



Early opportunity signals of a tipping point in the UK's second-hand electric vehicle market

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Abstract. The use of early warning signals to detect the movement of natural systems towards tipping points is well established. Here, we explore whether the same indicators can provide early opportunity signals (EOS) of a tipping point in a social dataset - views of online electric vehicle (EV) adverts from a UK car selling website (2018-2023). The daily share of EV adverts views (versus non-EV adverts) is small but increasing overall and responds to specific external events, including abrupt petrol/diesel price increases, by spiking upwards before returning to a quasi-equilibrium state. An increasing return time observed over time indicates a loss of resilience of the incumbent state dominated by ICEV advert views. View share also exhibits increases in lag-1 autocorrelation and variance consistent with hypothesised movement towards a tipping point to an EV-dominated market. Segregating the viewing data by price range and year, we find a change in viewing habits from 2023. Trends in EOS from EV advert views in low-mid price ranges provide evidence that these sectors of the market may have passed a tipping point, consistent with other evidence that second-hand EVs recently reached price parity with equivalent ICEV models. We provide a case study of how EOS can be used to predict the movement towards tipping in social systems using novel data.

1 Introduction

20 Tipping points, where a small change in forcing can cause a large response in a system have been widely researched in a number of different fields, such as ecology (Scheffer et al., 2009) and climate dynamics (Lenton et al., 2008). More recently, there has been a focus on tipping points in society, particularly 'positive tipping points' that accelerate actions to combat climate change (Lenton, 2020; Otto et al., 2020).

25 One such positive tipping point to consider is a market switch from internal combustion engine vehicles (ICEVs) to electric vehicles (EVs). Historically, some behavioural and technology changes in the transport sector have been rapid, with the diffusion of innovation seemingly passing a tipping point (Rogers et al., 2014). For example, the transition from horse drawn carriages to ICEVs was relatively quick, and happened over a time span of a decade (Grübler et al., 1999; Nakicenovic, 1986), although there was a twenty year interval of change and competing technologies beforehand (Geels, 2005).



30 Many interlinked factors could drive the market towards a tipping point to an EV dominated state, including declining cost of
batteries, government policy incentives for EV adoption or forthcoming bans on ICEVs, car manufacturers switching strategy
and technology investment, public and private investment in charging infrastructure, and increased public acceptance of EVs.
The dynamics of the marketplace are in general inherently much faster than those of climate systems. Already in Norway,
policy-enabled price parity in total cost of ownership and later in purchase price between EVs and ICEVs has caused a huge
35 growth in EV market share there (Sharpe and Lenton, 2021).

The early warning signals (EWS) of tipping points in natural systems are based on the theory of critical slowing down (CSD):
the phenomena that as a system loses stability, it will respond more sluggishly to perturbations and take longer to return to
equilibrium (Wissel, 1984). This is often referred to as the incumbent state of a system ‘losing resilience’. While EWS have
40 been found in many natural systems approaching tipping (Dakos et al., 2008; Dakos et al., 2023), it is less clear if EWS precede
the movement towards societal tipping points, although some studies suggest they may exist in certain social systems
(Brummitt et al., 2015; Neuman et al., 2011).

EWS generally assume a timescale separation; a long term, slow forcing towards tipping, and short term fluctuations which
45 move the system around its equilibrium. If known perturbations occur, the rate of recovery of the system to its original state
can be directly measured (Veraart et al., 2012). With a time series of the system, CSD can also be estimated by measuring the
lag-1 autocorrelation (AR(1)) and variance over time on a moving window (Held and Kleinen, 2004) - with both statistical
indicators predicted to increase if CSD is occurring (Ditlevsen and Johnsen, 2010). These indicators are detailed more in the
methods section. They are referred to as early “warning” signals because they have principally been applied to undesirable
50 tipping points in natural systems. Here, we look for them in the case of a more desirable tipping point in a social-technological
system. Hence we refer to them as early “opportunity” signals (EOS) – because if they exist, policymakers, firms, investors
and other actors could conceivably use them to steer further interventions to deliberately trigger tipping (Lenton, 2020).

Here we explore the possibility of predicting the movement towards tipping in the UK’s second hand car market from an
55 incumbent state of high interest in ICEVs to one of high interest in EVs, using EV online advert views as a social sensing tool
to gauge public interest. In the next section we discuss our data sources and EOS methods. Then we present our results. Finally,
we discuss their significance.



2 Data and Methods

60 2.1 Auto Trader Adverts and Views

Our data is taken from Auto Trader UK, a car selling website that allows both private sellers and car dealerships to advertise cars. We have used Auto Trader data as it is the UK's largest automotive marketplace, with over 75% of all minutes spent on automotive classified sites.

65 We focus on Auto Trader EV (full battery electric) adverts which have their engagement tracked from when the seller creates the advert. We have data on the daily number of views each advert has had, as well as its advertised price, from the start of 2018 up to July 2023. The dataset is split to consider both new and used cars, although only ~6% of adverts available on a given day are for new cars, thus our results here mainly apply to the second-hand EV market. Across the time period, 1.3% of used car advert views are on EV adverts, compared to 9.6% of the new car advert views. We consider the marketplace in two
70 ways. First, to understand the marketplace as a whole, we explore the daily share of views that were for EV compared to non-EV advert views. We then view different niches in the market by separating the data into different price bands, to determine if there are changes in attention in EVs of certain price ranges.

2.2 Early Opportunity Signals

We begin by measuring the return time from a perturbation within a time series. To measure this, we look for the amount of
75 time it takes for the time series to return 75% of the way to the minimum of the 10 days prior to perturbation. We originally considered calculating the return rate of the views as in Lenton et al. (2022). However, particularly for the first spikes, the fit of an exponential decay model was poor due to a fast post-spike decline. We found return time to be a better measure for this specific data.

80 Then, we explore two EOS indicators that are calculated on a moving window across a time series: AR(1) and variance. As these assume stationarity, the time series are first detrended using a kernel smoother (using a bandwidth of 50 unless otherwise stated), and then the indicators are calculated on the residuals, using a moving window (2 years as standard) which slides across the residual time series, creating a time series of the indicator itself. From this, the tendency in each indicator can be measured, for which we use Kendall's τ correlation coefficient which equals 1 if the time series is always increasing, -1 if the
85 time series is always decreasing, and 0 if there is no overall trend. Mathematically, an increase in these indicators is predicted if CSD is occurring (e.g., Ditlevsen and Johnsen (2010)). They can increase for other reasons so it is important to have independent evidence of the potential for a tipping point, which we take from the observed tipping of the car sales market in Norway towards EVs.



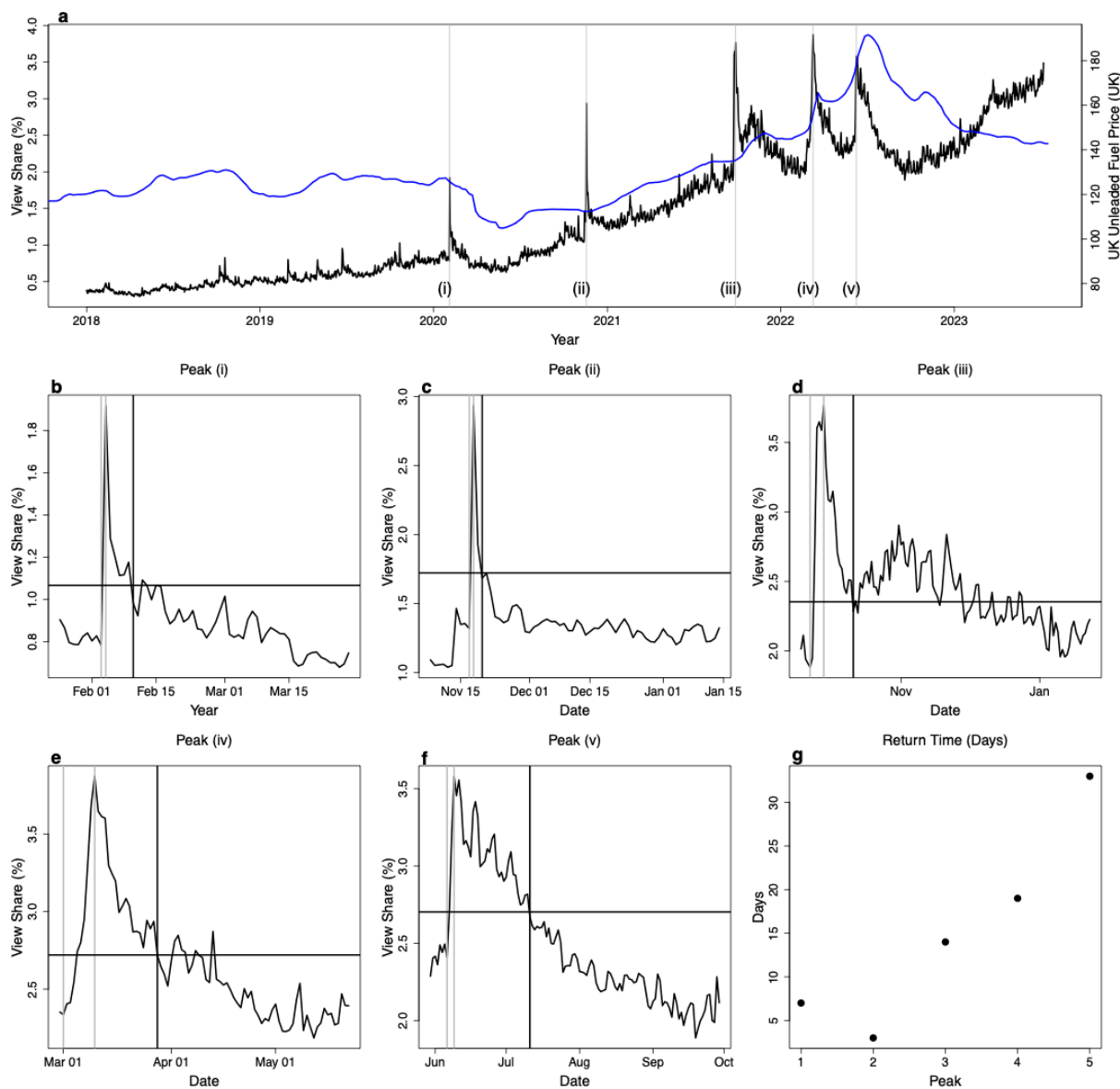
90 We calculate the significance of an obtained τ correlation coefficient through the use of null models (Dakos et al., 2008). We
randomly reorder the time series of residuals and calculate our EOS on this 10000 times, determining a p-value by calculating
the proportion of these that are above our AR(1) or variance τ from the original time series. For the time series that are taken
from price ranges, we use a tipping point detection algorithm called *asdetect* (Boulton and Lenton, 2019) to determine where
the tipping point is. This searches for anomalous changes in gradient in the time series of the system to determine where large
95 changes are likely to have occurred, providing a detection value, the maximum of this being where the tipping is likely to
occur.

3 Results

3.1 The Full Marketplace

We begin by exploring the proportion of advert views that are for EVs rather than non-EVs on Auto Trader's online platform
100 (Fig. 1). This view share is low, particularly at the start in 2018 as the market is dominated by second-hand ICEVs. However,
it is clear that there is an increase in the view share over the time period with 5 specific events that appear to drive an increase
in interest in EVs for a short space of time (Fig. 1a). These events are as follows:

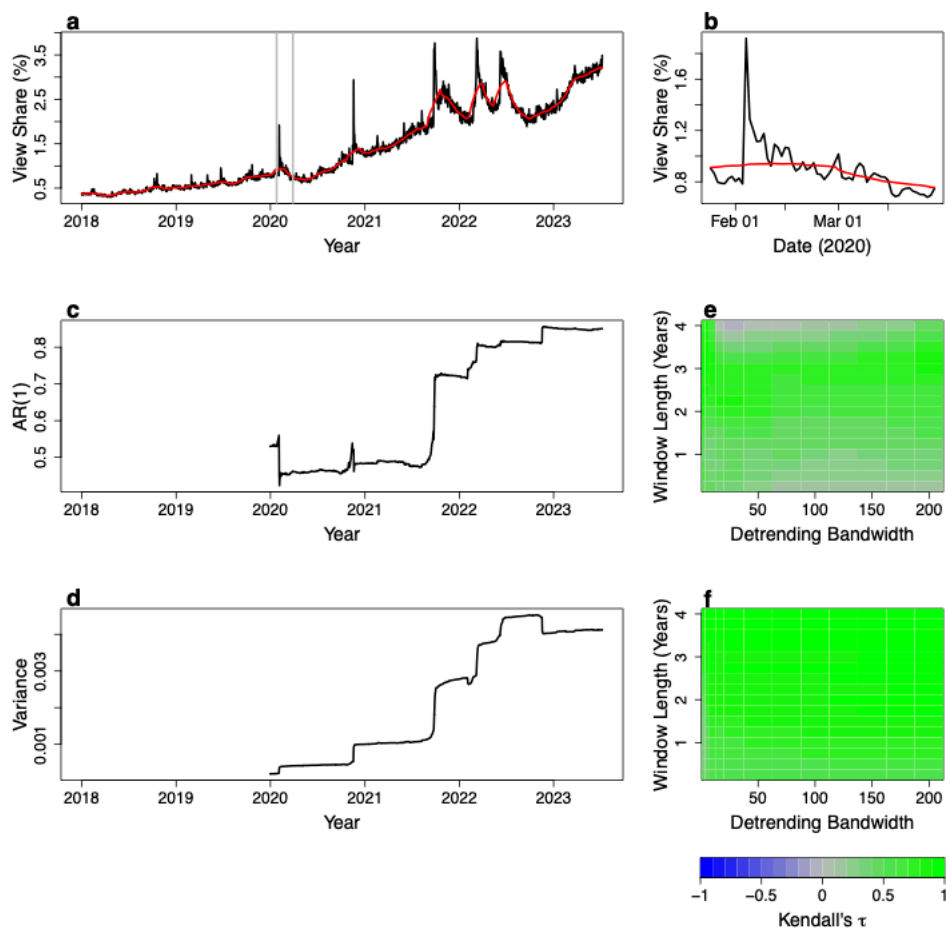
- i. **4th February 2020** The UK Government announces a ban on sale of new petrol vehicles by 2035.
- 105 ii. **18th November 2020** The UK Government brings forward the ban on sale of new petrol vehicles to 2030.
- iii. **29th September 2021** Potential HGV driver shortage, leading to uncertainty about petrol availability,
panic buying and fuel shortages in the UK.
- iv. **10th March 2022** Spike in UK fuel prices associated with international fossil fuel volatility from Russian
conflict in Ukraine.
- 110 v. **8th June 2022** Spike in UK fuel prices.



115 **Figure 1: Early warning signals on a daily time series of the percentage of views on Auto Trader’s website that are for electric**
vehicles (rather than non-electric vehicles). (a) The time series of view share (black), alongside the weekly mean UK unleaded fuel
price (blue). Marked in grey vertical lines (i-v) are specific external events detailed in the main text. (b-f) The return time from
each event is calculated as the number of days it takes for the time series to decrease by 75% of the distance from the spike back to
the pre-spike value. Dotted grey lines show the pre-spike and spike dates as vertical lines. The 75% value is shown as a horizontal
black line, and the date this is reached by the vertical black line. (g) The number of days after the spike it took for the system to
120 **reach the 75% value for each spike.**



Plotting the weekly UK fuel prices (Fig. 1a; blue line) alongside the view share, makes clear the association with peaks (iv) and (v). Observing how long it takes for attention to return to normal after spikes (i)-(v) shows that the system is slowing down and the incumbent state of ICEV dominance of view share is losing stability over time. After the first two spikes (Fig. 1 b,c), for each successive spike (Fig. 1 d-f), there is a clear increase in return time (Fig. 1g). Return time increases by more than a factor of 6 from point (ii) in November 2020, to point (v) in June 2022.



130 **Figure 2:** Early opportunity signals on the (a) daily time series of the percentage of views on AutoTrader’s website that are for electric vehicles. (b) AR(1) calculated from the time series in (a) once it has been detrended with a Kernel smoothing function with bandwidth=50 using a moving window equal to 2 years (as described in the Methods) and plotted at the end of the window used to create it. (c) As in (b) but for variance. (d) and (e) show robustness tests for AR(1) and variance signals respectively, by varying the Kernel smoothing detrending bandwidth and window length used to calculate the signals. The Kendall’s τ value for each combination is recorded in the contour plots, showing the tendency of the indicator time series.



135 To look for temporal EOS on the EV view share time series, we first detrend as described in the Methods (Fig. 2a; red is the
detrending line) to obtain a stationary series. After detrending the sharp spikes in attention remain (e.g., Fig. 2b). Calculating
AR(1) on the residual time-series shows a significant increase over the whole time period ($\tau=0.758$, $p=0.016$). The specific
events generally cause upward jumps in the AR(1) (Fig. 2c). The sharp decrease in AR(1) at the start may be linked to the start
of the COVID-19 pandemic. Variance also increases significantly (Fig. 2; $\tau=0.885$, $p<0.001$), and also appears to be influenced
140 by the spikes in attention. As a check of robustness, we vary the detrending bandwidth for the Kernel smoothing function and
the window length used to calculate the EOS. For both AR(1) (Fig. 2e) and variance (Fig. 2f) we find robust increases across
a range of window lengths and bandwidths. This includes using higher detrending bandwidths that better remove the spikes in
attention.

3.2 Looking for EOS in different niches of the market

145 Cheaper EVs are expected to reach price parity with equivalent ICEVs sooner than more expensive ones. Hence, different
niches of the market could tip at different times. The dataset presents us with the opportunity to look for EOS in different price
niches. We begin by looking at the absolute number of adverts, as well as the absolute number of views (rather than view
share). This allows us to see the evolution of EVs available without the influence of non-EVs. The analysis is split into different
price bands (Fig. 3) in each year (noting that 2023 is year-to-date). For simplicity, we use £5,000 bands from £0-£5000, up to
150 £125,000 and above.

It is clear from the number of adverts that more EVs become available over time and that these become particularly
concentrated in the £20,000-£30,000 range. Also, the diversity of the market increases in terms of the spread of prices, with
more expensive EVs becoming available in later years, which may signal a new niche emerging. In terms of advert views,
155 whilst it is difficult to determine much information from 2018, in 2019 and 2020 there appears to be strong viewing activity
in the £5,000-£10,000 and £35,000-£40,000 price band categories. Afterwards, this changes slightly with high views in the
£20,000-£30,000 categories, alongside views in a £100,000+ category, this category likely to be an interest in a specific car
each year. Up to and including 2022 the numbers of views are noisy across the categories, However, in 2023 we observe a
change in the viewing habits, with a spike occurring in the £25,000-£30,000 with clearer drop-offs away from it. We have also
160 looked at the advert share and view share per year for these price ranges and these results are discussed in the Supplement
(Fig. S1).

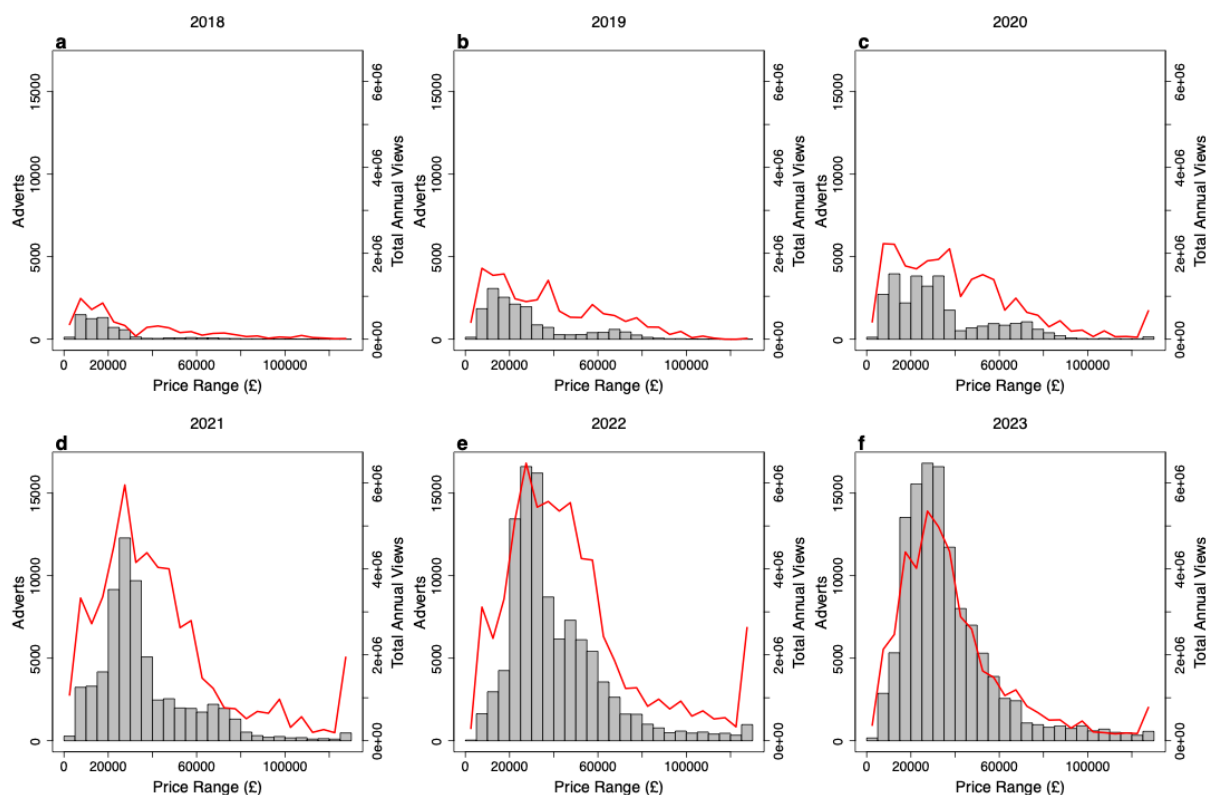


Figure 3: Histograms showing the number of EV adverts per price range in (a) 2018, (b) 2019, (c) 2020, (d) 2021, (e) 2022 and (f) 2023 (to July), alongside the total EV advert views (solid red lines).

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Based on this apparent change in behaviour, we looked for EOS in these different price niches. Using the daily view share time series for adverts that are in each price category, we calculate AR(1) and variance on a 2 year window, using a detrending bandwidth of 50 (as in Fig. 1). We begin by looking at individual time series, those in the £10,000-£15,000 and £15,000-£20,000 categories. These appear to show a tipping point in behaviour from December 2022 (Fig. 4a,b). The time series of other price ranges are shown in Fig. S2. Increases in EOS are observed in both categories (£10,000-£15,000 AR(1) τ : 0.536, variance τ : 0.639, £15,000-£20,000 AR(1) τ : 0.509, variance τ : 0.733, particularly from mid-2021 (AR(1) τ : 0.825, 0.756 from 1st June 2021, respectively). Also AR(1) reaches high values (approaching 1) which in the presence of large perturbations and a visible level of background noise would be expected to lead to tipping before the total loss of stability (at AR(1)=1). After assessing the time series in Fig. S2, we also calculate the view share on EV adverts under £35,000, finding that this too shows evidence of a tipping point (Fig. 4c) and similar EOS beforehand (AR(1) τ : 0.509, 0.719 from 1st June 2021, variance τ : 0.830, 0.698 from June 2021).

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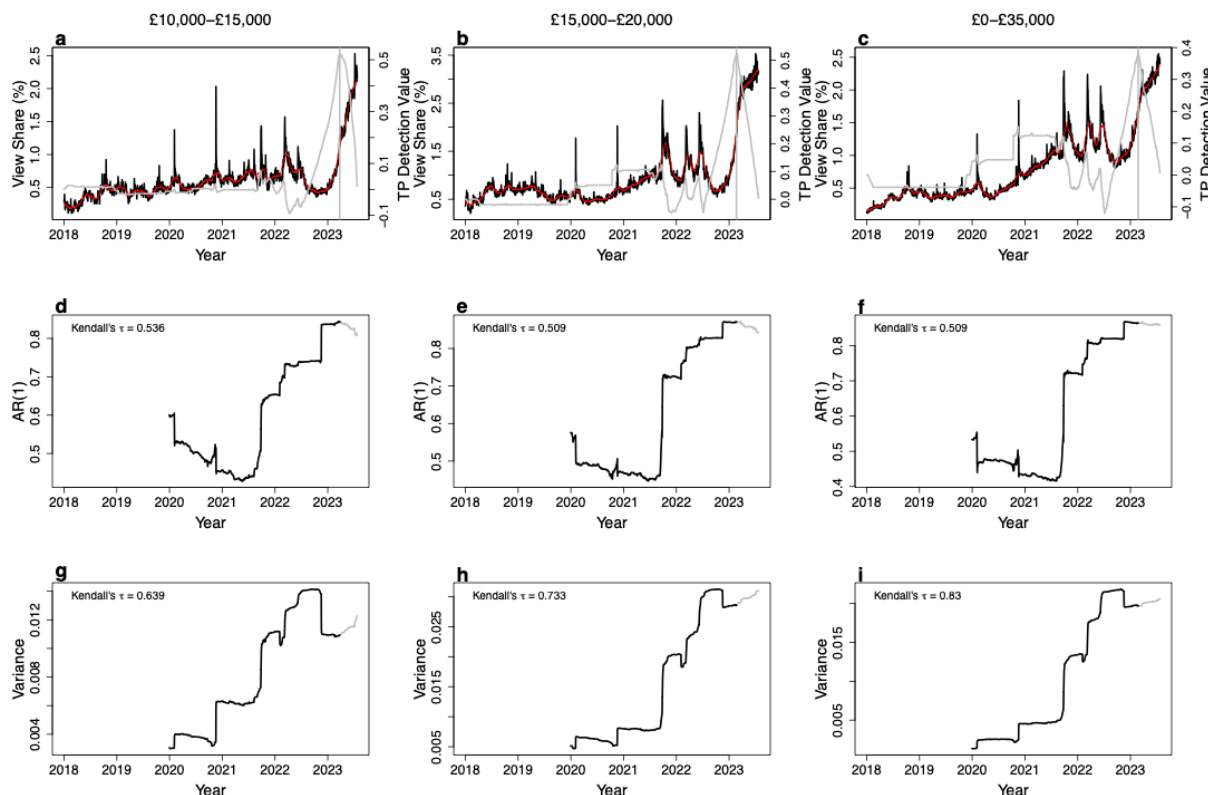


Figure 4: Early opportunity signals carried out on EV view share for price bands (a) £10,000-£15,000 and (b) £15,000-£20,000, and (c) under £35,000 (black solid lines), chosen as time series that appear to show tipping points being crossed. Using the asdetect package to determine where the tipping point occurs (solid grey line), we cut the time series at the place we determine the view share time series begins to tip (vertical solid grey line). (d)-(f) AR(1) time series up to the vertical line for the time series in (a)-(c) respectively as a solid black lines, and afterwards as sold grey lines. (g)-(i) same as (d)-(f) but for variance.

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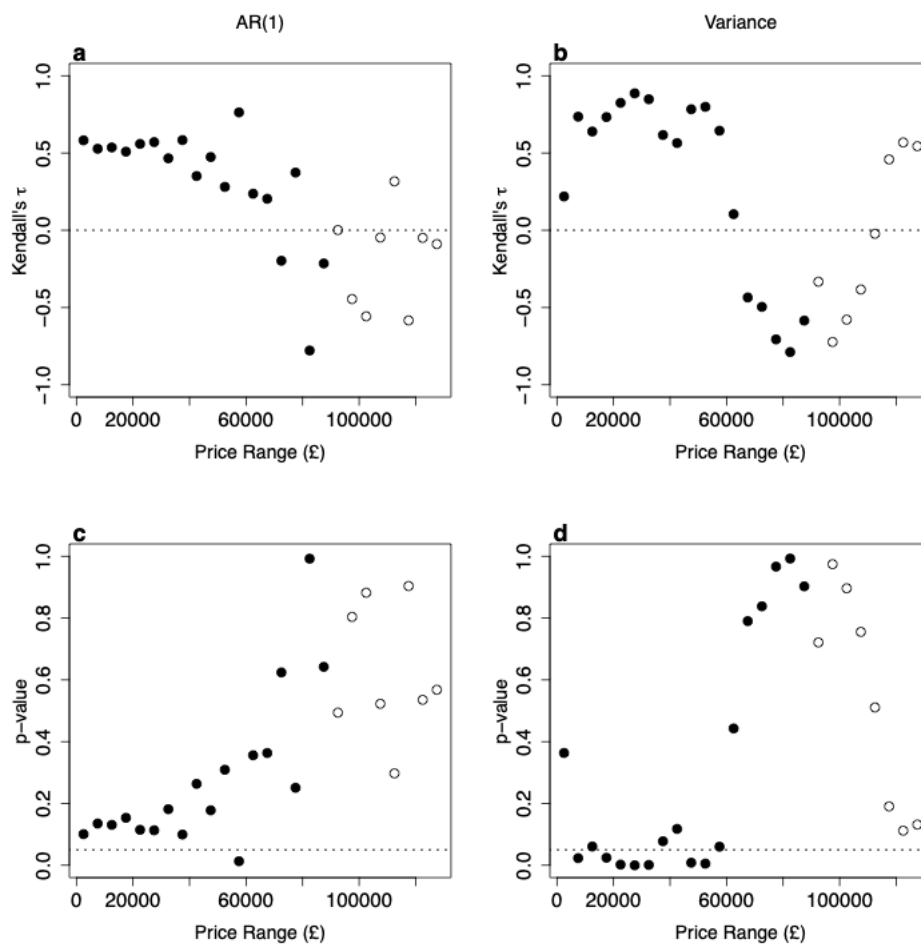
Looking across the full range of price bands, we calculate Kendall's τ correlation coefficient to measure the tendency of these two indicators for each time series. For certain higher price ranges, there are long periods of time where there are no adverts available for viewing and as such EOS are hard to calculate and prone to bias due to strings of zeros. Because of this, we use open circles to mark results from time series that have more than 10% of their length at 0% view share on Fig. 5.

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Figure 5 shows that for AR(1), positive τ values are observed for advert views of EVs that cost up to around £70,000. Variance signals show similar behaviour, in price bands below £60,000. Together this suggests that the tipping point may be being approached in niches below this threshold. For AR(1), the strongest signal is observed at £55,000-£60,000 (0.763). For variance, the highest τ is in the £25,000-£30,000 category (0.886) where we noted an emergent behaviour in annual viewing numbers (Fig. 3). With this partitioned data, the signals generally lack significance (Fig. 5c,d), particularly for AR(1) (Fig.

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5c).



200 **Figure 5: Kendall's τ values to show the tendency of the EOS (a) AR(1) and (b) variance calculated on the view share time series per price range. These view share time series are shown in Fig. S2. Open circles denote price range time series that have no views for more than 10% of the time, due to there being no adverts available to view in those times. The dotted vertical line at $\tau=0$ makes it clear where increases in trend are occurring. Significance of (c) AR(1) and (d) variance trends are shown as p-values as calculated with the use of null models. Any point below dotted vertical line at $p=0.05$ is deemed significant.**

4 Discussion

205 We find evidence that there are 'early opportunity signals' in EV advert views of the approach to a possible tipping point of greater attention on (mostly) second-hand EVs, and that in some price ranges such a tipping point has occurred. CSD is seen in both increasing return times from successive large perturbations and in long-term increases in AR(1) and variance. Events (i)-(v) cause pronounced spikes in attention to EV adverts, which are hard to detrend before calculating AR(1) and variance and can influence these statistics. However, when successfully filtering out the spikes using a low bandwidth kernel smoother, significant increases in AR(1) and variance are still present.



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The novel dataset we have used here focuses on public interest in EVs not the rarer purchase commitment reflected in sales data. We can expect advert view data to be more sensitive to specific events than sales data as it takes minimal effort to view adverts and it can be done multiple times, whilst buying a car is a rare, one-off event. Furthermore, advert views can react faster to events than sales, which always involve some delay.

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We expect the reactions to government changes in policy to be different to the reaction to fuel shortages, for example. Fuel events affect people in the present, whereas government policy affects people more than a decade into the future. As we tend to discount the future, one might expect a greater reaction to immediate events, all else being equal. Nonetheless, by looking at the *relative* changes in the system post-event, e.g. in our return time measure, we control for any such differences.

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Our results suggest a tipping point in UK public interest in (mostly) second-hand EVs is being approached and has been crossed for some price ranges. A tipping point in sales may be expected to follow. This is consistent with separate evidence analysed by Auto Trader. An increase in supply of EVs in the secondary market occurred from March 2023, as cars bought on 3-year leases began to be available for resale, following an abrupt increase in new EV sales that occurred back in 2020 (Lam and

225 Mercure, 2022; Geels and Ayoub, 2023). Increased supply caused a pronounced decrease in second-hand EV price which has plausibly driven the upturn in view share, noticeable in Fig. 4. Comparing EVs with their ICEV equivalent, Auto Trader find that price parity between 3-year-old vehicles in the secondary market has been reached in a number of niches early in 2023 (Auto Trader Uk, 2023).

5 Conclusion

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We have provided evidence that early opportunity signals of positive tipping points of climate-friendly action are possible in a key social-technological system. Cars are responsible for around 13% of the UK's total greenhouse gas emissions. Further research should examine whether such early opportunity signals are more widespread in sectors of the economy with the potential for tipping points.

Author Contributions

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All authors developed the research and drafted the paper, CAB ran the analysis, all authors commented on the final text.

Competing Interests

The authors declare that they have no conflict of interest.



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