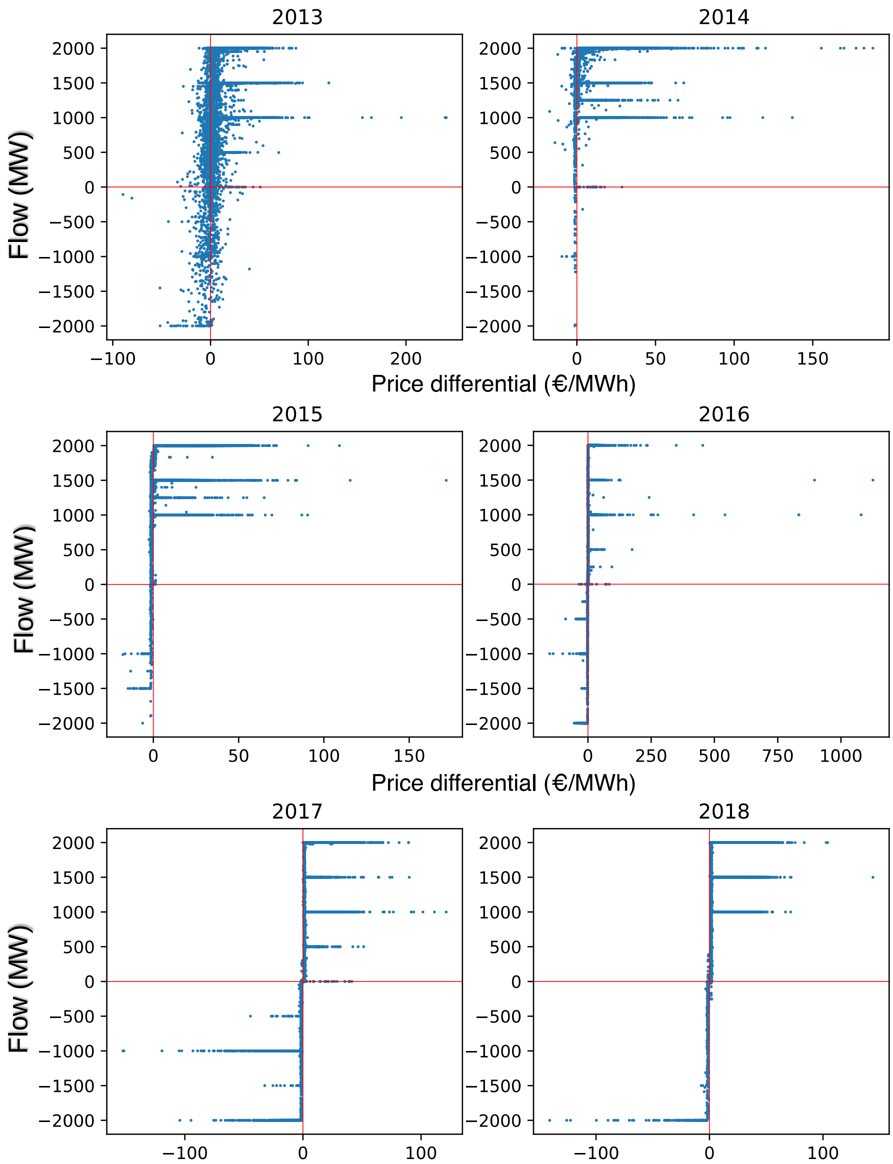

Figure A2. Plot of GB-FR Day-ahead price vs FR->GB RTE flow. Day-ahead NWE coupling went live on 04-02-2014.

Appendix 4: Measures of social welfare

Interconnectors increase welfare by reducing the overall cost of the interconnected electricity systems, creating consumer surplus for importers and producer surplus for exporters. Since social welfare is challenging to calculate, the metrics presented in the paper are used instead to estimate commercial interconnector efficiency, which is a good proxy for social welfare if markets are competitive and externalities properly priced. Some studies have calculated social welfare metrics directly, particularly for examining the potential impacts of deploying new interconnectors which may change prices (usually assuming efficient markets).

Models are used to estimate the change in social welfare due to adding an interconnector to connect two systems. For example, the UK electricity regulator, Ofgem, analysed welfare changes by estimating the consumer and producer surplus[5] changes for the proposed

[5] Consumer surplus is the difference between the highest price a retailer is willing to pay and the actual market price of electricity. Producer surplus is the difference between the electricity market price and the lowest price a generator would be willing to accept.

ElecLink interconnector between Great Britain and France.[6] This requires an electricity system model to examine the counterfactual situation in which the interconnector has/has not been deployed (depending on whether the study is taking place before or after deployment). Since models include numerous assumptions and simplifications compared with real markets, it is difficult to compare studies.

Social welfare should include all external costs of CO_2 emissions and other pollutants, as well as correcting for market power (or basing calculations on costs rather than prices). Mansur and White (2012) consider the impacts of moving from bilateral trading to simultaneous market dispatch and clearing. By comparing monthly prices before and after a bilaterally cleared zone joined the Pennsylvania-Jersey-Maryland (PJM) nodally-priced market area, they estimated reductions in price differentials and welfare gains, finding potential incremental gains of $3.6m/GW. Ott (2010) used a similar approach and found that the total benefit of efficiently pricing PJM was $2.2bn/yr. De Jong *et al.* (2007) simulated four EU countries, finding welfare effects of flow-based market coupling at about €200m/yr. Meeus (2011) studied historical data relating to the 600 MW Kontek cable linking Denmark to Germany over various coupling initiatives and found imperfect coupling with 5% UFAPDs even after coupling took place, with welfare gains of €10m/yr. The SEM Committee (2011) estimated the social costs of not coupling the two interconnectors between Great Britain and the Single Electricity Market (SEM) of the island of Ireland for 2010. The estimated social welfare gains from coupling were €30m/yr based on an average import capacity of 930 MW, or €32m/GWyr.

The relatively modest welfare and efficiency benefits in these studies may be underestimated because the models are too simplistic to account for all of the transmission failures that coupling may relieve, and because they are calibrated based on previous generation portfolios with lower renewable generation (and so less congestion) than seen at present (Newbery *et al.*, 2016). National Grid (2015) estimated that sharing reserves over interconnectors could reduce capacity needs by nearly 3 GW, which could be worth €15m/GWyr. These findings led to regulators requiring coupling of electricity markets in Europe, until 85% of the European power consumption was coupled in 2015 (Geske *et al.*, 2018).

Appendix 5: Methodological appendix: Metrics

5.1 Derivation of the new metrics

For any hour *h* of the day, in any two regions *A* and *B*, electricity flows of magnitude $\tilde{f}_h(MW)$ move across an interconnector in the direction *A*→*B* at a price differential (€/MWh) $D_{BA(h)} \coloneqq P_{B(h)} - P_{A(h)}$. Ideally,[7] arbitrageurs import electricity into market *B* from market *A* when prices are lower in *A* and conversely, import into *A* from *B* (*B*→*A*) when prices are lower in *B*. Efficient trading behaviour in idealised conditions give rise to the step-curve[8] (S-curve) pattern in Left diagram of Figure A3.

[6]https://www.ofgem.gov.uk/ofgem-publications/84685/appendix2-londoneconomicseleclinkreviewsummary.pdf

[7] Synchronicity of market gate closures and capacity allocation, perfect information set, no physical constrains such as ramping, loop-flows, etc.

[8] Under the idealised conditions, arbitrageurs should not import or export when the market prices in region A and B are equilibrated and there are positive losses across the link: Hence the $D_{BA} = 0$ discontinuity.

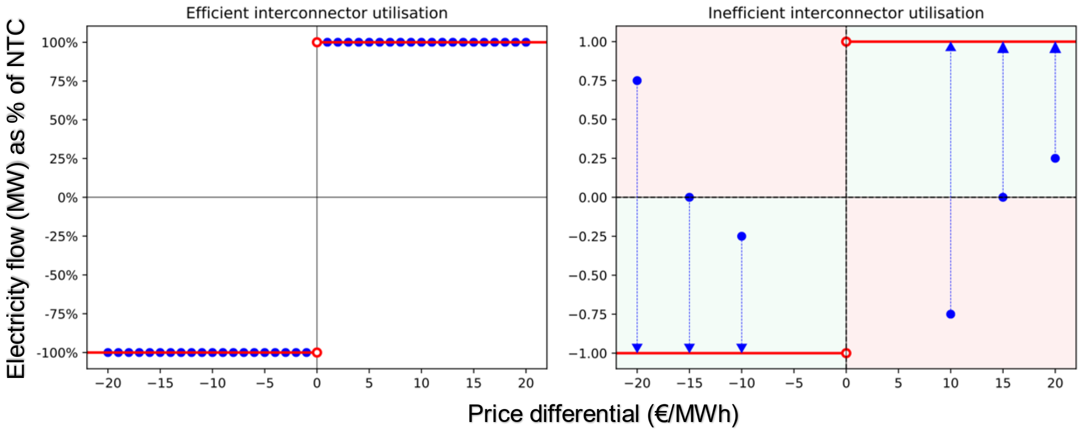

Figure A3. Here, the S-curve is reported as a ratio of available to used capacity, as opposed to Figure 1, for simplicity. LEFT: S-curve (in red) of the efficient utilisation pattern by interconnector arbitrageurs (blue points) across markets A, B. x-axis denotes the price differential $D_{BA(h)}$. The y-axis denotes the electricity flow as a percentage of NTC in direction A→B. RIGHT: Red and blue areas denote adverse and favourable flow quadrants; the blue line is the distance of the inefficient flow from the S-curve.

The distance of non-maximal flows from the S-curve in the right-hand side diagram of Figure A3 is then

distance(adverse-flows) + *distance(favourable-flows)* + *distance(no-flows)*

which we define as

$$I_4 = \left(\frac{N^-}{N}\right)\left(\frac{1}{N^-}\right)\sum_h^{N^-}\frac{(1+|f_h^-|)}{2} + \left(\frac{N^+}{N}\right)\left(\frac{1}{N^+}\right)\sum_h^{N^+}\frac{(1-|f_h^+|)}{2} + \left(\frac{N^0}{N}\right)\left(\frac{1}{N^0}\right)\sum_h^{N^0}\frac{(1-|f_h^0|)}{2}$$

where

$$\begin{aligned} N &= N^- + N^+ + N^0 \\ F &= f^- + f^+ + f^0 \\ |y| &= absolute\ value\ of\ y \\ f_h &= \frac{\tilde{f}_h}{NTC_h} \end{aligned}$$

with the superscripts '-' , '+', *0*[9], denoting adverse-flow,[10] favourable-flow and no-flow,[11] respectively. *NTC* denotes net transfer capacity and $\tilde{f}_h$ the hourly flow.

5.2 SCUWED as a limit for UIIU

When all flows are favourable and NTC is constant Equation(4) becomes

$$UIIU = \frac{1}{2}\left(\frac{1}{N}\sum_h^N\left(1-\left|\frac{\tilde{f}_h}{K}\right|\right)\right) = \frac{1}{2}\left(1-\frac{1}{N}\sum_h^N\left|\frac{\tilde{f}_h}{K}\right|\right) = \frac{1}{2}\left(1-\frac{\sum_h^N|\tilde{f}_h|}{\sum_h^N|K|}\right) = \frac{1}{2}(1-SCURED)$$

[9] By definition $f_h^0 = 0$.

[10] Adverse-flow is synonymous with flow against price differential (FAPD) and analogous with flows in the correct economic direction.

[11] A no-flow is the event of zero IC utilisation given that a non-zero price differential occurred.

5.3 Additional price-weighting schemes

Equation (5) adjusts to equation (4) by weighing the interconnector underutilisation by price differential weight according to w_h.

Other weightings schemes, such as

$$w_1 = \frac{x_h^2}{\sum x_h^2}$$
$$w_2 = \frac{e^{\beta x_h}}{\sum e^{\beta x_h}}$$
$$w_3 = \frac{e^{\beta |x_h|}}{\sum e^{\beta |x_h|}}$$

can be applied where the degree of convexity will determine the influence of price differential outliers on the computed metric. Note that surpluses and deadweight loss increase as the square of the price differential so w_1 may be a better welfare weight. Due to its linear nature, our choice of weighting scheme results in minimum bias from outliers. One could also[12] apply a scheme with symmetric emphasis on outliers via w_1 (or w_3 with $\beta = 0.05$), or with adverse flows asymmetrically penalised (w_2 with $\beta = -0.01$) as in figure A4 below.

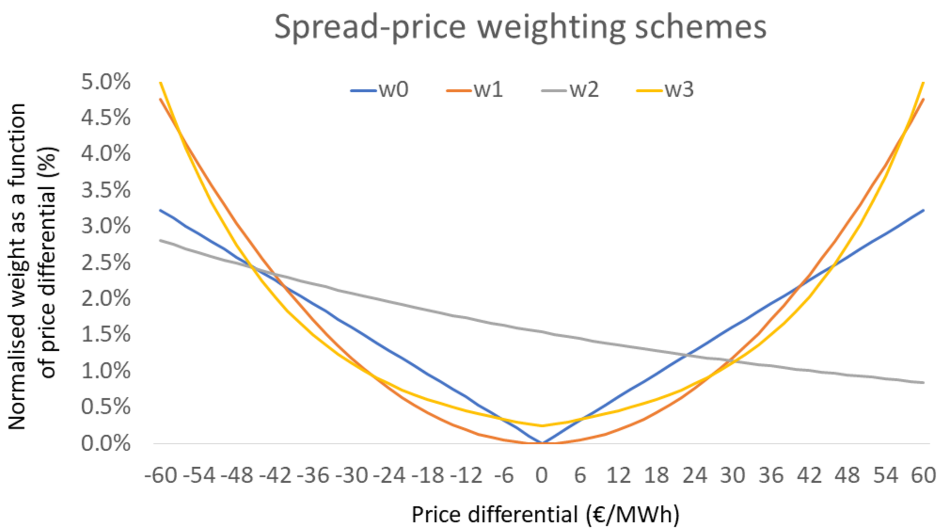

Figure A4. Price differential weighting according to different weighting schemes. w0 is the price differential weighting applied in equation (5), w^1-w^3 as per Section 1.3. of this document (SI) For w^2 and w^3, β = -0.01 and 0.05 respectively.

5.4 Data pre-processing

Pre-processing data can be helpful in deriving a meaningful price differential, or attempt to account for reverse flows, loss-factors, etc. This data reduction can lead to subjective choices of thresholds to filter out information to be (or not) included in analysis. In our analysis, we opted not to apply any filtering to the data. Applying a filter of €1 to the price differential, shows how the temporal evolution of the indices remain unchanged.

[12] When dealing with underdetermined systems and optimisation.

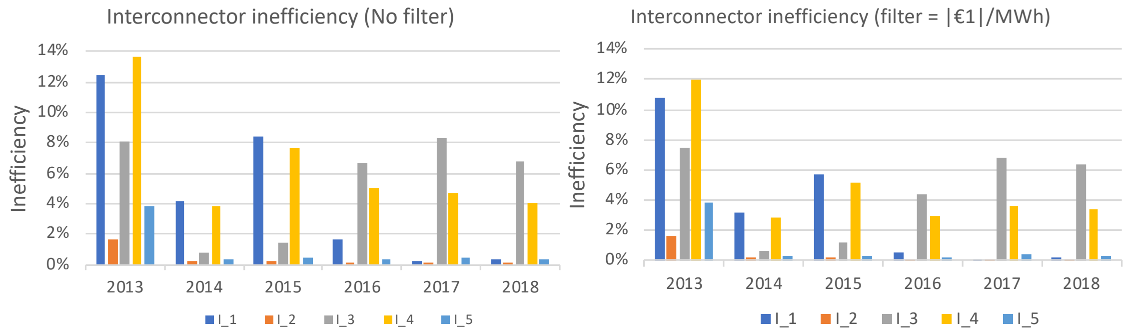

Figure A5. Results of metrics by year (IFA). LEFT: Original series without a filter. RIGHT: Series with a filter of (absolute) €1/MWh below which price differentials are ignored for the analysis, as done in many ACER and EU Commission reports.

5.5 *UIIU* and *PWIIU* by hour of the day

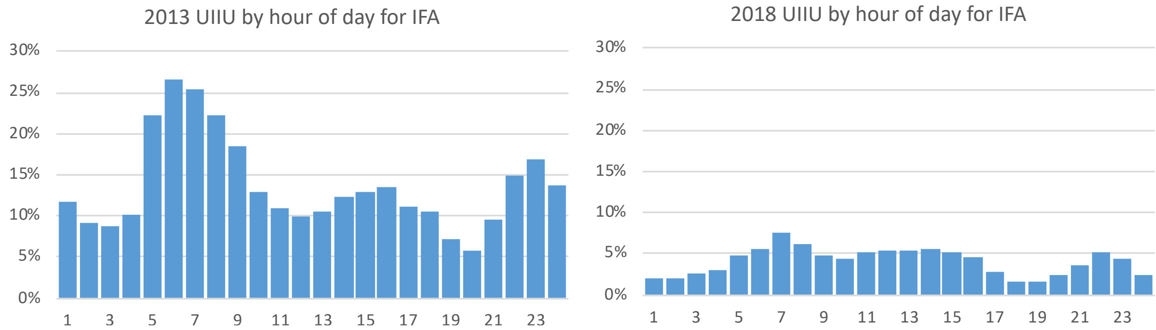

Figure A6(a). Unweighted interconnector inefficient utilisation metric (UIIU) (%, y-axis) averaged by hour of the day (x-axis) for selected years, for the IFA interconnector.

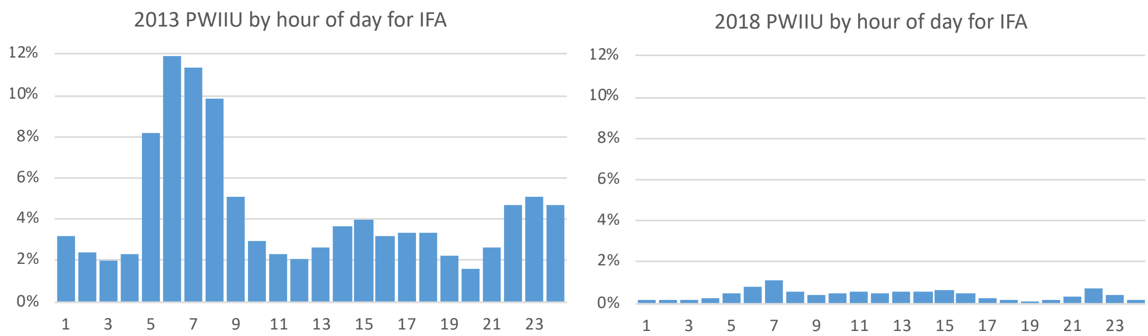

Figure A6(b). Price-Weighted Interconnector Inefficient Utilisation (PWIIU) metric (%, y-axis) averaged by hour of the day (x-axis) for selected years, for the IFA interconnector.

5.6 Worksheet prototype implementation of metrics

We provide a spreadsheet implementation of both indices here introduced, I_1 and I_5.

Date	hour	flow	NTC	gb -fr
01/01/2013	1	1500	1500	€ 24.30
01/01/2013	2	1500	1500	€ 28.54
01/01/2013	3	1500	1500	€ 23.42

Table A1. Summary table of user input data.

Interconnector utilisation data is first provided in the format of Table A2. Intermediate calculations in Table A3 are performed with corresponding formulae provided in Table A4.

flow_adj	year	month	y&m	flow/NTC	fpd	uD(S)	|gb_fr|	w_h(m)	w_h(y)	wD(S)_y	CR
1500	2013	1	2013-1	100%	1	0.00%	24.30	0.31%	0.02%	0.00%	€ 36,456
1500	2013	1	2013-1	100%	1	0.00%	28.54	0.37%	0.02%	0.00%	€ 42,817
1500	2013	1	2013-1	100%	1	0.00%	23.42	0.30%	0.02%	0.00%	€ 35,123

Table A2. Intermediate calculations required for estimation of metrics i1 -- I5. flow_adj is used only in the calculation of SCUWED.

column	Formula
flow_adj	=ABS(IF(ABS([@flow])<=[@NTC],[@flow],SIGN([@flow])*[@NTC]))
year	=YEAR([@date])
month	=MONTH([@date])
y&m	=[@year]&[@month]
flow/NTC	=[@flow]/[@NTC]
fpd	=SIGN([@[gb-fr]]*[@flow])
uD(S)	=IF([@fpd]=-1,1,0) * (1+ABS([@[flow/NTC]]))/2 + IF([@fpd]=1,1,0) * (1-ABS([@[flow/NTC]]))/2 + IF([@fpd]=0,1,0) * (1/2)
|gb_fr|	=ABS([@[gb-fr]])
w_h(m)	=[@[|gb_fr|]]/VLOOKUP([@[y&m]],**sum_abs_spreads_months**,2,FALSE)
wD(S)_m	=[@[w_h(m)]]*[@[uD(S)]]
w_h(y)	=[@[|gb_fr|]]/VLOOKUP([@year],**sum_abs_spreads_years**,2,FALSE)
wD(S)_y	=[@[w_h(y)]]*[@[uD(S)]]
CR	=[@[gb-fr]]*[@flow]

Table A3. Formulae for intermediate calculations in Table A7. Boldface denotes named ranges described in Tables A5 and A6.

The spreadsheet '*TableB'* object is the union of Tables A1 and A2 and is used in the final calculation of the annual and monthly results of Table A8 and A9 with their respective formulae provided in Tables A6 and A7.

Y&M	M_sum(| x |)	Formula
2013-1	7735	=SUMIFS(TableB[|gb_fr|],TableB[year],"=2013", TableB[month],"=1")
2013-2	5506	=SUMIFS(TableB[|gb_fr|],TableB[year],"=2013", TableB[month],"=2")
2013-3	10922	=SUMIFS(TableB[|gb_fr|],TableB[year],"=2013", TableB[month],"=3")

Table A4. Detail of 'sum_abs_spreads_months' named range. The named range is given by the first two columns. The thirds column is the formula for column two (M_sum|x|).

Year	Y_sum(|x|)	Formula
2013	152536	= SUMIF(TableB[year],"=2013",TableB[|gb_fr|])
2014	155106	= SUMIF(TableB[year],"=2014",TableB[|gb_fr|])
2015	153612	= SUMIF(TableB[year],"=2015",TableB[|gb_fr|])

Table A5. Detail of 'sum_abs_spreads_years' named range. The named range is given by the first two columns. The third column is the formula for column two (Y_sum|x|).

column	Formula
N	=COUNTIF(TableB[year],"=2013")
N+	=COUNTIFS(TableB[year],"=2013",TableB[fpd],"1")
N-	=COUNTIFS(TableB[year],"=2013",TableB[fpd],"-1")
N0	=COUNTIFS(TableB[year],"=2013",TableB[fpd],"0")
I1	=[@[N-]]/[@N]
I2	=ABS(SUMIFS(TableB[CR],TableB[year],"=2013", TableB[fpd],"=-1"))/(SUMIFS(TableB[CR],TableB[year],"=2013", TableB[fpd],"=1") + ABS(SUMIFS(TableB[CR],TableB[year],"=2013", TableB[fpd],"=-1")))
I3	=1 - (SUMIFS(TableB[flow_adj],TableB[year],"=2013",TableB[fpd],"=1")/ SUMIFS(TableB[NTC],TableB[year], "=2013",TableB[fpd],"=1"))
I4	=SUMIFS(TableB[uD(S)],TableB[year],"=2013")/[@N]
I5	=(SUMIFS(TableB[wD(S)_y],TableB[year],"=2013",TableB[fpd],"=1")+SUMIFS(TableB[wD(S)_y],TableB[year],"= 2013", TableB[fpd],"=-1")+SUMIFS(TableB[wD(S)_y],TableB[year],"=2013", TableB[fpd],"=0"))

Table A6. Formulae corresponding to columns in Table A4. The example provided is for calendar year 2013.

column	Formula
N	=COUNTIFS(TableB[year],"=2013", TableB[month],"=1")
N+	=COUNTIFS(TableB[year],"=2013", TableB[month],"=1",TableB[fpd],"1")
N-	=COUNTIFS(TableB[year],"=2013", TableB[month],"=1",TableB[fpd],"-1")
N0	=COUNTIFS(TableB[year],"=2013", TableB[month],"=1",TableB[fpd],"0")
I1	=COUNTIFS(TableB[year],"=2013", TableB[month],"=1",TableB[fpd],"-1")/COUNTIFS(TableB[year],"=2013", TableB[month],"=1")
I2	=ABS(SUMIFS(TableB[CR],TableB[year],"=2013", TableB[month],"=1",TableB[fpd],"=-1"))/(SUMIFS(TableB[CR],TableB[year],"=2013", TableB[month],"=1",TableB[fpd],"=1") + ABS(SUMIFS(TableB[CR],TableB[year],"=2013", TableB[month],"=1",TableB[fpd],"=-1")))
I3	=1-(SUMIFS(TableB[flow_adj],TableB[year],"=2013", TableB[month],"=1",TableB[fpd],"=1")/SUMIFS(TableB[NTC],TableB[year],"=2013", TableB[month],"=1",TableB[fpd],"=1"))
I4	=(SUMIFS(TableB[uD(S)],TableB[year],"=2013", TableB[month],"=1")/AK2)
I5	=(SUMIFS(TableB[wD(S)_m],TableB[year],"=2013", TableB[month],"=1",TableB[fpd],"=1")+SUMIFS(TableB[wD(S)_m],TableB[year],"=2013", TableB[month],"=1",TableB[fpd],"=-1")+SUMIFS(TableB[wD(S)_m],TableB[year],"=2013", TableB[month],"=1",TableB[fpd],"=0"))

Table A7. Formulae corresponding to the columns in Table A4. The example provided is for the month of January 2013.

Appendix 6: Monthly Historical Dataset Results

6.1 IFA

Year	Month	N	N+	N-	N0	*UFAPD*	*WFAPD*	*SCUWED*	*UIIU*	*PWIIU*
2013	1	744	567	177	0	23.8%	5.2%	15.5%	24.7%	10.2%
2013	2	672	482	190	0	28.3%	8.9%	23.8%	29.9%	16.6%
2013	3	744	608	136	0	18.3%	4.0%	14.8%	21.2%	9.0%
2013	4	721	604	117	0	16.2%	3.6%	8.6%	16.2%	6.7%
2013	5	744	717	27	0	3.6%	0.3%	0.4%	3.3%	0.4%
2013	6	720	713	7	0	1.0%	0.1%	0.5%	1.2%	0.2%
2013	7	744	726	18	0	2.4%	0.2%	0.8%	2.6%	0.4%
2013	8	744	721	23	0	3.1%	0.3%	1.7%	3.4%	0.8%
2013	9	698	648	50	0	7.2%	0.8%	5.0%	8.1%	1.7%
2013	10	744	644	100	0	13.4%	2.2%	9.1%	15.0%	4.6%
2013	11	720	623	97	0	13.5%	1.9%	13.4%	16.2%	4.7%
2013	12	744	596	148	0	19.9%	3.9%	17.8%	22.6%	7.6%
2014	1	744	698	46	0	6.2%	0.7%	2.3%	6.5%	1.1%
2014	2	672	649	23	0	3.4%	0.6%	1.7%	3.6%	0.9%
2014	3	720	705	15	0	2.1%	0.1%	0.8%	2.1%	0.2%
2014	4	720	702	18	0	2.5%	0.1%	0.8%	2.4%	0.2%
2014	5	744	734	10	0	1.3%	0.0%	0.4%	1.2%	0.1%
2014	6	720	702	18	0	2.5%	0.1%	0.5%	2.2%	0.1%
2014	7	744	744	0	0	0.0%	0.0%	0.0%	0.0%	0.0%
2014	8	744	740	4	0	0.5%	0.0%	0.0%	0.5%	0.0%
2014	9	720	704	16	0	2.2%	0.1%	0.2%	2.1%	0.1%
2014	10	744	669	74	1	9.9%	0.5%	0.6%	8.8%	0.6%
2014	11	720	703	17	0	2.4%	0.1%	0.3%	2.2%	0.1%
2014	12	744	621	120	3	16.1%	0.7%	2.1%	13.7%	1.1%
2015	1	744	597	147	0	19.8%	1.4%	2.2%	17.6%	1.7%
2015	2	672	513	156	3	23.2%	1.9%	7.1%	21.3%	2.9%
2015	3	744	657	86	0	11.6%	0.6%	2.0%	10.7%	0.9%
2015	4	720	701	19	0	2.6%	0.1%	0.5%	2.5%	0.1%
2015	5	744	739	5	0	0.7%	0.0%	0.2%	0.6%	0.0%
2015	6	720	717	3	0	0.4%	0.0%	0.0%	0.4%	0.0%
2015	7	744	722	22	0	3.0%	0.1%	0.1%	2.6%	0.1%
2015	8	744	743	1	0	0.1%	0.0%	0.0%	0.1%	0.0%
2015	9	720	712	8	0	1.1%	0.0%	0.1%	1.1%	0.1%
2015	10	744	631	112	0	15.1%	0.8%	3.1%	13.2%	1.3%
2015	11	720	632	88	0	12.2%	0.6%	3.0%	11.8%	0.9%
2015	12	744	655	89	0	12.0%	0.4%	2.6%	10.6%	0.7%
2016	1	744	689	55	0	7.4%	0.2%	3.9%	7.5%	0.4%
2016	2	696	675	21	0	3.0%	0.1%	0.3%	2.7%	0.1%
2016	3	744	734	10	0	1.3%	0.1%	0.1%	1.2%	0.1%
2016	4	720	718	2	0	0.3%	0.0%	0.4%	0.4%	0.0%
2016	5	744	744	0	0	0.0%	0.0%	0.3%	0.1%	0.0%
2016	6	720	720	0	0	0.0%	0.0%	0.0%	0.0%	0.0%
2016	7	744	744	0	0	0.0%	0.0%	0.8%	0.4%	0.0%
2016	8	744	737	7	0	0.9%	0.0%	5.9%	3.4%	0.3%
2016	9	720	692	28	0	3.9%	0.0%	24.7%	13.4%	0.7%
2016	10	725	704	8	13	1.1%	0.0%	20.9%	10.3%	0.9%
2016	11	720	698	4	18	0.6%	0.0%	23.1%	11.3%	1.3%
2016	12	744	718	6	20	0.8%	0.0%	18.2%	10.5%	1.3%

Table A8. Monthly historical dataset results for years 2013 to 2016 for all indices UFAPD–PWIIU (IFA).

6.2 BritNed

Year	Month	N	N+	N-	N0	*UFAPD*	*WFAPD*	*SCUWED*	*UIIU*	*PWIIU*
2013	1	745	593	150	2	20.1%	3.5%	21.4%	22.7%	9.8%
2013	2	670	584	86	0	12.8%	1.4%	16.1%	16.2%	5.2%
2013	3	744	630	113	1	15.2%	3.1%	7.6%	15.2%	5.1%
2013	4	720	528	191	1	26.5%	6.8%	24.4%	27.7%	15.7%
2013	5	744	563	181	0	24.3%	4.4%	18.0%	23.7%	11.1%
2013	6	708	585	123	0	17.4%	2.6%	16.8%	19.0%	8.2%
2013	7	744	666	78	0	10.5%	1.8%	7.5%	11.6%	3.7%
2013	8	744	662	82	0	11.0%	2.0%	8.9%	12.6%	4.5%
2013	9	603	525	74	4	12.3%	1.6%	14.4%	15.1%	5.1%
2013	10	744	616	123	5	16.5%	2.2%	14.2%	18.2%	5.8%
2013	11	720	635	85	0	11.8%	1.6%	10.9%	13.4%	4.6%
2013	12	744	635	108	1	14.5%	2.2%	13.5%	16.4%	6.1%
2014	1	694	634	60	0	8.6%	1.0%	4.3%	8.8%	2.2%
2014	2	0	0	0	0	N/A	N/A	N/A	N/A	N/A
2014	3	434	418	16	0	3.7%	0.2%	2.2%	4.0%	0.5%
2014	4	720	696	24	0	3.3%	0.2%	2.9%	4.1%	0.5%
2014	5	743	704	39	0	5.2%	0.4%	2.1%	5.1%	0.7%
2014	6	720	678	42	0	5.8%	0.5%	2.1%	5.7%	0.8%
2014	7	744	725	19	0	2.6%	0.2%	0.9%	2.5%	0.3%
2014	8	744	713	31	0	4.2%	0.3%	1.7%	4.1%	0.6%
2014	9	559	527	32	0	5.7%	0.5%	2.1%	5.8%	0.7%
2014	10	744	703	41	0	5.5%	0.4%	1.4%	5.4%	0.5%
2014	11	720	687	33	0	4.6%	0.2%	1.4%	4.6%	0.4%
2014	12	720	608	112	0	15.6%	1.2%	2.8%	14.0%	1.7%
2015	1	744	664	80	0	10.8%	0.6%	7.4%	11.5%	1.3%
2015	2	672	617	55	0	8.2%	0.4%	8.6%	10.0%	1.1%
2015	3	744	708	36	0	4.8%	0.2%	5.7%	6.3%	0.6%
2015	4	720	710	10	0	1.4%	0.1%	2.4%	2.2%	0.2%
2015	5	679	642	36	1	5.3%	0.2%	3.1%	5.6%	0.3%
2015	6	720	693	27	0	3.8%	0.2%	3.8%	4.8%	0.4%
2015	7	744	714	30	0	4.0%	0.2%	3.2%	4.5%	0.4%
2015	8	744	726	18	0	2.4%	0.1%	2.3%	3.0%	0.3%
2015	9	655	643	12	0	1.8%	0.1%	4.0%	3.5%	0.3%
2015	10	744	691	51	2	6.9%	0.3%	5.5%	7.9%	0.7%
2015	11	720	654	66	0	9.2%	0.4%	4.6%	8.9%	0.7%
2015	12	744	660	84	0	11.3%	0.3%	5.3%	10.8%	0.6%
2016	1	744	704	40	0	5.4%	0.2%	1.8%	4.8%	0.4%
2016	2	696	693	3	0	0.4%	0.0%	1.2%	0.9%	0.0%
2016	3	744	740	4	0	0.5%	0.0%	1.0%	1.0%	0.1%
2016	4	720	718	2	0	0.3%	0.0%	1.6%	1.0%	0.0%
2016	5	680	678	2	0	0.3%	0.0%	3.7%	2.1%	0.1%
2016	6	720	716	4	0	0.6%	0.0%	7.2%	4.0%	0.4%
2016	7	744	740	4	0	0.5%	0.0%	9.6%	5.2%	0.6%
2016	8	744	742	2	0	0.3%	0.0%	4.1%	2.2%	0.2%
2016	9	678	650	28	0	4.1%	0.2%	11.9%	8.9%	0.6%
2016	10	744	729	15	0	2.0%	0.1%	9.8%	6.2%	0.4%
2016	11	720	699	21	0	2.9%	0.1%	4.5%	4.5%	0.3%
2016	12	744	684	60	0	8.1%	0.4%	8.2%	9.7%	1.1%

Table A9. Monthly historical dataset results for years 2013 to 2016 for all indices UFAPD–PWIIU (BritNed).

Appendix 7: Methodological appendix: simulation

We use a simulation-based method to derive the expected cross-border price differentials between GB and France and the Netherlands, and flows for IFA and BritNed, had the interconnectors not been coupled. Our simulation assumes a cross-border market where, after the foreign price has been set, risk-averse traders have to forecast the GB price to make trading decisions, and any forecast errors would result in either an inefficient use of interconnectors or Flows Against Price Differences (FAPDs). We then compare the simulated price differentials and flows with actual data under market coupling to assess the impact of coupling the cross-border electricity markets. The simulation model is simplified from Geske *et al.* (2018). Our analysis in this section only focuses on the day-ahead market, where the GB electricity market is (up to end 2019) fully coupled with France and the Netherlands.

Before the 2014 market coupling came into force, the day-ahead (DA) market closed in France before it did in GB. This meant that traders had to predict GB prices, thereby facing uncertainty. Based on Geske *et al.* (2019), we assume that traders have a mean-variance utility function and, for simplicity, we assume the data is always collected from the import side (i.e. after accounting for transmission losses). Taking IFA as an example, we assume a single trader[13] who maximises her utility function, U_h, in each hour, *h*

$$\text{Max}\,\mathrm{E}(U_h) = T\big(\mathrm{E}\big(P_h^{GB}\big) - P_h^{FR}\big) - \frac{\lambda}{2}\left(T * C_{GB,h}^{''} * \sigma_{GB,D}\right)^2,$$

where $\mathrm{E}(U_h)$ is the expected utility of the trader, which is given by the difference between congestion revenue and a penalty term to evaluate the trader's level of uncertainty; T is GB's net import from France in GW; P_h^{GB} and P_h^{FR} are the GB and French DA electricity prices respectively in €/MWh; λ is the trader's discount factor towards price volatility; $C_{GB,h}^{'}$ is GB's aggregated marginal cost function and $C_{GB,h}^{''}$ is the marginal value of electricity sales; and $\sigma_{GB,D}$ is the standard error of traders' forecast of GB electricity demand.

Given the above, the utility maximisation problem (by equalising the first-order condition of $\mathrm{E}(U_h)$ to zero) finds the optimal trading (net import for GB in GW) $\hat{T}$ as:

$$\hat{T}\big(\mathrm{E}\big(P_h^{GB}\big), P_h^{FR}\big) = \begin{cases} Cap_h & Cap_h \le \theta \\ \theta & 0 \le \theta < Cap_h \\ 0 & \mathrm{E}\big(P_h^{GB}\big) = P_h^{FR} \\ \theta & -Cap_h \le \theta \le 0 \\ -Cap_h & \theta \le -Cap_h \end{cases}$$

$$\theta = \frac{\mathrm{E}\big(P_h^{GB}\big) - P_h^{FR}}{\lambda \cdot \left(C_{GB,h}^{''}\sigma\right)^2} = \frac{\mathrm{E}\big(P_h^{GB}\big) - P_h^{FR}}{\mu}$$

where θ denotes net import if there were no capacity constraint; and Cap_h denotes the net transfer capacity (NTC). The numerator of θ denotes the (expected) DA price differential between GB and France, while the denominator, $\mu = \lambda \cdot (C_{GB,h}^{''}\sigma)^2$, is a function of unknown parameters. It is worth noticing that instead of separately identifying λ, σ, and $C_{GB,h}^{''}$, we only need to identify μ to conduct our simulation. Intuitively, a greater expected price differential

[13] For simplicity, we assume there is only one trader who participates in day-ahead cross-border electricity trading. We assume that the trader can bid on a maximum volume equivalent to the net transfer capacity, then it is equivalent to assuming that there are n equivalent traders in the market.

indicates greater potential for imports, therefore θ is positively correlated with the expected DA price differential.

With forecast errors, θ can be expressed as

$$\theta = \frac{P_h^{GB} + \varepsilon_h^{GB} - P_h^{FR}}{\lambda(C_{GB,h}^{''}\sigma)^2}$$

where $\varepsilon_h^{GB} \sim \mathrm{N}(0, \sigma_{GB,P}^2)$.

We aim to identify parameters μ and $\sigma_{GB,P}^2$ such that the simulated[14] DA scheduled commercial exchange for IFA (and BritNed) in 2013 (when the markets are uncoupled) is reasonably close to the actual IFA (BritNed) day-ahead scheduled commercial exchange in 2013, by comparing proposed metrics of trading inefficiency in this paper.

Once the parameter values for IFA and BritNed have been identified, we can use the parameters and the observed DA prices for both markets to simulate the uncoupled IFA and BritNed flows and price differentials during the examined electricity years (2014-2019). We then compare the simulated uncoupled counterfactuals with the actual coupled flow and price differentials from the same period.

We measure the degree of interconnector inefficiency before and after market coupling using the metrics *PWIIU*, *UIUU*, *FAPD*, *WFAPD*, and *SCUWED*.

Appendix 8: Value of market coupling

8.1 Trading in uncoupled markets

In uncoupled markets, traders must separately buy electricity in one market, sell in another market, and buy and nominate interconnector capacity from the first market to the second market. Efficient day-ahead nominations require traders to accurately predict the magnitude and direction of the day-ahead auction price differentials. In practice, this can be quite challenging: prior to market coupling, day-ahead scheduled flow was frequently suboptimal, or even in the wrong direction (ACER, 2012).

Where day-ahead scheduled flow proves economically suboptimal, it is possible for traders to correct it in the intra-day markets. This requires them to buy and nominate intra-day capacity, and either to buy and sell in the different markets, or to accept exposure to the balancing mechanism. In practice, there are generally limited liquidity and significant transaction costs in intra-day markets, and a general reluctance to exposure to volatile prices in the balancing mechanism.[15] As a result, interconnector flow will often only be adjusted in the intra-day market where there is a large enough movement in the price differential, or for operational reasons such as an unexpected change in generation or demand. After Brexit, it is expected that GB will be uncoupled in the day-ahead market but coupled in the intra-day market.

8.2 Trading in coupled markets

Day-ahead coupling obviates the need to predict day-ahead price differentials. Instead, the EUPHEMIA algorithm will ensure that the DA flow is optimised, based on bids and offers in

[14] Note that the day-ahead scheduled commercial exchange in 2013 and 2014 are from ENTSO-E, but the data for 2015-2018 are from simulation as ENSTSO-E no longer provide this data since 2015.

[15] The SEM Committee (2019) found 92% of trades took place in or prior to the day-ahead market. The remaining 8% of trades took place in declining quantities in the three intraday and continuous markets, falling from 4% in the first intraday market to less than 0.5% in the continuous market.

the two markets and interconnector constraints. The interconnector may be constrained, in which case there is a price differential between the two markets, and capacity holders receive a financial settlement based on the price differential (adjusted for any losses applied by the interconnector operator). Alternatively, the interconnector may be unconstrained, in which case no settlement is made.

As a result of this ability to release interconnector capacity for optimised settlement based on the day-ahead auction, traders are less likely to manually nominate their interconnector capacity. Even if the interconnector capacity is being held as a hedge for offsetting physical positions in the two markets, it may still make sense for the capacity and the two physical positions to be closed out financially in the day-ahead market.

8.3 Simulation results for IFA

The measures of the inefficiency of the simulated flows (denoted as “Simulated flow 2013, BritNed” with different values of parameters $\sigma_{GB,P}$ and μ are reported in Table A10 and are compared with those of the actual uncoupled IFA flow in 2013, denoted as the “Actual flow 2013, IFA”.

We gradually increase the values of $\sigma_{GB,P}$ and μ until the measures of inefficiency (I_1 to I_5) are reasonably close to the actual measures of inefficiency in 2013. As it is shown in Table A10, when $\sigma_{GB,P}$ =7 and μ= 5, by comparing I_1 to I_5, the simulated flow and the actual flow are similarly inefficient. Therefore, when simulating the uncoupled flow for IFA for 2014-2019, we set $\sigma_{GB,P}$ =7 and μ= 5.

			I_1	I_2	I_3	I_4	I_5
Actual flow 2013, IFA			12.4%	1.7%	8.1%	13.6%	3.8%
Simulated flow 2013, BritNed	**Parameter Values**						
	$\sigma_{GB,P}$	$\lambda(C'_{GB,h}\sigma)^2$					
	4	4	8.7%	0.6%	8.5%	10.4%	1.7%
	5	4	9.7%	0.8%	8.3%	11.2%	2.1%
	5	5	9.6%	0.7%	10.6%	11.5%	2.4%
	6	5	11.3%	1.1%	9.8%	12.9%	2.9%
	7	***5***	***12.8%***	***1.6%***	***9.6%***	***14.1%***	***3.6%***

Table A10. Day-ahead actual and simulated flows for IFA in 2013

We then simulate scenarios where trading over IFA occurs without market coupling during 2014-2019 and compare them with the actual data under market coupling, in terms of net imports into GB, congestion revenue, infra-marginal surplus, and trading inefficiency. The results are reported in Table A11.

Among our main findings, based on annual averages, coupling caused the price differential between GB and France to fall by €0.26/MWh, net imports into GB to increase by 2.26 TWh (or by 21.5%), congestion Income increased by €13.71 million (or by 6%), and infra-marginal surplus increased by €3.3 million (or by 25%, or about 1.4% of uncoupled congestion revenue).

	Price Difference (€/MWh)			Net GB Imports (TWh)		
Electricity year	**Coupled**	**Uncoupled**	**Δ**	**Coupled**	**Uncoupled**	**Δ**
2014-2015	15.83	16.20	-0.37	15.20	12.34	2.86
2015-2016	18.76	19.00	-0.24	15.52	13.53	1.99
2016-2017	8.54	8.72	-0.18	8.17	6.65	1.52
2017-2018	10.49	10.75	-0.26	11.32	8.96	2.36
2018-2019	13.76	14.05	-0.29	13.66	11.06	2.60
Average	13.48	13.74	-0.26	12.77	10.51	2.26
2016-2017 w/o CPS	-0.45	-0.54	0.09	-0.13	0.55	-0.68
2017-2018 w/o CPS	2.59	2.42	0.17	0.54	1.81	-1.27
Average w/o CPS	1.07	0.94	0.13	0.20	1.18	-0.98
	Congestion Income (million €)			**Infra-marginal Surplus (million €)**		
2014-2015	256.84	244.53	12.31	17.17	13.84	3.33
2015-2016	318.28	307.42	10.86	18.35	16.03	2.32
2016-2017	197.33	184.13	13.20	12.48	9.56	2.92
2017-2018	210.82	194.16	16.66	16.78	12.77	4.01
2018-2019	234.06	218.54	15.52	16.81	13.10	3.71
Average	243.47	229.76	13.71	16.32	13.06	3.26
2016-2017 w/o CPS	154.34	136.85	17.49	12.11	7.72	4.39
2017-2018 w/o CPS	150.91	130.59	20.32	15.88	10.20	5.68
Average w/o CPS	152.62	133.72	18.91	13.99	8.96	5.03

Table A11. Price differential (€/MWh), net GB Imports (TWh), congestion income (million €), and infra-marginal surplus (million €) for coupled and uncoupled trading over IFA, by year.

We compare the inefficiency of the coupled and uncoupled markets using a range of trading inefficiency metrics, with results shown in Table A12. It is straightforward to see that market coupling reduced the inefficiency of cross-border trading. On average, during 2014-2019, the share of FAPDs fell from 12.1% to a negligible 2.8%, and the Weighted FAPDs (*WFAPDs*) from 1.6% to only 0.1%. *PWIIU*, *UIIU*, and *SCUWED* also considerably decreased.

Electricity year	Market condition	Metrics				
		UFAPD	*WFAPD*	*SCUWED*	*UIIU*	*PWIIU*
2014-2015	**Coupled**	7.6%	0.3%	1.2%	6.8%	0.5%
	Uncoupled	11.7%	1.3%	9.0%	12.9%	3.7%
2015-2016	**Coupled**	4.9%	0.1%	1.0%	4.6%	0.2%
	Uncoupled	8.3%	0.8%	7.0%	9.8%	2.6%
2016-2017	**Coupled**	0.7%	0.0%	8.6%	5.6%	0.6%
	Uncoupled	15.0%	2.0%	12.4%	17.0%	4.9%
2017-2018	**Coupled**	0.2%	0.0%	7.4%	4.2%	0.6%
	Uncoupled	13.4%	2.1%	14.4%	16.2%	5.9%
2018-2019	**Coupled**	0.4%	0.0%	7.4%	4.5%	0.4%
	Uncoupled	12.3%	1.8%	13.4%	14.7%	4.8%
Average 2014-2019	**Coupled**	2.8%	0.1%	5.1%	5.1%	0.5%
	Uncoupled	12.1%	1.6%	11.2%	14.1%	4.4%
2016-2017 w/o CPS	**Coupled**	3.1%	0.1%	4.8%	6.7%	0.7%
	Uncoupled	17.2%	3.5%	17.4%	19.3%	7.0%
2017-2018 w/o CPS	**Coupled**	5.3%	0.2%	4.5%	9.5%	1.3%
	Uncoupled	20.6%	4.3%	19.7%	23.2%	10.3%

Table A12. IFA trading inefficiency with and without market coupling, by year. Key: I_1, I_2, I_3, I_4, I_5 are *UFAPD* (or *FAPD*), *WFAPD*, *SCUWED*, *UIIU*, and *PWIIU*, respectively.

We also simulated the cases where the GB Carbon Price Support (CPS) is removed, finding that when GB and French day-ahead prices are reasonably close (in 2016-2018), and when markets are uncoupled, all metrics of inefficiency would be significantly higher than the cases where the CPS has been implemented and the GB price is much greater than the French price. This is because when prices are closer, it is much more difficult to accurately forecast the sign of price differentials between two markets and the direction of flows, resulting in greater trading inefficiency.

The impact of market coupling was also tested by relaxing the assumption of a British CPS and comparing differences between the coupled and uncoupled market. Average differences in price differential (€/MWh), net imports (TWh), congestion income (million €), and infra-marginal surplus (million €) for coupled and uncoupled trading over IFA between 2016-2018, are reported in the last three rows of Table A11. By removing the CPS, GB prices in 2016-2018 would have been reasonably close to the French price, and so the net imports are close to zero (although this is made up of considerable imports and exports, hence the substantial congestion income). Without the CPS, the impact of uncoupling on congestion income and infra-marginal surplus are slightly higher (by €5.2 million/yr and €1.3m./yr respectively) than in cases with the CPS.

8.4 Simulation results for BritNed

BritNed has an interconnector capacity of 1 GW, or half the 2 GW of IFA. Therefore, the change in flows due to market coupling (relative to uncoupling) may have lower impacts on the BritNed price differential, net imports, and private and social benefit, compared to IFA. As performed for the case of IFA, we begin by comparing the simulated 2013 BritNed DA scheduled commercial exchange with the actual value (from ENTSO-E[16]), with results shown in Table A13.

[16] For BritNed, ENTSO-E only provides the day-ahead scheduled commercial exchange before 2015, or after 2018.

			I_1	I_2	I_3	I_4	I_5
Actual flow 2013, BritNed			15.9%	2.7%	14.2%	18.2%	7.5%
Simulated flow 2013, BritNed	**Parameter Values**						
	$\sigma_{GB,P}$	$\lambda(C'_{GB,h}{}'\sigma)^2$					
	3	4	14.7%	2.2%	9.2%	16.4%	4.8%
	3	5	14.6%	1.9%	11.4%	16.9%	4.9%
	4	5	17.2%	3.2%	11.5%	19.1%	6.7%
	4	***6***	***16.7%***	***2.8%***	***13.7%***	***19.1%***	***6.8%***
	4	7	15.7%	2.2%	16.6%	19.2%	6.9%

Table A13. Day-ahead actual and simulated flows for BritNed.

When $\sigma_{GB,P} = 4$ and $\mu = 6$, the "simulated flow 2013, BriNed" is reasonably close to the "actual flow 2013, BritNed". We therefore assume the values for parameters to simulate the uncoupled BritNed flow during 2015-2018[17] is $\sigma_{GB,P} = 4$ and $\mu = 6$.

We then assess the impact of market coupling on BritNed, with results shown in Table A14. Similarly to IFA, market coupling facilitates price convergence, raises congestion revenue and infra-marginal surplus. GB also imports more thanks to market coupling because the GB price is almost always higher than the Dutch price during the period 2015-2018.

On average, market coupling reduced the price differential between GB and the Netherlands by €0.09/MWh (by 0.6%), increased net imports into GB by 0.42 TWh/yr (by 5.6%), raised congestion income by €1.9 m/yr (by 1.5%), and boosted infra-marginal surplus by €0.9 m/yr (by 0.7% of uncoupled congestion revenue). The impact of market coupling on BritNed is smaller than that on IFA. This is not only because of BritNed's lower capacity, but also because the price differential between GB and the Netherlands is much larger than that between GB and France, meaning there is less uncertainty on the sign of the GB-NL price differential. Uncoupling would therefore result in a lower share of FAPDs and an increase in congestion income and infra-marginal surplus.

Similarly to IFA, the removal of asymmetric carbon taxes would result in spot price convergence between GB and the Netherlands. As a result, uncoupling the interconnector would have higher impact on both congestion income and infra-marginal surplus.

[17] As there is no freely available public data for the BritNed day-ahead scheduled commercial exchange, we use the simulated data from Guo *et al.* (2019).

	Price Difference (€/MWh)			Net Import (TWh)		
Electricity year	**Coupled**	**Uncoupled**	Δ	**Coupled**	**Uncoupled**	Δ
2015-2016	17.00	17.09	-0.09	8.27	7.89	0.38
2016-2017	15.78	15.88	-0.10	7.85	7.41	0.43
2017-2018	12.82	12.91	-0.09	7.71	7.28	0.43
Average	15.20	15.29	-0.09	7.94	7.53	0.42
2016-2017 w/o CPS	9.60	9.38	0.22	4.26	4.70	-0.45
2017-2018 w/o CPS	7.36	7.08	0.28	3.68	4.32	-0.64
	Congestion Income (million €)			**Infra-marginal Surplus (million €)**		
Electricity year	**Coupled**	**Uncoupled**	Δ	**Coupled**	**Uncoupled**	Δ
2015-2016	148.02	146.77	1.24	11.65	11.01	0.63
2016-2017	137.10	135.03	2.07	11.17	10.25	0.92
2017-2018	112.62	110.12	2.51	10.73	9.62	1.11
Average	132.58	130.64	1.94	11.18	10.30	0.89
2016-2017 w/o CPS	87.76	84.08	3.69	9.23	7.25	1.98
2017-2018 w/o CPS	68.89	65.52	3.37	8.53	6.39	2.13

Table A14. Price differential (€/MWh), net GB Imports (TWh), congestion income (million €), and infra-marginal surplus (million €) for coupled and uncoupled trading over BritNed, by year.

Table A15 compares trading inefficiency for BritNed, with and without market coupling, for electricity years 2015-2018. Again, uncoupling increases trading inefficiency. *UFAPD* (*WFAPD*) increased from 3.1% (0.1%) to 7.9% (0.7%), while *SCUWED*, *UIUU*, and *PWIIU* also show substantial increases.

It is also worth mentioning that the metrics (I_1-I_5) shown in Table A15 based on uncoupled markets during 2015-2018 are smaller than the metrics in 2013 (Table A10), where BritNed was also uncoupled. This is because in 2013, the average GB-NL price differential is €7.11/MWh, which was much lower than in 2015-2018, shown in Table A15 (on average €15.2/MWh under market coupling). This confirms our earlier finding where if prices are closer, uncoupling would have a more negative impact on trading inefficiency.

Electricity Years	Market Condition	Metrics				
		UFAPD	***WFAPD***	***SCUWED***	***UIIU***	***PWIIU***
2015-2016	**Coupled**	4.4%	0.2%	3.1%	5.4%	1.1%
	Uncoupled	6.1%	0.4%	3.6%	7.0%	1.7%
2016-2017	**Coupled**	2.5%	0.1%	6.6%	5.6%	2.7%
	Uncoupled	8.1%	0.6%	5.9%	9.5%	3.7%
2017-2018	**Coupled**	2.3%	0.1%	9.0%	6.7%	1.6%
	Uncoupled	9.6%	1.0%	7.1%	11.4%	3.1%
Average 2015-2018	**Coupled**	3.1%	0.1%	6.2%	5.9%	1.8%
	Uncoupled	7.9%	0.7%	5.5%	9.3%	2.8%
2016-2017 w/o CPS	**Coupled**	0.9%	0.0%	8.9%	11.5%	5.2%
	Uncoupled	13.4%	2.0%	13.0%	16.5%	7.4%
2017-2018 w/o CPS	**Coupled**	1.3%	0.0%	10.9%	13.5%	4.4%
	Uncoupled	16.0%	2.6%	14.2%	18.7%	7.0%

Table A15. BritNed trading inefficiency with and without market coupling, by year. Key: I_1, I_2, I_3, I_4, I_5 are *UFAPD* (or *FAPD*), *WFAPD*, *SCUWED*, *UIIU*, and *PWIIU*, respectively.

Without carbon tax asymmetries, the electricity prices between GB and the Netherlands would further converge. As a result, the impact of market uncoupling would be severe, resulting in much higher inefficiency.