

# Identifying behavioural change among drivers using Long Short-Term Memory recurrent neural networks

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## Abstract

Globally, motor vehicle crashes account for over 1.2 million fatalities per year and are the leading cause of death for people aged 15 to 29 years. The majority of road crashes are caused by human error, with risk heightened among young and novice drivers learning to negotiate the complexities of the road environment. Direct feedback has been shown to have a positive impact on driving behaviour. Methods that could detect behavioural changes and therefore, positively reinforce safer driving during the early stages of driver licensing could have considerable road safety benefit. A new methodology is presented combining in-vehicle telematics technology, providing measurements forming a personalised driver profile, with neural networks to identify changes in driving behaviour. Using Long Short-Term Memory (LSTM) recurrent neural networks, individual drivers are identified based on their pattern of acceleration, deceleration and exceeding the speed limit. After model calibration, new, real-time data of the driver is supplied to the LSTM and, by monitoring prediction performance, one can assess whether a (positive or negative) change in driving behaviour is occurring over time. The paper highlights that the approach is robust to different neural network structures, data selections, calibration settings, and methodologies to select benchmarks for safe and unsafe driving. Presented case studies show additional model applications for investigating changes in driving behaviour among individuals following or during specific events (e.g., receipt of insurance renewal letters) and time periods (e.g., driving during holiday periods). The application of the presented methodology shows potential to form the basis of timely provision of direct feedback to drivers by telematics-based insurers. Such feedback may prevent internalisation of new, risky driving habits contributing to crash risk, potentially reducing deaths and injuries among young drivers as a result.

*Keywords:* Driver, Behavior, Neural network, Long short-term memory, Feedback, Transportation

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## 1. Introduction

Motor vehicle crashes contribute to over 1.2 million fatalities per year and up to 50 million injuries (WHO, 2013, 2015). Detailed investigation of crash statistics shows an over-representation of young adults among these figures, with those aged 15–29 particularly at risk. This over-representation has been tempered due to the introduction of various mitigating measures such as graduated licensing systems (Russell et al., 2011). However, the ongoing levels of road trauma (both road deaths and injuries) provides impetus for new approaches and technologies that may reduce road trauma. As such, a new methodology based on in-vehicle telematics technology is presented in this research with the potential to reduce high-risk behaviour regardless of driver age.

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### *1.1. Driving behaviour*

There is a strong relationship between driving behaviour and crash risk, with exceeding posted speed limits one of the key factors related to crash risk and severity (Finch et al., 1994; Mackay and Hassan, 2000; Peden et al., 2004). Although estimates vary between studies, there is consensus that in 95–99% of crashes, a driver behavioural error either caused or contributed to the incident (e.g., Sayed et al., 1995; Hendricks et al., 2001). Furthermore, driving behaviour is dynamic, changing over time (e.g., Wijnands et al., 2016). After a young driver obtains a driver’s licence, driving skills improve as they learn to negotiate the complexities of the road environment (Mayhew et al., 2003).

However, crash rates do not solely depend on personal driving style, but also on when and where a vehicle is driven. For example, Paefgen et al. (2014) performed a case control study using in-vehicle data recorders, exploring associations between exposure variables and crash risk. This work demonstrated that highway driving had a lower risk per kilometre travelled than urban driving, driving during weekends was associated with lower risks, and crash risk while driving between 6 p.m. and 9 p.m. was higher than during other periods.

Current performance feedback to drivers is usually provided in the form of punishment for poor driving. For example, drivers may receive feedback on their performance from law enforcement officers for speeding or dangerous driving. This feedback may be delivered as letters, apprehensions, arrests, fines, demerit points, seizure of assets (e.g., car), or losses of licence, etc. The basic principle of this form of feedback known as operant conditioning (Neavin, 1969) is that the driver will learn to associate their poor driving behaviour with an aversive consequence (e.g., the punishment), which then reduces or halts the poor behaviour.

Learning within operant conditioning models works best when associations between antecedents (the environment), behaviours (the actions of the individual) and consequences (the reward or punishment) are delivered in a manner that enables clear, timely connection between stages of the reinforcement regime to be recognised by the individual (Ammons, 1956). Ideally, these principles should also be inherent within road safety enforcement regimes (Fildes et al., 2005).

For example, in the case of fixed speeding cameras, drivers may receive notification of punishment weeks after they have committed an offence, reducing opportunity to link behaviour and consequences in a timely manner. Such issues have potentially contributed to levels of distrust among sub-populations of the community in relation to the legitimacy of such enforcement programs (Fleiter and Watson, 2012). Further, existing regimes largely ignore the complementary side of the operant conditioning model known as ‘positive reinforcement’ or more simply ‘reward’ (Fleiter et al., 2009). This limitation may further weaken the ability of existing punishment-based systems to positively influence driver behaviour. To this point, however, it has been difficult for enforcement authorities to identify behaviours with sufficient sensitivity to recognise small changes in either positive or negative driving behaviour that provide opportunity for reinforcement.

### *1.2. In-vehicle telematics*

A new technology that has the potential to improve driving behaviour is in-vehicle telematics. In-vehicle telematics technology forms the basis of an emerging insurance product, commonly referred to as Pay-As-You-Drive (PAYD) insurance (e.g., Bordoff and Noel, 2008). In these schemes, insurance premiums are determined based on actual driving behaviour of policy holders, which are captured by accessing information from internal vehicle systems or location tracking, rather than a comparison to claims of similar drivers. As such, in-vehicle telematics may provide a more sensitive and effective means through which positive driving behaviour can be shaped.

Evidence is emerging regarding the utility of using in-vehicle telematics technology in improving road safety through provision of financial incentives or direct driver feedback. For example, Bolderdijk et al. (2011) showed that PAYD insurance incentives for young drivers, opting to participate in the experiment, significantly reduced speed limit violations. Furthermore, Dijksterhuis et al. (2015) found a significant reduction in at-risk driving using low value incentives.

A systematic review by the Transport Research Laboratory on the effects of PAYD insurance provides various recommendations for future research on in-vehicle telematics (Tong et al., 2016); e.g., an investigation of the effects of different types of feedback. In general, Donmez et al. (2008) confirmed the positive impact

of feedback on driving behaviour. However, Prato et al. (2010) found that feedback based on in-vehicle data recorders only temporarily decreased risky behaviour for young, male drivers. Furthermore, the most effective way to deliver feedback in the context of driver behaviour is still uncertain (Horrey et al., 2012). Feedback should be timely, as argued earlier, however, reporting to the driver post-journey has been shown to be only slightly less effective than in-car feedback (Dijksterhuis et al., 2015). Lahrman et al. (2012) investigated the feasibility of a market introduction of an Intelligent Speed Adaption (ISA) system that provides verbal warnings every six seconds when speeding. The study experienced major difficulties in recruiting participants, even when offering a 30% insurance discount incentive, perhaps implying that the feedback mechanism employed was viewed negatively or the mechanism was too invasive. Therefore, the most appropriate means and methods of identifying changes in driver behaviour, determining the most appropriate mechanism for providing feedback, and determining situations where providing feedback has maximum safety benefits without exacerbating risk for drivers (e.g., through distraction) remain important unanswered questions (cf. Horrey et al., 2012).

### 1.3. Long Short-Term Memory recurrent neural networks

To model driver behaviour captured in telematics data, this study uses artificial neural networks (NNs) (Bishop, 1995; Dreyfus, 2005; Graupe, 2013; Samarasinghe, 2006). The building block of a NN is a neuron, which generally combines several inputs linearly using adjustable weights and passes the resulting potential through an activation function to provide a bounded output. Neurons are commonly combined in a network structure consisting of input, hidden, and output layers for advanced function estimation. Learning paradigms for model calibration include supervised and unsupervised learning. In supervised learning, given a set of input variables, internal weights are adjusted to approximate provided outputs. In contrast, unsupervised learning approaches such as autoencoders could be used for feature extraction by building a condensed representation of the input data in the hidden layer (Vincent et al., 2008). Recently, there has been a shift in research approaches from combined unsupervised and supervised learning towards supervised learning only (Schmidhuber, 2015). The NN design should be controlled for issues such as overfitting, which is also known as the bias–variance dilemma: too many neurons (i.e., free parameters) will lead to overfitting, while the complexity of the unknown targeted function cannot be matched when too few neurons are used in the NN. Furthermore, the NN should recognise normal fluctuations in individual driver behaviour and not falsely react to fluctuations at very short time intervals. Compare this to the stability–plasticity dilemma (Grossberg, 1988), which describes that adaptivity should be such that the NN does not adapt based on short term spurious disturbances, but does pick up meaningful changes in sufficiently short time.

NNs have been used in various studies related to road safety. For example, Xie et al. (2007) use Bayesian NNs to predict crash frequencies with road characteristics. Sohn and Shin (2001) used a NN to classify crash severity based on road type, speed before accident and the use of protective devices. Zeng et al. (2016) investigated NNs to predict the frequency of crashes with different severity classifications, combined with a rule extraction methodology to recover the sensitivity of the model to varying covariate values. Abdelwahab and Abdel-Aty (2002) investigated the use of multi-layer perceptrons and radial basis function NNs to analyse road safety around toll gates. Other studies focussing on road safety explored NNs for early warnings with respect to state changes. For example, King et al. (2006) used a NN for the rapid detection of fatigue in drivers based on brain activity measurements. Rapidly identifying changes using NNs also has applications in other complex, safety critical domains such as monitoring nuclear power plants (e.g., Uhrig, 1993; Santosh et al., 2007) and anomaly detection in relation to computer security (Mukkamala et al., 2002). The studies above show the potential of NN modelling for both the identification of change and application to road safety.

Frequently used NN designs include feedforward NNs and recurrent neural networks (RNNs); the latter incorporates feedback to previous layers (e.g., Schmidhuber, 1992; Dreyfus, 2005). Schmidhuber (2015) provides an overview of NNs with many hidden layers (i.e., deep NNs) and design elements of contest-winning NNs (up to 2014). One of these designs is a feedforward convolutional NN with *winner-takes-all* max-pooling layers, which has been particularly successful in image recognition. Another successful design is the Long Short-Term Memory (LSTM) RNN (Hochreiter and Schmidhuber, 1997). Applications of LSTMs include speech recognition (Graves et al., 2013), handwriting recognition (Pham et al., 2014), as well as

online driver distraction detection (Wöllmer et al., 2011). The latter used measurements collected during distraction scenarios, such as steering wheel angle and head rotation, to assess disruption in real-time situations. As LSTMs can learn from data sequences and capture the temporal evolution of these sequences, it is an appropriate method to monitor changes in driving behaviour over time.

*Mathematical formulation.* LSTMs are deep learning NNs, where the neuron is replaced by a memory cell with gate functions that control access to the cell’s internal memory  $c$ . Specifically, the input and output gates  $i$  and  $o$  provide write and read access, while forget gate  $f$  can (partially) reset  $c$ . The output of the memory cell is denoted as  $h$ . The memory cell structure used in this research includes peephole connections and is described in Equations (1)–(5), where bold variable names indicate vectors. In these equations,  $\sigma(\cdot)$  is the logistic sigmoid function,  $w_{ab}$  the weight on the connection from  $a$  to  $b$ ,  $\mathbf{x}_t$  the input variables at time  $t$ , and  $b$  the bias term. Supervised learning is used to set the network’s free parameters.

$$i_t = \sigma(\mathbf{w}_{xi}\mathbf{x}_t + w_{hi}h_{t-1} + w_{ci}c_{t-1} + b_i) \quad (1)$$

$$f_t = \sigma(\mathbf{w}_{xf}\mathbf{x}_t + w_{hf}h_{t-1} + w_{cf}c_{t-1} + b_f) \quad (2)$$

$$c_t = f_t c_{t-1} + i_t \tanh(\mathbf{w}_{xc}\mathbf{x}_t + w_{hc}h_{t-1} + b_c) \quad (3)$$

$$o_t = \sigma(\mathbf{w}_{xo}\mathbf{x}_t + w_{ho}h_{t-1} + w_{co}c_t + b_o) \quad (4)$$

$$h_t = o_t \tanh(c_t) \quad (5)$$

In summary, driving behaviour changes continuously through interactions with other drivers in a complex system. This research models a driver’s pattern of driving, as recorded by in-vehicle telematics devices, using LSTMs for the early detection of behavioural changes.

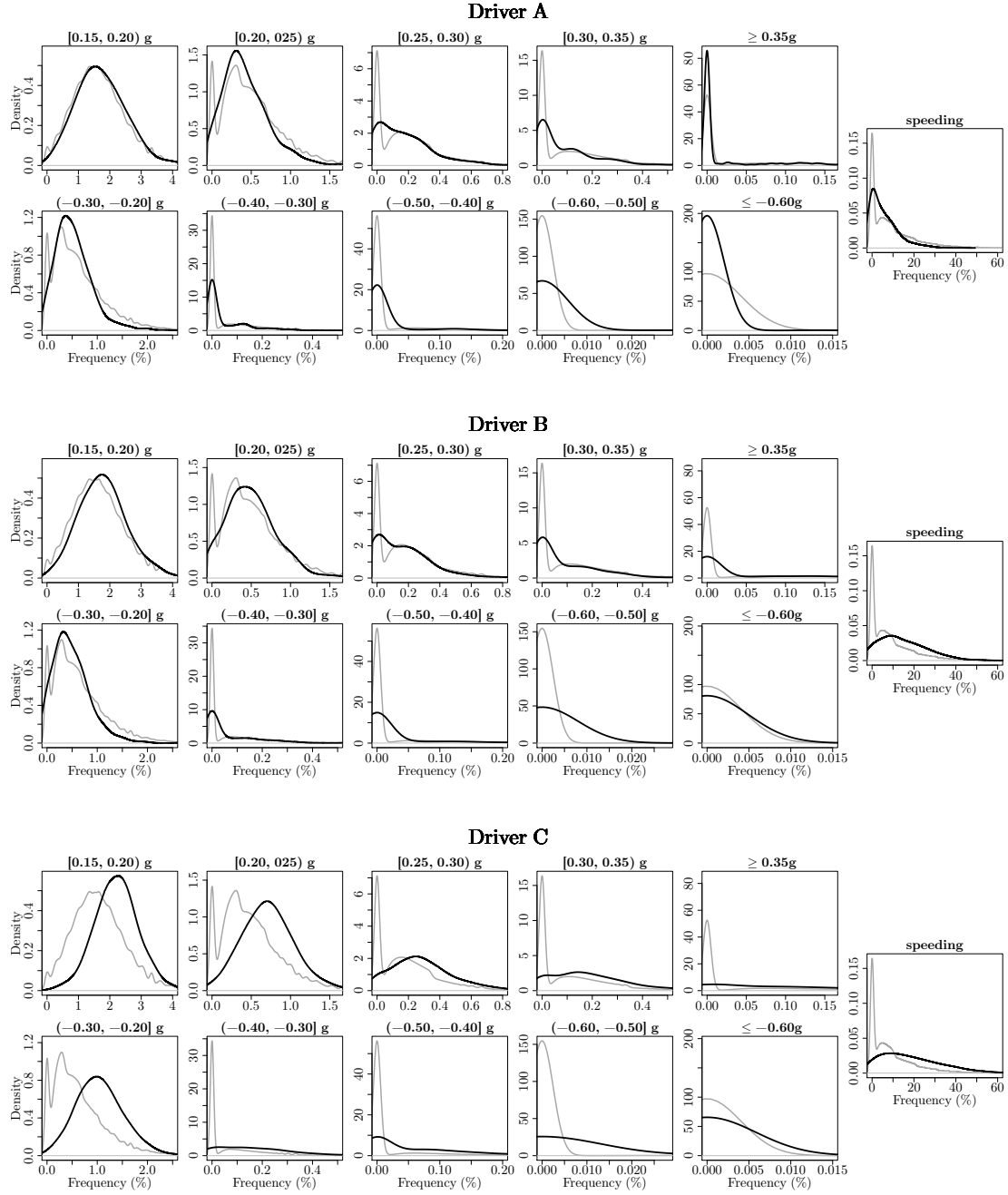
## 2. Methods

### 2.1. Telematics data

The database used in this research contains recorded data of insurance policy holders and is supplied by an insurance company that provides telematics devices as part of the insurance scheme. A sample of 3,000 vehicles was provided by the insurance company, with up to 2.5 years of driving data available per driver at the time of analysis. Data is collected every 30 seconds (i.e., 1/30 Hz) for all intervals where the vehicle is not parked, generating measurements at 87 million time points for our sample. The captured information is limited to GPS data only, which is then enriched using external map data to derive speed limits, road class, street name, and others. Furthermore, the in-vehicle telematics device retains vehicle speed at 1/30 Hz, while acceleration and deceleration information is derived at a 1 Hz frequency. Acceleration and deceleration information is converted to 1/30 Hz by counting the number of events for specific g-force intervals (see section 2.3).

### 2.2. Feasibility of driver identification using behavioural information

As highlighted, an association has been found between speeding and increased crash risk (Finch et al., 1994). Further, evidence for an association of acceleration and deceleration with crash risk has been found in various studies (e.g., Lajunen et al., 1997; Af Wählberg, 2008). Af Wählberg (2008) found that driver acceleration and deceleration behaviour is semi-stable over time, which implies that measurements of at-risk driving behaviours (i.e., acceleration, deceleration, and speeding) can be used to build a profile or signature of a driver with the purpose of driver identification. The generation of unique driver signatures using acceleration measurements has been previously explored by Robertson et al. (1992). Detailed measurements from various in-vehicle sensors were used by Enev et al. (2015) to investigate the re-identification of a driver from a group of 15 drivers based on collected data. Re-identification was successful using limited temporal data from just a few sensors, including positions of the brake pedal, accelerator and the steering wheel. Successful identification of drivers is a first step towards identifying behavioural change.



**Fig. 1.** Kernel density estimates of acceleration (top row), deceleration (bottom row) and speeding (right side) frequencies for all drivers (grey line) and drivers A, B and C (black lines). Frequencies are presented as percentage of time, calculated using event occurrences per trip the driver has taken.

Since brake, accelerator and steering wheel position sensors are not available in our data sample, driver identification is investigated using derived measurements stored in the telematics data. Results of this exploratory analysis for three different drivers are shown in Fig. 1, where distributions of the average hard acceleration, deceleration and speeding frequency in a single trip are presented. Records where the vehicle was not moving have been excluded. Drivers were selected using proprietary driver risk scores of the insurer: driver A is rated as a safe driver, driver B takes slightly more risks than the average driver, and driver C is rated as a high-risk driver. Various differences between the three drivers can be observed. For example, driver A shows fewer extreme acceleration and braking events recorded in g-forces (i.e.,  $\geq 0.35g$  or  $\leq -0.60g$ ) compared with driver B and is also less likely to speed, which is in line with the insurer’s classification of driver B as a higher risk driver. Similarly, compared with driver B, the distributions for driver C show a location shift in the low severity acceleration and braking events towards higher risk behaviours. In addition, differences can be observed for speeding and the more extreme acceleration and braking events. Hence, using telematics data, a driver’s behaviour can be represented by specific braking, acceleration and speeding frequencies, which together provide a profile of the driver’s interactions with the acceleration and brake pedals in the car. Research by Enev et al. (2015) reported that drivers can be identified using these type of parameters; this is the approach that is taken in our research.

### 2.3. Modelling driving behaviour using LSTMs

We used the following methodology to identify changes in the behaviour of a specific driver (referred to as the monitored driver). For a comparative assessment of the monitored driver’s behaviour, two groups of drivers were selected, not including the monitored driver, representing unsafe and safe drivers, respectively (i.e., the benchmarks). The drivers forming these benchmarks were selected using the insurer’s proprietary driver risk score, which ranges from zero (very unsafe) to 100 (very safe). A selection of 40 drivers was made for the unsafe driving benchmark (i.e., benchmark  $\mathcal{A}$ ) based on a proprietary driver risk score under 40 with at least six months of recorded data. For the safe driving benchmark (i.e., benchmark  $\mathcal{B}$ ) 40 drivers were selected based on a risk score over 90 and the same data availability requirement. Hence, benchmarks  $\mathcal{A}$  and  $\mathcal{B}$  represent driving behaviour on the extreme ends of the risk spectrum, namely very unsafe and very safe, respectively.

In this study, one monitored driver is compared to 40 drivers combined in benchmark  $\mathcal{A}$  and 40 drivers forming benchmark  $\mathcal{B}$  in a single NN. Various monitored drivers are investigated, however, the benchmarks remain fixed. The history of driving behaviours for the monitored driver and the drivers in benchmarks  $\mathcal{A}$  and  $\mathcal{B}$  is retrieved from the telematics database. Data selections could contain information not related to at-risk behaviours, for example, in Fig. 1, trip-based information is used; the duration of each trip is naturally not the same and, importantly, the average trip duration varies between drivers. As the NN should not be able to identify drivers based on trip duration, driving sequences were standardised to 30-minute blocks (i.e., a 60-record sequence with 30 seconds of observed behaviours per record) by combining records from sequential trips. Further, to minimise prediction bias, the number of blocks of each of the benchmarks was randomly reduced to the number of blocks available for the monitored driver and hence an equal number of blocks for all three groups is obtained. Typically, this resulted in 1,000 blocks for a six month training period, depending on the total travel distance of the monitored driver. These sequences are used to train an LSTM model which classifies each sequence as belonging to the investigated driver or one of the benchmarks. After calibration, new telematics data of the monitored driver (recorded beyond the training window) is fed into the model. The concept of this approach is that if the monitored driver’s behaviour has not changed, the model should be able to classify these new instances as belonging to the monitored driver. However, if a change in driving behaviour occurs, prediction performance should deteriorate, as the characteristics of the newly recorded behaviour are different from what was used for model calibration. Importantly, this method ensures that changes in prediction performance can be linked directly to changes in driving behaviour because all input variables are directly related to driving behaviour.

One LSTM is implemented for each driver that is monitored, and the LSTM memorises the range of the driver’s historical driving behaviour. The LSTM recurrent neural network was chosen as the preferred methodology, as modelling time dependencies is a key capability of LSTMs. Therefore, it is suitable for tasks such as sequence classification, which is the modelling approach taken here. The LSTM learns a driver’s

behaviour by adjusting internal weights to correctly classify the sample sequences during a calibration phase (i.e., supervised learning).

The network structure in our approach includes a normalised input layer of 11 nodes. The first five nodes describe counts of acceleration events in the intervals  $[0.15, 0.20)$ ,  $[0.20, 0.25)$ ,  $[0.25, 0.30)$ ,  $[0.30, 0.35)$  and  $\geq 0.35$  g over a 30-second period. Similarly, the next five nodes describe counts of deceleration events in the intervals  $(-0.30, -0.20]$ ,  $(-0.40, -0.30]$ ,  $(-0.50, -0.40]$ ,  $(-0.60, -0.50]$  and  $\leq -0.60$  g. The final node describes any exceedance of the posted speed limit in  $\text{km h}^{-1}$ . In case the speed limit was not exceeded, the value of this node is set to 0. This input layer is fully connected to a hidden layer consisting of ten LSTM memory cells, which, in turn, is fully connected to a softmax output layer with three nodes. Nodes in the output layer represent the monitored driver and the two benchmark groups. The network is a deep NN in the time dimension only [adding more hidden layers of LSTM memory cells for higher levels of abstract representations of the input variables was not required given the type and number of input variables that are used in this research]. Note that adding extra hidden layers did not lead to increased performance (see section 3.1). The described LSTM is calibrated using GPU computing with Microsoft’s CNTK software (Agarwal et al., 2014), renamed to Microsoft Cognitive Toolkit after completion of this research. GPU computing allows for efficient calibration of the LSTMs, while evaluating the model on new data only requires limited computing resources. The generation of input files has been implemented in R (R Core Team, 2014).

**Table 1.** A sample input sequence, showing for each line: record number (for explanation purposes only), sequence identifier, count of events in five acceleration intervals during the corresponding 30-second time frame, event counts in five deceleration intervals, any speed limit exceedance ( $\text{km h}^{-1}$ ) and (for the final record) the group this sequence belongs to using sparse data representation.

01	1	a 0 0 0 0 1	d 0 0 0 0 0	s 0	
02	1	a 0 0 0 0 0	d 0 0 0 0 0	s 0	
03	1	a 0 0 0 0 0	d 1 0 0 0 0	s 0	
04	1	a 1 0 0 0 0	d 0 0 0 0 0	s 0	
05	1	a 0 1 0 0 0	d 0 0 0 0 0	s 0	
06	1	a 0 0 0 0 0	d 0 0 0 0 0	s 0	
07	1	a 0 0 0 0 0	d 2 0 0 0 0	s 0	
08	1	a 0 0 1 0 0	d 1 0 0 0 0	s 0	
09	1	a 1 1 0 0 1	d 0 0 0 0 0	s 0	
10	1	a 1 0 0 0 0	d 0 0 0 0 0	s 0	
11	1	a 0 0 0 0 0	d 0 0 0 0 0	s 0	
12	1	a 0 0 0 1 0	d 0 0 0 0 0	s 0	
13	1	a 0 0 0 0 0	d 0 0 0 0 0	s 0	
14	1	a 2 0 0 0 0	d 1 0 0 0 0	s 1	
15	1	a 1 0 0 0 0	d 0 0 0 0 0	s 4	
		...			
		...			
58	1	a 0 0 0 0 0	d 0 0 0 0 0	s 0	
59	1	a 0 0 0 0 0	d 0 0 0 0 0	s 0	
60	1	a 0 0 0 0 0	d 0 0 0 0 0	s 0	class 2:1

The LSTM is calibrated using randomly sorted sequences of driving behaviour, to ensure the weights of the LSTM are not updated towards the prediction of a single driver or benchmark regardless of the input. A sample sequence is provided in Table 1. The large number of zeros in this sequence shows that extreme behaviours only occur sporadically (depending on the behaviour of the driver). It is also a consequence of pre-processing acceleration and deceleration data into intervals; the underlying measurement in g-force was not stored by the telematics device. Each sequence is processed record by record through the LSTM, updating the internal memory of each memory cell in the hidden layer based on the provided inputs

and calculated values of the gate functions. After the final record is processed, the LSTM model produces probabilistic estimates that the sequence belongs to the monitored driver, benchmark  $\mathcal{A}$  or  $\mathcal{B}$ . Weights in the NN, including weights of the input, forget and output gates, are updated over 1,000 epochs using truncated backpropagation through time to closely approximate the training labels. After model calibration, new real-time driving data for the monitored driver can be supplied to the model sequentially with the purpose of monitoring changes in prediction performance. If a change in driving behaviour is apparent, it is classified as negative for increased benchmark  $\mathcal{A}$  predictions, while increased predictions for benchmark  $\mathcal{B}$  indicate a positive change.

#### 2.4. Model validation

The absence of objective outcome measurements in relation to behavioural change has inherent complications for the development of a model that identifies behavioural change. Ideally, a list of time points where behaviour changed for a selection of drivers should be available, which could be used to validate if the new model correctly identifies these change points. Currently, when our model identifies a change in behaviour, it is unknown if the behaviour of the corresponding driver actually changed at that point, which presents challenges for model validation. Therefore, the focus here is on showing that the methodology itself is robust by a series of sensitivity analyses. These analyses test sensitivity to different data selections, model calibration parameters, methodologies to select benchmarks and network structures.

A description of the cases comprising the sensitivity analyses is provided in Table 2. The first three cases focus on the sensitivity of the model to different network structures. Exploratory analyses indicated that a network with only one or two memory cells had insufficient complexity to yield accurate performance. In contrast, a network with 50 memory cells led to overfitting; i.e., perfect classification on training data was achieved using the large number of adjustable weights, but performance on test data was poor (cf. bias–variance dilemma). This indicated that a network structure with around 5–15 memory cells is most appropriate for the described problem, achieving a balance between computational efficiency and an accurate fit on training data, while not overfitting the model. The impact of the number of these memory cells and their arrangement is assessed in cases A–C. Case D shows the impact of using different calibration settings to estimate weights in the LSTM. Finally, case E is a more extreme scenario, which provides background on the impact of methodological assumptions on model accuracy. In particular, selecting only one driver per benchmark could lead to better prediction performance as it may be easier to separate just three drivers. However, the methodology becomes more dependent on which driver is selected for each benchmark. Therefore, a broader benchmark leads to a more robust method. In addition, the data processing assumption of not removing records where the vehicle is stationary shows what happens if non-behavioural information is included. For example, the LSTM could now learn to separate the (remaining) three drivers based on the time each driver is not moving, which is indicative of the route that is taken rather than driving behaviour. Therefore, deteriorations in model performance for case E could not be attributed to changes in driving behaviour with certainty. Instead, the monitored driver may have started to take different routes that result in more (or less) stopping.

**Table 2.** Description of cases for sensitivity analyses.

Case	Description
A	Different network structure, using a hidden layer with five instead of ten memory cells;
B	As in Case A, but using 15 memory cells;
C	As in Case A, but using two fully connected hidden layers with six and three memory cells, respectively;
D	Different calibration settings; i.e., half the learning rate and five times the number of epochs;
E	Different data processing and methodology; i.e., the use of only one driver per benchmark combined with keeping records where a vehicle is stationary.

Training data consists of insurance policies starting in the first half of 2015 and each policy holder is considered a monitored driver, sequentially. That is, for each of the selected policies an LSTM model is

calibrated using fixed benchmarks  $\mathcal{A}$  and  $\mathcal{B}$ . In total, the sensitivity analysis has been completed for a sample of 100 drivers. Recorded behaviours until end of October 2015 are used for model calibration, while data from November 2015 to February 2016 is used for monitoring.

### 3. Results

#### 3.1. Sensitivity analysis

The plots in Fig. 2 all vary slightly as would be expected, however, the different cases show similar characteristics that lead to the same conclusions. For example, driving behaviour is stable during November, December and the first part of January. This is followed by a peak in predictions for benchmark  $\mathcal{A}$  which is a proxy for a deterioration in driving behaviours. The peak is visible in the same time period in all plots; for case E the amplitude is slightly lower. Note that plots with perfect model performance and no behavioural change would show three horizontal lines with the black line at prediction level 1 and the others at level 0.

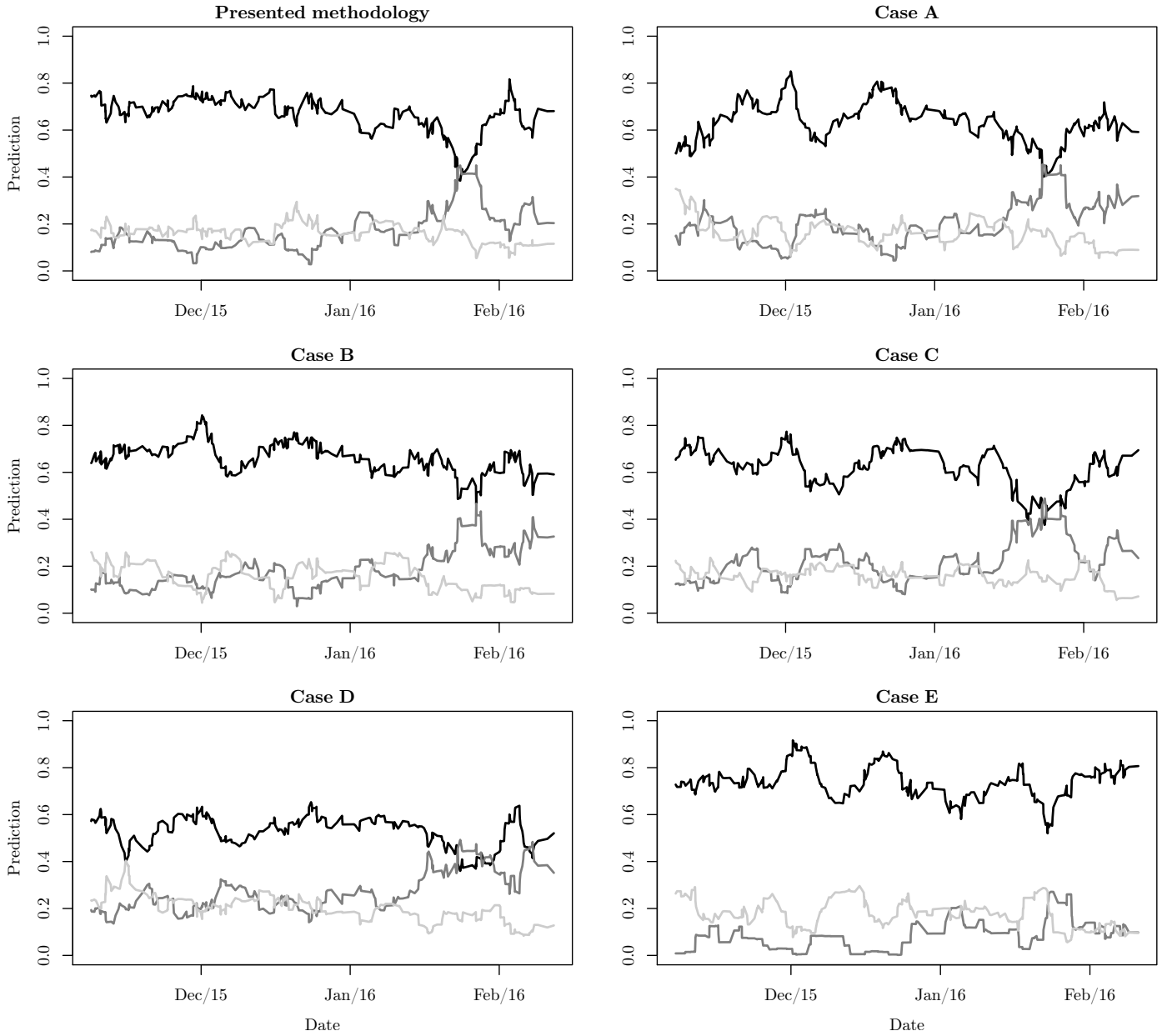
Results for the full selection of 100 drivers cannot easily be incorporated in the paper, as aggregating behavioural change over various drivers is not meaningful. Therefore, results for a further six drivers are provided in Appendix A, which provides additional evidence that the presented method is robust against a variety of different assumptions for the network structure, calibration parameters, data processing and benchmark selection.

#### 3.2. Output characteristics

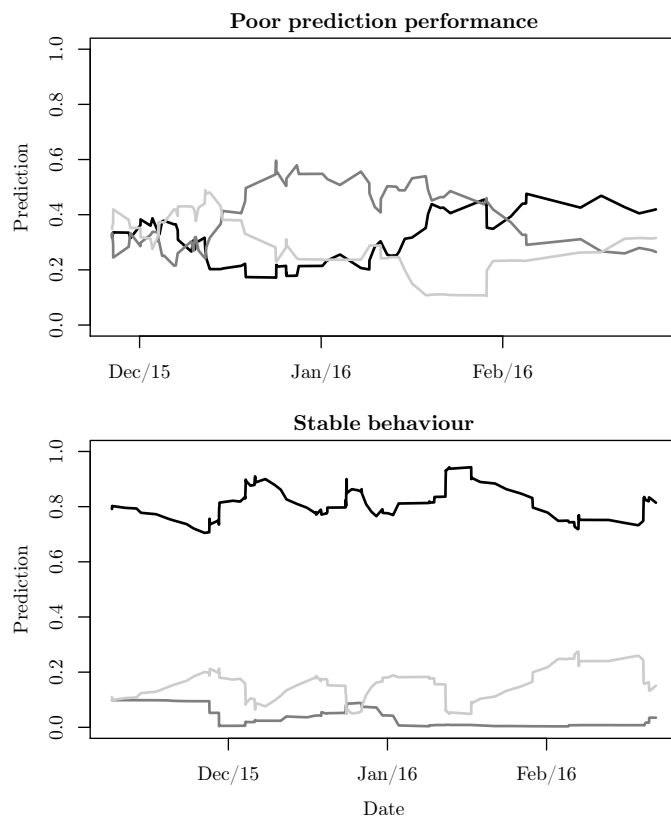
Results can be characterised into three categories: stable behaviour, changing behaviour, and poor prediction performance. Adequate prediction performance is a prerequisite for identifying behavioural change, as observed changes in predictions are otherwise likely to be associated with noise. A typical example of insufficient prediction performance is presented in the top plot of Fig. 3. Note that predictions of 1/3 for each group (i.e., horizontal lines at this level) indicate no predictive capability. As a substantial part of the studied drivers are affected to some extent by limited predictive capability, further model improvements should be investigated in future research. However, the analysis in section 3.1 indicates that the presented methodology is robust as it provides consistent conclusions based on the input data, suggesting that improvements of the input data may be required. This conclusion is reinforced by Enev et al. (2015), achieving high predictive capability for driver identification using very detailed measurements of braking, acceleration, speed and steering wheel angles. Specifically, 100% classification accuracy was obtained in the identification of 15 drivers using only measurements from a brake pedal position sensor during a 90 minutes driving period. In contrast, for our study only pre-processed data was available where acceleration was classified into several intervals, leading to redundant information (i.e., many zeros) in the model inputs (see Table 1). Enhanced data collection, requiring new in-vehicle telematics devices, therefore provides opportunities for further improvement of the predictive capability.

When prediction performance is adequate, behaviour can be classified as stable or ‘in transition’. The majority of drivers have a stable driving style and behavioural change is only detected in a smaller group of drivers. A typical example of stable driving behaviour as detected by our methodology is presented in the bottom plot of Fig. 3. The model accurately assesses the new data as belonging to the monitored driver and the prediction performance is stable over time. Stable predictions indicate that it is not likely that there was a change in the driver’s behaviour. Examples of changing behaviour are discussed in the following section.

### Sensitivity analysis – Driver $\alpha$



**Fig. 2.** Monitoring the prediction performance for driver  $\alpha$  using the presented methodology and cases A–E (see Table 2). Each point shows the average prediction performance over the last ten hours of driving. The LSTM predictions at each point in time sum to 1 and provide a probabilistic estimate that the supplied behaviours belong to the monitored driver (black line), high-risk driving benchmark  $\mathcal{A}$  (dark grey line) or benchmark  $\mathcal{B}$  (light grey line).

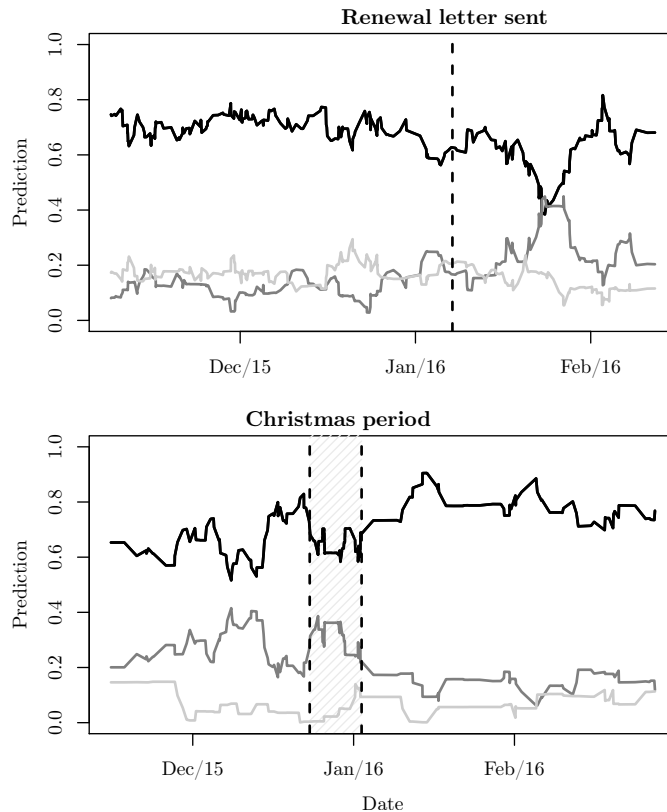


**Fig. 3.** Monitoring prediction performance shows insufficient predictive capability (top) and no change in behaviour (bottom). Note that the plots belong to different drivers.

### 3.3. Potential applications

The model in its current form provides an indication of behavioural change in several drivers. Further, it has various applications in addition to the real-time monitoring of non-specific behavioural change among drivers. For example, behaviour can be monitored during periods surrounding specific events such as policy renewals to determine whether reinforcement or punishment measures, delivered by the insurer at these times, affect driving behaviour. Before these annual events, the insurer sends a renewal letter to the policy holder that specifies a premium increase or decrease based on the driver's behaviour in the preceding 12 month period. This is the only time in the year that the driver is directly exposed to the financial incentive embedded in the insurance product and policy holders become aware of the financial consequences of the past 12 months of driving. To investigate potential changes in driving behaviour associated with this period in more detail, we overlaid the date that the renewal letter was sent to sampled drivers. Detailed information on the content of insurance policy renewal letters was also collected from the insurer.

The top plot in Fig. 4 is the same as depicted in the sensitivity analysis in section 3.1 (see Fig. 2). A renewal letter was sent by the insurer to this 25 year old driver on 8 January 2016 for a renewal date of 9 February 2016. The 18,000 km of driving in the past year undertaken by this policy holder had resulted in three claims: a not-at-fault collision, an at-fault collision and a malicious damage to the vehicle claim. However, because the recorded data indicated the driving style of the driver was better than average, a premium discount of 500 AUD was offered in the renewal letter. Despite the discount, the driver chose not to renew the insurance policy. According to our model, this period was immediately followed by a temporary change to more dangerous driving behaviours before data recording stopped on 12 February 2016. Whilst we cannot speculate on the exact causes of this sudden change, such an example shows the potential of the presented methodology to investigate effects of financial, or other, incentives on driving behaviour.



**Fig. 4.** Monitoring prediction performance after a renewal letter has been sent by the insurer (top) and during the Christmas holiday period (bottom). Note that the plots belong to different drivers.

Further, the method could be applied to investigate driving behaviours during specific, high-risk periods. For example, the bottom plot of Fig. 4 shows how it can be used to investigate behavioural change during holiday periods such as those surrounding Christmas or Easter breaks. In this case, the model shows a peak in benchmark  $\mathcal{A}$  predictions, which could indicate a deterioration in driving behaviours of this driver ( $\beta$ ) during Christmas. Sensitivity analyses for driver  $\beta$  have been included in Appendix A; all cases show peaks in benchmark  $\mathcal{A}$  predictions around the holiday period.

For both examples of this method’s potential application, further research is required using larger sample sizes and objective outcome measurements before robust conclusions on the effects of financial incentives or holiday periods can be made.

#### 4. Discussion

Motor vehicles crashes are linked to over 1.2 million fatalities per year worldwide, with crashes mostly caused by human errors. However, the most appropriate way to influence driver behaviour to reduce road toll is still under investigation. In this research, the early detection of behavioural changes is investigated, based on in-vehicle telematics technology. A new modelling approach using Long Short-Term Memory recurrent neural networks is proposed, capturing the temporal characteristics of data sequences. Drivers are successfully identified using acceleration, deceleration and speeding information only, as recorded by GPS-based in-vehicle telematics, providing a personalised profile of the driver’s usage of the accelerator and brake pedals in the motor vehicle. The study uses one LSTM per monitored driver, calibrated efficiently using GPU computing, which aims to separate the monitored driver from various other drivers combined in two benchmarks. As input variables are related to driving behaviour only, changes in the driver’s behaviour are identified by monitoring prediction performance on new, real-time data. When driving behaviour is stable, models with good predictive capability accurately classify new data as belonging to the monitored driver. Subsequently, the presented methodology can identify changes in driving behaviour, assessing the change as positive or negative by considering the model’s predictions for the selected benchmarks. The new method can be applied to provide timely feedback to drivers, which is essential to sustain positive changes or prevent deteriorations in driving behaviour and reduce crash risks (Ammons, 1956).

The main limitations are that first, objective measurements of behavioural change in drivers were not available (i.e., telematics data provides objective measurements of current behaviour, but no objective identifications of change points in behaviour were available). Hence, model performance could only be tested using sensitivity analyses. The results indicate that the methodology itself is robust to different network structures, data selections, methodologies to select benchmarks, and calibration settings. In future research, experiments can be designed that provide objective measurements of behavioural change to test correct identification of these changes. Further, the telematics device pre-processes acceleration and deceleration information, leading to many zeros in the model input (i.e., generating redundant information). This is the second limitation. Higher quality input data could result in additional improvements in model accuracy, allowing for objective, automated identification of behavioural change using specified thresholds. Further research is required to achieve this.

Enev et al. (2015) confirmed the plausibility of driver identification using high-frequency measurements of behavioural data only; e.g., the accelerator and brake pedal positions are measured at 50 and 66 2/3 Hz, respectively. Our research uses variables derived purely from location data, as measured by in-vehicle telematics devices. The advantage is that this methodology is independent of car make and model, however, performance of our model might be further improved with more detailed in-vehicle measurements of steering angles, accelerator and brake pedal positions, among other factors. The design of new telematics devices that record acceleration and deceleration behaviour in g-force at a higher frequency will be explored in future research. Without conversion to specific intervals, this would provide a more accurate approximation of how a driver uses the accelerator and brake pedals.

Other future research opportunities include an investigation of the period following transitions to a riskier driving style. We propose that the behavioural change to a riskier driving style may temporarily lead to increased crash risk as drivers are unfamiliar with the reduced safety margins. For example, safety margins (e.g., the chosen following distance from leading vehicles) that were sufficient for hazard avoidance given

the driver’s usual driving style may no longer be sufficient for a new, riskier driving style. To test this hypothesis, research could evaluate crash frequencies in the weeks following identified behavioural changes.

Some complications of driver identification are that vehicles may be shared by multiple drivers. This makes identification more difficult as telematics data does not capture who is operating the vehicle at any single point in time. For example, Zaidi et al. (2013) propose a framework for linking the driver’s identity to the vehicle, which allows for correct assignment of traffic violations. In our study, recorded sequences may not belong to the same driver, but the LSTM is trained to recognise any sequence as long as sufficient training data for each driver is available. The same concept is used to specify broad benchmarks. In theory, driving behaviour of multiple drivers sharing one vehicle could also be implemented using multi-block memory cells (i.e., sharing gate functions) to store driver-specific information. A simplified methodology with binary outputs (i.e., only safe and risky, without a driver calibration phase) could also be considered. This would allow for easier implementation, although it will likely take longer to identify behavioural change as less of the day-to-day variations are explained by the model. Note that timely feedback is important to positively influence driver behaviour. Furthermore, note that successful driver identification using recorded data has implications for the privacy of participating drivers, which should be carefully considered.

Currently, some insurance companies provide feedback to drivers based on the relative level of risk the driver takes (i.e., compared to other drivers). This study may complement the operational approach by providing feedback based on an early, more sensitive detection of positive and negative behavioural transitions; i.e., a driver’s behaviour relative to his/her own historical behaviour. Providing feedback directly following such an event, which is possible using the presented NN-based methodology, may be an important improvement in using feedback to positively influence driving behaviour. Fortunately, telematics-based insurance companies’ existing systems of delivering feedback (e.g., SMS text messaging or custom built phone apps) can directly incorporate new methods that successfully identify behavioural change.

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## Appendix A. Sensitivity analyses for additional drivers

This appendix provides additional detail for the sensitivity analyses in section 3.1. Figs. A.5–A.10 present results for six additional drivers. Given changes in the network structure, data processing, methodology and calibration (as exemplified by cases A–E), these results show similar characteristics, which provides confidence in the robustness of the presented methodology.

Sensitivity analysis – Driver  $\beta$

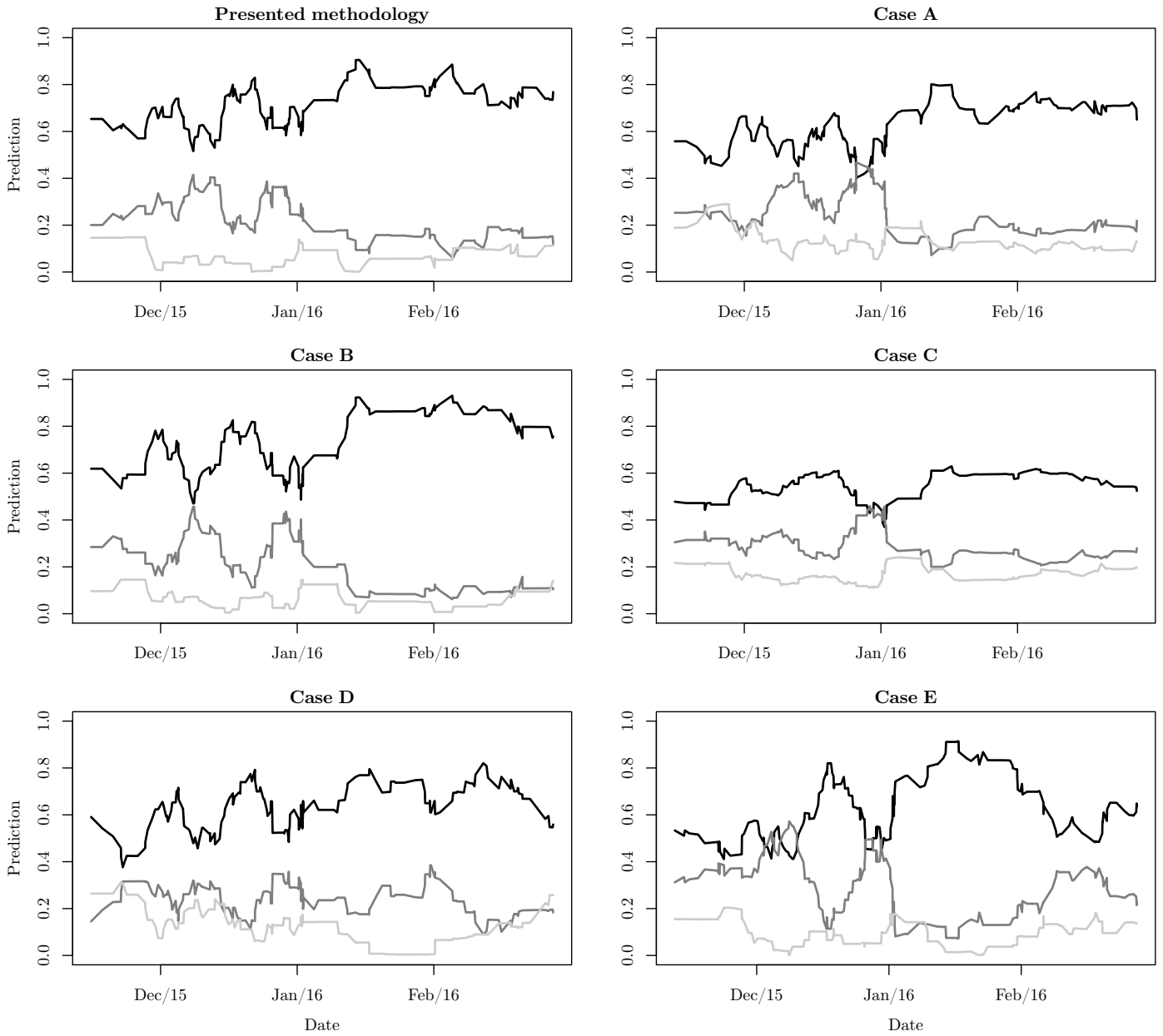


Fig. A.5. As per Fig. 2, but for driver  $\beta$ .

Sensitivity analysis – Driver  $\gamma$

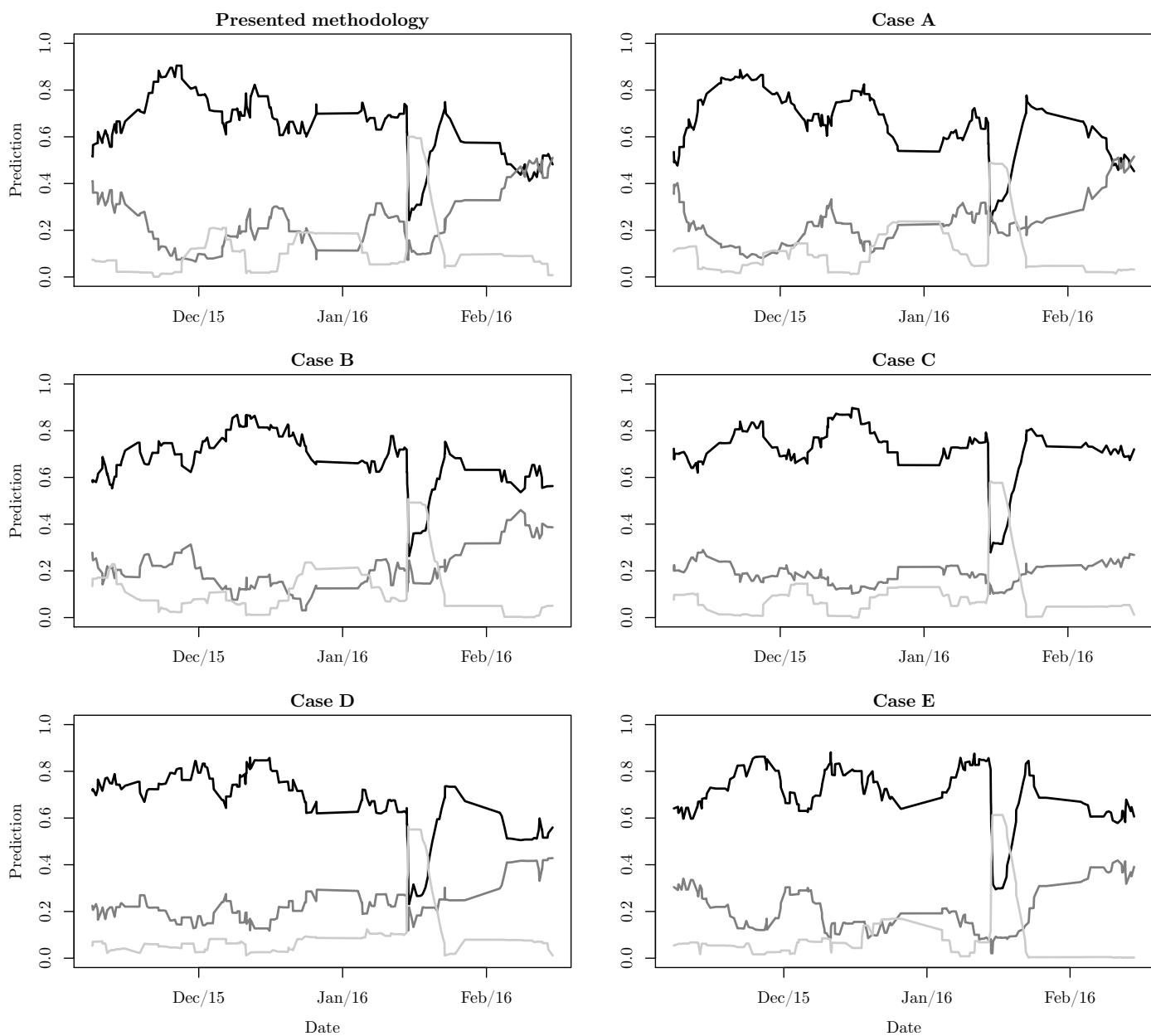


Fig. A.6. As per Fig. 2, but for driver  $\gamma$ .

Sensitivity analysis – Driver  $\delta$

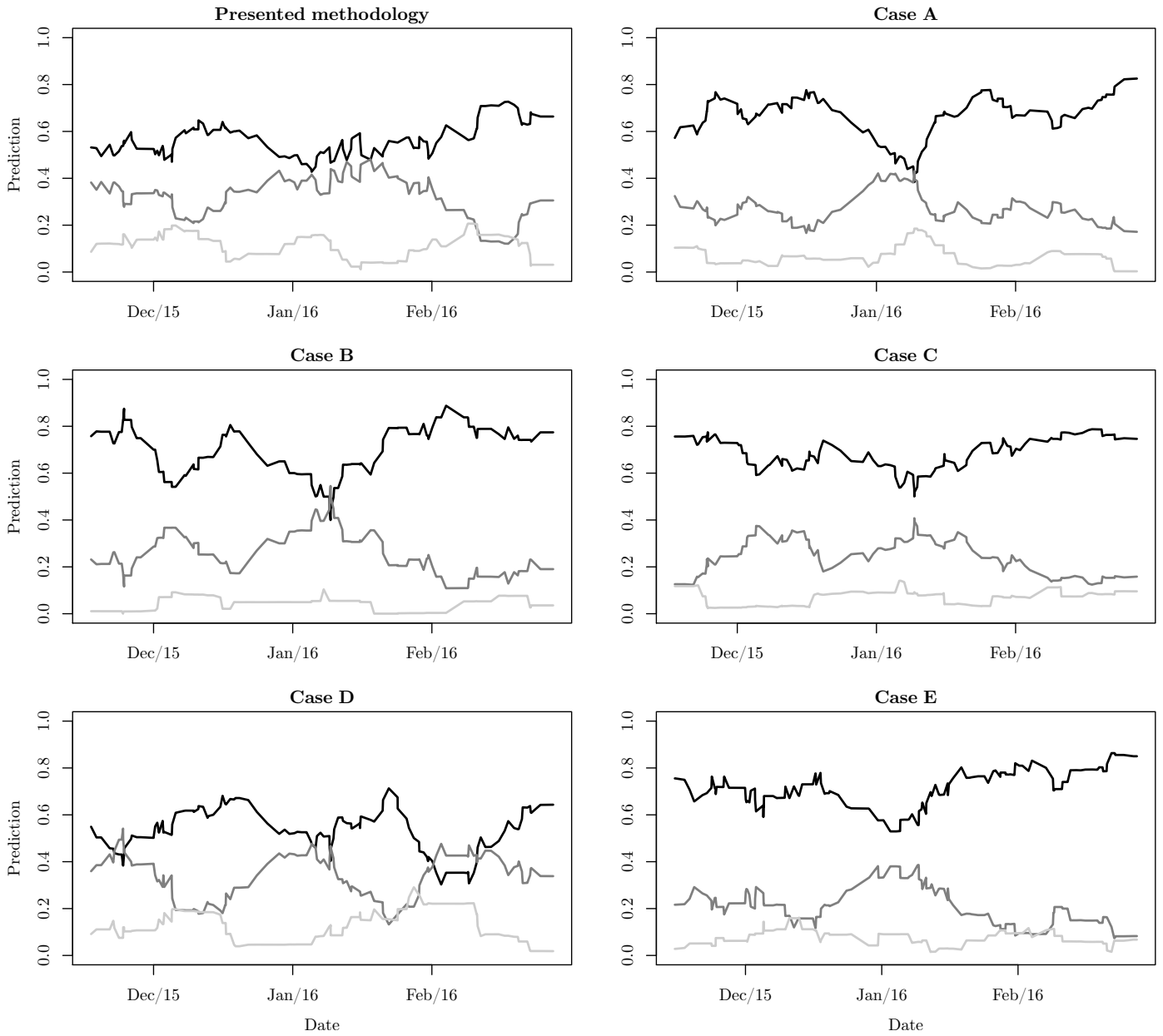


Fig. A.7. As per Fig. 2, but for driver  $\delta$ .

Sensitivity analysis – Driver  $\varepsilon$

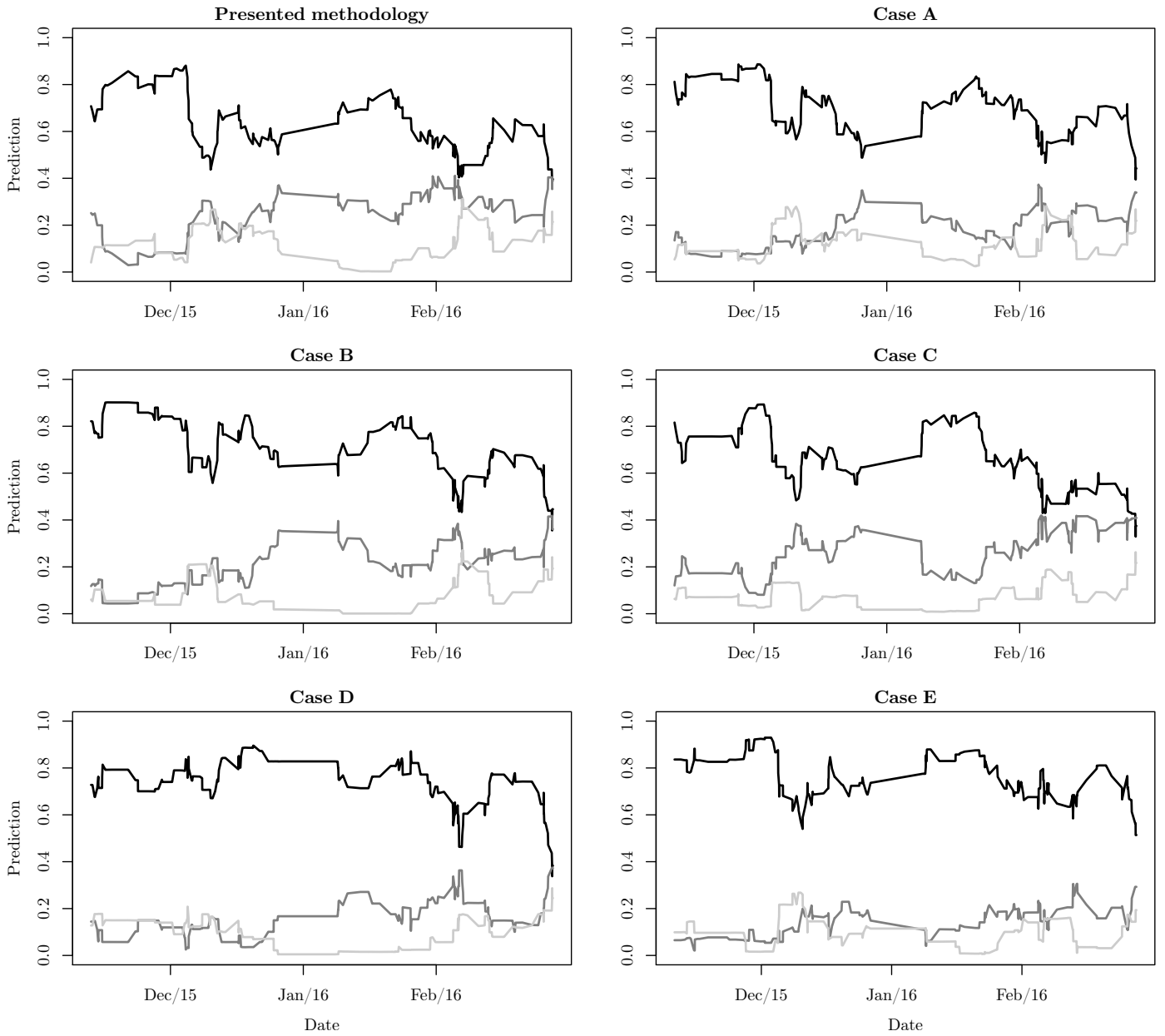


Fig. A.8. As per Fig. 2, but for driver  $\varepsilon$ .

Sensitivity analysis – Driver  $\zeta$

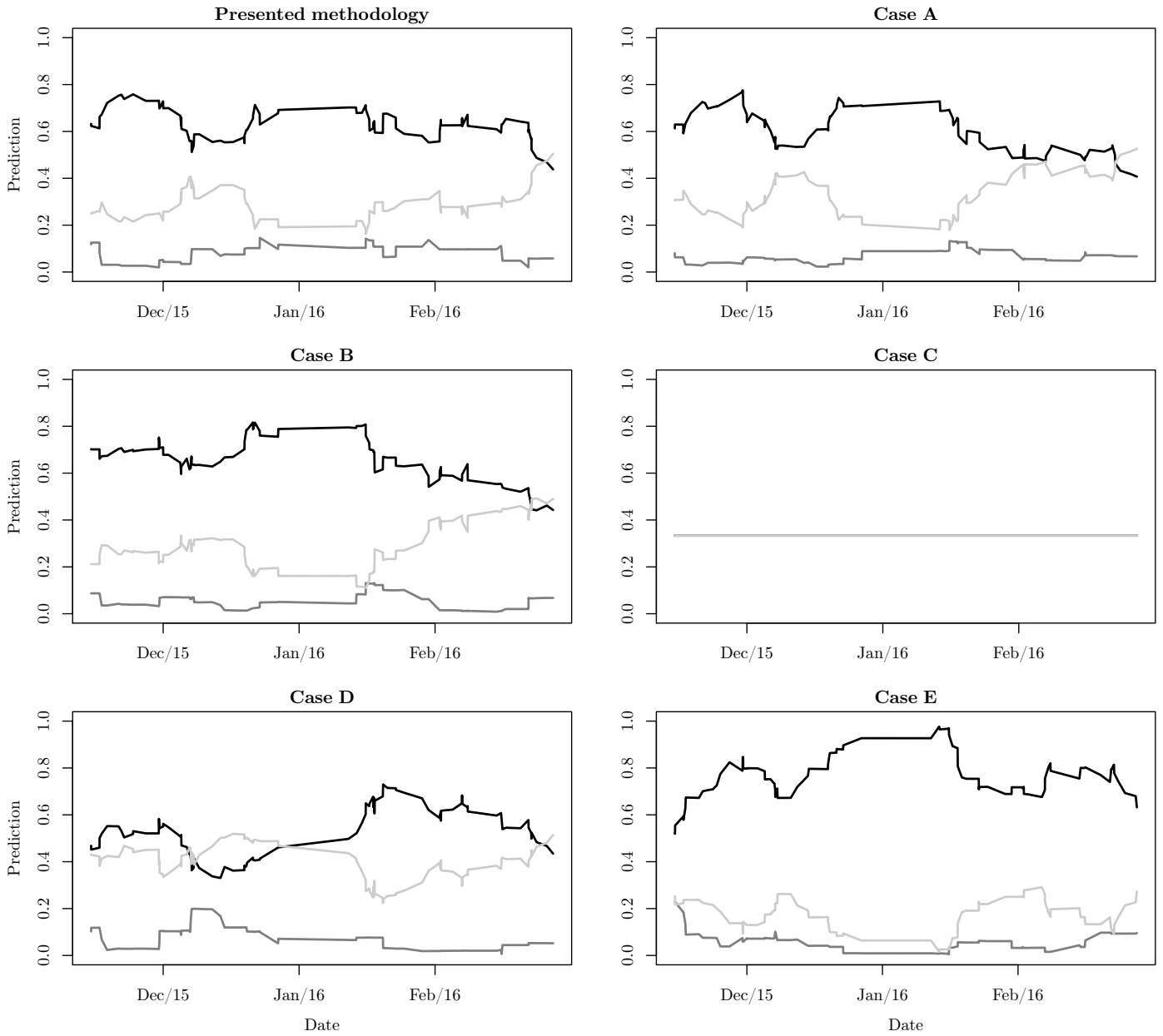


Fig. A.9. As per Fig. 2, but for driver  $\zeta$ .

Sensitivity analysis – Driver  $\eta$

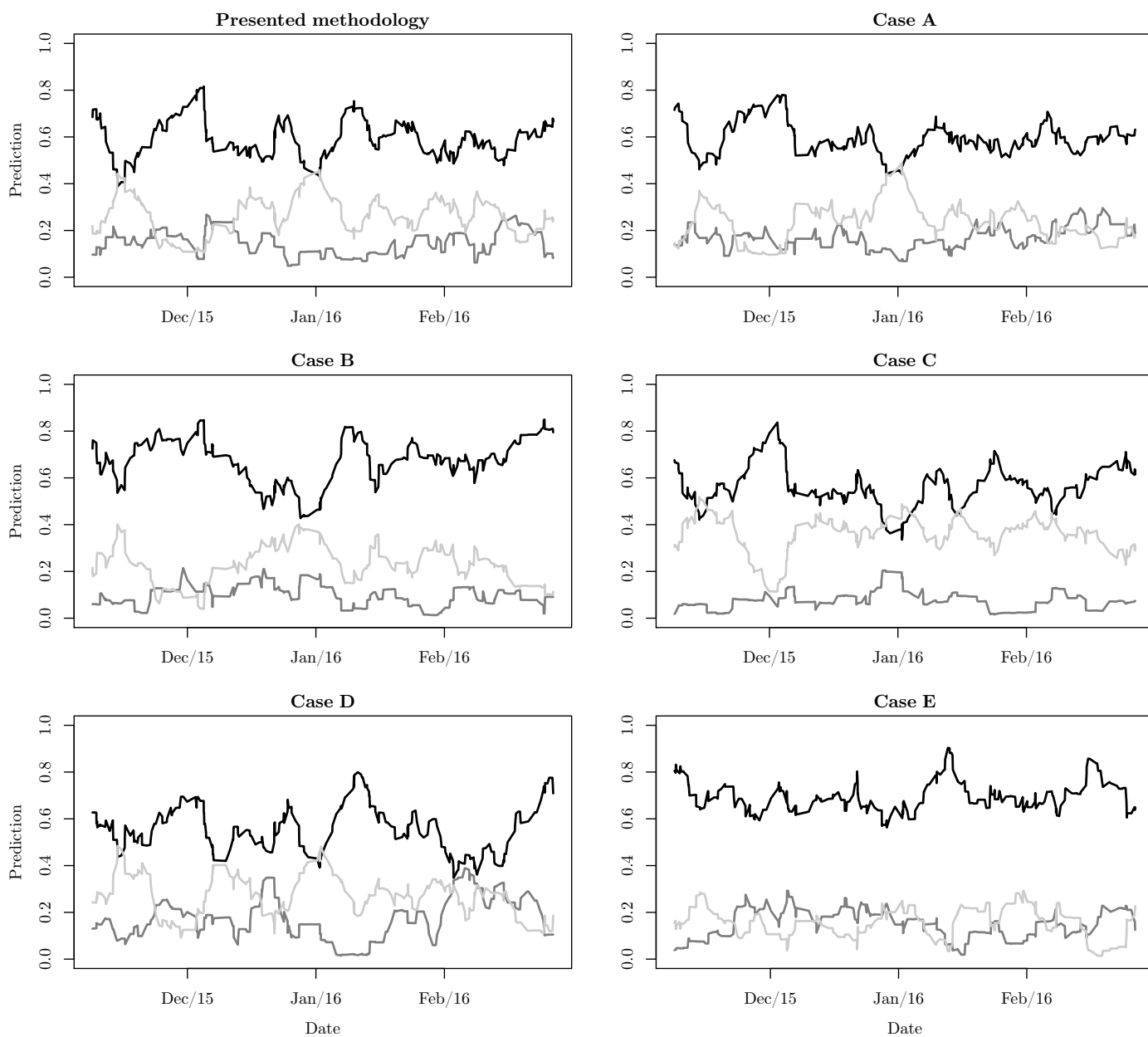


Fig. A.10. As per Fig. 2, but for driver  $\eta$ .

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