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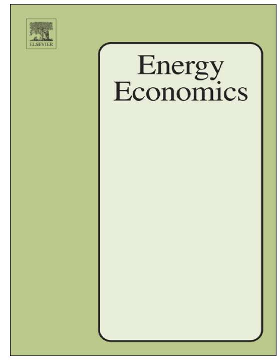

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Where did the time (series) go? Estimation of marginal emission factors with autoregressive components

by

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Abstract

This paper offers a novel contribution to the literature on Marginal Emission Factors (MEF) by proposing a robust empirical methodology for their estimation across both time and space. Our Autoregressive Integrated Moving Average models with time-effects not only outperforms the established models in the economics literature but it also proves more reliable than variations adopted in the field of engineering. Utilising half-hourly data on carbon emissions and generation in Great Britain, the results allow us to identify a more stable path of MEFs than obtained with existing methodologies. We also estimate marginal emission effects over subsequent time periods (intra-day), rather than focussing only on individual settlement periods (inter-day). This allows us to evaluate the annual cycle of emissions as a result of changes in the economic and social activity which drives demand. Moreover, the reliability of our approach is further confirmed upon exploring the cross-country context. Indeed, our methodology proves reliable when applied to the case of Italy, which is characterised by a different data generation process. Crucially, we provide a more robust basis for valuing actual carbon emission reductions, especially in electricity systems with high penetration of intermittent renewable technologies.

Keywords: electricity generation, marginal emission factors, time series analysis, regulation

JEL codes: C22, Q41, Q53

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1 Introduction

Greenhouse gas (GHG) emissions are the main target of energy policy aiming to reduce air pollution and to mitigate the damaging effects of climate change. A rich literature exists which covers the estimation of the intertemporal and spatial patterns of GHG emissions, primarily carbon dioxide (CO_2), produced by electricity generators operating at the margin of the merit order stack, where plants are dispatched in ascending order of marginal costs. The value of these methodological contributions derives from the power of the proposed methods to rigorously assess the impact of energy policy interventions on the GHG emitted by the marginal, price-setting generators operating at a given point in time. There is growing determination, at the national and international level, to implement policies which encourage the displacement of carbon intensive generation by low-carbon technologies and demand-side management (CCC, 2018; EC, 2018). Policy efficacy, however, will fundamentally depend on the carbon intensity of the generators which are displaced, compared to that of the generators replacing them.

Regressing daily carbon emissions on inter-day demand, i.e. within each settlement period, whilst controlling for spatial and/or temporal fixed effects, has formed the workhorse method adopted to estimate Marginal Emission Factors (MEFs) in the existing literature, as discussed in more detail in Section 2. The MEFs estimated herein follow the conventional interpretation, i.e. the carbon intensity of thermoelectric power units of generation (Li et al., 2017). Precise MEF estimates are central to an evidence-based understanding of the efficacy of fossil fuel displacement and to the accurate remuneration of the marginal, rather than average, carbon emission abatement. This approach has enabled researchers to explore the impact of economic events, policy interventions and new technologies on MEFs. Key contributions to this literature have evaluated the environmental impact of the introduction of real-time pricing (Holland and Mansur, 2008), of increased penetration of wind generation

(Callaway et al., 2009), of electricity storage (Carson and Novan, 2013) and of the fracking revolution (Holladay and LaRiviere, 2017). All these contributions investigated the United States' (US) electricity sector.

In this paper we suggest that the current practice could be complemented by exploiting the tools of econometric time series methods and for this reason, we propose the use of Autoregressive Integrated Moving Average (ARIMA) models to estimate MEFs. Our proposed approach involves modelling the time series data generating processes of CO_2 emissions and comparing and testing the outcome against estimates based on established methods in this field, in order to ascertain whether the prevailing empirical methodology is appropriate for modelling the data and to identify previously undetected biases, should they exist.

We contribute to the existing literature on three fronts. First, we establish whether using a time series approach is advantageous compared to the prevailing empirical frameworks. This is achieved by testing for stationarity in the emissions and energy demand time series for each settlement period (i.e. inter-day). We then assess the extent to which our proposed approach improves (in terms of model fit) the estimated MEFs, compared to previous approaches. In a similar way to more established approaches, our method focuses on the marginal contribution to emissions by generators using different types of fuel during specific settlement periods. By concentrating on individual settlement periods one can control for time invariant, intraday fixed effects, such as consumers' demand profiles and general socio-economic conditions.

Second, we propose an alternative approach which requires the estimation of MEFs using half hourly time series (i.e. intra-day). This approach can be computationally demanding, especially if the time series are non-stationary and involve fractional integration parameters. However, the interpretation of the results of this approach is more intuitive, since we can directly estimate the marginal change in emissions as a result of a change in generation from one settlement period to the next (i.e. by time period), as a result of variation in demand behaviour during the day, rather than the variation from one day to the next (i.e. by settlement period) as in the more established (inter-day) approach. For this reason, we defined the MEFs estimated with the former method as 'intra-day MEFs' and those estimated with the latter as 'inter-day MEFs'. From a technical point of view the new approach allows us to consider a larger sample size compared to the 'inter-day MEF' approach, where we rely only on a limited number of observations for each settlement period. The larger number of observations used in the 'intra-day MEF' methods also allows us to generate more robust parameter estimates. Furthermore, this approach permits the evaluation of the impact of policy measures aimed at influencing consumers' behaviour regarding the timing of energy production, storage or consumption activities[1], for instance through the introduction of time-of-use tariffs and real time pricing.

Finally, we establish the extent to which our model performs best across the context of space (i.e. Great Britain and Italy). This allows us to assess whether the proposed methodology is robust when applied to regions which differ by generation mix. The Italian case provides an interesting robustness check in this regard, as the emissions data are processed using disaggregated plant-level hourly information and the electricity generation data represents day-ahead values rather than actual values. We find that our proposed time series models outperform the methods currently applied in the literature in terms of model fit across the context of time and space. Moreover, they generate a more stable path, which can be used more effectively to assess the impact of policy measures on environmental targets and tax revenues, as discussed in section 5. The remainder of the paper is structured as follows: section 2 presents the related literature; section 3 describes the data; section 4 presents our

[1] This change in consumption patterns would be possible for consumers who acquire self-generation facilities, storage technology or electric vehicles.

empirical specification and results, before discussing policy implications and drawing conclusions in section 5.

2 Literature review

We categorise the prevailing methods in the existing literature into two groups. We define the first group as the 'US fixed-effects' approach, while the second is labelled as the 'Hawkes' approach, which was first applied to Great Britain's (GB hereafter) energy system.

The US fixed-effects (US-FE hereafter) approach, which has been utilised to estimate the impact of key policy interventions on marginal emissions, can be traced back to Holland and Mansur (2008) and to an early version of Callaway and Fowlie (2009).[2] The former developed an econometric framework to estimate the impact of demand variance on marginal emissions, while the latter used a similar approach to estimate the change in marginal emissions following the deployment of large-scale renewable generation and energy efficiency projects.

The key equation underpinning the generalised US-FE approach can be described as follows:

$$E_{hrt} = \beta_{hr} G_{hrt} + \alpha_{hr} + \varepsilon_{hrt} \quad (1)$$

where, E_{hrt} represent emissions (e.g. CO_2, Nitrous Oxide or Perfluorocarbons) and G_{hrt} electricity output (generation) at hour $h=1,\dots,H,$ within region $r=1,\dots,R$ of day $t=1,\dots,T$. The vector of time and regional fixed effects is represented by α_{hr} with values equal to 1 for each hour and for each region and 0 otherwise.[3] The hour-region fixed effects α_{hr} measure the average levels of emissions. The idiosyncratic shock is represented by the error term ε_{hrt} which is assumed to follow a Normal distribution.

Crucially, β_{hr} denotes the marginal change in emissions following a marginal increase (or decrease) in electricity output, the so-called marginal emission factor (MEF). In a recent contribution adopting this approach, Callaway et al. (2018) calculate seasonally weighted average point estimates of the MEFs following a unit (MWh) change in renewable generation

[2] Later published as Callaway et al. (2018).
[3] Seasonal indicator variables can also be included (see Callaway et al., 2018).

for six independent system operator regions. According to their results, 896 lbs/MWh (406 kg/MWh) were estimated for California – a region characterised by lower average emissions intensity – and 1870 lbs/MWh (848 kg/MWh) for the Midcontinent Independent System Operator's area – which, in contrast, exhibits a relatively high average emission intensity. Their results indicate that the marginal generators in California and the Midcontinent are most likely combined cycle gas plants (CCGT) and coal plants, respectively, since the estimated MEFs are close to the *Average* Emission Factor (AEF) i.e. the average level of CO_2 emitted within an energy system or by fuel type (Hawkes, 2014; National Grid, 2017).

Holladay and LaRiviere (2017) employ hour, day, and year fixed effects in order "to account for within and across day variation in emission rates" (Holladay and LaRiviere, 2017, p. 206). Importantly, they rely on exogenous variation in the natural gas prices as a result of the introduction of shale gas from fracking to estimate the impact of wind generation on marginal emissions. Their results suggest that, on average, a significant reduction in emissions at the margin (6%) can be attributed to wind generation, while the impact of solar generation at the margin is negligible on average (although with significant regional heterogeneity).

Building on the empirical framework of Holland and Mansour (2008) and Callaway and Fowlie (2009), Carson and Novan (2013) use the spatial and temporal variation in MEFs to simulate the environmental impact of price arbitrage (*i.e.* purchasing electricity off-peak to discharge during peak periods) using storage technology in the form of batteries. Perhaps counterintuitively, the authors' results reveal that charging batteries during the night in order to discharge at the peak the following day could actually *increase* carbon emissions due to the relatively high marginal emission factors associated with the periods of low demand during the night. Similar conclusions were drawn by Graff Zivin et al. (2014) using the case of plug-in electric vehicles as storage facilities.

Other researchers have applied a similar approach to the US-FE method when estimating the rate of pass-through of the costs attributed to carbon trading mechanisms in the power sector. For example, Fabra and Reguant (2014) estimate the impact of marginal emission costs (based on average emission rates) on market prices using linear regression with the inclusion of a suite of fixed effects.

Hawkes (2010) developed a modelling framework for MEFs that is similar to that of Callaway and Fowlie's early work (2009):[4]

$$\Delta E_{hrt} = \beta_{hr} \Delta G_{hrt} + \varepsilon_{hrt} \quad (2)$$

where Δ represents the difference operator and ΔE_{hrt} measures the difference in emissions between current and the preceding day, taking the *h* settlement period as constant, *i.e.*

$\Delta E_{hrt} = E_{hrt} - E_{hrt-1}$ for $h = 1,\ldots,H$, region $r = 1,\ldots,R$ and $t = 2,\ldots,T$, where T is the number of days in the sample period. The same structure applies to generation levels G_{hrt}. The effect of the marginal change in generation (or system load) on the change in system emissions gives rise to Hawkes' estimates of the MEF (β_{hr}).

Hawkes therefore suggests differencing the series in order to estimate a change (difference) in emissions from one period to the next. However, in a time series setting differencing is typically applied to control for seasonal effects, trends or long-run dependence, *i.e.* if the time series of interest is non-stationary of order d, denoted [I(d)], it has to be differenced to make it stationary, denoted [I(0)]. We test the choice of taking differences over time and discuss it further in section 4. Using data for GB between 2002 and 2009, Hawkes arrived at a MEF point estimate of around 690 $kgCO_2$/MWh. In a similar way to the US case, the estimated MEF exceeds the AEF of 510 $kgCO_2$/MWh for GB over the same period. The MEF lies between the AEF for coal and gas, which implies that the marginal generator might be switching between coal and gas fired power plants, on average, in the short-run.

[4] Note that in Hawkes' investigation, the subscript *r* denotes the whole of the GB energy system.

It is noteworthy that Hawkes (2010)' seminal paper considers short-run MEFs. Long-run MEFs, which encompass system-wide structural changes for the duration of a given intervention,[5] were proposed later (Hawkes, 2014). Small, short-run structural changes are relevant here, not only because this conceptual framework provides a consistent basis for comparison across the economic and technoeconomic literature cited above and is appropriate for the timescale of the present analysis (up to a couple of years, rather than decades).

Hawkes' short-run approach forms the basis for recent studies on emission displacement resulting from increased wind power (Thomson et al., 2017) and wind and solar power (Jansen et al., 2018; Li et al., 2017) in GB and the US. Jansen et al.'s approach to estimating MEFs is closest to our intra-day approach as they aggregate half-hourly information to daily frequency to be used in their regression analysis. They argue in favour of such aggregation by stating that "half-hourly [MEFs] may not reflect start-up and shutdown behaviour of power plants correctly. Accumulating the data set to daily averages alleviates this problem" (Jansen et al., 2018: 4). Their estimated MEFs for 2017 are of similar magnitude to those obtained in this paper, however their reliance on Hawkes' approach, as we discuss later, could be reconsidered on the grounds of greater methodological accuracy of our proposed approach[6]. Furthermore, their work differs from ours as the focus of their analysis is the effect of partial load of fossil fuel plants on MEFs calculations rather than the methodological issue of seeking a correct dynamic specification for the chosen regression equation.

[5] In a similar vein, whilst regression analysis is established as a precise yet flexible approach for short-run system-level phenomena, power plant dispatch simulation models may provide a credible alternative for long-run analyses, particularly when high frequency data is unavailable (Deetjen and Azevedo, 2019). Moreover, Deetjen and Azevedo (2019) recently identified that regression estimates of MEFs achieve lower error compared to dispatch modelling, hence lending further support to the approach proposed in the present paper.

[6] It is important to point out that Jansen et al.'s results should be considered as preliminary because their data do not allow them to correctly account for plants' start up and shutdown behaviour.

3 Data sources and description

We obtained the carbon-based generation data from ELEXON's 'instantaneous generation by fuel type' BMReports for all settlement periods between 01/01/2017 and 09/11/2018.[7] ELEXON is responsible for assessing and pricing the difference between proposed and actual electricity volumes in the UK. Our analysis relies on actual half hourly generation for combined cycle gas turbine (CCGT), open cycle gas turbine (OCGT), coal, oil, biomass and 'other'[8]. We follow this approach in order to avert biasing our marginal emission estimates, since non-fossil fuel generation (i.e. nuclear, hydro power, solar, wind) might be correlated with net load (as discussed by Callaway et *al.* (2018)). For this reason, it is noteworthy that we estimate marginal emissions for actual electricity generated, rather than electricity supplied to the grid plus imports via interconnectors (e.g. France, Netherlands), since ELEXON provides data on total actual generation imported which comprises fossil and non-fossil generation (*e.g.* electricity from nuclear generation is likely to be imported from France, as nuclear represents a much greater share of France's electricity generation). Moreover, the utilisation of national generation data, rather than load, hones in on the carbon intensity of generation, instead of consumption-based carbon intensity which suffers relatively more from the complexities associated with carbon accounting, particularly in the presence of cross-border flows (Tranberg et al., 2019).

We calculate total emissions E_{th} per settlement period h at day t as follows:

$$E_{th} = \sum_{f=1}^{F} G_{fth} \cdot c_f \tag{3}$$

[7] Data publicly available via: https://www.bmreports.com.
[8] Other includes non-fuel oil (e.g. gas diesel oil), coke and non-natural gas (e.g. blast furnace gas, refinery gas, waste/recovered gas from chemical processes) (BEIS, 2017).

where, G_{fth} and c_f denote generation of the fossil-fuel type f and the respective carbon intensity factor for fuel type f (see National Grid, 2017, Table 1).[9]

Table 1 presents the summary statistics for CO_2 emissions (tonnes) and fossil-fuel generation (MWh) between 2017-01-01 (00:00) and 2018-11-09 (23:30). Each observation represents a single half-hourly settlement period per day: for example, the first settlement window opens at 00:00 and closes at 00:30 each day. We have a complete set of observations for more than 30,000 settlement periods[10]. During this period, on average, 4.75 kilotons (kt) of carbon were emitted per settlement period and fossil-fuel generation averaged at 16.5 GWh per settlement period.

[INSERT TABLE 1 ABOUT HERE]

The summary statistics for CO_2 emissions and fossil-fuel generation in Table 1 are organised by season and show a pattern according to which CO_2 emissions rise during the autumn, peak in the winter and fall throughout the spring and reach the trough in summer.[11]

4 Model specification and results

This section presents our model specification which relies on two different approaches. The first approach sets out to estimate MEFs by settlement period as standard in the existing literature (i.e. inter-day analysis). Second, we estimate MEFs over the complete time series by season and by month (i.e. intra-day analysis). As will become apparent, the unit-root and stationarity tests and the information criteria favour the ARIMA or Autoregressive Fractionally Integrated Moving Average (ARFIMA) model over the US approach and in most instances over Hawkes' model with time effects. The same holds when moving from the time dimension to space, which we perform using Italian data in addition to GB data.

[9] Both generation and carbon emission data have been adjusted for daylight saving time (*i.e.* from UTC to BST).
[10] More precisely: N = 32,544 = 678 (days) x 48 settlement periods.
[11] Summary statistics for each 48 half-hourly settlement period for carbon emissions and fossil-fuel generation can be found in Tables A1 and A2 in the Reviewers' Appendix.

4.1 Across time: The inter- vs. intra-day context

Figure 1 presents the time series (TS), autocorrelation functions (ACF) and partial autocorrelation functions (PACF) of the residuals estimated using the seasonally adjusted and detrended CO_2 series for selected settlement periods taking place during the morning peak (08:00) and evening peak (19:00) and in two night-time periods (03:00 and 23:00). The plots have been produced using the residuals of a linear regression which removes seasonal effects by regressing CO_2 emissions on time indicators (*i.e.* day, month and year), a linear time trend and two indicators controlling for two unusually cold weather events.[12] In light of these events, we performed a unit root test that is robust to the presence of structural breaks.

[INSERT FIGURE 1 ABOUT HERE]

The time series and autocorrelation functions exhibit the properties of a stationary Autoregressive (AR) process of order 1 or at most an AR(2) series.[13], as confirmed by the test statistics for the Augmented-Dickey-Fuller (ADF), Phillips-Perron (PP) and Clemente-Montañés-Reyes (CMR) unit root tests and for the Kwaitkowski-Phillips-Schmidt-Shin (KPSS) and robust (RKPSS; see Pelagatti and Sen, 2013) stationarity tests listed in Table 2. The robust version is applied as the KPSS test can be biased in the presence of jumps in electricity generation (Grossi and Nan, 2019). The former three tests unanimously reject the null hypotheses of a unit root, while the latter two KPSS tests cannot reject the hypothesis of stationarity (*i.e.* short memory process) excluding one case at the 5% level.

[INSERT TABLE 2 ABOUT HERE]

An important consequence of these findings is that Hawkes' model does not represent, from a statistical perspective, the most parsimonious approach for estimating inter-day MEFs in the

[12] The 'Beast from the East' hit the UK between 24th February 2018 and 4th March 2018 and the 'mini-Beast from the East' followed during 17th March 2018 and 19th March 2018. All fixed time effects, excluding monthly seasonality, are not significant at conventional levels. Several series are detrended due to a generally weak but significant trend parameter (10% level).

[13] Similar results are observed when focusing specifically on average peaks (06:30-10:30 and 16:30-20:30) and average off-peaks (00:00-06:00; 10:30-16:30; and 20:30-23:30).

time period we examine for GB. Neither the autocorrelation functions nor the unit root and stationarity tests point towards the need to use the first difference of the carbon emissions series. In light of this result, we present the Hawkes and Hawkes-FE estimates only in the Appendix[14] and consider them as a robustness check. Going forward we focus on comparing our findings derived from the ARIMA model to the US-FE model, since both models are estimated in levels rather than differences.

We depart from the preceding literature by explicitly modelling the time series data generating process. This is achieved by utilising an ARFIMA model, whilst controlling for the time-effects, as per the US-FE approach, thereby labelling our model as ARFIMA-FE. Identifying the autoregressive and moving average structure of the emissions time series is needed in order to account for the dependence pattern of the data generating process. Time series data are often characterised by autocorrelation between the current and past periods. The order of the autoregressive and moving average process will be selected by using the Akaike and Bayesian information criteria.

However, a crucial assumption of ARMA models is the stationarity of the data generating process. Electricity prices and consumptions time series have been found to have long memory (see for instance Gianfreda and Grossi, 2012) which implies that the hypotheses of unit root and stationarity are both rejected. When a unit root hypothesis is rejected differentiating the original time series is not justified and for this reason MEFs estimated on the basis of the first difference of carbon emissions are questionable. On the other hand, when stationarity is rejected, it is necessary to introduce a possible order of fractional integration.[15] Indeed, some of the existing literature acknowledges time series elements contained within emissions data. For example, Carson and Novan (2013), Graff Zivin et al. (2014) and Holladay and LaRiviere (2017) control for serial correlation (and heteroskedasticity) using

[14] Reviewer's appendix, Tables A4 and A7.
[15] Represented by the 'FI' term in the ARFIMA abbreviation

Newey-West standard errors and clustering at either daily or hourly frequency. All key papers discuss issues surrounding seasonality.

The current literature does not specify the benefits of the current fixed effects method over a time-series approach, which explicitly accounts for the time-dependency of the data. The final goal is to take into account the autocorrelation of the residuals whilst estimating the marginal effect of electricity generation on emissions. To explore this issue, we employ the following regression model with ARFIMA errors[16]:

$$\Phi_p(L)(1-L)^d(E_{th}-\beta_h G_{th}) = \alpha_h + \Theta_q(L)\varepsilon_{th} \tag{4}$$

with $\varepsilon_h \sim WN(0, \sigma^2)$. As it has been established that the daily series used to estimate inter-day MEFs are stationary (see Table 2), the specification in Equation (4) is simplified to a standard ARMA, since the order of integration (d) equals zero:

$$\Phi_p(L)(E_{th}-\beta_h G_{th}) = \alpha_h + \Theta_q(L)\varepsilon_{th} \tag{5}$$

where L represents the lag operator, with $\Phi_p(L) = 1 - \sum_{i=1}^{p} \phi_i L^i$ and $\Theta_q(L) = 1 + \sum_{i=1}^{q} \theta_i L^i$ denoting the autoregressive (AR) and moving average (MA) polynomials, respectively. In this framework, the estimated coefficient $\widehat{\beta_h}$ has the same interpretation as in static regression shown in equation (1). Thus, in the case of estimating inter-day MEFs per settlement period neither integration, nor fractional integration, is required and our models have a simple ARIMA structure with zero order of integration.[17]

We account for seasonality α_{hr} using hour, month and year indicators and follow the more established literature by estimating the MEFs per cross-section of time, in our case for each

[16] The authors wish to thank an anonymous referee who has suggested the correct notation of the regression model with AR(F)IMA errors.
[17] The ARIMA order terms were selected on the basis of minimising the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), and generally specified as ARIMA(1,0,1), ARIMA(2,0,1) or ARIMA(1,0,2).

half hourly settlement period h = 1,…,48. It is important to note that the time indicators included are consistent across models in order to compare model fit – in other words we ensure that the US-FE model is nested within the ARIMA and that both models are nested within the ARFIMA. Moreover, we use robust standard errors to account for heteroskedasticity.[18] As in the unit root and stationarity tests, we include indicator variables to control for unusually cold events. Although the KPSS tests have not rejected the hypothesis of stationarity, the ARFIMA model is implemented, together with the Hawkes models, as an additional robustness check, with order of integration d in Equation (4) required to fall between -0.5 and 0.5.

In addition to the approaches discussed above, we also estimate MEFs using a more 'natural' or intuitive approach, that is, over a complete time series by meteorological season and by month, rather than within cross-sections of settlement periods day-on-day. As stated in the introduction, the estimated MEFs are labelled "intra-day" MEFs because they measure the emission changes connected to changes in consumption driven by underlying patterns of weather, which can be captured only when contiguous settlement periods are considered and compared over time. The parameters of interest are estimated by splitting the original time series into sub-series related to different seasons and months.[19]

Whilst all unit root tests presented in Table 3 suggest that the series by season are stationary, the RKPSS test consistently rejects the null of stationarity. Moreover, given the fact that the residuals' time series and (partial) autocorrelation plots are at odds with the unit roots tests (Figure 2), it is clear that the series are fractionally integrated.[20] Therefore, in contrast with

[18] The errors are robust and clustered by day for all other models (i.e. US-FE, Hawkes and Hawkes-FE) in order to capture serial correlation and heteroskedastic errors. The results are similar to those estimated using Newey-West standard errors.
[19] This approach has been applied in order to work with tractable sample sizes for the estimation of the computationally intensive fractional integrated ARIMA processes described in Equation (4) and Equation (5).
[20] A similar pattern emerges in tests on series split by month (See Table A5 in the Reviewers' Appendix). Taking this information together with Figures A.2 (A – F) we conclude that the monthly series are also likely to be fractionally integrated.

the *inter-day* approach which points towards ARIMA as the best fitting model, the *intra-day* approach appears to require ARFIMA.

[INSERT TABLE 3 ABOUT HERE]

[INSERT FIGURES 2 ABOUT HERE]

Figure 3 presents the average inter-day MEFs per half hourly settlement period for the following models: 1) the 'US-FE' (*i.e.* linear regression controlling for time-effects); 2) our ARIMA-FE and 3) the 'ARFIMA-FE' models; 4) the 'Hawkes' approach (*i.e.* linear regression in differences) and 5) the 'Hawkes-FE' model with time effects[21].

[INSERT FIGURE 3 ABOUT HERE]

The similarity between the ARIMA-FE and ARFIMA-FE estimates of inter-day MEFs clearly shows that the latter does not add much in the way of explanatory power and confirms the outcome of the unit root and stationarity tests in the sense that differencing the series (even fractionally) is unjustified. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) support the more parsimonious approach since in the majority of cases the criteria values are minimised by the ARIMA-FE model (Table 4)[22]. In the large majority of cases the information criterion values for ARIMA-FE fall below those of the US-FE model and of the ARFIMA-FE, hence, the ARIMA-FE outperforms all others in terms of model-fit.

[INSERT TABLE 4 ABOUT HERE]

In Figure 3 the ARIMA-FE results lie between the US-FE and Hawkes-FE and appear to generate an average path for marginal emissions between these models. This is, in our opinion, a key advantage of the general ARIMA approach because it generates the most stable trajectory over time, compared to the traditional models. The stable trajectory refers to

[21] The point estimates for all GB models are provided in the Reviewers' Appendix (see Tables A3- A4)
[22] See Table A6 in the Reviewers' Appendix for the results covering the period 13:00-23:30 and Table A7 for information criteria values for Hawkes and Hawkes-FE models.

the most precise path of MEFs estimated across models. The increased stability of the parameters according to our proposed approach is most notable when observing: 1) the path of the ARIMA-FE and ARFIMA-FE results, in Figures 3 to 5[23]; and 2) the variation level and the coefficient of variation for the ARIMA-FE and ARFIMA-FE MEFs estimates which are at most equal to and in nearly all cases lower than for the established approaches (Table 5) thereby lending support to the claim that our approach improves the precision of MEF estimation[24].

[INSERT TABLE 5 ABOUT HERE]

It is noticeable that the US-FE estimates (dashed line in Figure 3) paint a slightly different picture to all others. Whilst peaks and troughs for carbon emissions follow a similar path there is an almost fixed difference of around 50 $kgCO_2/MWh$, on average. Given the fact that the choice of the ARIMA model is supported by the information criterion, it could be argued that the approach currently taken in the literature, which relies upon controlling for fixed effects, is biased upwards. A similar argument can be applied to the Hawkes approach, which appears biased towards zero in the range of 2 $kgCO_2/kWh$, on average.

[INSERT FIGURE 4 HERE]

The ARFIMA-FE model was also applied to a complete set of half-hourly time series of emissions on generation by season (Figure 4a – 4c). The AR and MA orders are selected by minimising the Bayesian Information Criterion (Table 6). As with the preceding analysis we present the estimated intra-day MEFs for all models for comparative purposes.

[INSERT TABLE 6 ABOUT HERE]

The estimated intra-day MEFs at seasonal frequency appear to be highest in winter both according to our method and to the more established ones, as would be expected (Figure 5).

[23] See also low values of standard errors for the point estimates listed in Tables A3- A4 in the Reviewers' Appendix.

[24] It is worthwhile noting that when the inter-day MEFs are estimated using 47 half hourly indicators interacting with fossil-fuel generation, rather than breaking the sample down into 48 cross-sections, the ARIMA-FE model always provides a better model fit (Reviewers' Appendix, Table A8 and A9).

The seasonal oscillation between 400 $kgCO_2$/MWh and 550 $kgCO_2$/MWh across warmer and cooler periods becomes even clearer upon estimating the MEFs by season and by month. All the estimation methods identify a declining trend in MEFs from February to August driven by declining demand in warmer months.[25]

In the case of intra-day MEFs, we find that our ARFIMA-FE approach generates a more stable path when adopting either the season or the month as the period of observation. This is particularly true when compared with the Hawkes approach which presents a rather 'spiky' profile when using the seasonal disaggregation, while the 'spiky' behaviour is observed when applying the US-FE approach at the monthly level of aggregation (Figures 5 and 6).

[INSERT FIGURES 5 AND 6 ABOUT HERE]

The comparison between inter-day MEFs and intra-day MEFs estimates leads us to the following considerations: 1) using the concept of intra-day MEFs it is possible to make an efficient analysis of the annual cycle of emissions which is not allowed by inter-day MEF approach because of small sample sizes; and 2) when we estimate intra-day MEFs with Hawkes' method the results are very similar to those of the ARIMA method[26]; when estimating inter-day MEFs, the ARIMA procedure produces more stable results than those obtained with the Hawkes method.

4.2 Across space: The Italian context

We now proceed to explore the validity of the ARIMA models across space by applying our suggested approach to Italian (IT) data. Moreover, to our knowledge, this is the first paper to provide an empirical cross-country comparison of MEFs.

[25] The ARFIMA-FE model outperforms the ARIMA-FE in 64% (46%) of cases according to AIC (BIC) – this is not surprising considering the increased tendency to reject the null of stationarity under the KPSS tests (See Table A13 in the Reviewers' Appendix). Note also that the absolute value for the order of integration $|d|$ lies between 0 and 0.5 for all seasonal and monthly estimates and significantly different from 0 in all but 6 months between 2017 and 2018.

[26] However, it is important to note that the ARFIMA-FE fits the data best when estimating seasonal MEFs in all instances (Reviewer's Appendix, Table A11); when estimating MEFs by season and by month the ARIMA-FE and ARFIMA-FE fits the data best for 100% (20%) of the time compared to Hawkes-FE according to AIC (BIC). The BIC results indicate that when using monthly series the order of integration switches between $0<d<1$ and [I(1)], hence the similarity between Hawkes' model (once time effects are included).

The Italian case offers several interesting empirical opportunities. The first relates to deriving CO_2 emissions using fossil-based plant level data – similar to the approach adopted in the US – an approach not feasible for GB at the time of the study due to the lack of access to reliable disaggregated data on emissions, as also discussed by Jansen et al. (2018)[27]. The second and third salient opportunity relates to the fact that only *hourly* and *accepted generation* on the day-ahead market data is available in IT rather than actual generation as in GB. Whilst it is reassuring that the Italian data represents nearly 80% of final actual ex-post generation (Terna, 2019), we believe our method should have the necessary cross-country flexibility to outperform competing models even when: 1) CO_2 is derived from disaggregated data; 2) a proxy needs to be utilised when actual generation data is unavailable; and 3) the data is processed at a more aggregate (hourly) level.

Our data on IT carbon-based generation – coal, natural gas, oil and oil/natural gas – covers hourly accepted settlement periods in 2018[28]. The Italian day-ahead market (Mercato del Giorno Prima, MGP) data is sourced from the supply and demand bids, reported for each unit of production, monitored by the Italian electricity market operator (Gestore dei Mercati Energetici, GME)[29] Emissions are calculated at the plant level prior to aggregating to the national level per hour as follows:

$$E_{i,th}^{f} = \sum_{f=1}^{F} g_i^f(Q_{i,th}) \cdot e_f \cdot \lambda \tag{7}$$

where *i* represents individual power plants, g(Q) is the plant-level generation model and λ the Gcal/h to TJ/h conversion factor (Beltrami et al., 2020). The data contains *N=8760* complete observations. In 2018, generation and carbon emissions averaged at 15.2GWh and 8.36kt

[27] Note also that, as pointed out by Jansen et al. (2018), efficiency data is unavailable for many individual plants in GB, as such the authors applied the same baseline carbon intensities as in our paper to 147/234 (62%) of generators units used in their analysis.
[28] As with GB, we approach the seasonal analysis meteorologically. However, with only one year of Italian data, we break the seasons into five periods: Winter 17/18 (January-February 2018), Spring 18 (March-May 2018), Summer 18 (June-August 2018), Autumn 18 (September-November 2018) and Winter 18/19 (December 2018).
[29] Data publicly available via: https://www.mercatoelettrico.org/It/Download/.

respectively. Accordingly, the average emissions factor is 537 $kgCO_2$/MWh. In comparison, the Climate Transparency (2017) reports that the average carbon emission intensity in Italy stands at around 331 $kgCO_2$/MWh – including all fossil and renewable generation.

For brevity, we present the key analytical insights together with the MEF plots (Figures 7 to 9)[30]. In the first step, we remark on the behaviour of the ACF and PACF plots for both *inter-day* and *intra-day* CO_2 seasonally adjusted series. Whilst the ACF *inter-day* correlation dies out quicker in Italy (6 days) than GB (16 days), the PACF behaves almost identically to GB with the initial significant partial correlation $\varphi_{11} \approx 0.6$. Likewise, the IT and GB *intra-day* series show similar traits in the ACF plot (with correlations dying out after >100 hours) and the PACF displaying either AR(2) or AR(3) characteristics with φ_{11} close to but strictly less than 1.[31]

In the second step, we can confirm that the unit root tests reject the presence of a unit root in the *inter-day* series.[32] As in the GB case, the KPSS and RKPSS tests cannot reject the null of stationarity. Differencing will lead to misspecification, so that the Hawkes approach can be ruled out. The *intra-day* series by season behave like the GB series, that is the tests unanimously reject the presence of a unit root and concomitantly the null of stationarity ((R)KPSS) is rejected. From this it is possible to infer that differencing would be unwarranted. As mentioned previously however, the seemingly contradictory outcomes between the unit root and stationarity tests is indicative of partial integration and the need for ARFIMA in the intra-day context.

The (P)ACF plots and tests for a unit root and stationarity indicate that the analysis should rely on models in levels, such as the US-FE, ARIMA-FE and ARFIMA-FE. We note that the

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[30] All other tables and figures can be made available upon request
[31] See Reviewers' Appendix, Figure A.3.
[32] I.e. the generalised ADF and PP tests. Whilst the ADF test stands apart from all others in failing to reject a unit root, the generalised ADF rejects the null all but six times. Unit root tests allowing for unknown structural breaks to account for extreme weather events support these findings.

ARFIMA-FE 'nests' ARIMA-FE which also nests the US-FE model, and this allows us to perform tests of model fit. The AIC and BIC support ARFIMA-FE over ARIMA-FE and US-FE both for the inter-day and intra-day approaches. In support of ARFIMA, the estimate of the absolute value of the partial order of integration $|d|$ lies between 0 and 0.5 for all but one season (Winter 2017) and one month (September 2018).

Figure 7 presents the inter-day MEFs, whilst Figure 8 and Figure 9 display the seasonal and monthly intra-day MEF plots for Italy, respectively. Overall the MEFs centre around 600 kgCO_2/MWh to 607 kg/MWh, markedly higher than Italy's national AEF of 331 kgCO_2/MWh. On average, the marginal plants are likely to be Open Cycle Gas Turbine (OCGT) plants, which typically have a carbon intensity close to 600 kgCO_2/MWh. The season-on-season changes (Figure 8) become more apparent month-by-month (Figure 9), where the winter months approach 550 kgCO_2/MWh compared to the 650 kgCO_2/MWh during the remaining months of the year.

[INSERT FIGURES 7 TO 9 ABOUT HERE]

Furthermore, according to Figure 7, the Hawkes model tends to underestimate the inter-day MEFs compared to ARIMA[33], while the US approach tends to overestimate it. In contrast, the Hawkes model appears to overestimate the seasonal intra-day MEFs, while the opposite holds for the US model. Reassuringly, as established in GB, the ARIMA-FE and ARFIMA-FE inter-day and intra-day estimate MEFs present the most stable path. This finding further validates our approach as IT data provides important contextual differences, not only geographically, but also in terms of the data generation process (i.e. firm-level aggregation, hourly level frequency, accepted rather than actual generation).

[33] The average inter-day MEF for US-FE is 617 kgCO2/MWh and 607 kgCO2/MWh for ARIMA-FE. In contrast, the US-FE average intra-day is 594 kgCO2/MWh and 602 kgCO2/MWh for ARIMA-FE.

5 Policy implications and conclusions

According to our results the MEFs estimated using ARIMA in the inter-day approach (within settlement period) and ARFIMA in the intra-day (across settlement periods) approach are consistent, but more stable than those which would be obtained using other established methods. The estimated values however are significantly different and higher than the average effects[34] published for 2016 by the UK's Department for Business, Energy and Industrial Strategy (BEIS, 2018) which represent the official UK GHG measure used for policy purposes, including environmental policy.

To illustrate the potential policy implications of our results, in environmental and financial terms, we calculate: 1) the average and median of the MEFs estimated by each model within the inter and intra-day classes. This allows us to gauge the impact of the displacement of fossil-based generators operating at the margin compared to using AEFs which consider the whole generation fleet or a single fuel type[35]; and, 2) the revenue effect, that is, the total revenue collected or lost on average by UK's HMRC via the carbon price support[36] (CPS) for plants operating at the margin. The latter is also important for understanding the implied rate of cost pass-through applied to consumers by electricity generators operating at the margin or the saving accruing to consumers as a result of generators displaced at the margin.

Table 7 presents BEIS' most recent AEF (281 $kgCO_2/MWh$) for electricity generated (i.e. supplied to the grid) in 2016 (BEIS, 2018: 26). Alongside this, we include the AEF for CCGT (394 $kgCO_2/MWh$, according to National Grid, 2017). The AEFs are held constant (Columns 1-2, Table 7) whilst comparing the average and median of the MEFs estimated by key models in the present paper, i.e. US-FE, HAWKES-FE, ARIMA-FE (inter-day) and ARFIMA-FE

[34] A sizeable difference between estimated marginal and average effect factors is consistent with the results obtained by Hawkes (2010) for the UK and Callaway et al. (2018) for the US.
[35] Our analysis focuses on CCGT for comparative purposes given that our best estimates of the MEFs are closest to this fuel's average emission factor.
[36] The carbon price support is added on to the European Union's Emission Trading Scheme (EU ETS) price in order to meet the Carbon Price Floor (CPF) introduced by the British Government in 2013.

(intra-day) (Columns 3-8). It is important to note that the comparisons focus specifically on CCGT as this fuel type appears to operate most frequently at the margin in GB based on our estimated MEFs and the average/median of the inter-day and intra-day seasonal MEFs presented for the key models in Table 7.

[INSERT TABLE 7 ABOUT HERE]

Concentrating on the BEIS and CCGT AEF benchmarks, for every MWh increase in renewable generation or demand-side response, the AEFs appear to underestimate the amount of CO_2 emissions displaced at the *margin*. For example, the AEFs are around 153.3 $kgCO_2$ and 42.3 $kgCO_2$ lower, respectively, in comparison with the median MEFs estimate by the ARIMA-FE model.

In contrast, the median of the inter-day MEFs estimated using US-FE and HAWKES-FE appear to overstate CO_2 emissions displaced at the margin by 1.56 $kgCO_2$ and 13.8 $kgCO_2$, respectively, in comparison with the ARIMA-FE model. Similarly, the median of the intra-day MEFs overestimate emissions by 6.53 $kgCO_2$ and 7.38 $kgCO_2$, respectively, compared with the ARFIMA-FE model.

Table 7 presents several potential values of the carbon price to shine further light on the amount of revenue potentially collected or lost at the margin as a result of a 1MWh variation in fossil-based electricity generation. For example, the 2015/2016 HM Treasury's budget set the carbon price support to £18.08/tCO_2 (Hirst, 2018; Staffell and Wilson, 2018). The amount paid by electricity generators is simply the difference between the UK's target carbon price and the EU ETS carbon price, accounting for variation in carbon intensity:

$$\textit{CPS Rate (£/MWh)} = \textit{(Target Price – EU-ETS Price) x (Average Emission Factor}_j\textit{)} \quad (7)$$

Based on this formulation, relying on AEFs, HMRC would expect to collect revenues equivalent to £7.12/MWh (£18.08/tCO_2 x 0.394 tCO_2/MWh) from CCGT installations operating at the margin. This is equivalent to £0.77/MWh less than if HMRC used the average of the ARIMA-FE (inter-day) MEF estimates and £0.80/MWh less than the average of the ARFIMA-FE (intra-day) MEF estimates. By contrast, using the average of the MEFs estimated by the US-FE and HAWKES-FE models would lead to implied revenues that are too large: between £0.03/MWh and £0.25/MWh for the inter-day MEFs, and around £0.18/MWh for the intra-day MEFs. It is important to note that these differences are conservative compared to rates closer to a realistic value of the social cost of carbon.[37]

Let us further suppose, for example, that marginal displacement of generators represents 1% of total fossil-fuel generation. Under the inter-day MEF approach, the US-FE and HAWKES-FE estimates would imply that the HMRC would have collected between £0.04m and £0.38m extra from fossil-based generators operating at the margin in 2017 relative to the ARIMA-FE estimates, whilst their intra-day MEF estimates imply additional revenues of £0.28m. Charging generators according to the MEFs could help to correct the cross-subsidisation effects that occur under the current CPS methodology which, at the margin, charges too much during periods of high emission intensity and too little during periods of low intensity[38]. Our results would also suggest that firms are currently paying less than would be required if the marginal plants were charged a rate which reflects marginal, rather than average, emissions.

At the European level, the differences in the estimated GB and IT MEFs can provide useful guidance to national policy makers in their process of implementation of the Clean Energy for all Europeans package (European Commission, 2019). Our results suggest that European regulators should consider cross-country differences – apparent in GB and IT MEFs – and identify the most robust methodologies to evaluate the replacement of emissions attributed to

[37] We considered the following values: £19 (Stern, 2007); £20 (EU-ETS: Sandbag, 2019); and £31 and £64 (World Bank, 2017).
[38] See Figures A.4 and A.5 in the Reviewers Appendix.

the deployment of plants operating at the margin when devising incentive schemes for the reduction of fossil fuel generation in the national energy systems .

To conclude, this paper has proposed a robust methodology to estimate MEFs and applied the proposed approach to the analysis of CO_2 emissions data for GB between January 2017 and November 2018. The proposed inter-day ARIMA and intra-day ARFIMA models with fixed time-effects not only outperforms all the existing methods, but also provides a more stable trajectory of results, making it a more predictable and reliable source of information for emissions-related policy interventions. Our results indicate that CCGT plants are predominantly operating at the margin in the GB system. This pattern is most salient during the morning (00:00-07:00) and the evening (18:00-23:30) as the estimated MEFs in those periods approach the average emission factors of CCGT plants, i.e. 394 $kgCO_2$/MWh (National Grid, 2017). We are also able to identify, relying on a relatively large number of observations, a significant difference in MEFs across seasons and months of the year. Moreover, the ARIMA and ARFIMA models are found to be consistent across space. Whilst the IT context created some empirical challenges, we found that also in this context our time-series-based approach consistently outperforms all other models, and provides an even more stable path of MEFs with OCGT plants generally being displaced at the margin (at approximate values of 600 kg/MWh). Finally, our proposed approach provides a more robust basis for the valuation of actual, as opposed to average, carbon emission reductions which can be effectively used in the future to assess the impact of environmental policies across different countries. Indeed, our approach not only has implications for establishing the revenue effects at the margin, but also provides a more rigorous basis for the compensation of storage, demand response and other flexible technologies which displace fossil-fuel generation at the margin. These developments are crucial for future research attempting to include renewable generation within regression-based models of MEFs. This is an issue of increasing importance across energy systems characterised by high penetration of intermittent renewable energy, given the challenging conditions for the commercial viability of untested technologies and business models.

References

Beltrami, F., Fontini, F. and Grossi, L. (2020) The value of carbon emission reduction induced by renewable energy sources in the Italian power market. *University of Padua mimeo.*

Callaway, D.S. and Fowlie, M. (2009) Greenhouse gas emissions reductions from wind: Location, location, location. *Working Paper, AERE Workshop, Washington DC.*

Callaway, D.S., Fowlie, M. and McCormick, G. (2018) Location, location, location: the variable value of renewable energy and demand-side efficiency resources. *Journal of the Association of Environmental and Resource Economists*, 5(1): 39-75.

Carson, R. T. and Novan K. (2013) The private and social economics of bulk electricity storage. *Journal of Environmental Economics and Management*, 66: 404-423.

Climate Transparency (2017) Brown to green: The G20 transition to a low carbon economy. [online] http://www.climate-transparency.org/g20-climate-performance/g20report2017 (Accessed 9th December 2019).

Committee on Climate Change (2018) Reducing UK emissions: 2018 progress report to Parliament. London, United Kingdom: CCC.

Deetjen, T.A. and Azevedo, I.L. (2019) Reduced-order dispatch model for simulating marginal emissions factors for the United States power sectors. *Environmental Science and Technology*, 53: 10506-10513.

Department for Business, Energy and Industrial Strategy (2017) *Electricity statistics – data sources and methodologies*. London, United Kingdom: HM Government.

Department for Business, Energy and Industrial Strategy (2018) *Government GHG conversion factors company reporting. Methodology paper for emission factors: final report, July*. London, United Kingdom: HM Government.

European Commission (2018) A clean planet for all: A European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy. COM(2018) 773 Final. Brussels, Belgium: EC.

European Commission (2019) Clean Energy for all Europeans. [online] https://op.europa.eu/en/publication-detail/-/publication/b4e46873-7528-11e9-9f05-01aa75ed71a1/language-en?WT.mc_id=Searchresult&WT.ria_c=null&WT.ria_f=3608&WT.ria_ev=search (Accessed 2nd January 2020).

Fabra, N. and Reguant, M. (2014) Pass-through of emissions costs in electricity markets. *American Economic Review*, 104(9): 2872-2899.

Financial Times (2017) Europe has a problem with its SUV habit. [online] https://www.ft.com/content/2967c9c2-ffc3-11e9-b7bc-f3fa4e77dd47 (Accessed 31 December 2019).

Gianfreda, A. and Grossi, L. (2012) Forecasting Italian electricity zonal prices with exogenous variables. *Energy Economics*, 34 (6): 2228-2239.

Graff Zivin, J. S., Kotchen, M.J. and Mansur, E. T. (2014) Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies. *Journal of Economic Behaviour and Organization*, 107: 248-268.

Grossi, L. and Nan, F. (2019) Robust forecasting of electricity prices: Simulations, models and the impact of renewable sources. *Technological Forecasting and Social Change*, 141: 305-318.

Hawkes, A.D. (2010) Estimating marginal CO_2 emissions rate for national electricity systems, *Energy Policy*, 38:5977-5987.

Hawkes, A.D. (2014) Long-run marginal CO_2 emissions factors in national electricity systems. *Applied Energy*, 125: 197-205.

Hirst, D. (2018) Carbon Price Floor and the price support mechanism. *House of Commons*, Briefing Paper No. 05927.

Holladay, S. and LaRiviere, J. (2017) The impact of cheap natural gas on marginal emissions from electricity generation and implications for energy policy. *Journal of Environmental Economics and Management*, 85: 205-227.

Holland, S. P. and Mansur, E.T. (2008) Is real-time pricing green? The environmental impacts of electricity demand variance. *The Review of Economics and Statistics, MIT Press*, 90(3): 550-561.

Jansen, M., Staffell, I. and Green, R. (2018) Daily marginal CO_2 emissions reductions from wind and solar generation. *International Conference on the European Energy Market, EEM.*

Li, M., Smith, T.M., Yang, Y. and Wilson, E.J. (2017) Marginal emission factors considering renewables: A case study of the U.S. midcontinent independent system operator (MISO) system. *Environmental Science and Technology*, 51: 11215-11223.

National Grid (2017) *Carbon intensity forecast methodology*. Issue No. December 2017. [online] https://github.com/carbon-intensity/methodology/ (Accessed 9th October 2018).

Pelagatti, M. and Sen, P.K. (2013) Rank tests for short memory stationarity. *Journal of. Econometrics*, 172(1): 90–105.

Sandbag (2019) *Carbon price viewer*. [online] https://sandbag.org.uk/carbon-price-viewer/ (Accessed 10th February 2019).

Staffell, I. and Wilson, I.A.G. (2018) Rapid fuel switching from coal to natural gas through effective carbon pricing. *Nature Energy*, 3(5): 365-372.

Stern, N. (2007) *Stern Review: The economics of climate change*. London, United Kingdom: HM Treasury.

Terna (2019) Transparency report: Actual generation. [online] https://www.terna.it/en/electric-system/transparency-report/actual-generation (Accessed 9th December 2019).

Tranberg, B., Corradi, O., Lajoie, B., Gibon, T., Staffell, I., and Andresen, G. B. (2019) Real-time carbon accounting method for the European electricity markets. *Energy Strategy Reviews*, 26(100367): 1-4.

Thomson, R.C., Harrison, G.P. and Chick, J.P. (2017) Marginal greenhouse gas emissions displacement of wind power in Great Britain. *Energy Policy*, 101: 201-210.

World Bank (2017) *Report of the high level commission on carbon prices*. International Bank for Reconstruction and Development and International Development Association / The World Bank.

Table 1. Summary statistics for Great Britain

Variable	T	Mean	Standard Deviation (SD)	Min	Max
All settlement periods					
CO_2 (t)	32544	3690.00	1874.65	551.21	10181.63
Fossil-Fuel Generation (MWh)	32544	8568.02	3395.71	1657.50	19448.00
Spring 2017					
CO_2 (t)	4416	3297.70	1118.27	1050.31	7240.93
Fossil-Fuel Generation (MWh)	4416	8274.25	2454.25	2907.00	15947.00
Summer 2017					
CO_2 (t)	4416	2621.78	894.38	900.69	4847.10
Fossil-Fuel Generation (MWh)	4416	6781.27	2134.51	2065.50	11485.00
Autumn 2017					
CO_2 (t)	4368	3900.74	19[illegible].75	551.21	9752.79
Fossil-Fuel Generation (MWh)	4368	8713.93	[illegible]709.97	1657.50	18324.00
Winter 2017					
CO_2 (t)	4320	5[illegible]93.[illegible]4	2221.30	732.30	10181.63
Fossil-Fuel Generation (MWh)	4320	11540.64	4040.99	2063.50	19448.00
Spring 2018					
CO_2 (t)	4416	3728.01	1750.13	790.10	9307.57
Fossil-Fuel Generation (MWh)	4416	8661.80	2923.07	2395.50	17277.50
Summer 2018					
CO_2 (t)	4416	2691.26	909.77	592.92	5075.49
Fossil-Fuel Generation (MWh)	4416	7258.81	2277.48	1888.50	11752.50

Table 2. GB Augmented-Dickey-Fuller (ADF), Phillips-Perron (PP) and Clemente-Montañés-Reyes (CMR) unit root tests and Kwaitkowski-Phillips-Schmidt-Shin (KPSS) and robust (RKPSS) stationarity tests per half hourly settlement period.

Period	ADF	PP	CMR	KPSS	RKPSS	Period	ADF	PP	CMR	KPSS	RKPSS
00:00	-4.83	-13.08	-7.04	0.15	0.15	12:00	-5.31	-13.37	-12.94	0.09	0.11
00:30	-4.76	-12.82	-6.90	0.15	0.14	12:30	-5.32	-13.45	-13.01	0.09	0.11
01:00	-4.71	-12.74	-6.76	0.15	0.13	13:00	-5.33	-13.54	-13.11	0.09	0.11
01:30	-4.76	-12.72	-6.81	0.14	0.13	13:30	-5.36	-13.71	-8.18	0.10	0.11
02:00	-4.81	-12.94	-6.84	0.14	0.12	14:00	-5.34	-13.68	-8.07	0.10	0.11
02:30	-4.83	-13.01	-6.87	0.14	0.12	14:30	-5.35	-13.56	-8.04	0.10	0.11
03:00	-4.80	-13.13	-6.87	0.14	0.12	15:00	-5.32	-13.30	-7.98	0.09	0.11
03:30	-4.85	-13.36	-4.36	0.14	0.11	15:30	-5.40	-12.95	-7.76	0.09	0.11
04:00	-4.80	-13.80	-4.32	0.14	0.12	16:00	-5.58	-12.73	-5.09	0.09	0.11
04:30	-4.78	-14.00	-4.35	0.14	0.12	16:30	-5.68	-12.40	-5.14	0.08	0.11
05:00	-4.83	-13.89	-4.50	0.14	0.12	17:00	-5.63	-12.37	-7.83	0.08	0.11
05:30	-4.88	-13.77	-4.56	0.14	0.12	17:30	-5.66	-12.16	-10.32	0.08	0.11
06:00	-5.10	-13.30	-10.54	0.12	0.11	18:00	-5.73	-11.90	-10.27	0.08	0.10
06:30	-5.34	-13.56	-6.05	0.11	0.10	18:30	-5.78	-11.92	-10.27	0.08	0.10
07:00	-5.37	-13.70	-6.01	0.11	0.10	19:00	-5.80	-12.04	-10.36	0.08	0.11
07:30	-5.43	-13.66	-5.99	0.10	0.10	19:30	-5.69	-12.04	-5.96	0.09	0.11
08:00	-5.43	-13.44	-6.40	0.09	0.10	20:00	-5.47	-12.17	-5.73	0.10	0.11
08:30	-5.38	-13.56	-4.93	0.09	0.11	20:30	-5.41	-12.40	-5.66	0.10	0.12
09:00	-5.32	-13.48	-5.19	0.09	0.11	21:00	-5.39	-12.73	-5.68	0.11	0.12
09:30	-5.27	-13.40	-10.55	0.09	0.11	21:30	-5.32	-13.19	-5.49	0.11	0.13
10:00	-5.18	-13.32	-10.66	0.09	0.11	22:00	-5.21	-13.25	-5.30	0.13	0.14
10:30	-5.17	-13.28	-12.87	0.09	0.11	22:30	-5.12	-12.98	-5.11	0.15	0.16
11:00	-5.22	-13.33	-12.90	0.09	0.11	23:00	-5.06	-13.09	-5.25	0.15	0.15
11:30	-5.25	-13.37	-12.93	0.09	0.11	23:30	-5.04	-12.98	-12.69	0.15	0.15

Notes. ADF (H_0: Unit Root) critical values -3.470 (1% level) and -2.862 (5% level). PP (H_0: level stationary) critical values -3.468 (1% level) and -2.862 (5% level). CMR (H_0: Unit Root) 5% critical value -3.560. KPSS (H_0: level stationary) critical values 0.739 (1% level) and 0.463 (5% level). RKPSS (H_0: level stationary) critical values 0.216 (1% level) and 0.146 (5% level).

Table 3. GB seasonal MEF estimates. Augmented-Dickey-Fuller (ADF), Phillips-Perron (PP) and Clemente-Montañés-Reyes (CMR) unit root tests and and Kwaitkowski-Phillips-Schmidt-Shin (KPSS) and robust (RKPSS) stationarity tests.

Period	ADF	PP	CMR	KPSS	RKPSS
Spring 2017	-9.32	-9.58	-11.34	0.39	0.281
Summer 2017	-7.34	-7.89	-8.66	1.20	1.16
Autumn 2017	-10.07	-9.56	-10.64	0.097	40.2
Winter 2017	-5.60	-5.50	-6.70	1.38	40.2
Spring 2018	-8.44	-8.49	-10.14	0.43	0.47
Summer 2018	-7.38	-7.87	-8.93	0.39	0.40

Notes. ADF (H_0: Unit Root) critical values -3.470 (1% level) and -2.862 (5% level). PP (H_0: level stationary) critical values -3.468 (1% level) and -2.862 (5% level). CMR (H_0: Unit Root) 5% critical value -3.560. KPSS (H_0: level stationary) critical values 0.739 (1% level) and 0.463 (5% level). RKPSS (H_0: level stationary) critical values 0.216 (1% level) and 0.146 (5% level).

Table 4. GB AIC and BIC per half hourly settlement period (00:00 – 13:00).

	1. US-FE		2. ARIMA-FE		3. ARFIMA-FE	
Period	AIC	BIC	AIC	BIC	AIC	BIC
00:00	318.70	345.82	-271.88	-231.21	-249.16	-203.97
00:30	343.83	370.94	-273.05	-232.38	-272.45	-227.26
01:00	340.37	367.48	-301.56	-260.88	-289.80	-249.13
01:30	324.18	351.30	-300.92	-260.24	-304.47	-254.76
02:00	302.00	329.11	-300.03	-254.84	-292.56	-251.89
02:30	284.12	311.23	-299.84	-259.17	-296.30	-255.63
03:00	264.98	292.10	-301.14	-260.47	-301.38	-251.67
03:30	243.11	270.22	-285.60	-244.93	-291.29	-237.06
04:00	229.97	257.08	-277.48	-236.81	-276.53	-231.34
04:30	227.93	255.04	-269.49	-233.34	-271.53	-230.85
05:00	246.34	273.46	-272.34	-231.67	-271.25	-226.06
05:30	290.52	317.64	-266.17	-225.50	-265.34	-220.15
06:00	343.02	370.14	-223.96	-183.29	-221.75	-172.04
06:30	347.20	374.31	-193.21	-152.54	-192.77	-147.58
07:00	390.51	417.63	-100.47	-59.80	-98.54	-53.34
07:30	432.93	460.05	-18.59	22.08	-13.82	31.37
08:00	462.15	489.26	15.79	56.46	20.30	65.49
08:30	480.59	507.71	14.04	54.71	16.00	61.19
09:00	478.24	505.35	2.23	42.90	5.84	51.03
09:30	475.87	502.98	-19.64	21.03	-17.26	27.93
10:00	483.79	510.90	-40.50	0.18	-37.96	7.24
10:30	487.09	514.21	-56.40	-15.72	-54.43	-9.24
11:00	480.66	507.77	-66.08	-25.41	-64.20	-19.01
11:30	474.11	501.22	-74.71	-34.04	-73.25	-28.06
12:00	481.73	508.84	-63.20	-22.53	-61.20	-16.01
12:30	476.16	503.28	-71.02	-30.35	-69.03	-23.84
13:00	471.22	498.33	-80.31	-39.63	-65.78	-25.11

Table 4 (continued). GB AIC and BIC per half hourly settlement period (13:00 – 23:30).

	1. US-FE		2. ARIMA-FE		3. ARFIMA-FE	
Period	AIC	BIC	AIC	BIC	AIC	BIC
13:30	467.47	494.59	-77.35	-36.68	-75.39	-30.20
14:00	464.22	491.33	-81.04	-40.37	-79.02	-33.83
14:30	461.32	488.43	-83.46	-42.79	-82.04	-36.85
15:00	450.97	478.08	-87.08	-46.40	-85.71	-40.52
15:30	456.28	483.40	-88.74	-48.07	-73.79	-33.12
16:00	472.89	500.00	-96.37	-55.70	-95.05	-49.86
16:30	499.57	526.69	-83.58	-42.91	-82.27	-37.08
17:00	506.10	533.21	-59.33	-18.66	-58.18	-12.98
17:30	501.09	528.21	-75.60	-34.93	-74.53	-29.34
18:00	500.05	527.17	-84.23	-43.56	-83.04	-37.85
18:30	492.80	519.92	-96.74	-56.07	-96.64	-46.93
19:00	486.44	513.56	-111.19	-70.52	-91.51	-50.84
19:30	492.73	519.84	-121.13	-80.46	-122.03	-72.32
20:00	505.59	532.70	-121.37	-80.70	-119.78	-74.59
20:30	477.99	505.11	-158.82	-122.66	-161.79	-116.60
21:00	442.03	469.14	-225.37	-184.70	-228.27	-178.56
21:30	368.77	395.88	-309.25	-268.57	-309.28	-259.57
22:00	296.91	324.02	-380.83	-340.15	-381.13	-331.42
22:30	253.24	280.35	-418.19	-377.52	-416.76	-367.05
23:00	252.79	279.91	-362.18	-321.50	-360.93	-315.74
23:30	262.16	289.27	-302.29	-261.62	-301.33	-256.14

Table 5. GB variance and coefficient of variation for MEFs across all models

	US-FE	HAWKES	HAWKES-FE	ARFIMA-FE	ARIMA-FE
Variance					
Figure 3	0.001	0.001	0.001	0.001	0.001
Figure 4					
A	0.00130	0.00081	0.00083	0.00029	0.00025
B	0.00045	0.00035	0.00034	0.00026	0.00025
C	0.00296	0.00147	0.00159	0.00117	0.00114
D	0.00054	0.00109	0.00109	0.00041	0.00040
E	0.00388	0.00204	0.00214	0.00064	0.00061
F	0.00024	0.00032	0.00033	0.00005	0.00005
Figure 5	0.00300	0.00214	0.00201	0.00161	0.00164
Figure 6	0.00410	0.00263	0.00265	0.00179	0.00179
Coefficient of variation					
Figure 3	0.058	0.053	0.056	0.055	0.055
Figure 4					
A	0.088	0.065	0.066	0.037	0.040
B	0.050	0.045	0.044	0.039	0.039
C	0.117	0.079	0.082	0.071	0.072
D	0.042	0.065	0.065	0.040	0.040
E	0.143	0.093	0.095	0.053	0.054
F	0.038	0.044	0.045	0.018	0.018
Figure 5	0.119	0.103	0.097	0.090	0.089
Figure 6	0.143	0.112	0.113	0.094	0.094

Table 6. GB seasonal MEF estimates - AIC and BIC

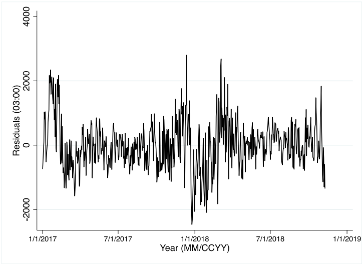
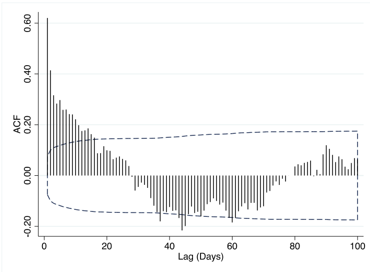
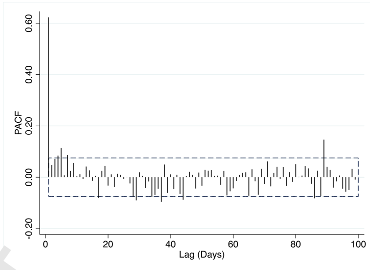
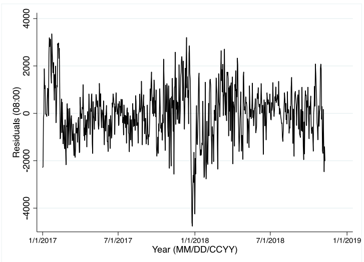
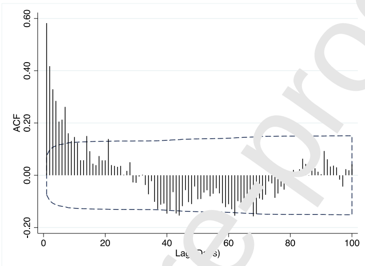
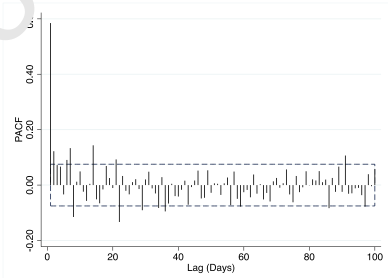
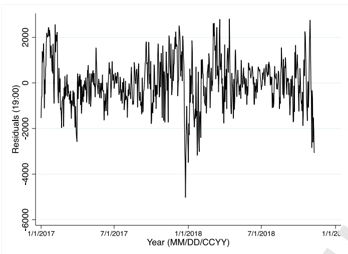
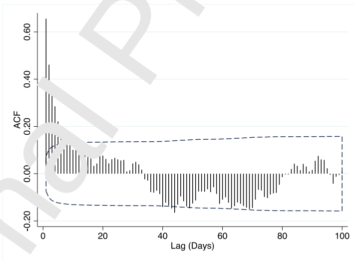
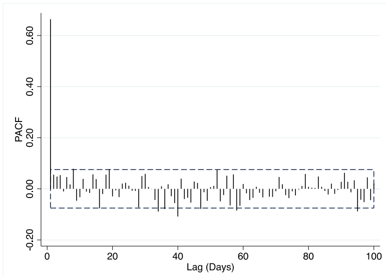
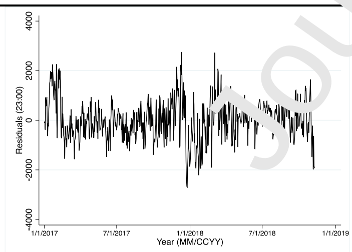
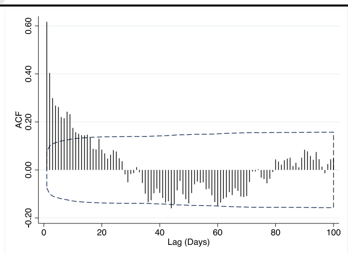
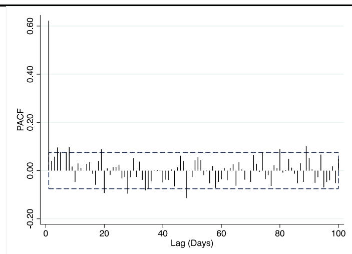
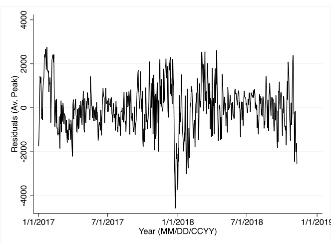
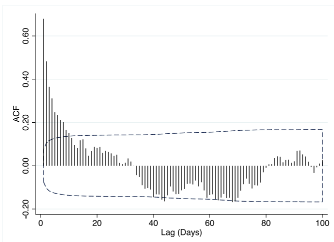
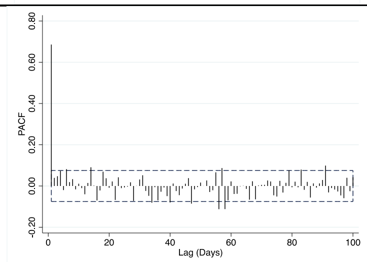
	1. HAWKES-FE		2. ARIMA-FE		3. ARFIMA-FE	
Period	AIC	BIC	AIC	BIC	AIC	BIC
Spring 2017	-19253.55	-19215.2	-20149.86	-19785.46	-20171.95	-19807.55
Summer 2017	-20917.33	-20878.97	-21524.63	-21179.41	-21551.63	-21206.41
Autumn 2017	-14662.44	-14624.15	-15697.66	-15346.65	-15729.58	-15378.57
Winter 2017	-13199.2	-13160.98	-14175.74	-13831.70	-14206.08	-13868.42
Spring 2018	-14019.32	-13980.97	-15597.62	-15233.22	-15654.23	-15315.4
Summer 2018	-21844.63	-21806.27	-22900.84	-22562.01	-22948.44	-22603.22

Table 7. GB comparison of BEIS' system average emission factor (AEF) and CCGT average emission factors (AEF) and the average and median of the Marginal Emission Factors (MEF) estimated by (1) US-FE, (2) HAWKES-FE, (3) inter-day ARIMA-FE and (4) intra-day ARFIMA-FE.

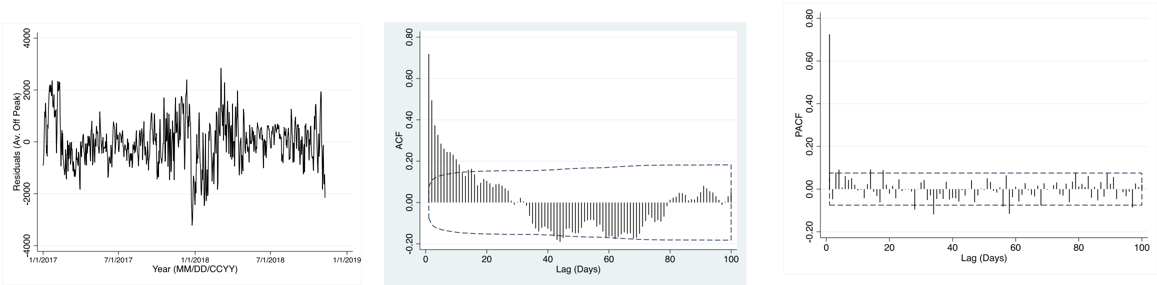
	Benchmark AEFs (tCO_2/MWh)		Inter-day Seasonal MEFs (tCO_2/MWh)			Intra-day Seasonal MEFs (tCO_2/MWh)		
	BEIS	CCGT	US-FE	HAWKES-FE	ARIMA-FE	US-FE	HAWKES-FE	ARFIMA-FE
Mean	0.281	0.394	0.448	0.457	0.448	0.456	0.457	0.450
Median	0.281	0.394	0.438	0.450	0.436	0.448	0.448	0.438
Carbon Price	Revenue (£/MWh)							
£18.08	£5.08	£7.12	£7.92	£8.14	£7.89	£8.10	£8.10	£7.92
£19	£5.34	£7.49	£8.32	£8.55	£8.29	£8.52	£8.51	£8.32
£20	£5.62	£7.88	£8.76	£9.00	£8.73	£8.96	£8.96	£8.76
£31	£8.71	£12.21	£13.58	£13.95	£13.53	£13.89	£13.89	£13.58
£64	£17.98	£25.22	£28.03	£28.81	£27.92	£28.68	£28.68	£28.03
	Revenue at margin (£M)		Using Median EF/MEF and £18.08/MWh (CPS Rate)					
1% ND (2017)	£7.82	£10.97	£12.19	£12.53	£12.15	£12.48	£12.48	£12.19
1% ND (2018)	£6.30	£8.83	£9.82	£10.09	£9.78	£10.05	£10.05	£9.82

Notes: £18.08 (CPS Rate), £19 (Stern (2007) Rate), £20 (EU-ETS, 04/02/2019, Sandbag (2019)), £31-64 (World Bank (2017) Rate). Marginal revenue calculated as 1% of total fossil fuel generation in 2017 (Jan-Dec) and 2018 (Jan-Oct).

Figure 1. GB time series (TS), autocorrelation functions (ACF) and partial ACFs of residuals estimated using seasonally adjusted and detrended carbon dioxide (CO_2) series for settlement periods (A) 03:00, (B) 08:00, (C) 19:00 and (D) 23:00 and (E) average peak hours and (F) average off-peak hours.

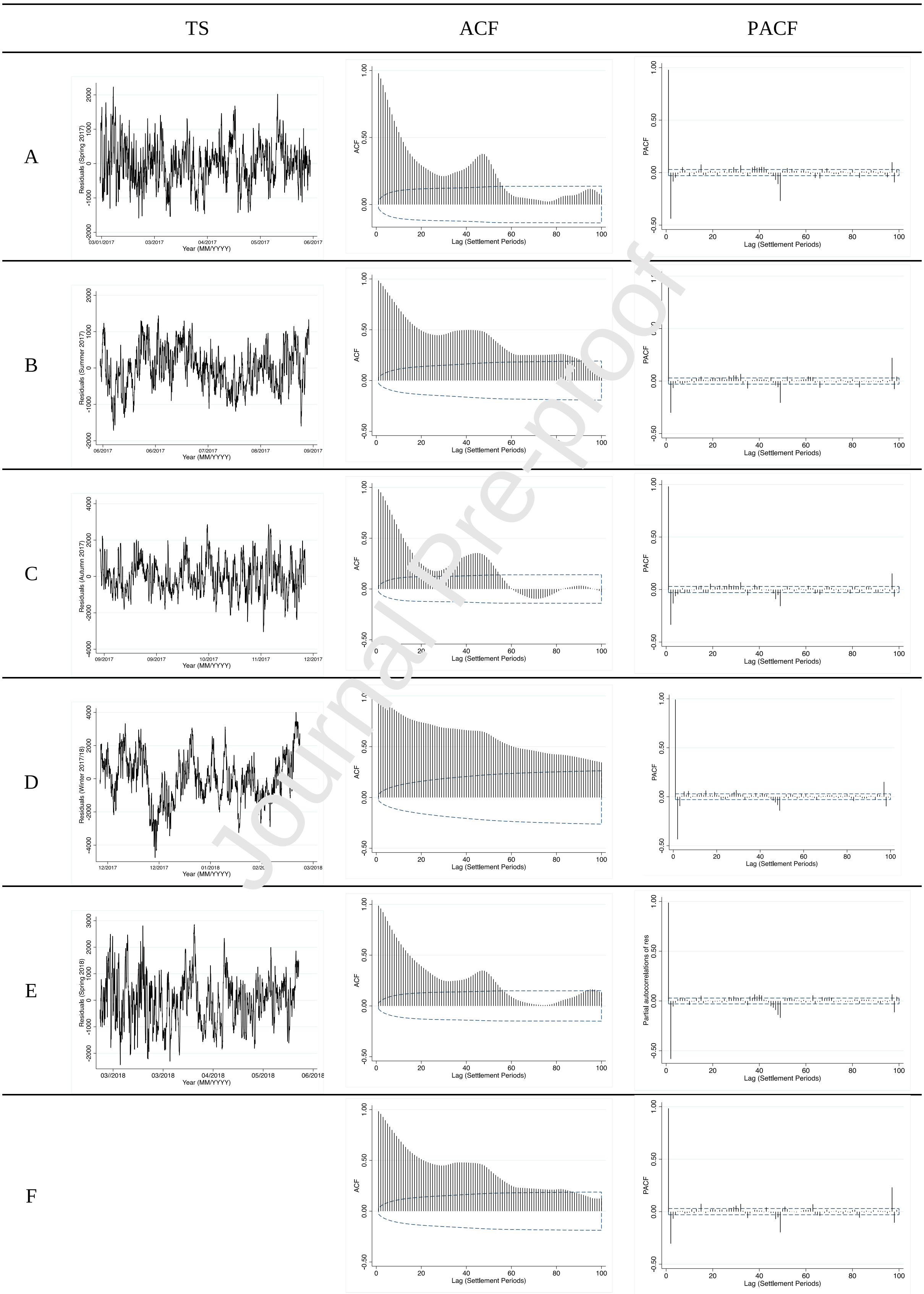
	TS	ACF	PACF
A			
B			
C			
D			
E			

F



Residuals (Av. Off Peak)
Year (MM/DD/CCYY)
1/1/2017
7/1/2017
1/1/2018
7/1/2018
1/1/2019
ACF
Lag (Days)
PACF
Lag (Days)

Figure 2. GB time series (TS), autocorrelation functions (ACF) and partial ACFs of residuals estimated using seasonally adjusted and detrended carbon dioxide (CO_2) series for seasons (A) Spring 2017, (B) Summer 2017, (C) Autumn 2017, (D) Winter 2017/18, (E) Spring 2018 and (F) Summer 2018.



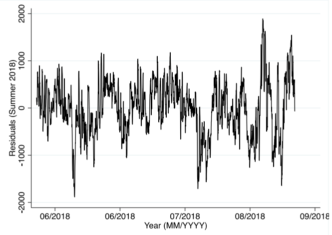

Residuals (Summer 2018)
2000
1000
0
-1000
-2000
06/2018
06/2018
07/2018
08/2018
09/2018
Year (MM/YYYY)

Figure 3. GB marginal emission factors per half hourly settlement period.

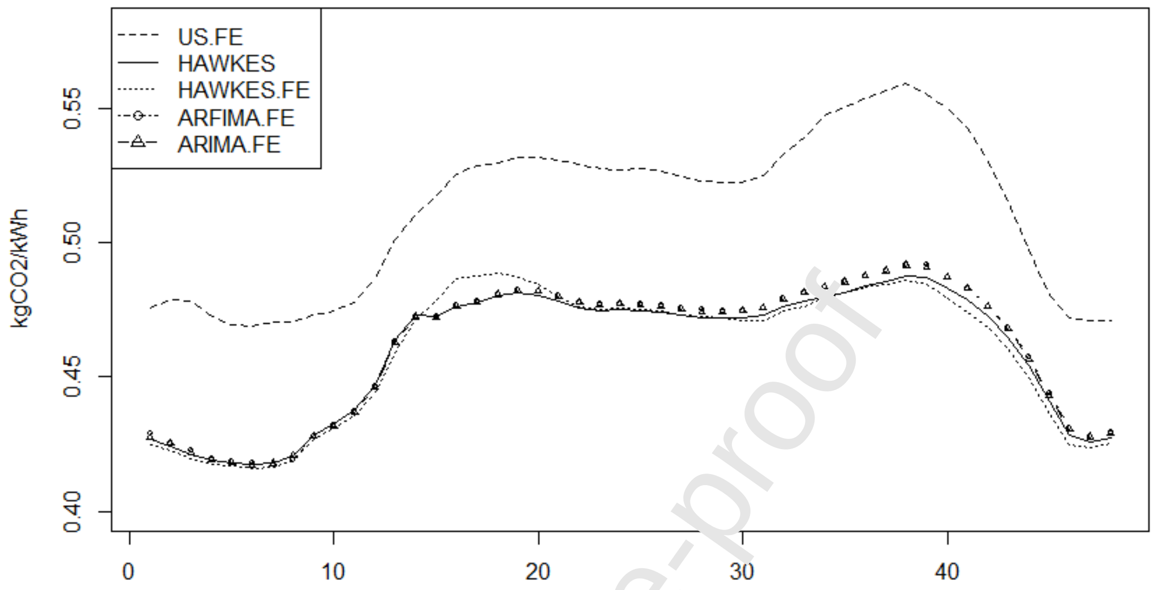


Figure 4a and 4b. GB spring and summer 2017. Marginal emission factors per half hourly settlement period.

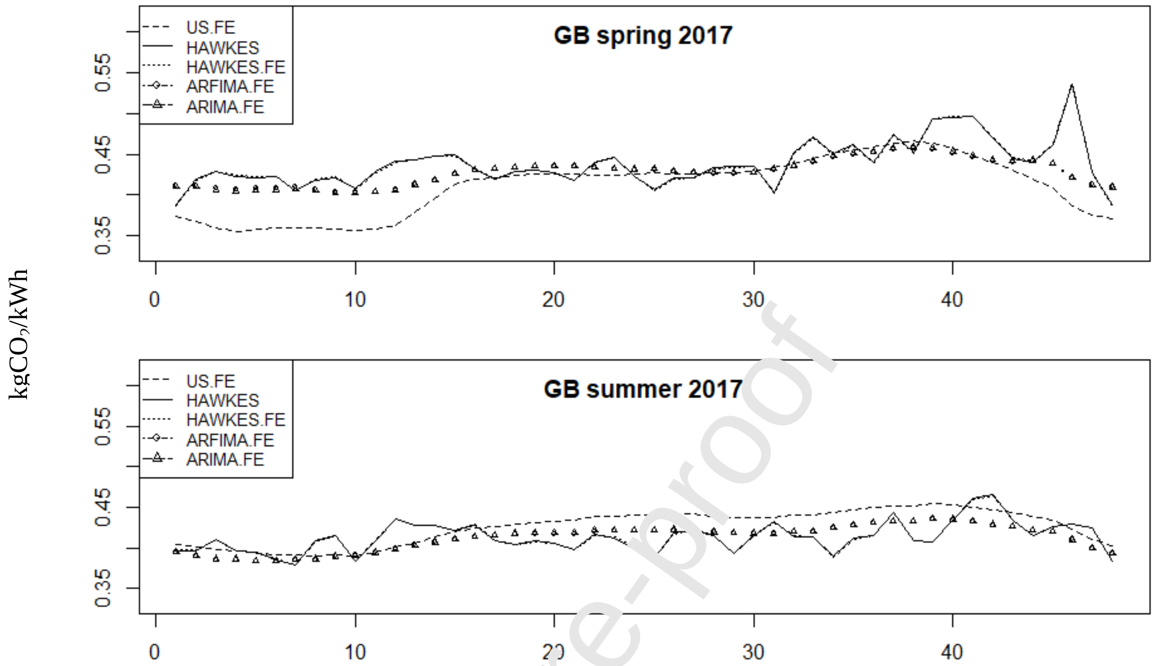


Figure 4c and 4d. GB autumn and winter 2017. Marginal emission factors per half hourly settlement period.

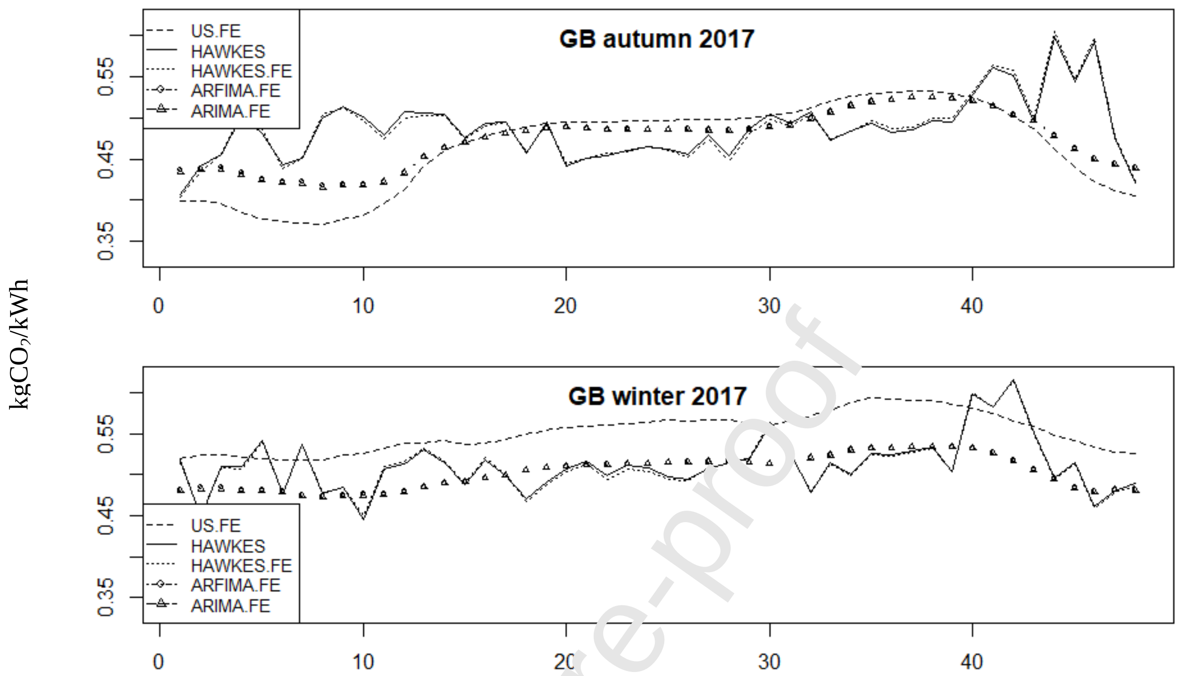


Figure 4e and 4f. GB spring and summer 2018. Marginal emission factors per half hourly settlement period.

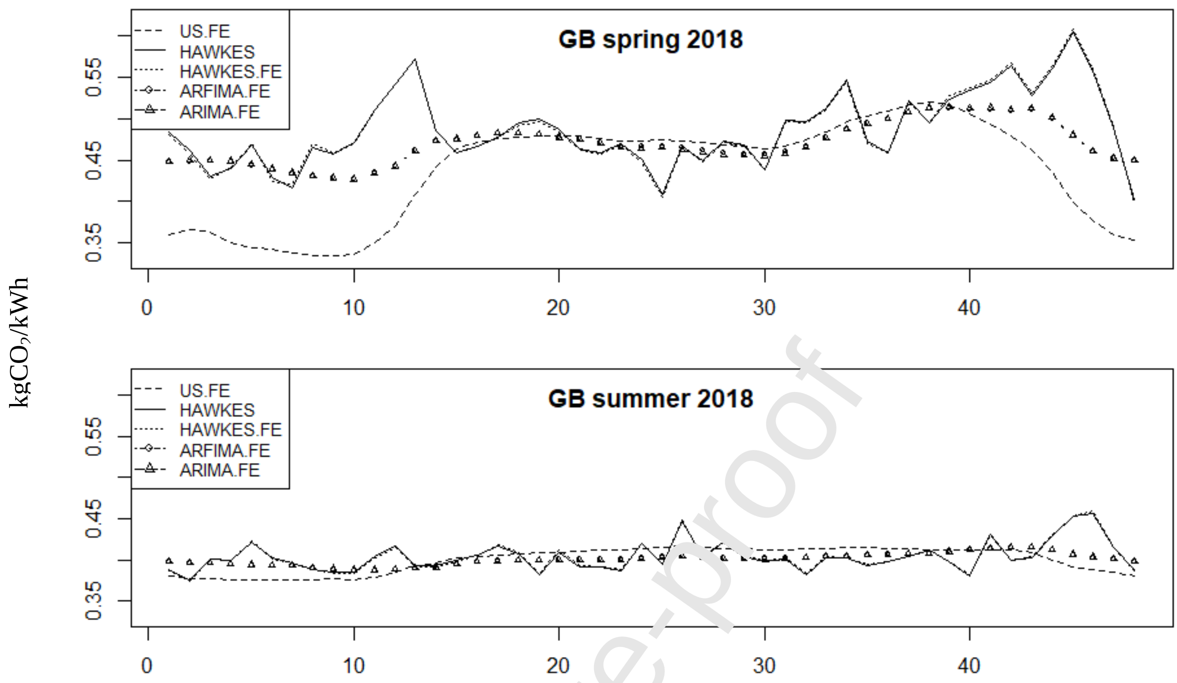


Figure 5. GB seasonal MEFs by different estimators (intra-day).

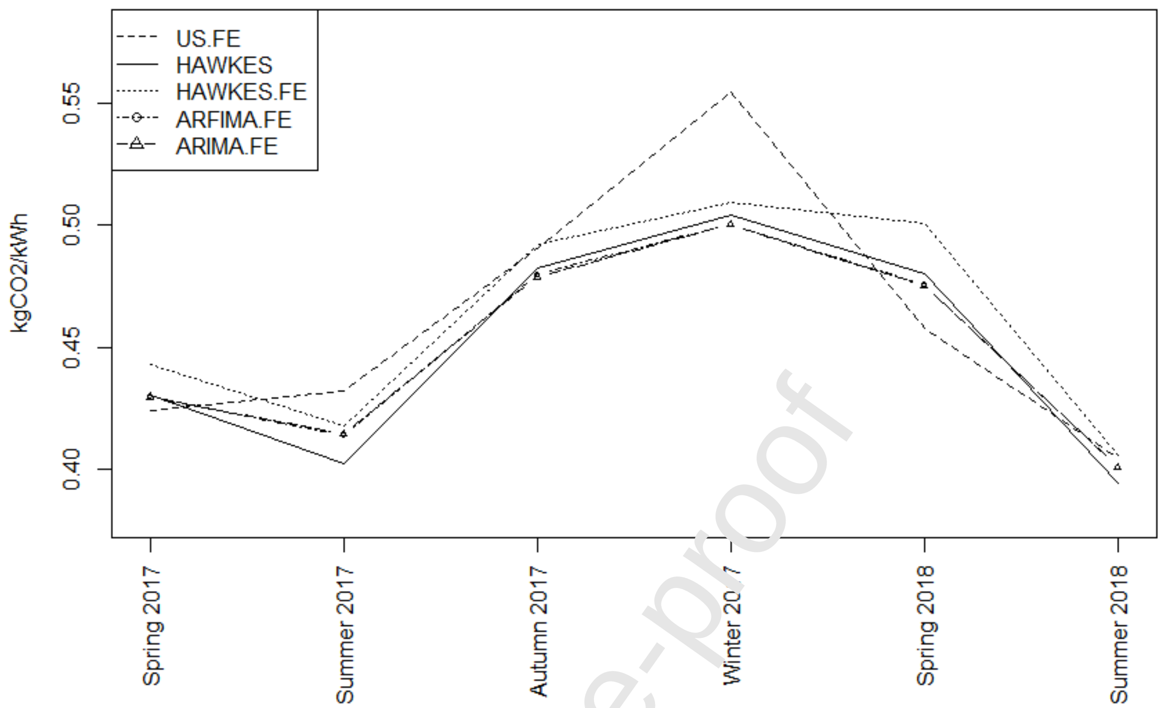


Figure 6 GB monthly MEFs (intra-day)

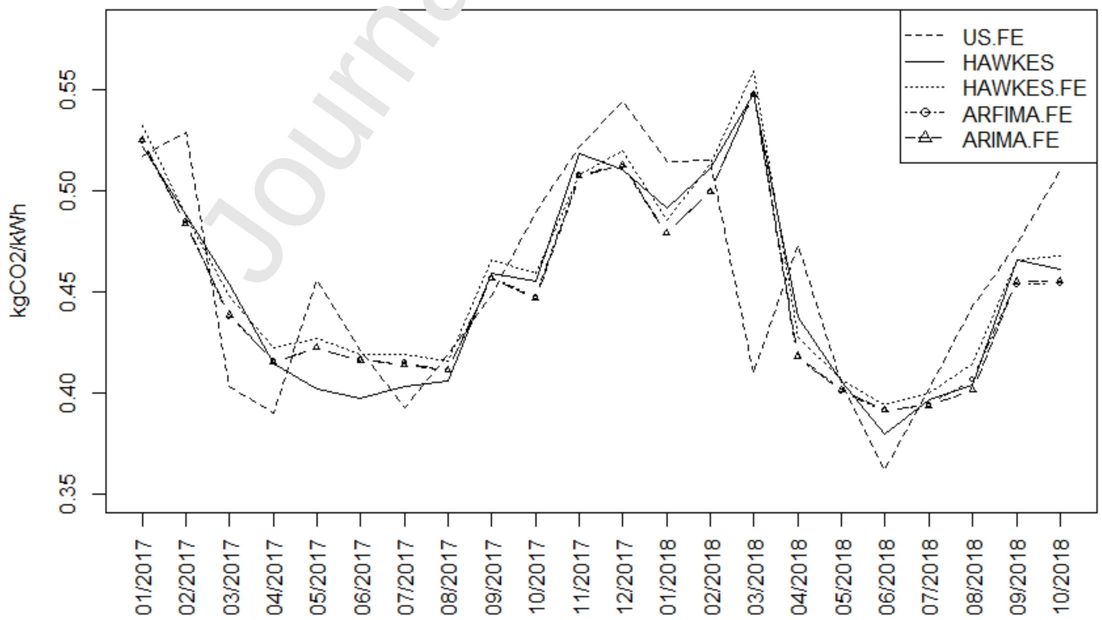


Figure 7. IT marginal emission factors per hourly settlement period (inter-day).

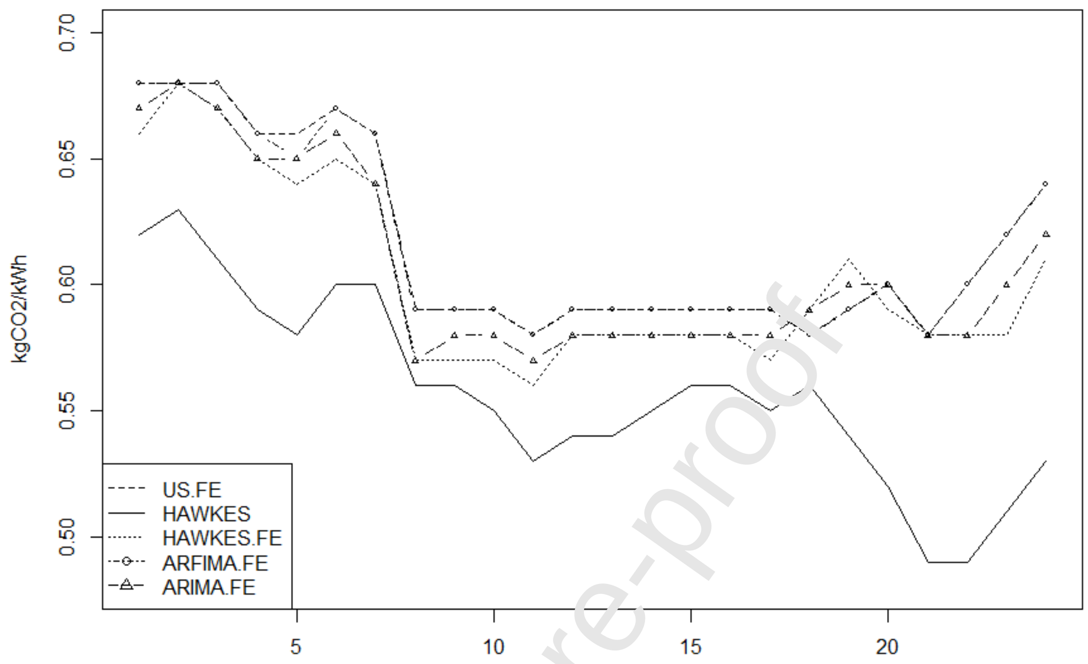


Figure 8. IT seasonal MEFs by different estimators (intra-day).

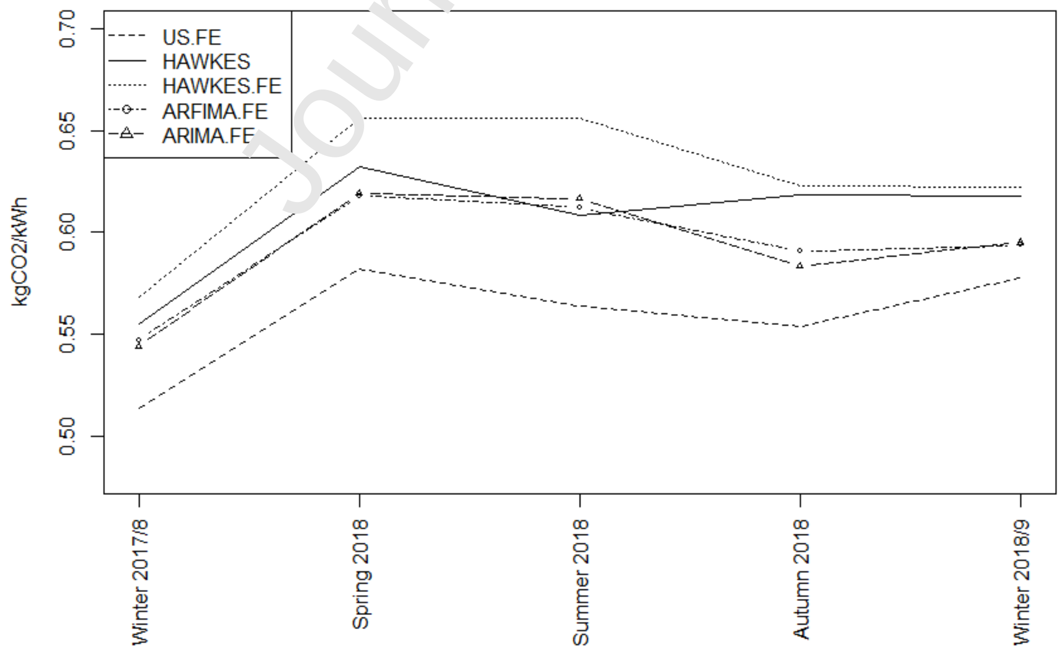
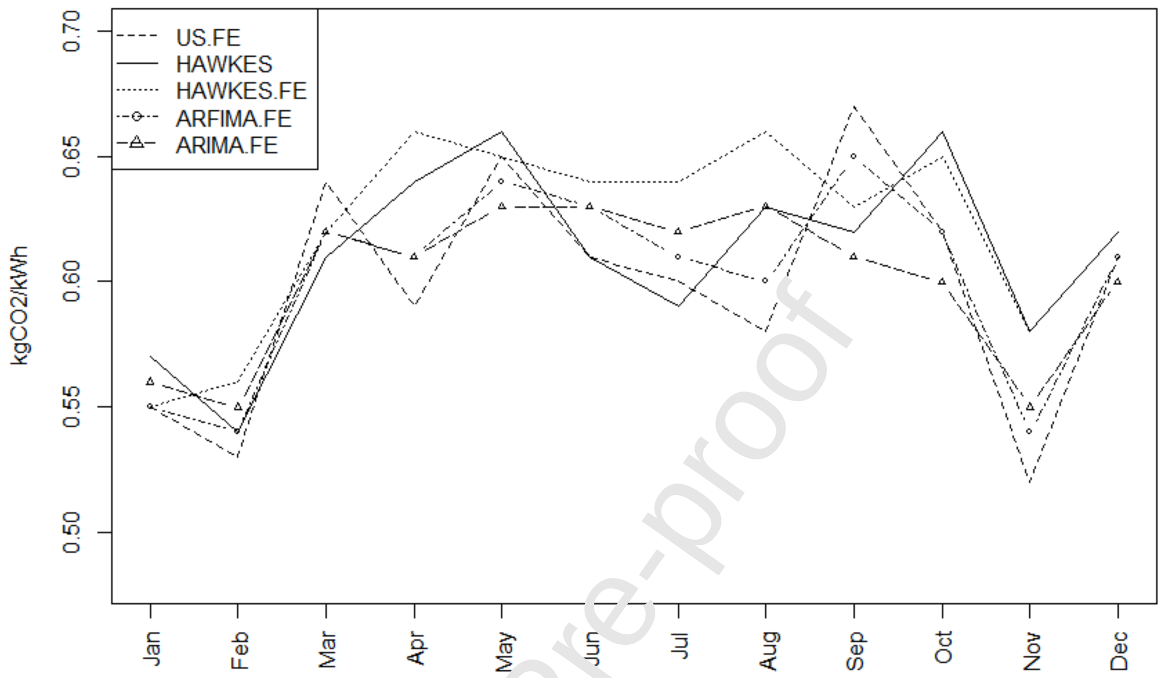


Figure 9. IT monthly MEFs by different estimators (intra-day).



Where did the time (series) go? Estimation of marginal emission factors with autoregressive components

Credit author statement

All authors contributed equally to the paper

Where did the time (series) go? Estimation of marginal emission factors with autoregressive components

Highlights

- A robust method is proposed to estimate marginal emission factors
- Our ARIMA outperforms established models for MEFs estimation
- Consistent results are obtained when using both UK and Italian data
- We provide a robust basis for valuing actual carbon emission reductions

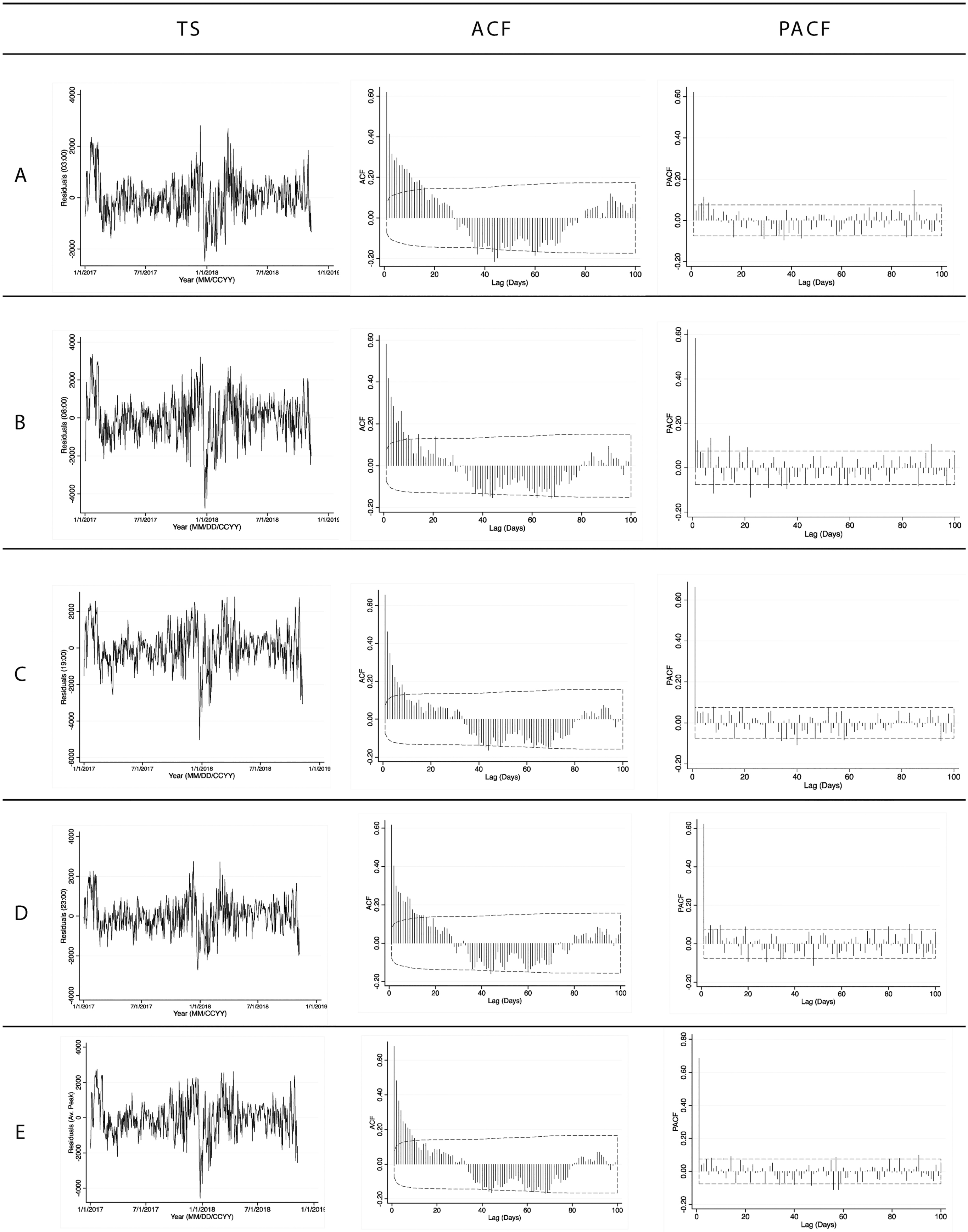
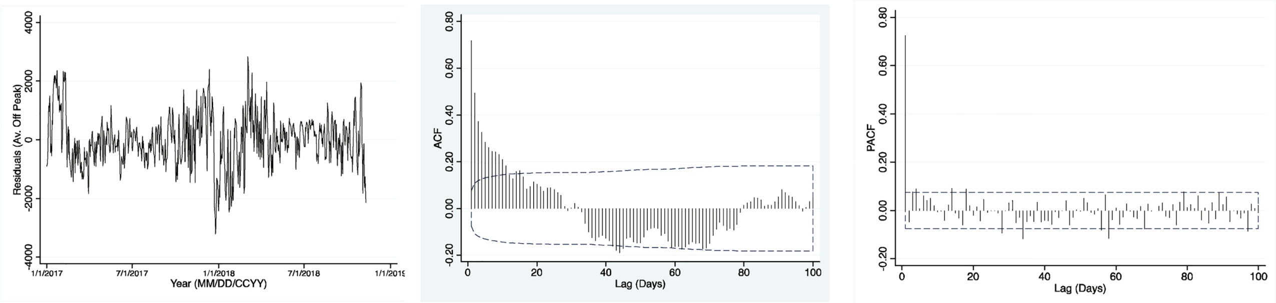

TS
ACF
PACF
A
B
C
D
E
Residuals (03:00)
Residuals (08:00)
Residuals (19:00)
Residuals (23:00)
Residuals (Av. Peak)
Year (MM/CCYY)
Year (MM/DD/CCYY)
ACF
PACF
Lag (Days)

Figure 1A

F



Residuals (Av. Off Peak)
4000
2000
0
-2000
-4000
1/1/2017
7/1/2017
1/1/2018
7/1/2018
1/1/2019
Year (MM/DD/CCYY)
ACF
0.80
0.60
0.40
0.20
0.00
-0.20
0
20
40
60
80
100
Lag (Days)
PACF
0.80
0.60
0.40
0.20
0.00
-0.20
0
20
40
60
80
100
Lag (Days)

Figure 1B

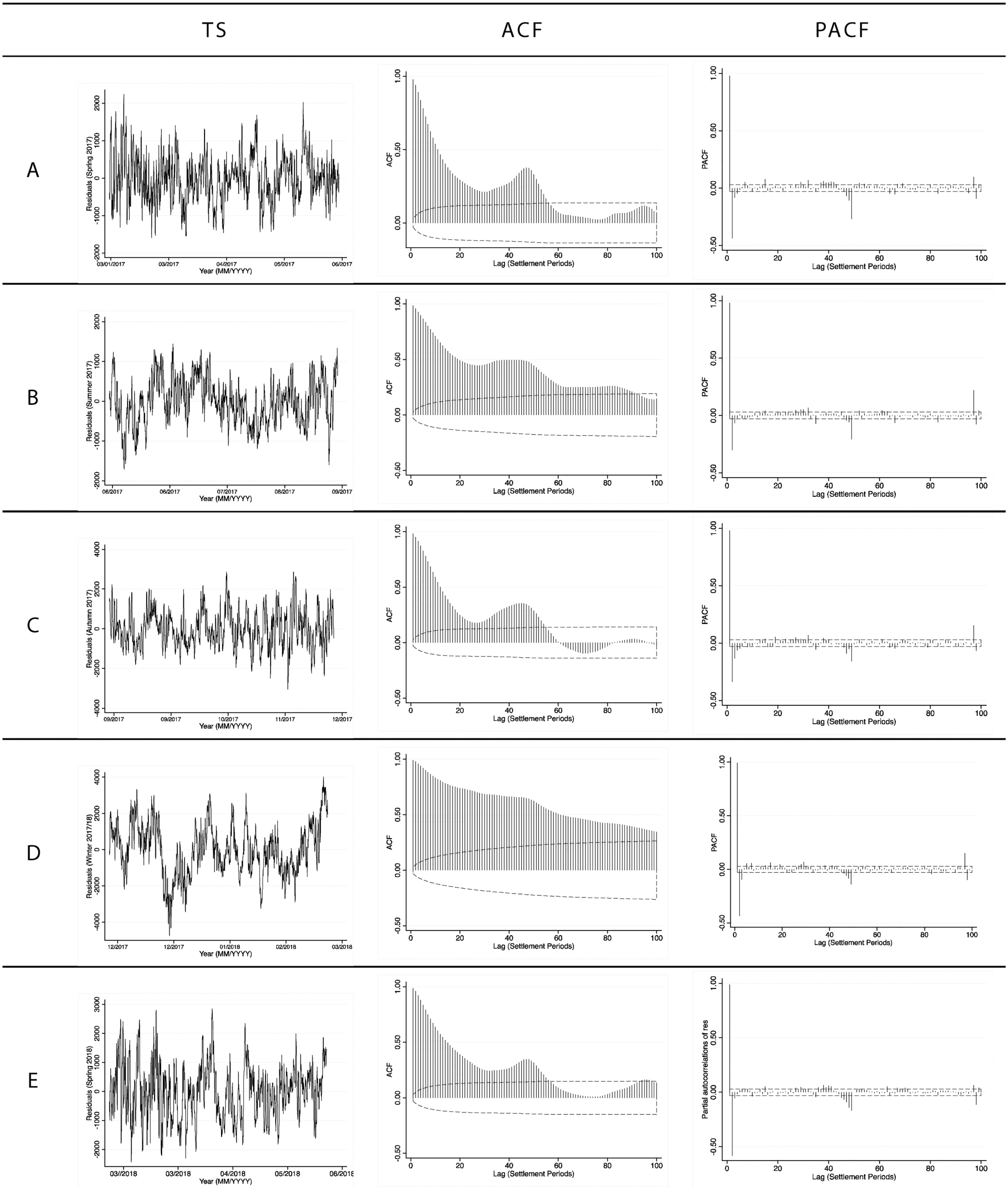
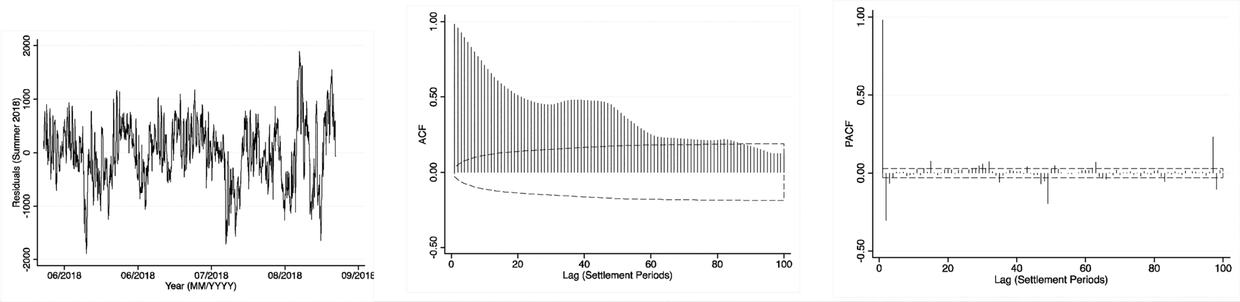

TS
ACF
PACF
A
B
C
D
E
Residuals (Spring 2017)
Residuals (Summer 2017)
Residuals (Autumn 2017)
Residuals (Winter 2017/18)
Residuals (Spring 2018)
Year (MM/YYYY)
ACF
PACF
Partial autocorrelations of res
Lag (Settlement Periods)

Figure 2A

F



Residuals (Summer 2018)
2000
1000
0
-1000
-2000
06/2018
06/2018
07/2018
08/2018
09/2018
Year (MM/YYYY)
ACF
1.00
0.50
0.00
-0.50
0
20
40
60
80
100
Lag (Settlement Periods)
PACF
1.00
0.50
0.00
-0.50
0
20
40
60
80
100
Lag (Settlement Periods)

Figure 2B

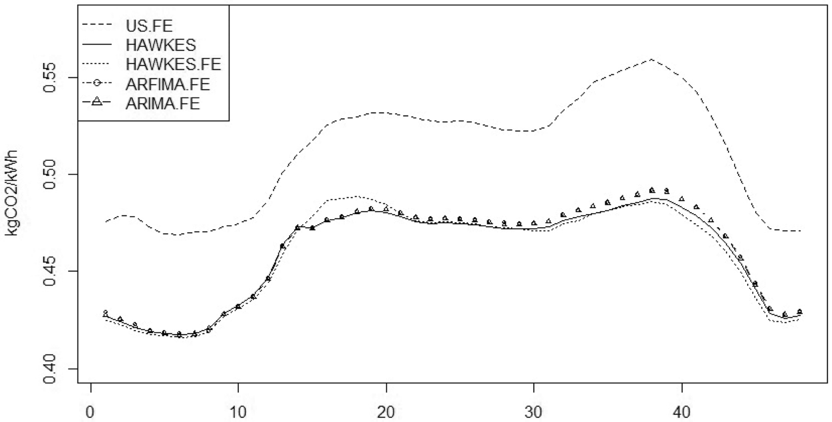

US.FE
HAWKES
HAWKES.FE
ARFIMA.FE
ARIMA.FE
kgCO2/kWh
0.40
0.45
0.50
0.55
0
10
20
30
40

Figure 3

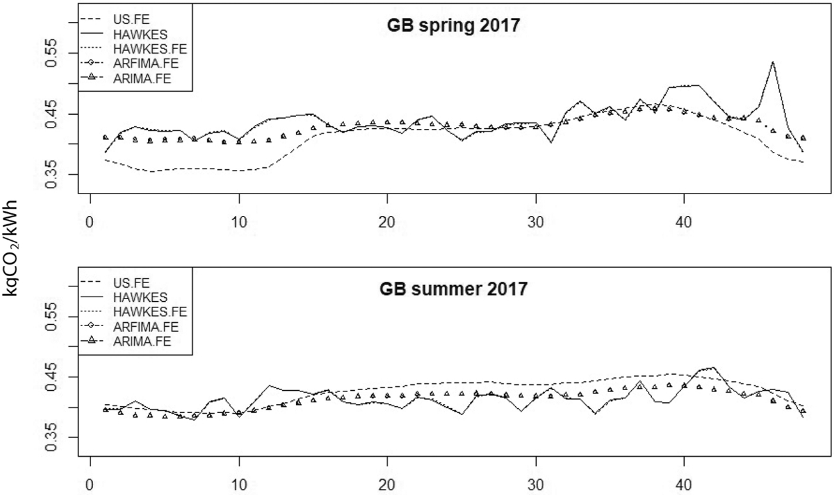
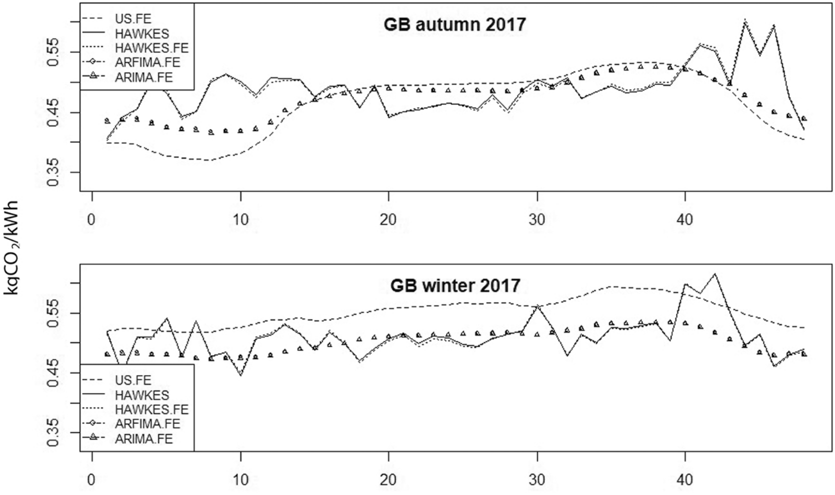
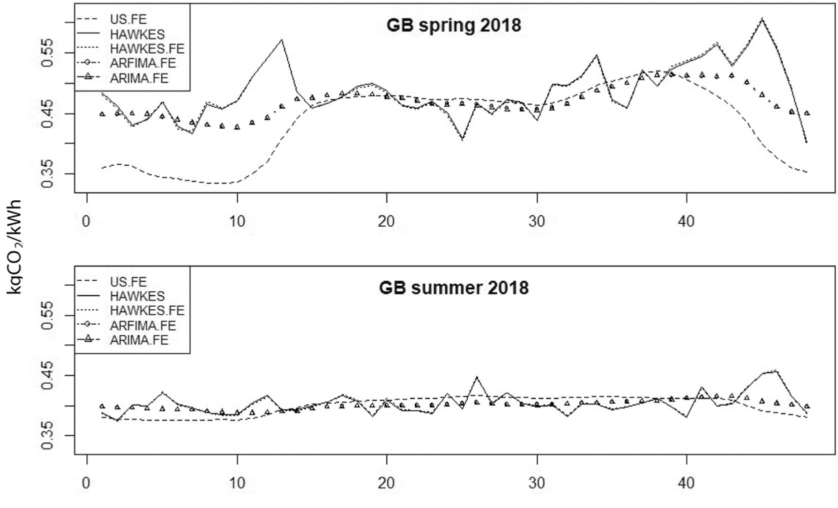

GB spring 2017
GB summer 2017
US.FE
HAWKES
HAWKES.FE
ARFIMA.FE
ARIMA.FE
kgCO2/kWh
0.35
0.45
0.55
0
10
20
30
40

Figure 4



GB autumn 2017
GB winter 2017
US.FE
HAWKES
HAWKES.FE
ARFIMA.FE
ARIMA.FE
kgCO2/kWh
0.35
0.45
0.55
0
10
20
30
40

Figure 5



US.FE
HAWKES
HAWKES.FE
ARFIMA.FE
ARIMA.FE
GB spring 2018
0.35
0.45
0.55
0
10
20
30
40
kgCO2/kWh
US.FE
HAWKES
HAWKES.FE
ARFIMA.FE
ARIMA.FE
GB summer 2018
0.35
0.45
0.55
0
10
20
30
40

Figure 6

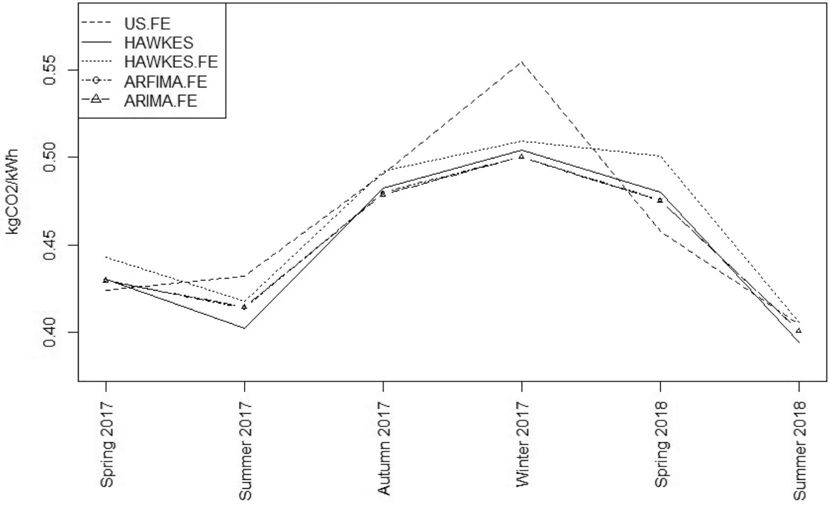
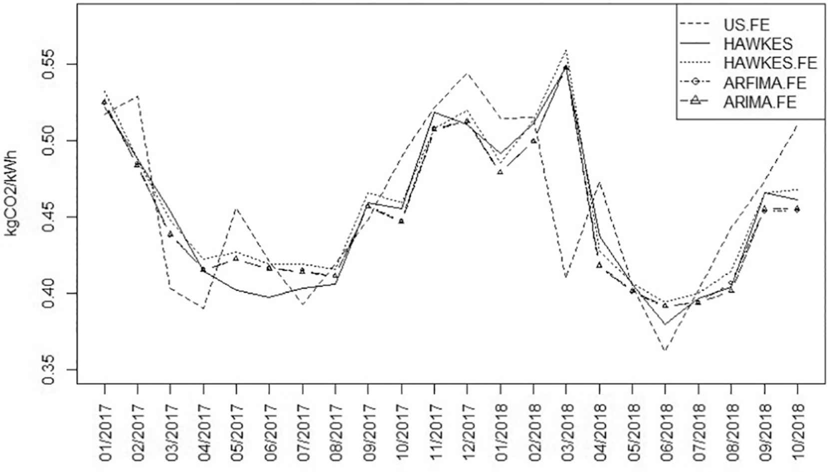

US.FE
HAWKES
HAWKES.FE
ARFIMA.FE
ARIMA.FE
kgCO2/kWh
0.40
0.45
0.50
0.55
Spring 2017
Summer 2017
Autumn 2017
Winter 2017
Spring 2018
Summer 2018

Figure 7



US.FE
HAWKES
HAWKES.FE
ARFIMA.FE
ARIMA.FE
kgCO2/kWh
0.35
0.40
0.45
0.50
0.55
01/2017
02/2017
03/2017
04/2017
05/2017
06/2017
07/2017
08/2017
09/2017
10/2017
11/2017
12/2017
01/2018
02/2018
03/2018
04/2018
05/2018
06/2018
07/2018
08/2018
09/2018
10/2018

Figure 8

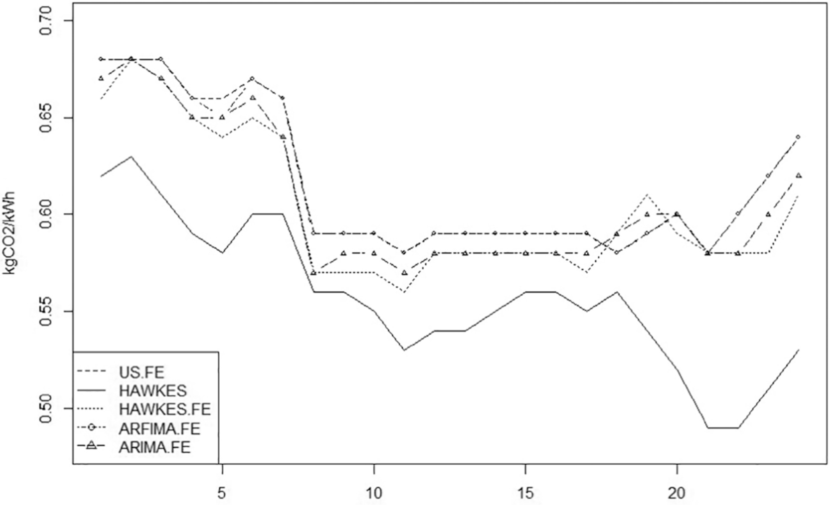

0.70
0.65
0.60
0.55
0.50
kgCO2/kWh
5
10
15
20
US.FE
HAWKES
HAWKES.FE
ARFIMA.FE
ARIMA.FE

Figure 9