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Abstract

In this research paper accuracies (percentage errors, MAPE) of different procedures (growth, ARIMA(X), exponential smoothing and deterministic trend models) in forecasting new passenger car registrations in Germany are presented. It is found that the Logistic Growth Model provides rather accurate predictions of the number of new registrations (total number, which still refers to predominantly conventional gasoline and diesel vehicles) for the forecast period of the study. However, the Bass diffusion model is recommended for predicting the new registration numbers of the innovative battery-electric technology. Furthermore, it is exemplarified that the Bass coefficient of imitation q, in contrast to the coefficient of innovation p, is robust to a variation of the assumed market potential M. Therefore, q should also contribute to a stable short-term forecast (given a variation of M), provided that a period in the early phase of the product life cycle is considered.
The study also shows that with the bulk of the procedures, percentage forecast errors are obtained which lie in a narrow margin for the established product passenger car, but not for the innovative battery-electric propulsion technology. So while the careful selection of the forecasting model seems rather negligible for the established product, it is essential for the innovative product.
In addition, new registration figures in the German federal states were forecasted, which in turn were used to calculate pooled forecasts for Germany. In general, no increase in forecast accuracy was achieved by means of pooling compared with direct forecasting (i.e. from the national time series).

Introduction

Concerning the Market Diffusion of Electric Mobility

In view of the announced transition to electric mobility, market participants are uncertain about which propulsion technologies will prevail in the near future. Both automotive manufacturers, who organize production processes, and consumers, who make purchasing decisions, are faced with a choice between different technologies and the associated investment risks.

Several scenarios are conceivable with regard to the further market penetration of electric mobility and thus with regard to the development of the fleet composition with different drive technologies: If innovative battery-electric and hybrid technologies successfully penetrate the automobile market, these cars will replace conventional gasoline and diesel fleets in whole or in part. At least in an interim phase, cars with different innovative or conventional drive technologies will participate in traffic side by side. It is possible that a phase with significant market shares of several technologies will last for a long time or that a single innovation will become the dominant technology earlier. The success of market diffusion of battery-electric (i.e., pure electric) [1] cars in particular should depend on the provision of the necessary infrastructure, which is preferably an area-wide and dense network of fast charging stations.

The German government is supporting the market diffusion of electric mobility with a (purchase) incentive scheme. So do other countries, and some, such as China and the United Kingdom, even intend to ban the sale of cars with internal combustion engines.[2]

Innovation cycles are becoming shorter, and so it could be that the (current) battery-electric technology will only be an interim solution, that prevails on the markets for a short time before being replaced by another promising technology. For example, there is already speculation about the rise of hydrogen fuel cell technology. Overall, it should be stated that the success of the diffusion process of battery-electric propulsion technology is uncertain and therefore market potential projections are vague.

In addition, consumer preferences are changing in terms of body type. For example, the market share of sport utility vehicles (SUVs) has increased over the years. A revolution in individual transportation is also taking place in other respects: The emergence of autonomous driving. This is also still taking place in an uncertain economic environment, currently dominated by the Corona crisis.

Decision-makers in business and politics, as well as private consumers, are trying to anticipate upcoming developments in individual transportation in order to make wise decisions. It would therefore be desirable to have procedures that provide accurate forecasts of (near-real-time) developments on the world car markets, of the sales or registration figures for passenger cars in the next years and, in particular, of the diffusion processes for innovative drive technologies. This paper supports the reader with information for a selection of a suitable forecasting procedure. An attempt is made to find out which procedures work best in forecasting new passenger car registration figures for conventional and innovative propulsion technologies. For this purpose, the percentage forecast

[1] In this article, the terms "battery-electric" and "pure electric" are used interchangeably.
[2] For example, on November 11, 2020, the World Economic Forum headlined on its website “China joins list of nations banning the sale of old-style fossil-fuelled vehicles” (last accessed April 6, 2021) https://www.weforum.org/agenda/2020/11/china-bans-fossil-fuel-vehicles-electric/

errors (PE) for forecasts of German new vehicle registrations from 2017 to 2019 are reported, as well as the mean absolute percentage forecast errors (MAPE) for the German federal states.

The Financial Incentive Scheme for Promotion of Electric Mobility in Germany and the Corona Crisis

The German government is promoting the market penetration of electric mobility. An ecological premium was introduced for the purchase and leasing of electric cars from May 18, 2016.[3] However, demand was initially restrained. Despite the premium, new registrations of battery-electric cars actually declined in 2016 compared to 2015.[4] However, demand for passenger cars with conventional drive systems increased in 2016. A regression analysis conducted for the study revealed that the premium was also unable to produce a statistically significant increase in the number of new registrations of battery-electric passenger cars in 2017 and 2018. It could be supposed that the premium was initially still too small to compensate for the (perceived) disadvantages of electric cars. For the purposes of the study, it is assumed that the purchase premium had a negligible effect on the purchase decision at that time. Demand for battery-electric cars has only increased significantly following the further topping up of the purchase incentive in November 2019. For accurate ex-post forecasts, the effects of the purchase premium on the number of new registrations of battery-electric passenger cars from 2019 would therefore have to be explicitly taken into account.[5] However, the research paper already includes an evaluation of a bundle of time series models. It was therefore decided not to adapt the forecast models, as this would go beyond the scope of the study. The same applies to the Corona crisis, which affected the entire automobile market in 2020 and beyond. However, this negligence should not affect the results of the study, which aims, among other things, to identify suitable time series models for (predicting) new registration numbers. It remains for a follow-up study to empirically examine the impact of purchase incentives and the Corona crisis on car purchases.

Research Questions

In general, analysts are subject to model uncertainty. Among other things, the study investigates which time-series analytical models are suitable for predicting the numbers of newly registered passenger cars. To the extent that one of the methods included in the study is clearly superior to the others, it would be of interest to know how accurate it is compared to the others. This can be done by comparing the (percentage) forecast errors.

To the extent that the predictions of different models agree, this should strengthen the prediction and confirm the quality of the procedures that process information differently. Moreover, uncertainty in model selection is negligible, provided the predictions fall within a narrow range. From

[3] cf. Bundesanzeiger BAnz AT 05.11.2020 B1, see https://www.bundesanzeiger.de (last accessed on March 9, 2021).

[4] In this context, for example, the Berlin daily newspaper "Der Tagesspiegel" termed the ecological premium as flop on January 2, 2017: "Die Prämie für E-Autos ist ein Flop", see https://www.tagesspiegel.de/wirtschaft/staatlicher-umweltbonus-die-praemie-fuer-e-autos-ist-ein-flop/19200790.html (last accessed July 12, 2021).

[5] Due to a renunciation of explicit modeling of such effects, the forecasts made ex-post are more comparable to ex-ante forecasts, i.e. from the perspective of a point in time when the occurrence of future events is not yet known.

another perspective: The gain in forecast accuracy from informed model selection is then rather small.[6]

To the extent that the models' forecasts differ substantially, however, other questions arise: Are some models better in certain constellations,[7] for example, in predicting new registrations of vehicles of conventional or innovative technologies? Are advanced forecasting models better than simple ones?

To obtain answers to these questions, the predictive accuracies of procedures from different (univariate) model families are evaluated: Growth, ARIMA(X), Exponential Smoothing and Deterministic Trend models. This is done in a common framework for the established product passenger car (all technologies) and for the innovative battery-electric propulsion technology. Results of the models are presented and discussed for each federal state and for the national level (i.e. the whole of Germany).

A particular focus is on the Bass model, which gained popularity through studies on modeling diffusion processes of innovative products. In the paper, the Bass diffusion model is confronted with other growth models and time series analysis techniques: Estimated Bass parameters are presented and commented: Market potentials (M) and innovation (p) and imitation coefficients (q) for the federal states and at the national level.

Further, it is investigated whether pooling regional forecasts (more specifically, adding the forecasts for the federal states) results in a more accurate national forecast than direct forecasting based on historical national values (i.e., Germany time series).

While practitioners certainly prefer simple and univariate forecasting procedures, the research community would rather try to exploit (additional) information from the application of multivariate models (e.g., on panel data) to increase forecast accuracy. Then, the prediction accuracy of the best univariate procedure can at least serve as a benchmark for an assessment of the quality of multivariate procedures. However, it is left to a subsequent study to find out whether an improvement in prediction is achieved at all in the multivariate context.

In addition, this article complements the existing literature that looks at stated or revealed preferences in individual choices between different propulsion technologies in an attempt to predict market share based on micro-level decisions.

Structure of the Research Paper

This paper is structured as follows: In the next section, the literature is discussed that addresses forecasting procedures, pooled forecasts, market diffusion of propulsion technologies, and consumer purchase decisions as a function of (innovative) vehicle characteristics. Subsequently, the dataset of new passenger car registrations is presented and the neighborhood relationships of the associated geographic units (i.e., the subdivision of Germany into federal states) are described. In the third section, the study design is explained: the division of the time series into estimation and forecast areas, the applied forecast error measures to assess the predictive accuracy of the models, and the

[6] Certainly, the requirement on the accuracy of a forecast model depends on the tolerance or responsiveness in case of deviations from the plan. For example, an automobile manufacturer should answer the question to what extent it is possible to adjust production processes during the forecast period if a deviation from the point forecast becomes apparent.

[7] Several constellations result from combinations of estimation periods, forecast horizons, technology category (battery-electric or all cars), forecasts of national numbers (direct or pooled), or for a particular federal state.

concept of pooling time series are described. In the fourth section, the forecasting procedures are described. In the second-to-last section, the results are presented and discussed. Finally, the results are summarized, and an outlook is given for research work that builds on them.

Literature Review

Mahajan et al. (1990), Mahajan et al. (2000), and Meade and Islam (2006) review product diffusion models. In particular, the authors focus on Bass' (1969) model of diffusion of innovations.

Vieira and Hoffmann (1977) discuss features of growth processes and compare the Logistic and the Gompertz growth functions. Schacht (1980) describes the Exponential and the Logistic functions in the context of population growth modeling.

Al-Alawi and Bradley (2013) review the literature on the penetration rate of vehicles with innovative battery-electric propulsion technologies (electric vehicles, hybrids, and plug-in hybrids). They recommend improving models of penetration rates by establishing relationships with other determinants of automobile markets (e.g., policy, competition, market volume, etc.).

Meyer and Winebrake (2009) investigate the market penetration of complementary goods using the example of hydrogen vehicles and a compatible refueling infrastructure. They conclude that rapid adaptation can be achieved through coordinated policy measures: At the same time, the purchase of cars and the construction of infrastructure should be promoted.

Effects of (monetary) incentive schemes on passenger car demand are studied in Mueller and de Haan (2009) and in de Haan et al. (2009). The authors propose to forecast market shares and to evaluate policy measures based on information about individual vehicle choice decisions. In their model, a decision maker evaluates vehicle alternatives based on a weighted set of attributes (derived from information about previously owned cars).

Gnann et al. (2015a, 2015b) examine the impact of market determinants (energy and fuel prices) and policy measures (subsidies) on the market diffusion of electric vehicles and, in particular, review the methods and recommendations of such studies. They find that energy and battery prices have a significant impact on the market penetration of plug-in electric vehicles. Gnann et al. (2015a) focus primarily on passenger cars used for commercial purposes. They find that plug-in hybrid electric technology is better suited for commercial vehicles than for private vehicles. This is due to higher average annual mileage and more frequent trips by commercial vehicles.

Hackbarth and Madlener (2016) and Dimitropoulos et al. (2013) examine consumer preferences and calculate willingness-to-pay for vehicle attributes. Both studies focus in particular on driving range and fast-charging options, i.e. features that are crucial for the market penetration of pure electric technology. Hackbarth and Madlener (2016) find that willingness to pay varies widely between different consumer groups in Germany. Dimitropoulos et al. (2013) report that willingness to pay for range varies across countries.

Lebeau et al. (2012) investigate the market potential of battery-electric vehicles and plug-in hybrids in Flanders (Belgium). They predict that in 2030, battery-electric vehicles could have a market share of 15% and plug-in hybrids of 29%.

Letmathe and Suares (2017) set up an operating cost model to assess the vehicle models available on the German market. They conclude that just a few battery and hybrid electric vehicles are economically efficient.

Kourentzes et al. (2019) discuss the selection and combination of forecasts in the context of forecast pooling approaches. The authors question whether forecast combinations are generally beneficial. In addition, they discuss under which conditions some forecast pools are at least as beneficial as others.

Ruth (2008) examines whether pooling is a promising strategy for forecasting European macroeconomic variables. His results indicate that pooled forecasts obtained from separately specified and estimated models for subgroups of member states are more accurate compared to pooled forecasts from a single model.

Wan and Song (2018) predict turning points in growth cycles and investigate whether combined probability forecasts have higher accuracy. They observe that nonlinear combination approaches in particular are sensitive to the quality of the forecasts in the pool.

Steel (2020) explains that model uncertainty, for example, often prevails when different theories exist. He suggests model averaging as a way to handle uncertainty. This could have broader application in the future through software implementation.
In the context of uncertainty in the choice between (multivariate) models, Longford (2021) discusses the combination of estimators from several models. He suggests reducing compositions to the simplest and the most complex model.

Data

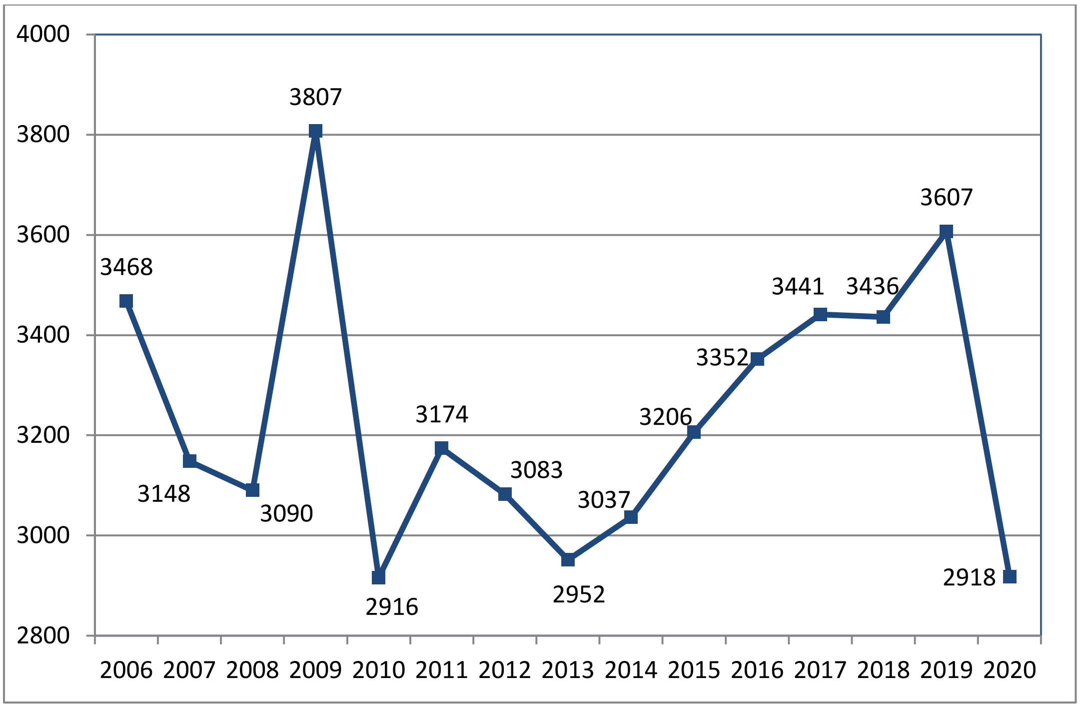
Source of Time Series of New Registrations and Interpretations on the Economic Situation

The German authority "Kraftfahrt-Bundesamt" (KBA) in Flensburg - which is the Federal Office for Motor Traffic - publishes regularly figures on new passenger car registrations in Germany.[8] Data on new registrations in the German federal states and differentiated by propulsion technologies is supplied by the KBA statistics report series fz8. From this data source, annual time series of new registration figures in Germany (see figure 1) and in the federal states are compiled for the present study.
For battery-electric (i.e., pure electric) technology, figures for annual new registrations in Germany are available from 2003 (see figures 2 and 3) and for the German federal states from 2006.
For the statistical calculations and for the purpose of ex-post prediction, this study relies on time series for all passenger cars and the subgroup with battery-electric drive technology in Germany and in the sixteen German federal states and the years 2006 to 2020. Since some new registrations are not assigned to a federal state, there is also a time series that is referred to in the paper as "not specified (n. s.)" [9] In the study, this is treated like a time series for a federal state. It was verified that the reported annual numbers of new registrations in Germany correspond to their associated totals of the reported figures for the federal states plus the category "not specified".

Usually, studies on the market diffusion of innovative products are based on sales figures. In Germany, however, car registrations are centralized at the authority KBA, unlike car sales. As a rule, however, a new registration is made immediately after the purchase of a car. Thus, registration figures are an adequate representative of vehicle sales.

[8] The KBA data are available on the KBA website at https://www.kba.de/DE/Home/home_node.html. (last accessed on April 9, 2021)
[9] Some organizations are not subordinate to the federal states, for example the “Bundeswehr“ (i.e. the German Federal Armed Forces) and the “Technisches Hilfswerk“ (i.e. the Federal Agency for Technical Relief). The vehicles of these organizations are therefore not assigned to a federal state. In 2016, this affected 996 newly registered passenger cars.

Figure 1 New Passenger Car Registrations (in Thousands) in Germany from 2006 to 2020, All Technologies



Data source: Kraftfahrt-Bundesamt in Flensburg (Germany), www.kba.de

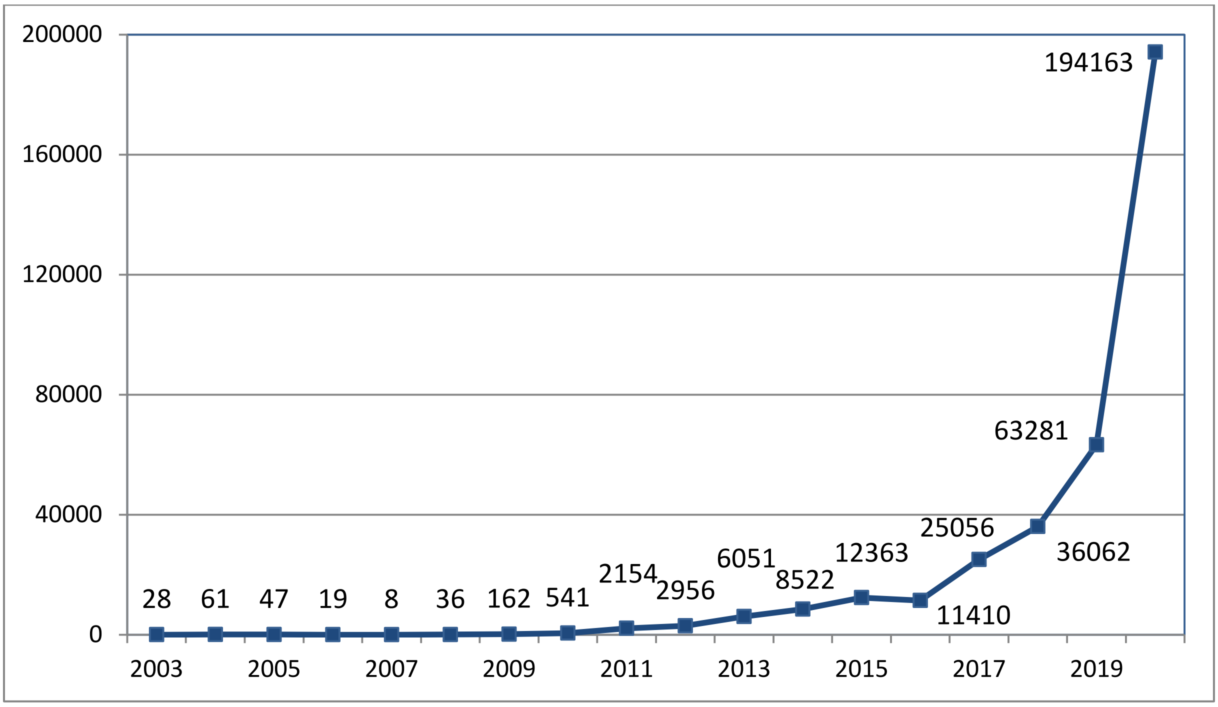
Figure 1 shows that new registration figures declined in a recessionary environment of the financial crisis in 2007 and 2008. The financial crisis reached a sad climax with the insolvency of the U.S. investment bank Lehman Brothers in 2008 and impacted the global economy in the years that followed. The peak in new car registrations in 2009 was due to the scrappage scheme (so-called "Abwrackpämie") introduced by the German government to counteract an economic downturn. This political measure certainly anticipated car purchases that would otherwise not have been made until subsequent years. The trend of declining new registration figures then continued between 2011 and 2013. After 2013, new registration figures rose, promoted by the European Central Bank's accomodative monetary policy (with low interest rates). In addition, population effects may have supported this increase. In 2020, new passenger car registrations dropped by about 19% compared to 2019 due to the Corona crisis.

Figure 2 shows the numbers of new registrations of battery-electric passenger cars from 2003 to 2020, whose development resembles an exponential curve.

In the logarithmic representation of the time series (Figure 3), a decline in the number of new registrations of battery-electric cars during the financial crisis in 2007 is clearly visible. Admittedly, this occurred at an early stage of the innovation process, when no more than a few dozen electric cars were newly registered in Germany each year. Thus, the lack of purchases of just a few cars leaves its mark on the curve.
Obviously, the Corona crisis had no impact on the exponential growth of new registrations of battery-electric passenger cars. The accelerated growth in purchases of battery-electric vehicles in 2020 is certainly due to the increase in the purchase premium for electric cars in November 2019 and the temporary reduction in the general (i.e. not just applicable to car purchases) value added tax in the second half of 2020. The reduction in VAT was a measure taken by the German government to counter the economic effects of the Corona crisis. In this study, it is left to speculation (i.e., it is not

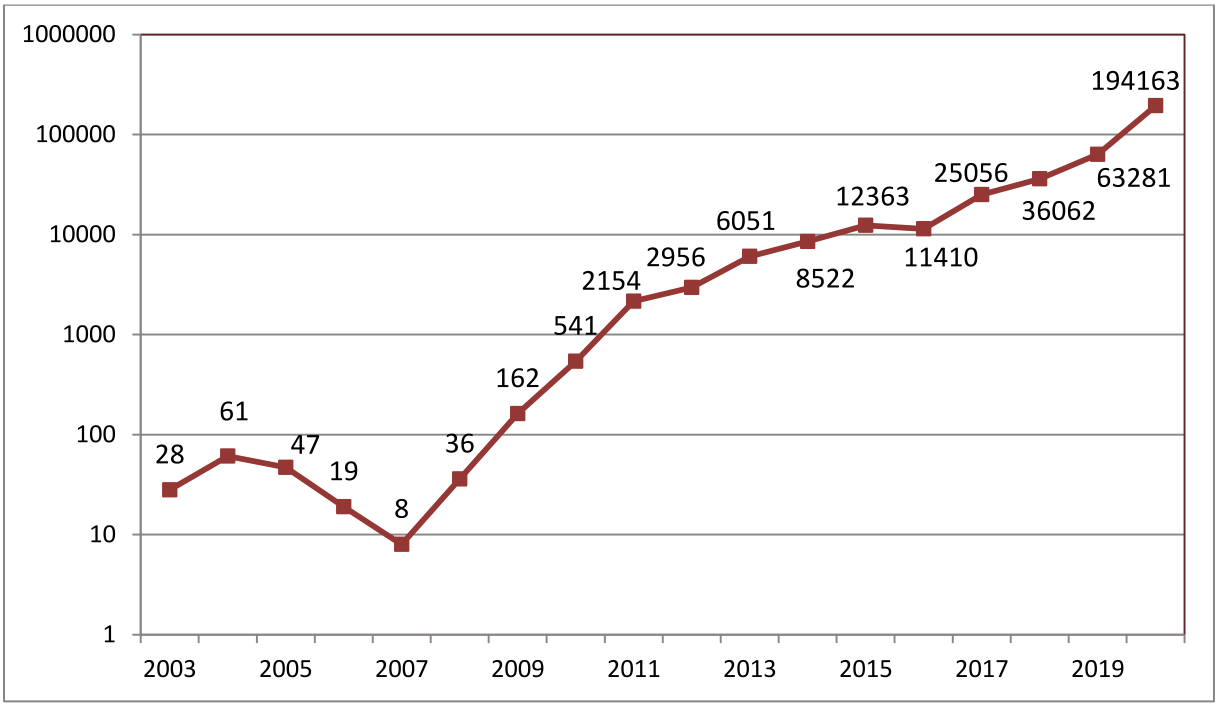
investigated) which shares of sales are attributable to the respective policy measure and how many electric cars would have been sold if the Corona pandemic had not occurred.

Figure 2 New Registrations of Battery-Electric Passenger Cars in Germany from 2003 to 2020



Data source: Kraftfahrt-Bundesamt in Flensburg (Germany), www.kba.de

Figure 3 New Registrations of Battery-Electric Passenger Cars in Germany from 2003 to 2020, on a Logarithmic Scale



Geographical Units: The Federal States of Germany

This article presents results primarily for the national territory (i.e., Germany), but also for each federal state (NUTS 1 units).[10] Germany's sixteen federal states and their neighborhood relations are listed in the following table.[11]

Table 1 Germany's Federal States and their National Neighbours

Federal States of Germany	Abbr.	Population, End 2016 [1)]	New Registr. in 2016 [2)]	Neighbour Federal States	
West-Germany		in thousands	in thousands	**Abbreviation**	**#**
North					
Schleswig-Holstein	**SH**	2 882	86	HH, NI, MV	3
Hanseatic City of Hamburg*	**HH**	1 810	136	SH, NI	2
Lower Saxony	**NI**	7 946	353	NW, ST, SH, HE, TH, HB, HH, MV, BB	9
Hanseatic City of Bremen*	**HB**	679	27	NI	1
North Rhine-Westphalia	**NW**	17 890	673	NI, HE, RP	3
South					
Hesse	**HE**	6 213	354	BY, BW, RP, NW, NI, TH	6
Rhineland Palatinate	**RP**	4 066	131	BW, HE, NW, SL	4
Baden-Wuerttemberg	**BW**	10 952	459	BY, RP, HE	3
Bavaria	**BY**	12 931	661	BW, HE, TH, SN	4
Saarland	**SL**	997	36	RP	1
East-Germany					
Berlin*	**BE**	3 575	87	BB	1
Brandenburg	**BB**	2 495	63	BE, SN, ST, MV, NI	5
Mecklenburg Western Pomerania	**MV**	1 611	38	BB, SH, NI	3
Saxony	**SN**	4 082	120	BB, ST, TH, BY	4
Saxony-Anhalt	**ST**	2 236	59	BB, NI, TH, SN	4
Thuringia	**TH**	2 158	67	BY, HE, ST, SN, NI	5

*Berlin and Hamburg are city federal states, Bremen is a two-cities federal state. Berlin belongs to the old eleven federal states of the former Federal Republic of Germany (FRG) while it is geographically located in the east. The other five federal states in eastern Germany were newly formed after the annexation of the territory of the former German Democratic Republic (GDR) to the FRG. In the course of the reunification of the two German states, Berlin (East), the capital of the GDR, was also annexed to the former federal state of West-Berlin.

[1)] Data source on population size: Statistisches Bundesamt in Wiesbaden (Germany), www.destatis.de
[2)] Data source on vehicle registrations: Kraftfahrtbundesamt in Flensburg (Germany), www.kba.de

It should be noted that the German federal states differ considerably in terms of population size and thus vehicle registrations. Although the three city states have a higher population density than the

[10] For the NUTS classifications of geographical units in Europe, see Eurostat (2020). According to the NUTS classification, regions are classified as NUTS-1 if they have an average population of three to seven million. For Germany, this applies to the federal states.

[11] In this study, two federal states are classified as neighbors if they are geographically contiguous with at least point contact.
Berlin, Bremen and Saarland have the lowest number of neighboring federal states, with only one neighboring relationship. The most closely connected federal state is Lower Saxony, with nine neighboring federal states. Although most of the federal states also border on foreign countries, these relationships are not taken into account here. The summary statistics of neighbor relations are: first quartile: 2.75, median: 3.5, mean: 3.625, third quartile: 4.25.

other federal states, they are among the federal states with below-average population and registration figures. Thus, a large proportion of registrations in Germany are accounted for by a few large federal states. The states with above-average populations are North Rhine-Westphalia, Bavaria, Baden-Württemberg, Lower Saxony and Hesse.

It could be hypothesized that socioeconomic characteristics of a household play a (significant) role in the selection of a particular drive technology. In this context, reference should be made to studies analyzing micro-level data, e.g. from household surveys or individual car purchases, and addressing stated or revealed preferences.

Socioeconomic conditions differ in the federal states or smaller geographic units. But the (economic) situation in neighboring regions is often similar or spatially correlated. If spatial autocorrelation exists, it could possibly be exploited for forecasting purposes. However, this is more likely to be detectable for smaller geographic units and to disappear at the state level.

Furthermore, it could be that the federal states are in different phases of market diffusion processes. This could have an impact on the forecast (errors) for the various federal states.

In recent years, the number of new registrations in Hamburg was of a similar order of magnitude to that in the territorial federal states of Rhineland-Palatinate and Saxony and much higher than in the more populous city of Berlin. This is due to the fact that Hamburg is home to companies that offer rental cars or car sharing. Although the rental cars are registered at the company's headquarters in Hamburg, they are also driven by customers in other German federal states. A breakdown for 2019 by owner group and federal state shows that of the 139,286 newly registered passenger cars in Hamburg, only 19,467 are in the owner group "Employees and non-employed persons" and 81,569 are in the owner group "Rental of motor vehicles without provision of a driver and car sharing".[12] In Berlin, 87,483 passenger cars were newly registered. Of these, 30,145 vehicles were assigned to "employees and non-employed persons" and 5,372 to rental or car sharing. Also a high proportion of the new passenger cars registered in Bavaria, Hesse and North Rhine-Westphalia are used as rental cars or in carsharing.

Study Design

Design of the Ex-Post Forecasts

The accuracy of various time series analysis procedures in predicting the variable of interest y_t (i.e., new passenger car registrations) in year t, is examined.

The evaluation of the forecasting procedures is carried out within the framework of ex-post forecasts. For this purpose, each time series is divided into two sections: The first section (up to year *T*) is referred to below as the **estimation period** and the second section (from year *T+1*) as the (ex-post) **forecast period**. The forecast model is fitted (i.e., the parameter values are estimated) based on the observations of the estimation period (*1* to *T*). Subsequently, ex-post forecasts are calculated for the forecast period (*T+1* to *T+H*) based on the parameter estimates of the fitted model. For the evaluation of a forecast procedure, forecast errors are calculated as deviations of the forecasts from the corresponding actual values available in retrospect for the forecast period. Time series of two categories are available for the analyses: One refers to all new passenger car registrations, i.e., all technologies with a (still) predominance of gasoline and diesel vehicles. The other refers to battery-electric passenger cars, which still account for a small subset of all new registrations but are

[12] see KBA report series FZ 24

experiencing dynamic development in market penetration as an innovation. The calculations are based on annual new registration figures from 2006 to 2020 in Germany and in the German federal states. Ex-post forecasts are made for each of the following four compilations of time series sections:

1. Based on new registration figures in the period 2006 to 2016 (estimation period), ex-post forecasts are calculated for 2017 to 2020 (forecast period).

2. ditto, with estimation period 2006 to 2017 and forecast period 2018 to 2020

3. ditto, with estimation period 2006 to 2018 and forecast period 2019 to 2020

4. ditto, with estimation period 2006 to 2019 and forecast for year 2020

Results for the forecast year 2020 are not fully reported because no explicit modeling of significant effects in the Corona year was performed.
For the time series of the federal states and Germany as a whole, the models are fitted separately, i.e. the parameters are estimated, unless otherwise stated.

Forecast Error Measures

There are numerous measures discussed in the scientific literature that can be used to evaluate the ability of a procedure to accurately predict data. Kim and Kim (2016) claim that the Mean Absolute Percentage Error (MAPE) *"is one of the most widely used measures of forecast accuracy".*[13] Despite potential criticisms of MAPE and suggestions in the literature to improve this measure,[14] this study relies largely on MAPE alongside percent error (PE). So results are presented for this fairly intuitive measure.

Assumed there is a time series segment or time series y_t (e.g., of new vehicle registrations) for a number of *T* periods, in this study years. Here, the first value y_1 refers to new registrations in year $t = 1$ and the last value y_T refers to new registrations in year $t = T$. Then, the forecast error of the *h* -step forecast made at the end of year (or, in the case of ex-post observation, from the point of view of time) *T* for the value of the time series in year *T+h* is calculated as

$$E_{T+h} = \hat{y}_{T+h} - y_{T+h}$$

Accordingly, the percentage forecast error *PE* is calculated as follows:

$$PE_{T+h} = 100 \cdot \frac{\hat{y}_{T+h} - y_{T+h}}{y_{T+h}}$$

It should be noted that in this paper the actual value y_{T+h} is considered as the reference value, so **a negative (percentage) error means that the predicted value $\hat{y}_{T+h}$ underestimates the actual value y_{T+h}**. This is in opposition to other studies that use the converse position of the actual and predicted values, i.e., calculate $y_{T+h} - \hat{y}_{T+h}$. The MAPE measure averages absolute percentage errors calculated, for example, for different regions (here *N=16* federal states).[15] Thus, exchanging the positions of the actual with the predicted value in the numerator has no effect on the calculated MAPE value:

[13] In the context of forecasts, this measure is also described in more detail in the literature as "Mean Absolute Percentage Forecast Error (MAPFE)". In this paper, however, the shorter term MAPE is used, although results are presented in the context of forecasts. Similarly, "Percentage Forecast Error" is simply referred to here as "Percentage Error (PE)". In this context, the "Absolute Percentage Error (APE)" is also frequently referred to, when only the amount of the error is considered, i.e. without the sign.
[14] cf. Makridakis (1993)
[15] Absolute values are taken to avoid netting out positive and negative errors in the aggregate MAPE number.

Mean Absolute Percentage (Forecast) Error (MAPE)[16]

$$MAPE_{T+h} = \frac{100}{N}\sum_{n=1}^{N}\left|\frac{\hat{y}_{n,T+h} - y_{n,T+h}}{y_{n,T+h}}\right|$$

The (absolute) percent errors and MAPE values are calculated for different forecasting procedures, as well as for different combinations[17] of estimation periods, forecast horizons *h*, and categories battery-electric or all vehicles.

An evaluation of forecasting procedures by means of "absolute" percentage forecast errors implies equal treatment of positive and negative forecast errors. However, this is not self-evident, because the purpose of forecasting may require a different evaluation of positive and negative deviations in the same amount.

The MAPE concept includes all federal states with equal weighting. By contrast, when pooling the forecasts for the German federal states to produce a forecast for Germany, the states with the highest number of new registrations (usually with large populations) are given a correspondingly higher weighting.

Pooling of Time Series

Assumed a country is subdivided into *N* regions (e.g., federal states). And for each region there is a time series $y_{n,t}$, where the first subindex *n* denotes the region and the second subindex *t* denotes the period (e.g. the year) of observation. It can then be examined whether the richer information resulting from the bundle of regional time series improves the prediction of the national value. To this end, a pooled forecast of the national value is produced here by summing the forecasts for the federal states. The accuracy of the pooled forecast is compared with that of the (unpooled) forecast derived directly from the historical national values (i.e. the Germany time series). The pooling strategy should be preferred if it results in higher forecast accuracy, i.e., a smaller forecast error:

$$\left|\left(\sum_{n=1}^{N}\hat{y}_{Region\ n,T+h}\right) - y_{Nation,T+h}\right| < \left|\hat{y}_{Nation,T+h} - y_{Nation,T+h}\right|$$

For calculations of pooled forecasts, it was also necessary to forecast numbers of new registrations not assigned to a federal state. For this purpose, the time series "not specified" of a federal state was treated in the same way as the federal state time series when applying the forecasting procedures and pooling.[18] In contrast, the reported MAPE values only include forecasts for the sixteen federal states, so forecasts for new registrations not attributable to a federal state are not included.

Particular attention is paid to the pooled forecasts made using the Logistic or Bass model, as these were also shown to be particularly suitable for the direct forecasting of new registration figures for all passenger cars or purely electric ones.

For an evaluation of pooling, however, the other forecast models are also taken into account: First, the proportion of models (including variants and scenarios) that achieve a more accurate pooled than direct forecast is calculated. These proportions are calculated differentiated by technologies (all

[16] In this formula, a further subindex $n = 1, \dots, N$ is introduced, which identifies the federal states. The subindex is omitted again in formulas if an abstraction from the region is possible.

[17] hereinafter also referred to as "settings" or "constellations"

[18] Other study designs for (ex-post) predictions, for an evaluation of pooling, or for an investigation of the impact of lack of assignability of cases on prediction accuracy are conceivable: Alternatively, the national registration numbers could be reduced by the registrations that cannot be assigned to a state. Perfect forecasts could also be assumed for the unassignable cases, i.e., with a forecast error of zero.

techs or battery-electric), estimation period, and forecast horizons. Accordingly, pooling would be considered if a more accurate pooled than direct forecast is obtained with more than half of the forecast models. However, the proportion value should be close to one to demonstrate a clear advantage of pooling.

In addition, the deviations in the magnitude of the percentage forecast errors of the pooled forecasts from those of the direct forecasts are determined and their means are calculated across all forecasting methods. Accordingly, pooling would be favored if the forecast error is reduced on average, i.e., the calculated ratio value is negative.

Finally, it should be explicitly mentioned that the key figure values obtained depend on the models included in the study. In particular, model variants and scenarios for market potentials are also considered in the present work, so that the results for the growth models are given particular weight. It therefore goes without saying that an advantageousness of pooling is most likely to be substantiated by distinct key figure values.

In the evaluation, the ratio value for pooling (or direct forecast) deteriorates if the pooled (or direct) forecast is missing. It was expected that for some settings (from technology, estimation period, forecast horizon) direct but not pooled forecasts would be obtained. This happens when no forecast is obtained for at least one federal state with the selected forecast model (which in turn is due to a missing return of parameter values for forecasts from the estimation algorithm).

In fact, in some constellations, forecasts are obtained for all federal states and a pooled forecast for Germany is also obtained, but not a direct forecast from the Germany time series. This was not necessarily expected, as rather unstable estimates are obtained or forecasts are even missing for small states due to low registration numbers.

It should be taken into account that in the first years of the study period (from 2006), rather small numbers of battery-electric passenger cars were newly registered, in some cases only single-digit numbers. Therefore, even small changes in unit numbers in successive years lead to high volatility in the relevant time series period.[19] In earlier years (up to 2010), many states often did not register any new registrations of battery-electric passenger cars at all. Then the estimation algorithm can be interrupted due to the zero in the time series. It then does not provide an estimated value for the applied prediction method. This may be due, among other things, to the fact that algorithms for estimating optimal parameter values calculate reciprocal values. However, no reciprocal value exists for the zero. Accordingly, the estimated parameter values are often not significant, if the estimation algorithm produces a (meaningful) result at all. From this point of view, the forecasts for the populous German states, which tend to have higher registration figures, are likely to be more reliable.

In principle, it can be considered to pool forecasts that have been produced using different methods (so-called "mixed methods" pooling). In doing so, an attempt can be made to identify a (different) method for each regional time series with which the best forecast is obtained.[20] In addition, forecasts can be produced using different methods even for individual territorial units, from which in turn a weighted forecast value is calculated.

[19] Acquisitions of company car fleets with electric drives by individual companies or public authorities can already cause a deviation of the growth curve from an ideal-typical course or overlay the trend in such a way that it becomes unrecognizable. This can lead to missing or insignificant parameter estimates of a time series model and thus to missing or inaccurate forecasts.

[20] Finally, the dynamics of market diffusion of an innovation may be different in a growth region than in a shrinking region, for example.

Kourentzes et al. (2019) claim that there is ample evidence in the literature of the benefits of forecast combinations. The benefits could be in the form of lower forecast error or in mitigating the modeling uncertainty that would accompany the choice of a single model. Timmermann (2006) argues that one reason for using forecast combinations is that individual forecasts are affected very differently by structural breaks caused, for example, by institutional change or technological developments.[21]

Here, however, only pooled forecasts were produced using a uniform forecasting procedure for all federal state time series. However, the results of the forecasts for individual states also allow conclusions to be drawn about the potential benefits of mixed-method pooling strategies.

Forecasting Procedures

Overview

Various forecasting procedures are applied in the study, which can be classified into the following model families of time series analysis:

- Deterministic trend models: Essentially, the time series variable is regressed on a function of a temporal index or on its associated date variable (e.g., the years 2006-2016). Thus, a linear or nonlinear deterministic trend is fitted to the observations.
- Autoregressive Integrated Moving Average (ARIMA) models: Current values of a time series are regressed on previous values and "innovations" (i.e., residuals). In this way, a time series is explained from its own past values.
- Growth models: These are particularly suitable for modeling growth processes, such as diffusion processes
- Exponential smoothing models: These are useful for short-term forecasts (one period ahead).[22]

Details of the Forecasting Procedures

Traditional Time Series Analysis: Deterministic Trend-Models

Traditionally, deterministic trends were fitted to time series.[23] So, the values of the variable y_t are explained by a deterministic function of time *t.*[24] For this study, Deterministic Trend models are also fitted to the time series of new registrations. For example, the parameters b_j and residuals ε_t of the following regression equations are estimated:

$$y_t = b_0 + b_1 t^1 + b_2 t^2 + b_3 t^3 + \varepsilon_t$$

A compact representation of this equation is

$$y_t = \sum_{j=0}^{J=3} b_j \, t^j + \varepsilon_t$$

Each time series is regressed on a constant b_0 (for *j = 0*) and deterministic terms of higher order (linear: $j = 1$, quadratic: $j = 2$, cubic: $j = 3$). A top-down approach is followed, in which insignificant

[21] Timmermann (2006) refers to numerous authors in making this statement.

[22] Generally, smoothing is applied to eliminate seasonal patterns in time series with periods of less than one year (i.e., monthly, quarterly, semiannual) to emphasise the trend of the series.

[23] In modern time series analysis (see next section) this approach is rejected if a unit root test confirms the existence of a stochastic trend instead of a linear deterministic trend in the respective time series.

[24] Time is represented by a time index or the associated date variable (here, for example, the years 2006-2016).

intermediate terms are successively eliminated again. For this purpose, the 10% significance level was chosen.

Since this regression equation is linear in the parameters, the Ordinary Least Squares (OLS)-method is suitable for estimation of the values of the parameters b_j and the residuals ε_t.[25]

Fitted values (for the estimation period *1* to *T*) and forecasts (for the prediction period, e.g. years *(T+1), (T+2), ...*) are obtained from the model equation employing the parameter estimates $\hat{b}_j$:

$$\hat{y}_t = \sum_{j=0}^{J} \hat{b}_j \, t^j$$

For each federal state or the Germany time series, it is evaluated separately which model order $J =$ 0, 1, 2 or 3 fits best.

Modern Time Series Analysis: ARIMA-Models

Box and Jenkins (1970) introduced Autoregressive Integrated Moving Average (ARIMA)-models to fit time series. Since then, these models have been the state-of-the-art in modern time series analysis. The application of the ARIMA(*p*,*d*,*q*)-methodology requires the determination of the integration order *d* of a time series.[26] To specify the orders of integration of the national and federal states' new registrations time series, the Augemented Dickey Fuller (ADF) unit root test is conducted.[27] After stationarity is established,[28] in ARMA(*p*,*q*)-models the current value of this (stationary) time series $\Delta^d y_t$ is regressed on its own lagged values $\Delta^d y_{t-1}, \Delta^d y_{t-2}, \dots, \Delta^d y_{t-p}$ and / or on lagged residuals (stated differently "innovations") $\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-q}$. One aim of this study is to exemplify the impact of model variations on forecast accuracy. Therefore, three different strategies concerning the selection of the lag orders *p* and *q* are followed in this study:

1. The both **lag orders (i.e. the numbers of lags) *p* and *q* are set to two** in fitting ARIMA(2,d,2)-models to each of the national and federal states' time series. So, it is assumed that each process is well approximated by a model with (not necessarily more than) two autoregressive and two moving average lags.[29] However, this strategy already implies overparameterization if a more parsimonious model is adequate.
2. The **lag orders *p* and *q* of the national (i.e. Germany) time series are optimized** according to the Bayes Information Criterion (BIC), where each of the lag orders *p* and *q* is limited to a maximum of two. The lag orders optimized for the national time series are then also taken to

[25] The Ordinary Least Squres (OLS)-method is explained, for example, in Gujarati (2003). For this study, the regression estimates are performed with OLS using the "lm"-function of the "R"-software.

[26] The concepts of stationarity and integration as well as unit root tests to specify the order of integration of a time series are described, for example, in Neusser (2015).

[27] The ADF test is done using the R-package "urca". The number of lags incorporated in the ADF test is selected based on the Bayes Information Criterion. The ADF test variant with trend is selected in the study if a significant slope is detected in a time series at the 10% level. Otherwise, the test variant with constant and no trend is chosen.

When applying the ADF test, the critical values of the Dickey-Fuller distribution are used, see Dickey and Fuller (1979). For testing the null hypothesis of the ADF test that there is at least one unit root, the 1% significance level is applied.

[28] If a time series $y \sim I(d)$ is integrated of order *d*, differencing it *d* times $\Delta^d y \sim I(0)$ results in a time series which is integrated of order zero, i.e. is "difference stationary".

[29] Generally $AR(\infty)$- and $MA(\infty)$-processes are well approximated by $ARMA(p, q)$-models with more parsimonious lag-structures *p* and *q*. The invertible representation of a MA(1)-process by an AR(∞)-process is described for example in Hamilton (1994).

fit the ARIMA models of the regional time series. Thus, it is refrained from identifying optimal lag orders for the time series of the individual federal states.

3. The **lag orders *p* and *q* are optimized separately for each time series (national and federal states)**. Again, each of the lag orders *p* and *q* is limited to a maximum of two lags. Thus, this is the most flexible variant and allows the most accurate fit of the ARIMA models to the individual federal states' time series. However, the effort required to determine lag orders increases with the number of regional time series.

In any case, the values of the parameters φ_i and θ_j are estimated separately for the national and each of the regional time series. Results for the **three different model variants** can be found in the table section under the following names:

1. **ARIMA(2,d,2)**
2. **ARIMA(p,d,q)-national**
3. **ARIMA(p,d,q)-f.states**

The ARMA(*p*,*q*)-process is represented by the following equation, cf. Hamilton (1994):[30]

$$y_t = \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j}$$

The specific ARMA(2,2)-process can be written as

$$y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2}$$

The values of the parameters φ_i and θ_j represent the impact of the *i*-th and *j*-th lags, respectively, on the current value of the time series. For each time series, the parameter values are estimated independently using the Maximum Likelihood method.[31]

The prediction of time series values using ARMA(*p*,*q*)-processes with *h*-steps in advance is described, for example, in Hamilton (1994).[32] For example, if observations of a stationary time series are available up to year *T*, the one-step ahead forecast (*h = 1*) for year *T+1* is obtained with an ARMA(2,2)-model using the function

$$\hat{y}_{T+1} = \hat{\varphi}_1 y_T + \hat{\varphi}_2 y_{T-1} + \hat{\theta}_1 \hat{\varepsilon}_T + \hat{\theta}_2 \hat{\varepsilon}_{T-1}$$

Taking $E(\varepsilon_{T+1}) = 0$, the two-step forecast is calculated by means of

$$\hat{y}_{T+2} = \hat{\varphi}_1 \hat{y}_{T+1} + \hat{\varphi}_2 y_T + \hat{\theta}_2 \hat{\varepsilon}_T$$

Extension: ARIMAX-Models

If an exogenous variable x is additionally included in an univariate ARIMA model, a multivariate ARIMAX model is created.

For the prediction of new registration numbers, a variable x is added to the ARMA framework, which is lagged by one period.[33] The ARMAX(2,2) process can then be specified as follows:

$$y_t = \boldsymbol{\beta x_{t-1}} + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2}$$

[30] In the following representation, stationarity is already assumed for the time series, i.e. $y \sim I(0)$.
[31] The parameter estimates are done with the R function "ARIMA", choosing the Maximum Likelihood method "ML".
[32] For this study, the forecasts are done with the R function "predict".
[33] In the following representation it is assumed that the time series is already of integration order *d = 0*.

The following strategy is used for this study:[34] For the national time series and the time series of the individual federal states, the lag orders are determined according to the procedure described in the previous section (ARIMA models). Then, for each time series y, it is checked with which of the other (regional or national) time series x the performance of the model is optimized according to the BIC criterion.

Analogous to the ARIMA models, three different strategies are followed, referred to below as **ARIMAX(2,d,2)**, **ARIMAX(p,d,q)-national**, and **ARIMAX(p,d,q)-f.states**.

Table 3 reports for the variant ARIMAX(*p*,*d*,*q*)-f.states which other time series x was selected with the BIC criterion to forecast the values of the time series y. If spatial dependencies exist, it would be expected that BIC would often select a time series from a neighboring federal state. However, the strategy pursued would also allow a result where x is not a direct neighbor of y.

If observations of a stationary time series are available up to year *T*, the one-step forecast for year *T+1* with an ARMAX(2,2)-model is obtained with the function

$$\hat{y}_{T+1} = \hat{\boldsymbol{\beta}} \boldsymbol{x_T} + \hat{\varphi}_1 y_T + \hat{\varphi}_2 y_{T-1} + \hat{\theta}_1 \hat{\varepsilon}_T + \hat{\theta}_2 \hat{\varepsilon}_{T-1}$$

Another strategy was also pursued to exploit information on neighboring relations or the geographical subdivision of Germany into federal states for forecasting purposes. Thereby, an ARIMAX model was designed in which the exogenous variable x is calculated as the average number of new registrations in the respective neighboring federal states lagged by one year. However, with this design of an ARIMAX model, no increase in forecasting accuracy could be achieved compared to simple ARIMA models.[35]

Exponential Smoothing

Simple Exponential Smoothing

Brown (1959) contributed to the popularization of Exponential Smoothing models. The smoothed value $\hat{y}_{t+1}$ for year *t+1* is calculated as a weighted average of the actual value y_t for year t and the previous smoothed value $\hat{y}_t$: [36]

$$\hat{y}_{t+1} = \alpha\, y_t + (1-\alpha)\, \hat{y}_t$$

If time series observations are available up to year T, the smoothed value $\hat{y}_{T+1}$ is obtained for a given α. This smoothed value also corresponds to the 1-step forecast for the year $T+1$ as well as the multi-step forecasts for the following years:

$$\hat{y}_{T+1} = \alpha\, y_T + (1-\alpha)\, \hat{y}_T$$

Insertion of

$$\hat{y}_T = \alpha\, y_{T-1} + (1-\alpha)\, \hat{y}_{T-1}$$

results in

$$\hat{y}_{T+1} = \alpha\, y_T + (1-\alpha)(\alpha\, y_{T-1} + (1-\alpha)\, \hat{y}_{T-1})$$

Further substitutions result in

[34] The ARIMAX models are also estimated with the R function "ARIMA". The exogenous variable is assigned to the R function with argument "xreg".
[35] Due to the low predictive power of this ARIMAX design, a report of specific results was omitted.
[36] If the first time series observation is indexed by *t = 1*, then $\hat{y}_1$ can be set equal to y_1.

$$\hat{y}_{T+1} = \alpha \left(\sum_{i=0}^{T-1} (1-\alpha)^i y_{T-i} \right) + (1-\alpha)^T y_1$$

Usually, and in this study, the value of the smoothing parameter α is restricted to $0 < \alpha < 1$.[37] According to the Sum of Squared Errors (SSE) criterion, the optimal estimate for $\hat{\alpha}$ is the one that minimizes the following expression :

$$\hat{\alpha} = \underset{\alpha}{arg\ min} \left(\sum_{t=2}^{T} (\hat{y}_t - y_t)^2 \right)$$

The closer α is to one, the more weight is put to the most recent observation. The closer α is to zero the more weight is put to historical values of the time series y_t.

Double Exponential Smoothing

Brown (1956) and Holt (1957) recommended extended Exponential Smoothing models to cope with time series with trends. For the study, Brown's Double Exponential Smoothing model was implemented to forecast new vehicle registrations as follows:

The formula of simple Exponential Smoothing

$$y'_{t+1} = \alpha\, y_t + (1-\alpha) y'_t$$

is complemented by a second step of smoothing

$$y''_{t+1} = \alpha\, y'_t + (1-\alpha) y''_t$$

The level l_{t+1} of the smoothed time series in year $t + 1$ is calculated as

$$l_{t+1} = 2y'_{t+1} - y''_t$$

and the slope s_{t+1} as

$$s_{t+1} = \frac{\alpha}{1-\alpha} (y'_{t+1} - y''_t)$$

After all, by adding both components, the doubly smoothed time series is obtained:

$$\hat{y}_t = l_t + s_t$$

The optimization of the parameter α is performed analogously to the procedure described in the previous section.

If the actual values are available up to year T, the h-step forecast for year $T + h$ is obtained as follows:

$$\hat{y}_{T+h} = l_T + h \cdot s_T$$

[37] The smoothed value i.e. forecast value $\hat{y}_{T+1}$ thus corresponds to a weighted average of all historical values up to *T*. Thereby decreasing weights are used for values from further back in time.
For a long time series, the impact of the first observation y_1 on the forecast $\hat{y}_{T+1}$ approaches zero: $\lim_{T\to\infty} (1-\alpha)^T y_1 = 0$

Growth-Models

Some growth models were discovered and popularized as early as the late 18th or early 19th century and are still used to model growth processes today.

Scenarios for Market Potentials

Life cycles of products or technologies are typically illustrated by S-shaped curves which represent cumulative sales over time:[38] After the market launch of an innovation, its market diffusion accelerates - in the ideal-typical case of a successful product until the inflection point of the curve is reached. Beyond the inflection point, which is in the product's maturity phase, sales figures decline again.

The growth curve is limited by a saturation level. In the context of this study, where the growth curve represents sales figures, **the saturation level is interpreted as the market potential M of the (innovative) propulsion technology**. Since the diffusion process of an innovation (or of a product that in its late phase would no longer be described as innovative but as established or conventional) is limited by its market potential, forecasts involve an estimate or assumption regarding this market potential.

In some growth models, the saturation level is represented by a parameter that can alternatively be determined model-exogenously or estimated model-endogenously. In this study, both alternatives are performed for the Bass, the Gompertz and the Logistic model. Therefore, results (Percentage Errors and MAPE) for these growth models are presented for forecasts with exogenously given or endogenously estimated market potential.

Even with a model-endogenous estimation of the market potential, the algorithm of the optimization procedure requires starting values for this model parameter. One way of selecting a starting value is to take a market potential that is assumed to be plausible or would be selected for the model variant with exogenous market potential.

The estimated parameters for a model as well as the resulting forecasts can in principle depend on the exogenously determined saturation limits or the selected initial values. However, for an acceptable procedure, it would be desirable to obtain robust or only slightly varying results for different starting values. To check the robustness of the forecasts, three scenarios for market potentials are run for the growth models. Each of the three scenarios refers to the numbers of new passenger car registrations (of all technologies) in 2016, i.e. multiple of these is applied. The numbers of new registrations in the German states in 2016 are shown in Table 1. A total of 3,351,607 passenger cars were newly registered in Germany in 2016. 996 of these passenger cars are not assigned to any federal state.[39]

The x-fold values of the new passenger car registration figures for 2016 are used as scenarios for market potential. The multipliers x are given in the following table:

Table 2 Multipliers X for Three Market Potential Scenarios (A, B and C)

	A	B	C
All Technologies	25	50	75
Battery-Electric	1	10	50

[38] cf. Andersen (1999)

[39] cf. footnote 9

Thus, in scenario A, a market potential *M* for battery-electric passenger cars is assumed that corresponds to the number of new registrations (of all technologies) in 2016. In scenario C, a 50-fold *M* of the number of new registrations in 2016 is assumed for battery-electric passenger cars.
Scenarios A to C thus cover a range of the assumed market potential for new registrations of battery electric passenger cars in Germany between around 3.35 and 167.58 million. For Hamburg, for example, a range between 136 thousand and 6.8 million is assumed.

The Bass Diffusion Model

The model of Frank Bass (1969) has become established in research on diffusion processes of innovative products. In Bass' interpretation, the coefficients *p* and *q* of the model represent the influences of innovators and imitators, respectively, in the diffusion process. Thereby, the lower the influence of the innovators (i.e. the closer the positive coefficient *p* is to zero),[40] the longer it takes to introduce an innovative product to the market and the more time elapses until noteworthy sales figures are achieved. Usually, a small *p* relative to *q* is found in empirical studies.[41]

The model equation is[42]

$$y_t = Y_t - Y_{t-1} = p(M - Y_{t-1}) + qY_{t-1}\frac{1}{M}(M - Y_{t-1}) + \varepsilon_t$$

with variables

- quantity of new registrations y_t in year t [43] and
- cumulative new registrations Y_{t-1} from the first new registration in the first year (or generally in the reporting period) until the end of year t-1 (or until the beginning of year t).
  So, for an application of the Bass procedure, the complete time series of observations should be available.[44]

Parameters are

- the market potential (i.e., the saturation limit) *M* of the innovation,

as well as

[40] The coefficients *p* and *q* should be between 0 and 1. In some cases, negative coefficients are estimated, but these cannot be interpreted in a meaningful economic way.
[41] cf. the literature survey of estimates for *p*- and *q*- parameters in Massiani and Gohs (2015).
[42] In presentations of the equations of growth models, the residual is often omitted. Nevertheless, these random deviations do exist. This comparative study also deals with ARIMA models, in whose formulation (historical) residuals play a central role and therefore have to be explicitly considered. For the sake of completeness, it therefore seems reasonable to include residuals in the equations of the growth models.
In the following, the residuals are alternatively denoted as ε_t or ϵ_t, since the residuals from transformed or alternative models also change in value.
[43] or generally number of sales, observations, etc. of a product, technology, process, phenomenon, etc. in period *t*
[44] However, the complete time series of new registrations in Germany since the invention of the automobile was not available for this study. Nevertheless, forecasts were made using the Bass model based on the available time series of new passenger car registrations (of all technologies). In doing so, the cumulative new registrations that precede the estimation period were assumed to be zero.
For battery-electric passenger cars, the entire history of new registrations was also not available. However, modern (lithium-ion) battery technologies that meet the requirements of everyday mobility have just been developed in the recent past. It is assumed that the data available for the study actually include approximately all new registrations with respect to these modern battery technologies. From this perspective, the Bass model's requirement for complete time series would be approximately satisfied for battery-electric passenger cars.

- the coefficient of innovation *p* and
- the coefficient of imitation *q*.

The model equation is fulfilled by a residual ε_t that captures idiosyncratic deviations (i.e., random errors) of each period *t*.

If, in addition to *p* and *q*, the market potential *M* is also to be estimated model-endogenously, the Ordinary Least Squares (OLS) method is not suitable for estimating these parameters. Since in this case the model equation is not linear in the parameters, the Nonlinear Least Squares (NLS) method is applied for parameter estimation. This is done with the function "nlsLM" of the R library "minpack.lm".[45] Here, the optimization algorithm requires starting values for the parameter estimation: For *M*, the values from the three described scenarios A, B and C for saturation levels (or market potentials) are used. The results (percentage errors and MAPE) for the three scenarios are reported in the tables in the appendix. This shows whether the results are stable or vary (strongly) depending on the starting values.
The model-endogenously estimated market potentials *M* and the parameter estimates for the innovation coefficient *p* and the imitation coefficient *q* from the application of NLS are also given in the appendix for the different scenarios of starting values and technologies (All Technologies, Battery-Electric) (see Appendix B). [46]

With model-exogenously specified market potential *M*, the model equation is linear in the parameters and can be written as follows:

$$y_t = pP_{t-1} + qQ_{t-1} + \epsilon_t$$

with variables

$$P_{t-1} = M - Y_{t-1}$$

$$Q_{t-1} = Y_{t-1}\frac{1}{M}(M - Y_{t-1})$$

In this case, the parameters *p* and *q* can be estimated using the OLS-method.
For the variant of the Bass model with exogenously specified market potential *M*, the three scenarios A, B and C are also run through for forecasting.

By inserting an estimated or assumed market potential *M* and estimated parameter values for *p* and *q* into the equation of the Bass model, both fitted values (if $t \leq T$) and forecasts (if $t > T$) can be calculated for all time points t (iteratively).[47]

[45] Alternatively, for a linearized model, it is possible to estimate parameters using the OLS method (with the R function "lm"), see e.g. Massiani and Gohs (2015). In this study, however, the OLS estimates of *p*, *q*, and *M* differed substantially from their NLS counterparts and were often implausible. For example, OLS often estimated negative parameter values, although only positive ones are meaningful. Therefore, the OLS parameter estimates obtained were neither used for forecasting nor reported here. However, negative parameter values were also estimated with the NLS method in some cases.
In some literature, it is suggested to use the OLS estimates as starting values for the parameter estimates using NLS. However, due to the sometimes obtained implausible (including negative) OLS parameter estimates, this approach was not followed here.
[46] Starting values of *M* for the NLS-algorithm are taken from the assumed scenarios A to C, and for *p* and *q* from the OLS-estimates of the exogenous model-variant.
[47] Besides forecasts for the forecasting period, fitted values for the estimation period can be calculated from the model-equation. Thereby, the expected value zero is inserted for the errors (i.e. residuals), $E(\varepsilon_t) = 0$.

The Gompertz Model

Gompertz (1825) discovered a growth function represented by the following equation:

$$y_t = M \cdot \exp\,(-\beta \cdot \exp\,(-\gamma \cdot t)) + \varepsilon_t$$

with

- number of new registrations y_t in year *t*

and

- saturation level (here market potential) M of the innovation,
- parameters β and γ.

For the Gompertz model, too, both variants are run through - with exogenously given and endogenously estimated market potential *M*. In addition, the three scenarios described (A to C) for market potentials *M* are again played through. The model parameters are estimated using the Non-linear Least Squares (NLS) method by applying the R library "minpack.lm". Then forecasts are made using the R library "growthmodels".

For the variant with endogenously estimated market potential *M*, the starting values for the parameter *M* are taken from the scenarios A to C described above. Suitable starting values for the other coefficients were found to be $\beta = 50$ and $\gamma = 0{,}5$.

The Gompertz function can be linearized by logarithmic transformation:[48]

$$\ln\left(\ln\left(\frac{y_t}{M}\right)\right) = \ln(-\beta) - \gamma \cdot t + \epsilon_t$$

So, for an exogenously given *M*, parameter estimates for β and γ can be obtained from the linearized model equation. These in turn can be used as starting parameters for the optimization algorithm of the NLS method. However, in this study, a different estimation method is employed for the variant with exogenously specified *M*: The model equation $\frac{y_t}{M} = y_t^* = \exp\,(-\beta \cdot \exp\,(-\gamma \cdot t)) + \varepsilon_t$ is estimated by NLS, and again the starting values $\beta = 50$ and $\gamma = 0.5$ are used.

Based on the estimated or assumed market potential $\widehat{M}$ and the estimated parameters $\hat{\beta}$ and $\hat{\gamma}$, fitted values (for the estimation period) or forecasts (for the forecast period) are obtained from the model equation for each point in time t.[49]

The Logistic Growth Model

Pierre François Verhulst introduced the Logistic growth model in his research on population growth.[50] A Logistic growth function can be described by the following equation:

$$y_t = \frac{M}{1 + \left(\frac{M-\alpha}{\alpha}\right) \cdot exp(-g \cdot M \cdot t)} + \varepsilon_t$$

with

- growth parameter g *a*nd
- for $t = 0$ the equation collapses to $y_t = y_0 = \alpha$ if it is abstracted from the residual.[51]

[48] cf. Tjørve and Tjørve (2017) for variants of the Gompertz model and linearization by logarithmic transformation

[49] for this purpose, for residuals the expected value zero is inserted, i.e. $E(\varepsilon_t) = 0$

[50] cf. Cramer (2004) about the origins of the Logistic function

Often, the Logistic growth function is presented in a more compact representation:

$$y_t = \frac{M}{1 + b \cdot exp(-\gamma \cdot t)} + \varepsilon_t$$

with $\gamma = g \cdot M$ and $b = \left(\frac{M-\alpha}{\alpha}\right)$

The linearized representation of this function is

$$ln\left(\frac{M}{y_t} - 1\right) = \ln(b) - \gamma \cdot t + \epsilon_t$$

Forecasts are also made for the Logistic model with exogenously determined and endogenously estimated market potentials *M* (three *M* scenarios each). The parameters are estimated using the Non-linear Least Squares (NLS) method. For this purpose, the initial values are taken from the OLS estimation of the linearized equation.

For a time series up to the most recent year *T*, the 1-step forecast for year *T+1* is calculated based on the assumed or estimated market potential *M* and on the estimated growth parameter g as follows:

$$\hat{y}_{T+1} = y_T + \hat{g} \cdot y_T \cdot \left(\widehat{M} - y_T\right)$$

The Exponential Growth Model

The Exponential growth model is given by the function[52]

$$y_t = \alpha \cdot \exp\left(\gamma \cdot t\right) + \varepsilon_t$$

and

- the parameter γ represents the continuous growth rate and
- for $t = 0$ the equation collapses to $y_t = y_0 = \alpha$ (if the residual ε_t is abstracted, i.e. its expected value zero is entered).

In this paper, on the one hand, results are presented that are based on parameter estimates of the linearised model with the OLS method. This involves regressing the logarithmized values of y_t on a linear deterministic trend representing the time points *t* of the observations: [53]

$$\ln(y_t) = \mathrm{a} + \gamma \cdot t + \epsilon_t$$

with

$$\alpha = \exp(\mathrm{a})$$

By inserting the estimated constant a and the slope coefficient γ into the model equation, fitted values (for the estimation period) or forecasts (for the forecast period) are obtained for all time points *t* :

$$\ln\left(\hat{y}_t\right) = \hat{\mathrm{a}} + \hat{\gamma} \cdot t$$

and $\hat{y}_t = e^{\ln(\hat{y}_t)}$.[54]

In addition, for the purpose of alternative forecasting, the parameters of the exponential growth model were estimated using the nonlinear least squares (NLS) method. For this purpose, the OLS

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[51] Stated differently $E(y_0) = \alpha$. Cf. footnote 42 concerning the residuals.

[52] T.R. Malthus (1798) was an early researcher on population growth and popularized the Exponential growth model. He was born in 1766 and died 1834.

[53] For the estimation via Ordinary Least Squares (OLS) method, the function "lm" of the software R is applied.

[54] Alternatively, the $\hat{y}_t$ are calculated from the original model equation where $\hat{\alpha} = \exp\left(\hat{\mathrm{a}}\right)$ is inserted.

estimates of the parameters α and γ were taken as initial values. The received NLS-parameters $\hat{\alpha}$ and $\hat{\gamma}$ are directly inserted into the model equation to calculate fitted values and forecasts, respectively:

$$\hat{y}_t = \hat{\alpha} \cdot \exp\,(\hat{\gamma} \cdot t)$$

About the Application of Logarithmized Values or Growth Rates in Forecasting Models

Usually, a successful innovation spreads over time with stable growth rates (i.e., percentage changes) rather than stable quantity increases. Consequently, this could also be presumed for the market diffusion of a new (propulsion) technology.

As can be seen from figure 2, the market diffusion of battery-electric vehicles also takes a trajectory similar to that of an exponential function.[55] The logarithmized new registration values follow an approximately deterministic trend (see figure 3). An appropriate model of market diffusion should capture this.

So, also at the essence of the Exponential growth model, the logarithmized values of a time series are regressed on a deterministic linear time variable.

It is common to fit ARIMA(X) models to logarithmized values when analyzing financial time series such as stock prices. The study also fitted ARIMA(X) models to time series of logarithmized new registrations.

The idea of using logarithmic values in the core of a procedure was also pursued for other forecasting procedures in the study. The results for this are marked with the prefix "log-" in the table section.

Discussion of the Results

Adequacy of the Procedures for Forecasting New Passenger Car Registration Figures

The most accurate forecasts of new passenger car registration figures (i.e. with regard to the figures covering all drive technologies) in Germany were obtained for the present data set using the Logistic growth model. Here, the model variant with exogenously given market potential (i.e. saturation limit) provides slightly more accurate forecasts than the one with endogenous estimation. This could possibly be explained by the fact that the loss of one degree of freedom due to model-endogenous estimation of an additional parameter has an impact for short time series. The forecasts are fairly stable across the three scenarios run for market potentials (A to C). The requirement formulated in the paper for a viable growth model to provide stable short-term forecasts regardless of market potential is therefore met by the logistic model.

In concrete terms, direct and pooled 1-step and 2-step forecasts for Germany are produced ex-post for the three years 2017 to 2019 using the Logistic model, with absolute percentage errors not exceeding 4.7% and 5.3%, respectively. In particular, the 1-step forecast (i.e., from a year-end 2017 perspective) for 2018 is accurate (-0.4% to 0%). For the 3-step forecast for 2019, an absolute percentage error of 10.3% is not exceeded. For forecast horizons of up to three years, the accuracy of the Logistic model is thus significantly higher than that of the other models.

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[55] In the case of exponential growth of a quantity, the growth and thus the slope of the growth curve change over time. However, the logarithmized quantity develops linearly, i.e. has a constant slope. The linear progression can also be seen when the exponential function is mapped onto a logarithmic scale. The first differences of the logarithmized values can then be understood as continuous growth rates (called returns in the case of securities). If the original time series is (approximately) exponential, the growth rates are (almost) invariant over time. The slope parameter of a linear model fitted to the logarithmized values should then be significant.

For future (ex-ante) forecasts, it should be taken into account that the estimation periods of the available annual time series comprise just a moderate number of observations. It cannot be excluded that from longer time series (or time series of higher frequency) more accurate forecasts are achieved with (seasonal) ARIMA(X) or other models.

Adequacy of the Procedures for Forecasting the Numbers of Innovative Battery-Electric Technology

With regard to battery-electric passenger cars, the results (percentage errors of the direct and pooled forecasts) for the national time series as well as for the federal states (MAPE) show that acceptable forecasts are rather than anything else received with the Bass model. Convincing results are also obtained with the Exponential Growth (NLS) model.

The Bass forecasts are quite stable for both model variants (i.e., with endogenous and exogenous estimation of market potentials) and across the three different scenarios of market potentials (A to C). Only for the market potential scenario C in the endogenous variant, often no or less plausible forecasts result. Although the percentage errors of the Bass forecasts are sometimes in the double-digit range, the forecasts from other methods are even less accurate. Nevertheless, a fairly accurate 1-step forecast is obtained for 2018 with the Bass model (for example, -3.8% in scenario B of the endogenous variant). The new registration figures for battery-electric passenger cars in 2017 would have been substantially underestimated from the perspective of 2016 with the Bass model, but also with other forecast models. However, the increase in new registration figures for battery-electric passenger cars in 2017 would not necessarily have been expected either due to the decline in the same period of 2016. The new registrations of battery-electric passenger cars in 2019 are underestimated from the perspective of 2018 with the Bass model by about 15.5%. The unexpectedly strong increase in new registration figures is due to an increase in the purchase premiums for electric cars in November 2019.[56]

For an evaluation of the forecast performance, it should be taken into account that the number of new registrations of purely electrically powered passenger cars is still low in relation to the overall market. Therefore, small changes in quantities can at the same time represent large percentage changes and can also be accompanied by large percentage forecast errors. Due to the nearly exponential increase in new registration numbers, at least moderate forecast errors should be acceptable.

The results show by way of example that actual values of the market diffusion of a young technology can deviate greatly from the forecasts if the market is hit by unforeseen crises or other relevant events (e.g. purchase incentives, change in general VAT, etc.). However, the results for the Bass model also show that (in a tranquil market environment) some quite accurate forecasts are obtained even when sales are still relatively low and growing exponentially.

Often, the Exponential Growth (NLS) model produces similar results (i.e., percent errors and MAPE) as variants of the Bass model. In some settings, the Exponential Growth (NLS) model even produces more accurate results than the Bass model, while in other cases the Nonlinear Least Squares (NLS) algorithm does not spit out estimates. For example, from the perspective of 2017, no forecast is available for 2018 because the Exponential Growth (NLS) model estimation algorithm fails. However, using the Bass model, a forecast is obtained that deviates from the actual value only with a small percentage error.

[56] It can be assumed that the forecast error largely reflects this effect. Cf. also the section The Financial Incentive Scheme for Promotion of Electric Mobility in Germany and the Corona Crisis

In this context, it should also be mentioned that the Ordinary Least Squares (OLS) variant of the Exponential Growth model is not an adequate alternative to NLS. The OLS forecasts differ substantially from the NLS forecasts and are often not plausible or at least less plausible. With the Logistic Model, which was convincing in predicting the number of new passenger car registrations (number that includes all technologies), valid forecasts are often not obtained for the subgroup of battery-electric vehicles.

Even with variants of the ARIMA(X) procedure, small percentage errors are obtained for some settings. However, due to the omission of explicit modeling of the increase in the purchase premium, an accurate forecast for 2019 would not necessarily have been expected. The accuracy of the direct and pooled ARIMA(X) forecasts could be influenced by chance and not the result of a powerful forecasting model.

Forecasting of New Registration Figures in the Federal States

Passenger Cars (Number Comprising All Technologies)

The MAPE results show that also for the level of the German federal states, the Logistic growth model in the exogenous variant mostly predicted new passenger car registrations figures more accurately than the other procedures. On average, the forecast accuracy is somewhat lower than for the superordinate national territorial unit Germany. The endogenous variant has a much lower performance in the federal state forecasts.[57] For both model variants, the results are robust across the three market potential scenarios.

For federal states with high populations or registrations, the Logistic model and the other models tend to generate more accurate forecasts.
For the big five German federal states, either the exogenous or the endogenous variant of the Logistic model yields the best forecasts. The endogenous variant provides more accurate forecasts for Bavaria, Hesse and Berlin. The exogenous variant can be recommended for forecasting the number of new registrations in the remaining thirteen federal states. In some settings (i.e., combinations of federal states and forecast years), the forecast accuracy of the Logistic Model is also achieved with one of the other models. For the federal states of Rhineland-Palatinate, Saxony, Saxony-Anhalt, Saarland and Mecklenburg-Western Pomerania, an alternative model beats the Logistic model in all three forecast years 2017 to 2019. However, even in these cases, the yield of using the alternative method is rather small (i.e. is often below one percentage point). The small divergence of the obtained forecasts (or forecast errors) from different models is again interpreted here as emphasizing the predicted value (or range of values). Moreover, if the accuracy of an alternative model is only slightly higher, it could be questioned whether it is significant or rather random.

Accurate forecasts for Lower Saxony's new car registration figures are also obtained using other growth models. The forecasts for Rhineland-Palatinate with the ARIMA(X)-national variant are also convincing. For Berlin, Saxony-Anhalt and Mecklenburg-Western Pomerania, accurate forecasts are also obtained with the exponential smoothing model. With respect to Mecklenburg-Western

[57] The lower forecast quality for the federal states could again be explained by smaller observation scopes (i.e. registration numbers) than at the national level, which only allow less accurate fits of the forecast models to the short time series. In the endogenous variant, the parameter M also has to be estimated. I.e., another degree of freedom is lost and thus stability of the fitted model.

Pomerania as well as Schleswig-Holstein, the ARIMA(p,d,q) f.states variant is also suitable. Accurate forecasts for Hamburg are obtained with a number of models.

For ARIMAX forecasts of new registration figures in a federal state, the number of new registrations in one of the other federal states lagged by one year is taken as the exogenous predictor variable X. This is done by using the Bayes information criterion (BIC) to identify which country time series as exogenous variable X provides the best fit of the model. Often, this resulted in the selection of the time series of the federal state of Hamburg as predictor X (see table 3). This is probably also due to the good predictability of Hamburg's new registration figures themselves. Due to the high ratio of rental cars or cars used in car sharing in Hamburg's new registrations, this time series may also contain information on Germany's economic development, which has a lead over private car purchases.

The ARIMA(X) variants provide some more accurate forecasts, especially for 2019, and should be considered for future (ex ante) forecasts.

Battery Electric Passenger Cars

With regard to the subgroup of battery-electric vehicles, the high MAPE values show that the forecasts of new registrations in the federal states are inaccurate. However, nearly matching MAPEs are obtained with the Bass-exogenous, Gompertz-exogenous, and Exponential Growth (NLS) model variants. The higher performance of the exogenous model variants could possibly be related to the fact that the already small number of degrees of freedom in short time series would be further reduced by a model-endogenous estimation of the parameter *M*. The convergence of results from three growth models to a large extent promises more accurate forecasts when longer time series become available in the future.

Especially for the six most populous German federal states (including Rhineland-Palatinate), the Bass model achieves very accurate forecasts for battery-electric vehicles in several settings. In any case, the Bass model achieves more accurate forecasts than all other procedures included in the study.

Similar results are also often obtained with the Exponential Growth (NLS) method.

The Bass forecasts of the exogenous and endogenous variants and for the market potential scenarios B and C hardly differ from each other. Assuming market potential scenario A, a deviating percentage error is obtained in some cases. With additional consideration of the results for the national time series, this rather argues for the medium or high market potential (B or C).

For some German federal states, none of the forecasting procedures provide convincing predictions. Berlin's new registration figures for battery-electric passenger cars in 2018 are severely underestimated with Bass as well as with other forecasting procedures. Only the ARIMA procedure applied to logarithmized new registration figures achieves a forecast error in the mid-single digits for 2018.[58] In concrete terms, the log-ARIMA(2,d,2) variant is used to generate 1-step forecasts for the years 2017 to 2019, obtaining forecast errors of -13.2%, 5.1%, and -24.5%. One possible explanation for this would be that market diffusion in Berlin initially progressed at a relatively stable diffusion rate. However, it changed due to the increase in purchase premiums in 2019.

[58] Results for the log-ARIMA variant are not included in the table section because the performance of the log-models was not convincing in the case of the other federal states.

Pooling Strategies and Forecast Combinations

Appropriate Forecasting Procedures and Suggestions for Forecast Combinations

It can be seen that a pooled forecast of new passenger car registrations in Germany generated from the forecasts for the federal states is almost identical to its unpooled counterpart (i.e. direct forecast based on the Germany time series) in the Logistic Model.[59] The corresponding percentage forecast errors are the same or differ by only a tenth of a percent.
The pooled Bass forecasts for the battery-electric vehicle subset are significantly less accurate than their unpooled counterparts. However, for some time series segments (i.e., estimation periods), the algorithm is unable to provide a forecast based on the national time series, though it can provide forecasts for the time series of all sixteen states (and for the "not specified" category). Under these circumstances, pooled, but not direct, national forecasts can be made for the battery-electric cars.

In "mixed-methods" pooling, additional possibilities for combinations of forecasts are obtained, since for the subdivided territorial units also different methods can be employed. Thus, it is possible to determine an optimal forecast model for each federal state. In addition, combinations are thinkable in which weighted forecasts from several procedures are already produced for individual federal states.
It would make sense to pursue a mixed methods strategy, provided that it can be expected to increase forecast accuracy. However, this is not to be expected, since generally the same forecast models are identified as suitable for the federal states or the forecast accuracy can hardly be increased by alternative models.

Due to the rather imprecise forecasts in a turmoil market environment, comparisons of the forecasts of different models are useful. For a forecast of new vehicle registrations in a federal state, consideration could also be given to combining forecasts from the exogenous and endogenous variants of the Logistic Model or pooled and direct forecasts. For the battery-electric technology, a weighted forecast from the Bass and Exponential Growth (NLS) models could be considered.
In addition, consideration should be given to aggregating time series of smaller German federal states to form time series for larger geographic units (e.g., all eastern federal states (excluding Berlin), Rhineland-Palatinate and Saarland, as well as Bremen and Lower Saxony). Due to the higher number of cases, it can be assumed that more accurate forecasts are obtained for the combined areas. Provided that this avoids high forecast errors for smaller federal states, a more accurate pooled Germany forecast could also be received. The estimated parameters of a forecast model for a pooled territorial unit could alternatively be transferred to forecasts for the individual federal states.

Evaluation of Pooling Taking into Account All Forecasting Procedures

For each individual forecasting procedure, it was checked whether the pooled or the direct forecast was more accurate. Subsequently, the share of procedures was calculated in which a forecast improvement is achieved by pooling. A share value exceeding 0.5 would argue in favor of pooling. In addition, it was calculated how the absolute percentage forecast error changes on average for the procedures as a result of pooling. An average reduction (i.e., negative change) in the absolute percentage forecast error argues in favor of pooling. Table 4 shows the results for both ratios, differentiated by propulsion technology categories (all or battery-electric), forecast years and forecast horizons.

[59] In general, for the other forecasting methods included in the study, it appears that pooled forecasts of new passenger car registrations are no more accurate than direct forecasts.

It should be noted, however, that both indicators depend on the number of forecast models, model variants and market potential scenarios incorporated into the study. The growth models are given a high weight, since several scenarios are run for each of them. Nevertheless, the calculated ratios should inform whether pooling is a promising strategy for increasing forecast accuracy. This assumption would be particularly supported by definite results. Otherwise, uncertainty would remain as to whether pooling is preferable to direct forecasting.

For the 1-step (and also 2- and 3-step) forecasts of new registrations (of all passenger cars) for the years 2017 to 2019, it is found for 60% to 78% (see ratios in table 4) of the models and their variants that pooled forecasts are more accurate compared to their unpooled counterparts (i.e., direct forecasts).[60] On average (across all methods), however, the absolute percentage forecast error is not reduced by pooling, or only by less than one percentage point (see table 4). However, the direct forecasts for the period 2017 to 2019 are already quite accurate, so that there is also little potential for error reduction.

Among the forecasts for the year 2020, only 21% to 35% of the models achieve a higher accuracy by pooling. On average, the absolute percentage forecast error increases by 0.3% to 3%. Due to a lack of explicit modeling of the effects of the Corona crisis, only inaccurate national forecasts were obtained for 2020.[61] The forecast errors for the federal states are even higher. Here again, it is assumed that this is due to a low robustness of the models fitted to short time series, combined with lower observation numbers (i.e. new registrations) per period in smaller territorial units. Thus, there is a potential for higher forecast errors, which may come into play in crisis years. This suggests that, especially when unforeseen events or crises occur, pooled ex-ante forecasts perform worse than direct ones.

For battery-electric cars, pooling cannot increase the forecast accuracy for about half of the models (see share values in table 4). Very different results are obtained for the individual constellations. Nevertheless, the absolute percentage forecast error for forecasts for 2017 and 2018 is reduced significantly (i.e., by several percentage points) on average in some cases. On average (across all models), the 1-step forecasts for 2018 become more accurate by 5.5 percentage points, although a more accurate forecast is achieved by pooling in only 48% of the forecast models. Here, the high percentage errors of the direct forecasts result in a potential for a substantial error reduction (through pooling). Altogether, in the case of innovative propulsion technology, uncertainty remains as to whether direct or pooled forecasting is preferable.

The new registration figures for battery-electric passenger cars in 2019 and 2020 are affected by the increases in purchase premiums and the sudden pandemic. In some cases, much less accurate pooled than direct forecasts are obtained. In the pooled forecast from the perspective of 2016 for 2019, the forecast error increases by 36.2%, and from the perspective of 2016 and 2017 for 2020 by 3201% and 22.9%, respectively. The small numbers of newly registered battery-electric passenger cars in earlier years (in smaller territorial units) are unlikely to allow a robust model fit to the short time series.

It can be seen that even an inaccurate forecast for a single territorial unit can lead to a strong deterioration in the accuracy of the pooled forecast. Therefore, especially in a turbulent market environment with a high probability of unforeseen events and thus of inaccurate ex ante forecasts, the direct forecast would be preferable to the pooled forecast. It seems reasonable to check the

[60] Pooled forecasts for the national level are only available if forecasts are available for all federal states (and for new passenger car registrations not assigned to any federal state). Therefore, missing forecasts for at least one federal state are considered as unsuccessful pooling and thus worsen the reported ratio.

[61] Detailed results (percentage forecast errors) for the year 2020 are not reported.

forecasts for all territorial units for plausibility and to correct them if necessary. A comparison of the pooled forecast with the direct forecast could be helpful for this purpose, among other things.

The inconclusive results suggest that a general advantageousness of pooling over direct forecasting cannot be confirmed for the present data sets.

On Forecasting with Logarithmized Variables

With respect to the innovative battery-electric technology, one hypothesis might be that diffusion will be reflected in stable rates (i.e., percentage changes) rather than stable amount changes. This assumption is confirmed by the forecasting performance of the Exponential Growth (NLS) model, which processes logarithmized values at its core.

Moreover, the idea of fitting models to logarithmized variables has been applied to other classes of models. However, a general improvement in forecasting ability through applications to log new registrations was not found for the other model families.

Estimated Market Potentials and Bass-Parameters

With regard to the model-endogenously estimated market potentials *M*, it can be seen that the sums of the market potentials for the federal states do not equate to the national market potentials (see tables 5 to 7). In addition, market potentials *M* are estimated for some federal states that are not plausible (e.g., negative values). While the estimated Bass parameters *p* and *M* vary considerably for different starting values (i.e. initial values of the estimation algorithm) of parameter *M* (scenarios A to C), the estimated imitation coefficient q is quite robust. Even for a successively increasing estimation period, Bass parameters *q* are estimated which change only moderately. Early in the product life cycle, this robust parameter *q* should provide stable short- to medium-term forecasts (one or a few years ahead) for various starting values and over an increasing window of the estimation period. This can be explained as follows: In the first periods after market launch, the cumulative sales Y_t are typically low. The innovation term $(M - Y_{t-1})$ in the Bass formula thus corresponds approximately to the market potential *M* of a successful product. It follows that the innovators' impact $p(M - Y_{t-1})$ on product sales y_t in the first periods *t* after market launch is approximately pM. The estimated value of the parameter *p* thus essentially depends on the assumed market potential *M* of an innovation. As for the impact of imitators on sales y_t it follows $qY_{t-1}\frac{1}{M}(M - Y_{t-1}) = q\left(Y_{t-1} - \frac{{Y_{t-1}}^2}{M}\right)$. This should correspond approximately to qY_{t-1} in the first periods. Thus, the estimated imitation coefficient *q* depends on the cumulative sales until the end of period *t -1* and barely on the assumed market potential. Given a balanced partitioning of the sales y_t between the terms pM and qY_{t-1} with large *M* and low Y_{t-1}, the estimation algorithm should yield a small *p* relative to *q*. Moreover, *p* should decrease to the same extent as *M* increases.

Appropriateness of Growth Models for Prediction of New Registration Figures

For the growth models (Bass, Gompertz, Logistic), it is found that the results obtained for short-term forecasts (percentage errors, MAPE) hardly depend on the assumed scenario (A to C) for the market potential.[62] Therefore, a correct appreciation of the market potential is negligible for the purpose of a short-term forecast (in the early product life cycle phase). Since market potential is difficult to predict, a robust short-term forecast obtained regardless of assumed market potential argues for the suitability of a growth model. However, the estimation algorithms of the models cannot calculate valid parameter estimates for some settings (composed of vehicle technology categories battery-

[62] In the context of this study, the saturation limit is understood as market potential.

electric or all cars, forecast horizons, forecast years) (see entry "NA" in the table section).[63] The results for new passenger car registrations in Germany are confirmed by those for the German federal states (MAPE values). Somewhat more accurate forecasts are obtained for the federal states when market potential scenario C is assumed. This indicates that the scenarios with higher market potential are more realistic.

In the case of short time series, the sacrifice of a degree of freedom required by the estimation of an additional parameter *M* could be of relevance. This argues in favor of using the model variants with exogenously specified market potential. The study results support this assumption: At least in the case of the forecast models (Logistic, Bass), which proved to be particularly suitable, more accurate forecasts are obtained with the exogenous variant.

Range of Results: Agreement of the Forecasts of Different Procedures

If forecasts from models that process historical information (from time series) differently agree or at least lie within a narrow range, this should confirm the forecast value or range of values. Furthermore, there is a conclusion regarding the coping with uncertainty in the model selection: The smaller the deviations of the forecasts of different models from each other, the less profitable is a careful model selection and thus possibly neglectable.

An examination of the results for the direct 1-step forecast of the national new registration figures in the years 2017 to 2019 shows: By means of 90% (or 50%) of the procedure variants (including scenarios on market potentials), forecasts are obtained whose percentage forecast errors do not differ by more than 10.7 (or 5.8) percentage points (see table 20). Thus, with a mass of the procedures included in the study and their variants, forecast values are obtained that lie within a small or at least manageable range.[64] The forecast errors of the pooled forecasts sometimes form a somewhat wider range.

For a forecast of new passenger car registrations, careful model selection is thus rather negligible if the purpose of the forecast allows for a certain (or the specified) margin of error. If pooling is intended or in a turbulent market environment (year 2020), careful model selection is more important.

A different result is obtained for the battery-electric passenger car subgroup (see table 21). With half (50%) of the model variants whose forecasts are most closely matched, forecast errors are calculated for 2017 (or 2018 and 2019) that are in the range of 25.6 (10.2 and 7.3) percentage points. Because the forecasts for the innovative propulsion technology vary widely, profound model selection (leading to a decision for Bass) is essential.

However, it is possible to speculate whether the decreasing range of results up to 2019 (to 7.3 percentage points) already indicates that the time series will also develop more stably as sales figures

[63] The absence of a result for a scenario should be rather uncritical, since the estimation can be performed again with a different starting value (or scenario). A wide range of results for different starting values, on the other hand, would be problematic, since this would imply the dependence of the (correct) individual forecast on the selected starting value.

[64] Certainly, the acceptability of the level of forecast error depends on the purpose of the forecast. For example, the short-term adjustment possibility of a production process within an acceptable reaction time or during the period to which the forecast refers would have to be taken into account. However, in addition to the range of forecast results, the expected forecast error of the best model and, if necessary, a safety margin in the sense of a value-at-risk would also have to be taken into account.

increase or this innovative technology becomes established. This could provide a basis for more reliable forecasts, with forecasts from different models also continuing to converge (for now).[65]

Conclusion and Suggestions

The study provides information on simple or univariate procedures that could be considered for forecasting the sales or new registration figures of vehicles. A distinction is made between established and innovative drive technologies. Taking into account the results for the mass of forecasting models included in the study, conclusions are drawn about how to manage model uncertainty. Furthermore, for the dataset subdivided into NUTS1-territorial units, it is investigated whether an increase in the accuracy of the national forecast can be achieved by pooling the forecasts for the territorial units. In this context, it is exemplified for the Bass diffusion model that uncertainty about the market potential of an innovation has little impact on the accuracy of short-term forecasts.

For the forecast period of 2017 to 2019, accurate forecasts of new passenger car registrations (number encompassing all technologies) were obtained using the Logistic Growth Model.
New passenger car registrations (of all technologies) trended upward over the 2013-2019 period. Therefore, a growth model was most likely to provide accurate ex post forecasts. However, if sales were to stagnate over the next few years, perhaps ARIMA models could provide better forecasts. Also, if more observations are available, i.e. time series for a longer period or with lower periodicity (i.e. sub-annual), possibly (S)ARIMA models could lead to more accurate forecasts.

For forecasts on the subgroup of battery-electric (i.e., all-electric) passenger cars, the Bass model was found to be most suitable. This is concluded even though forecast errors in the low single-digit percentage range are only obtained for the 1-step forecasts for 2018. The Bass model gained popularity in marketing and is successfully used in modeling diffusion processes of innovative processes.
The study argues that the robustness of the imitation coefficient q under different assumptions about the market potential M contributes to a stable short-term forecast. In contrast, fitting the Bass model to the short time series (typically available for a young technology) revealed that the estimated parameter values of the innovation coefficient p and the market potential M are unstable. This is also likely to contribute to the fact that - as shown by way of example - model-endogenously estimated market potentials for German federal states do not necessarily correspond in total to the national market potential.
Besides this, the Exponential Growth (NLS) model was also convincing in forecasting the number of new registrations of battery-electric passenger cars.

For forecasts of new registration figures in the years from 2020, (significant) effects of the Corona crisis, repeatedly increased purchase premiums, supplier-side restrictions such as supply bottlenecks for chips in the semiconductor industry, etc. should be explicitly formulated in forecast models. Results for an extended Bass model, which allows not only accurate forecasts but also an estimation of the effects of purchase premiums, will be presented in a follow-up study.[66]

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[65] The special features of special time series models may only come into play with much longer time series. More accurate forecasts can be expected with a special model if the observed values follow an ideal course and there are no structural breaks.
[66] Possible changes in the Bass coefficients p and q triggered by purchase incentives could be captured using interaction variables (for the innovation and imitation terms).

The forecast quality for the federal states differs and tends to be higher for the five federal states with above-average populations than for the smaller territorial states. In particular, less accurate forecasts are obtained for the smaller territorial states in eastern Germany. In general, the same models are appropriate for the federal states forecasts as for the Germany forecast. Mixed-methods pooling is therefore unlikely to be fruitful. However, for some federal states such as Hamburg, accurate forecasts are obtained using several methods. In addition, the time series of Hamburg's new registration figures is suitable as predictor variable X in ARIMAX models for forecasting the figures of some other federal states.

In the study, no (substantial) increase in forecast accuracy was achieved using pooling compared to direct forecasting, or uncertainty remains as to whether pooling is beneficial.

Pooled forecasts were calculated for the year of the Corona crisis 2020, which show high percentage forecast errors. Especially in a distressed market environment, the direct forecast of new registration figures in Germany (i.e. based on the national time series) should therefore be preferred. Alternatively, it is recommended to produce a pooled forecast in addition to the direct one in order to reduce uncertainty. In this case, however, the forecasts for the individual German federal states should be checked for plausibility.

The results also show that unstable models are estimated for smaller territorial units or innovative technologies with low numbers of observations in the years of market introduction. These have a potential for high forecast errors.

Provided that the results from the application of procedures that process information differently agree or at least are close, this should emphasize the prediction(-range) found. It could be argued that uncertainties in model selection are then negligible and the gain from careful model selection is small. It was found that the results from the various forecasting procedures for the conventional product (i.e., passenger cars) fall within a manageable range. However, for the subset of innovative battery-electric vehicles, careful model selection is essential and leads to the Bass- or Exponential Growth (NLS)-model.

With Bass, as with other growth models, forecasts are obtained that hardly differ for different market potential scenarios (A to C). Since the market potential of an innovative technology can hardly be estimated, the stable short-term forecasts argue for the applicability of the growth models.

Appendix A: Spatial Relationships

Table 3 Explanatory X Variables for Forecasts with the ARIMAX(p,d,q)-F.States Procedure, Selected According to the Bayes Information Criterion

	Battery-Electric				All Technologies			
Estimation Period	2006 - 2016	2006 - 2017	2006 - 2018	2006 - 2019	2006 - 2016	2006 - 2017	2006 - 2018	2006 - 2019
Forecast Variable Y	Exogenous explanatory X-variable in ARIMAX(p,d,q)-f.states procedure							
Germany (D)	HE	HE	HE	HE	HH	HH	HH	HH
BW	BE	RP	RP	RP	HH	HH	HH	HH
BY	BE	ST	HE	ST	RP	HH	HH	HH
BE	MV	MV	MV	D	HH	HH	HH	HH
BB	SN	HE	HE	BW	HH	HH	HH	HH
HB	MV	MV	MV	MV	RP	TH	TH	TH
HH	D	TH	BE	n.s.	HE	HE	n.s.	HE
HE	SH	BW	BW	BW	BE	SH	SH	BB
MV	HH	SN	SN	SN	HH	HH	HH	HH
NI	RP	TH	HE	TH	RP	MV	MV	ST
NW	n.s.	HE	HE	D	HH	HH	HH	HH
RP	HB	ST	HE	NW	HH	HH	HH	HH
SL	BB	HB	HB	n.s.	HE	HE	HE	HE
SN	BE	RP	BE	HH	HH	HH	HH	HH
ST	BW	BW	HE	HE	HH	HH	HH	HH
SH	BE	ST	BW	HE	HH	HH	HH	HH
TH	HB	ST	HE	n.s.	HH	HH	HH	HH
n.s.	BB	D	D	D	NI	NI	HB	BW

Appendix B: Pooling

Table 4 Increase in Forecast Accuracy When Using Pooled Instead of Direct Forecasts

Time Series until Year	2016	2017	2018	2019	2016	2017	2018	2016	2017	2016
Forecast Year	2017	2018	2019	2020	2018	2019	2020	2019	2020	2020
Forecast Horizon (h)	1	1	1	1	2	2	2	3	3	4
New Passenger Car Registrations (Number Including All Technologies)										
Proportion of Successful Pooling (should be > 0.50)	0.60	0.74	0.78	0.21	0.60	0.76	0.25	0.60	0.21	0.35
Average Change in Absolute Percentage Error due to Pooling (should be Negative)	0.1	-0.8	-0.2	1.2	0.2	-0.8	0.3	-0.5	0.6	3.0
New Registrations of Battery-Electric Passenger Cars										
Proportion of Successful Pooling	0.53	0.48	0.43	0.73	0.47	0.45	0.49	0.44	0.52	0.44
Average Change in Absolute Percentage Error	-1.3	-5.5	-4.8	-2.3	-2.2	-3.2	-2.2	36.2	22.9	3201

Appendix C: New Registrations of Battery-Electric Passenger Cars: Model-Endogenously Estimated Market Potentials from Bass- and Gompertz-Models, Bass-Coefficients of Innovators and Imitators

Table 5 Estimated Bass Parameters for the Time-Series Period from 2006 to 2017

Battery Electric	Bass Parameters (Scenario A)			Bass Parameters (Scenario B)			Bass Parameters (Scenario C)		
2006-2017	p	q	M	p	q	M	p	q	M
Germany	6.16E-06	0.487	150,564,240	5.56E-06	0.487	166,747,610	-3.88E-04	0.479	-2,435,487
BW	8.73E-07	0.478	176,186,732	2.50E-07	0.478	616,951,270	7.20E-08	0.478	2,139,561,847
BY	2.70E-07	0.568	469,533,098	8.84E-08	0.568	1,432,658,077	2.43E-08	0.568	5,211,628,690
BE	7.68E-06	0.325	8,920,210	1.09E-06	0.325	63,019,048	3.06E-07	0.325	223,844,867
BB	5.74E-09	0.636	527,791,932	4.39E-09	0.636	689,968,339	4.54E-09	0.636	667,873,423
HB	5.70E-02	0.419	570	-1.97E-05	0.079	-2,301,562	-3.74E-06	0.079	-12,134,193
HH	1.19E-03	0.358	40,124	1.19E-03	0.358	40,124	-3.51E-07	0.346	-138,667,334
HE	-4.79E-06	0.439	-67,418,186	-1.82E-06	0.439	-177,607,096	-4.53E-07	0.439	-713,836,152
MV	1.34E-07	0.493	29,313,405	4.33E-08	0.493	90,946,249	2.37E-08	0.493	166,280,058
NI	-3.69E-05	0.309	-8,100,999	-7.19E-06	0.310	-41,623,225	-1.22E-06	0.310	-244,650,988
NW	4.54E-07	0.503	272,482,292	1.22E-07	0.503	1,015,681,201	3.98E-08	0.503	3,111,058,756
RP	5.64E-07	0.551	30,902,363	8.37E-08	0.551	208,348,085	2.63E-08	0.551	663,794,274
SL	6.18E-06	0.247	3,720,070	6.49E-07	0.247	35,464,367	3.70E-07	0.247	62,211,008
SN	4.71E-07	0.434	58,034,213	1.63E-07	0.434	167,728,577	4.62E-08	0.434	591,995,562
ST	1.16E-06	0.558	9,344,512	2.68E-07	0.558	40,404,645	9.73E-08	0.558	111,295,850
SH	7.19E-07	0.590	36,108,774	2.67E-07	0.590	97,244,435	5.62E-08	0.590	462,176,609
TH	1.40E-08	0.636	268,466,299	6.75E-09	0.636	556,151,175	5.11E-09	0.636	734,962,610
not specified	4.40E-06	0.763	440,270	1.79E-06	0.763	1,083,838	7.69E-07	0.763	2,522,105
Sum of Ms*			1,815,765,679			4,794,157,549			13,039,916,991

* sum of model-endogenously estimated market potentials for federal states

Table 6 Estimated Bass Parameters for the Time-Series Period from 2006 to 2018

Battery-Electric	Bass Parameters (Scenario A)			Bass Parameters (Scenario B)			Bass Parameters (Scenario C)		
2006-2018	p	q	M	p	q	M	p	q	M
Germany	5.67E-07	0.501	1,483,425,049	7.69E-07	0.501	1,094,038,234	3.90E-08	0.501	21,599,177,466
BW	2.45E-06	0.471	66,333,630	3.83E-07	0.471	423,487,126	-3.16E-04	0.462	-533,602
BY	3.04E-07	0.568	416,889,605	3.69E-07	0.568	343,615,015	2.02E-08	0.568	6,279,257,736
BE	4.52E-08	0.453	502,999,580	2.95E-08	0.453	771,303,629	1.37E-08	0.453	1,657,878,744
BB	-2.71E-08	0.775	316,313,158	-1.43E-08	0.775	599,436,954	-6.06E-09	0.775	1,416,801,847
HB	3.04E-05	0.180	1,130,936	5.61E-06	0.180	6,128,876	1.04E-06	0.180	33,235,373
HH	6.57E-08	0.449	332,833,930	2.84E-08	0.449	770,376,328	8.77E-09	0.449	2,496,160,452
HE	-3.49E-06	0.426	-95,119,590	-1.71E-06	0.426	-195,027,225	-4.55E-07	0.426	-731,392,960
MV	1.24E-09	0.565	872,521,393	8.74E-10	0.565	1,238,522,429	9.00E-10	0.565	1,203,286,134
NI	4.42E-06	0.349	58,276,637	1.38E-06	0.349	187,423,168	3.07E-07	0.349	839,948,244
NW	1.96E-07	0.514	574,288,024	8.75E-08	0.514	1,287,323,363	2.06E-08	0.514	5,457,614,107
RP	3.39E-07	0.555	49,139,452	-4.22E-04	0.533	-45,274	1.42E-08	0.555	1,170,964,447
SL	4.19E-07	0.344	29,664,996	1.14E-07	0.344	109,375,617	4.20E-08	0.344	296,054,207
SN	1.89E-11	0.549	23,687,295,987	1.79E-11	0.549	24,914,436,947	1.59E-11	0.549	28,028,433,406
ST	9.96E-09	0.666	337,969,179	5.70E-09	0.666	590,287,311	3.99E-09	0.666	844,072,901
SH	2.84E-08	0.654	474,200,823	1.54E-08	0.654	875,525,947	7.59E-09	0.654	1,776,789,255
TH	-2.74E-09	0.705	985,050,595	-1.56E-09	0.705	1,731,044,827	-1.08E-09	0.705	2,501,390,200
not specified	4.72E-02	0.917	54	-6.91E-05	0.116	-97,618	-3.15E-05	0.116	-214,378
Sum of Ms*			28,609,788,391			33,653,117,417			53,269,746,113

Table 7 Gompertz Model: Endogenously Estimated Market Potentials for Battery-Electric Passenger Cars, Estimation Periods 2006-2017 and 2006-2018

Battery-Electric	Gompertz Parameters (2006-2017)			Gompertz Parameters (2006-2018)		
Region	M (Scenario A)	M (B)	M (C)	M (A)	M (B)	M (C)
Germany	95,462,495	128,658,392	159,651,370	242,361,113	334,602,039	418,216,018
BW	42,297,858	61,264,414	95,604,238	29,358,232	41,653,185	40,094,800
BY	86,026,284	149,298,922	189,785,978	45,406,752	57,756,361	76,350,882
BE	1,465,112	1,456,129	1,130,392	77,298,373	107,032,517	116,430,652
BB	64,534,668	72,530,250	99,294,690	14,612,609	19,172,869	22,206,090
HB	76	76	76	131,942	115,998	125,420
HH	11,177	11,176	11,176	66,756,324	106,551,985	120,747,136
HE	3,081	3,079	3,079	7,215	7,215	7,215
MV	9,819,069	11,419,411	17,275,486	7,070,942	9,588,084	12,655,304
NI	3,276	3,276	3,276	5,937,183	6,040,702	5,577,306
NW	79,020,780	99,010,875	143,569,633	66,846,904	113,426,497	143,660,874
RP	5,332,631	6,896,644	7,449,243	6,225,877	9,448,140	10,122,549
SL	2,723,525	4,952,925	5,145,401	18,554,080	27,285,720	33,372,873
SN	20,906,187	24,335,076	33,127,903	60,986,385	68,845,773	101,738,096
ST	4,775,635	5,973,276	7,827,326	8,342,364	10,753,169	19,079,957
SH	10,053,227	14,696,027	16,555,560	20,567,985	22,735,223	30,707,790
TH	29,393,213	41,649,003	61,758,630	6,646,026	7,625,522	9,886,223
not specified	413,179	780,231	864,230	18	18	18
Sum of Ms*	356,778,976	494,280,790	679,406,317	434,749,209	608,038,979	742,763,186

* sum of model-endogenously estimated market potentials for federal states

Appendix D: (Mean Absolute) Percentage Errors in Forecasting New Passenger Car Registrations (Number Comprising All Technologies)

Table 8 Percentage Errors (PE) of Direct Forecasts of New Passenger Car Registrations in Germany

Time Series until Year	2016	2017	2018	2016	2017	2016
Forecast Year	2017	2018	2019	2018	2019	2019
Forecast Horizon (h)	1	1	1	2	2	3
Germany - direct	PE	PE	PE	PE	PE	PE
Bass - exog. (A)	-16.1	-15.6	-20.0	-18.7	-22.4	-25.3
Bass - exog. (B)	-11.4	-9.0	-11.9	-12.2	-14.1	-17.3
Bass - exog. (C)	-10.8	-8.1	-10.7	-11.3	-12.9	-16.2
Bass - endog. (A to C)	-10.4	-7.4	-9.8	-10.8	-12.0	-15.6
Gompertz - exog. (A to C)	-10.2	-7.2	-9.6	-10.6	-11.8	-15.4
Gompertz - endog. (A to C)	-8.7	-6.8	-10.7	-8.6	-11.3	-13.0
Logistic - exog. (A and C)	-3.2	0.0	-4.7	-3.6	-4.9	-8.7
Logistic - exog. (B)	-3.2	NA	-4.7	-3.6	NA	-8.7
Logistic - endog. (A)	-3.7	-0.1	-4.7	-4.7	-5.1	-10.2
Logistic - endog. (B)	-3.5	NA	-4.7	-4.3	NA	-9.7
Logistic - endog. (C)	-3.6	0.0	-4.7	-4.4	-4.9	-9.8
Exponential Growth (OLS)	-10.2	-7.3	-9.7	-10.5	-11.8	-15.3
Exponential Growth (NLS)	-10.2	-7.2	-9.6	-10.6	-11.8	-15.4
Deterministic Trend	-6.9	-6.2	-10.2	-6.8	-10.7	-11.2
ARIMA(2,d,2)	-11.8	-7.3	-2.2	-5.8	-11.4	-13.2
ARIMA(p,d,q)-national	-6.9	-6.2	-10.2	-6.8	-10.7	-11.2
ARIMAX(2,d,2)	-12.2	3.8	-6.9	-3.2	2.8	-6.7
ARIMAX(p,d,q)-national	-7.8	-1.2	-6.0	-7.5	-5.1	-11.9
Exponential Smoothing	-7.1	-5.1	-8.2	-6.9	-9.6	-11.4
Exp. Smooth. 2nd Order	-8.8	-6.9	-10.2	-8.3	-11.0	-12.3
log-Deterministic Trend	-7.2	-6.5	0.7	-7.0	-10.9	-11.5
log-ARIMA(2,d,2)	-11.9	-7.5	-1.4	-6.0	-11.6	-13.2
log-ARIMA(p,d,q)-national	-7.2	-6.5	-10.4	-7.0	-10.9	-11.5
log-ARIMAX(2,d,2)	-11.9	4.4	-1.4	-6.0	-1.9	-13.2
log-ARIMAX(p,d,q)-national	-7.2	-6.5	-10.4	-7.0	-10.9	-11.5

Some results are Not Available (NA) due to a missing return of the estimation algorithm.

Table 9 Percentage Errors (PE) in Forecasts of New Passenger Car Registrations in Germany due to Pooling of Federal State Forecasts

Time Series until Year	2016	2017	2018	2016	2017	2016
Forecast Year	2017	2018	2019	2018	2019	2019
Forecast Horizon (h)	1	1	1	2	2	3
Germany - pooled	PE	PE	PE	PE	PE	PE
Bass - exog. (A)	-16.0	-15.5	-19.9	-18.6	-22.3	-25.2
Bass - exog. (B)	-11.3	-9.0	-11.8	-12.1	-14.0	-17.2
Bass - exog. (C)	-10.7	-8.0	-10.6	-11.2	-12.8	-16.1
Bass - endog. (A)	-29.0	-9.6	-17.1	-29.2	-14.0	-32.9
Bass - endog. (B)	-21.6	-13.4	-15.1	-21.8	-17.6	-25.8
Bass - endog. (C)	-15.7	-13.4	-16.9	-15.9	-17.6	-20.3
Gompertz - exog. (A)	-10.1	-7.1	-9.6	-10.5	-11.7	-15.2
Gompertz - exog. (B and C)	-10.1	-7.1	-9.5	-10.5	-11.6	-15.2
Gompertz - endog. (A to C)	-9.0	-6.8	-9.3	-8.9	-11.1	-13.3
Logistic - exog. (A and C)	-3.2	0.0	-4.6	-3.5	-4.9	-8.6
Logistic - exog. (B)	-3.2	NA	-4.6	-3.5	NA	-8.6
Logistic - endog. (A)	-4.1	-0.4	-4.6	-5.2	-5.3	-10.2
Logistic - endog. (B)	-3.9	NA	-4.7	-4.9	NA	-10.2
Logistic - endog. (C)	-3.9	-0.2	-4.6	-4.9	-5.1	-10.3
Exponential Growth (OLS)	-10.0	-7.1	-9.6	-10.3	-11.6	-15.0
Exponential Growth (NLS)	-10.1	-7.1	-9.5	-10.4	-11.6	-15.1
Deterministic Trend	-4.9	-0.8	-3.3	-2.6	-2.2	-4.4
ARIMA(2,d,2)	-9.9	-1.9	-5.0	-2.8	-3.4	-6.7
ARIMA(p,d,q)-national	-7.5	-5.6	-8.2	-7.4	-10.1	-11.8
ARIMA(p,d,q)-f.states*	-5.9	-1.7	-5.6	-4.1	-4.5	-6.5
ARIMAX(2,d,2)	-1.4	-0.1	-3.2	0.9	-5.6	3.2
ARIMAX(p,d,q)-national	-7.4	-0.9	-5.8	-7.0	-3.7	-12.0
ARIMAX(p,d,q)-f.states*	-2.8	1.5	-3.2	0.5	0.5	-0.3
Exponential Smoothing	-6.6	-4.5	-7.2	-6.5	-9.0	-10.9
Exp. Smooth. 2nd Order	-9.2	-7.0	-9.9	-8.6	-11.2	-12.6
log-Deterministic Trend	-5.3	-0.7	-3.0	-2.2	-1.1	-2.0
log-ARIMA(2,d,2)	-9.9	-0.8	-3.8	-3.1	-2.1	-6.2
log-ARIMA(p,d,q)-national	-7.8	-5.9	-8.5	-7.6	-10.4	-12.0
log-ARIMA(p,d,q)-f.states*	-5.0	-1.7	-6.2	-2.8	-4.4	-4.1
log-ARIMAX(2,d,2)	-3.0	-0.6	-4.1	-2.4	-7.9	-3.0
log-ARIMAX(p,d,q)-national	-7.8	-3.7	-7.0	-7.6	-8.2	-11.9
log-ARIMAX(p,d,q)-f.states*	-4.7	0.1	-4.9	-0.3	-1.6	2.8

Some results are Not Available (NA) due to a missing return of the estimation algorithm.
*not applicable for national time series

Table 10 Mean Absolute Percentage Errors (MAPE) in Forecasting of New Registrations in the Federal States

Time Series until Year	2016	2017	2018	2016	2017	2016
Forecast Year	2017	2018	2019	2018	2019	2019
Forecast Horizon (h)	1	1	1	2	2	3
All Federal States	MAPE	MAPE	MAPE	MAPE	MAPE	MAPE
Bass - exog. (A)	15.8	16.2	19.1	19.0	21.4	24.1
Bass - exog. (B)	11.9	10.5	11.7	13.7	14.2	17.5
Bass - exog. (C)	11.5	9.8	10.8	13.1	13.3	16.8
Bass - endog. (A to C)	NA	NA	NA	NA	NA	NA
Gompertz - exog. (A)	11.3	9.4	10.1	13.0	12.8	16.7
Gompertz - exog. (B and C)	11.2	9.4	10.0	13.0	12.8	16.7
Gompertz - endog. (A to C)	9.3	7.5	8.1	10.3	10.2	13.4
Logistic - exog. (A and C)	5.3	2.8	4.1	7.6	5.1	10.7
Logistic - exog. (B)	5.3	NA	4.1	7.6	NA	10.7
Logistic - endog. (A)	7.9	4.6	5.6	12.7	9.2	18.2
Logistic - endog. (B)	7.1	NA	5.2	11.2	NA	16.2
Logistic - endog. (C)	7.0	3.7	5.0	10.8	7.7	15.6
Exponential Growth (OLS)	11.0	9.1	9.7	12.5	12.3	16.1
Exponential Growth (NLS)	11.2	9.4	10.0	12.9	12.7	16.5
Deterministic Trend	8.2	8.7	5.3	12.6	11.2	16.6
ARIMA(2,d,2)	10.1	7.9	5.4	8.8	8.2	12.4
ARIMA(p,d,q)-national	6.4	4.9	5.8	6.8	7.3	9.3
ARIMA(p,d,q)-f.states*	8.7	5.9	4.9	10.9	7.3	13.3
ARIMAX(2,d,2)	7.2	9.3	7.9	14.8	18.2	28.2
ARIMAX(p,d,q)-national	6.4	4.2	5.5	7.5	6.7	10.0
ARIMAX(p,d,q)-f.states*	7.4	5.8	4.8	10.5	8.6	14.2
Exponential Smoothing	6.1	4.1	5.3	6.6	6.4	9.1
Exp. Smooth. 2nd Order	10.1	7.3	8.8	9.3	9.2	10.9
log-Deterministic Trend	9.1	9.3	5.4	13.7	12.6	19.2
log-ARIMA(2,d,2)	10.5	5.9	5.3	9.1	6.5	11.9
log-ARIMA(p,d,q)-national	6.6	5.2	6.0	7.0	7.6	9.6
log-ARIMA(p,d,q)-f.states*	8.4	6.1	5.0	10.8	7.6	14.0
log-ARIMAX(2,d,2)	7.9	6.5	6.4	14.5	9.2	20.9
log-ARIMAX(p,d,q)-national	7.3	5.1	5.7	8.2	7.4	10.6
log-ARIMAX(p,d,q)-f.states*	8.0	6.3	5.6	15.6	8.9	34.8

Some results are Not Available (NA) due to a missing return of the estimation algorithm.
*not applicable for national time series

Appendix E: (Mean Absolute) Percentage Errors in the Prediction of New Registrations of Battery-Electric Passenger Cars

Table 11 Percentage Errors (PE) of Direct Forecasts of New Registrations of Battery-Electric Passenger Cars in Germany

Time Series until Year	2016	2017	2018	2016	2017	2016
Forecast Year	2017	2018	2019	2018	2019	2019
Forecast Horizon (h)	1	1	1	2	2	3
Germany - direct	PE	PE	PE	PE	PE	PE
Bass - exog. (A)	-23.8	-4.7	-16.6	-26.1	-20.3	-41.5
Bass - exog. (B)	-23.6	-3.9	-15.5	-25.4	-18.6	-40.4
Bass - exog. (C)	-23.5	-3.8	-15.4	-25.4	-18.5	-40.3
Bass - endog. (A)	-23.5	-3.8	-15.4	-25.4	-18.5	-40.2
Bass - endog. (B)	NA	-3.8	-15.4	NA	-18.5	NA
Bass - endog. (C)	NA	-2.6	NA	NA	-16.0	NA
Gompertz - exog. (A)	-28.2	-11.9	-23.0	-34.6	-31.9	-51.9
Gompertz - exog. (B)	-27.2	-9.5	-20.7	-32.8	-28.3	-49.7
Gompertz - exog. (C)	-26.8	-8.5	-19.7	-32.0	-26.7	-48.7
Gompertz - endog. (A)	-46.9	-9.0	-19.7	-61.3	-27.3	-77.3
Gompertz - endog. (B)	-46.9	-8.8	-19.6	-61.3	-27.0	-77.3
Gompertz - endog. (C)	-46.9	-8.6	-19.4	-61.3	-26.8	-77.3
Logistic - exog. (A)	NA	NA	-19.9	NA	NA	NA
Logistic - exog. (B und C)	NA	NA	NA	NA	NA	NA
Logistic - endog. (A)	NA	NA	11.9	NA	NA	NA
Logistic - endog. (B und C)	NA	NA	NA	NA	NA	NA
Exponential Growth (OLS)	219.6	231.6	174.8	388.4	297.4	512.2
Exponential Growth (NLS)	-24.7	NA	-14.7	-27.4	NA	-42.7
Deterministic Trend	-35.3	-29.9	-31.2	-45.6	-51.9	-62.0
ARIMA(2,d,2)	-57.6	-50.5	-20.7	-83.7	-43.9	-97.9
ARIMA(p,d,q)-national	-55.8	-37.9	-5.5	-81.7	-43.4	-96.6
ARIMAX(2,d,2)	-18.7	-11.1	-10.3	-45.7	-29.5	-52.3
ARIMAX(p,d,q)-national	-20.3	-10.8	-14.9	-28.5	-25.5	-37.8
Exponential Smoothing	-54.5	-30.5	-43.0	-68.4	-60.4	-82.0
Exp. Smooth. 2nd Order	-36.8	-14.1	-18.5	-62.8	-60.8	-81.3
log-Deterministic Trend	-86.6	-43.5	-59.0	-98.3	-70.7	-99.1
log-ARIMA(2,d,2)	-46.4	56.5	2.9	-37.0	52.6	-44.9
log-ARIMA(p,d,q)-national	-58.0	52.6	-18.0	-73.1	90.9	-85.8
log-ARIMAX(2,d,2)	-47.6	-43.4	115.0	-73.0	-55.4	-85.1
log-ARIMAX(p,d,q)-national	-56.3	29.7	-10.0	-70.8	38.1	-84.0

Some results are Not Available (NA) due to a missing return of the estimation algorithm.

Table 12 Percentage Errors (PE) in Forecasts of New Registrations of Battery-Electric Passenger Cars in Germany by Pooling Federal State Forecasts

Time Series until Year	2016	2017	2018	2016	2017	2016
Forecast Year	2017	2018	2019	2018	2019	2019
Forecast Horizon (h)	1	1	1	2	2	3
Germany - pooled	PE	PE	PE	PE	PE	PE
Bass - exog. (A)	-28.2	-6.5	-16.9	-31.5	-21.8	-46.4
Bass - exog. (B)	-28.0	-5.7	-15.8	-30.9	-20.1	-45.4
Bass - exog. (C)	-28.0	-5.6	-15.7	-30.8	-19.9	-45.3
Bass - endog. (A)	-29.5	-5.8	-18.1	-32.8	-20.1	-47.1
Bass - endog. (B)	-28.0	-5.6	-18.0	-30.8	-20.0	-45.3
Bass - endog. (C)	-56.8	-44.9	-56.6	-59.5	-54.4	-68.7
Gompertz - exog. (A)	-27.1	-10.1	-21.6	-33.2	-29.5	-50.5
Gompertz - exog. (B)	-26.2	-7.4	-19.3	-31.3	-24.9	-48.1
Gompertz - exog. (C)	-25.8	-6.2	-18.3	-30.5	-22.7	-47.0
Gompertz - endog. (A)	-50.5	-13.7	-20.8	-63.7	-30.3	-78.5
Gompertz - endog. (B)	-50.5	-13.5	-20.6	-63.7	-29.9	-78.5
Gompertz - endog. (C)	-50.5	-13.4	-20.5	-63.7	-29.6	-78.5
Logistic - exog. A	NA	NA	-19.3	NA	NA	NA
Logistic - exog. (B and C)	NA	NA	NA	NA	NA	NA
Logistic - endog. A	NA	NA	2.3	NA	NA	NA
Logistic - endog. (B and C)	NA	NA	NA	NA	NA	NA
Exponential Growth (OLS)	146.7	160.8	119.0	262.4	202.5	338.7
Exponential Growth (NLS)	-24.6	NA	-13.4	-27.0	NA	-41.9
Deterministic Trend	-42.3	-29.2	-31.8	-52.5	-50.4	-68.4
ARIMA(2,d,2)	-27.8	1.5	-27.3	-56.1	-18.2	-64.9
ARIMA(p,d,q)-national	-53.8	10.0	-10.7	-79.4	-1.4	-93.9
ARIMA(p,d,q)-f.states*	-35.6	7.5	-23.1	-55.1	-9.9	-68.3
ARIMAX(2,d,2)	-57.1	-39.6	-16.9	-72.2	-67.6	-86.9
ARIMAX(p,d,q)-national	-63.4	0.1	-13.0	-92.2	13.6	-108.9
ARIMAX(p,d,q)-f.states*	-56.3	-4.9	-16.9	-77.3	-15.0	-90.0
Exponential Smoothing	-53.5	-32.9	-44.0	-67.7	-61.8	-81.6
Exp. Smooth. 2nd Order	-39.5	-13.0	-18.5	-64.2	-61.0	-81.9
log-Deterministic Trend	21.7	50.7	38.1	71.8	54.7	119.8
log-ARIMA(2,d,2)	-27.3	-14.1	-2.2	-47.8	-11.6	-59.4
log-ARIMA(p,d,q)-national	-50.0	55.7	-17.0	-58.6	126.8	-70.8
log-ARIMA(p,d,q)-f.states*	-41.3	10.8	-0.5	-49.7	37.6	-57.2
log-ARIMAX(2,d,2)	128.5	-12.9	11.5	157.8	24.7	486.2
log-ARIMAX(p,d,q)-national	-25.6	41.3	31.0	-5.0	84.2	7.8
log-ARIMAX(p,d,q)-f.states*	-17.9	36.4	-7.9	-7.9	114.4	454.5

Some results are Not Available (NA) due to a missing return of the estimation algorithm.
*not applicable for national time series

Table 13 Mean Absolute Percentage Error (MAPE) in Predictions of New Registrations of Battery-Electric Passenger Cars in the Federal States

Time Series until Year	2016	2017	2018	2016	2017	2016
Forecast Year	2017	2018	2019	2018	2019	2019
Forecast Horizon (h)	1	1	1	2	2	3
All Federal States	MAPE	MAPE	MAPE	MAPE	MAPE	MAPE
Bass - exog. (A)	32.4	18.5	26.7	42.5	34.2	54.4
Bass - exog. (B)	32.2	18.1	26.7	42.2	33.4	53.9
Bass - exog. (C)	32.2	18.1	26.7	42.1	33.3	53.9
Bass - endog. (A)	36.2	19.8	NA	46.7	34.6	58.3
Bass - endog. (B)	32.2	18.2	NA	42.1	33.5	53.9
Bass - endog. (C)	NA	NA	NA	NA	NA	NA
Gompertz - exog. (A)	30.8	20.0	28.1	42.8	38.8	59.6
Gompertz - exog. (B)	30.1	18.1	27.4	41.8	36.6	58.7
Gompertz - exog. (C)	29.7	17.3	27.2	41.3	35.9	58.2
Gompertz - endog. (A)	56.1	21.2	25.2	70.0	37.5	80.7
Gompertz - endog. (B)	56.1	21.1	25.2	70.0	37.4	80.7
Gompertz - endog. (C)	56.1	21.0	25.2	70.0	37.3	80.7
Logistic - exog. A	NA	NA	26.3	NA	NA	NA
Logistic - exog. (B und C)	NA	NA	NA	NA	NA	NA
Logistic - endog. A	NA	NA	24.9	NA	NA	NA
Logistic - endog. (B und C)	NA	NA	NA	NA	NA	NA
Exponential Growth (OLS)	85.4	86.6	78.8	141.9	120.0	188.8
Exponential Growth (NLS)	30.5	NA	26.9	42.4	NA	58.9
Deterministic Trend	43.5	37.2	33.6	56.7	54.9	71.5
ARIMA(2,d,2)	52.6	22.0	30.2	66.0	40.0	78.5
ARIMA(p,d,q)-national	49.8	23.7	28.1	70.7	34.7	88.6
ARIMA(p,d,q)-f.states*	48.7	19.8	27.3	61.6	30.1	76.3
ARIMAX(2,d,2)	51.7	70.6	31.5	69.9	77.6	85.7
ARIMAX(p,d,q)-national	63.3	65.3	24.2	89.2	112.5	108.8
ARIMAX(p,d,q)-f.states*	48.9	45.2	29.7	66.2	64.2	83.9
Exponential Smoothing	53.9	38.3	41.3	70.8	63.6	82.6
Exp. Smooth. 2nd Order	40.3	22.2	28.1	67.5	63.5	82.8
log-Deterministic Trend	87.8	64.4	76.5	134.1	109.6	240.8
log-ARIMA(2,d,2)	34.8	30.5	44.3	41.4	43.6	57.5
log-ARIMA(p,d,q)-national	47.3	45.3	25.9	60.0	102.3	70.8
log-ARIMA(p,d,q)-f.states*	49.5	50.1	31.0	66.1	92.4	75.7
log-ARIMAX(2,d,2)	96.5	50.0	61.4	115.9	196.2	280.6
log-ARIMAX(p,d,q)-national	35.1	83.6	63.4	57.8	178.9	109.9
log-ARIMAX(p,d,q)-f.states*	46.5	83.1	44.6	84.9	251.6	387.5

Some results are Not Available (NA) due to a missing return of the estimation algorithm.
*not applicable for national time series

Appendix F: Percentage Errors in Forecasts of New Registration Figures in the German Federal States (Number Comprising All Technologies)

Table 14 Percentage Errors of 1-Step Forecasts of New Passenger Car Registrations in 2017

Federal State	BW	BY	BE	BB	HB	HH	HE	MV	NI	NW	RP	SL	SN	ST	SH	TH	n.s.
Forecast Year	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017
Bass - exog. (A)	-15.6	-18.2	-13.6	-22.7	4.1	-15.8	-14.5	-16.4	-9.4	-17.8	-13.4	-15.2	-18.7	-19.0	-19.0	-19.8	-19.3
Bass - exog. (C)	-10.3	-12.9	-8.4	-18.4	10.7	-10.3	-8.9	-11.5	-2.9	-12.8	-7.9	-10.5	-13.9	-14.5	-14.2	-15.3	-14.1
Bass - endog. (A)	-9.9	-12.5	-8.0	-18.3	11.9	-10.0	-8.3	-11.5	-2.3	NA	-7.7	-16.8	-13.9	NA	-14.0	-15.2	-12.3
Bass - endog. (C)	-9.9	-12.4	-8.0	NA	12.5	NA	-8.3	-11.5	-2.2	-12.4	-7.7	-16.8	-13.9	-14.5	-14.0	-15.2	-12.2
Gompertz - exog. (A)	-9.7	-12.3	-7.7	-18.1	11.9	-10.0	-8.1	-11.9	-2.1	-12.1	-7.5	-11.0	-13.8	-14.7	-13.8	-15.4	-13.4
Gompertz - exog. (C)	-9.7	-12.3	-7.8	-18.1	12.0	-10.0	-8.1	-11.8	-2.0	-12.1	-7.4	-10.9	-13.8	-14.7	-13.8	-15.3	-12.7
Gompertz - endog. (A)	-9.1	-12.2	-5.5	-15.1	11.8	-7.9	-12.2	-9.9	-2.1	-8.3	-5.6	-10.4	-9.8	-10.5	-6.4	-12.2	-11.9
Gompertz - endog. (C)	-9.1	-12.2	-5.5	-15.1	11.9	-7.9	-12.2	-9.9	-2.1	-8.3	-5.6	-10.4	-9.8	-10.5	-6.4	-12.2	-11.9
Logistic - exog. (A)	-3.1	-5.9	3.8	-9.0	22.2	-4.4	-3.5	-3.9	-1.1	-1.3	-1.4	-5.2	-5.3	-5.1	-4.2	-6.1	3.5
Logistic - exog. (C)	-3.1	-5.9	3.7	-9.0	22.3	-4.4	-3.5	-3.9	-1.1	-1.3	-1.4	-5.1	-5.3	-5.1	-4.2	-6.1	3.6
Logistic - endog. (A)	-3.3	-5.9	2.7	-13.3	27.1	-6.3	-2.7	-10.4	-1.0	-2.7	-2.8	-2.8	-10.5	-15.4	-7.6	-12.0	221.4
Logistic - endog. (C)	-3.1	-5.9	2.8	-12.3	25.0	-5.8	-2.9	-7.9	-1.1	-2.5	-2.4	-3.1	-9.1	-10.4	-7.0	-9.9	116.1
Exponential Growth (OLS)	-9.8	-12.4	-7.7	-17.6	11.0	-9.8	-8.2	-11.3	-2.1	-11.8	-7.3	-11.2	-13.2	-13.9	-13.2	-14.8	-19.3
Exponential Growth (NLS)	-9.7	-12.3	-7.8	-18.0	12.2	-10.0	-8.1	-11.6	-2.0	-12.1	-7.4	-10.6	-13.7	-14.5	-13.8	-15.2	-10.2
Deterministic Trend	-7.9	-11.8	5.5	-6.3	16.8	2.9	9.4	-12.6	-4.5	-6.6	0.2	-11.8	-0.1	-15.3	-4.2	-15.8	10.2
ARIMA(2,d,2)	-11.5	-17.1	-2.1	-16.7	15.1	0.4	7.7	-5.6	-15.2	-12.4	-4.4	-10.5	-12.7	-8.2	-11.1	-10.5	-12.8
ARIMA(p,d,q)-national	-7.9	-11.8	-3.2	-9.5	15.0	-3.1	-11.6	-1.9	-4.5	-7.0	-0.2	-3.5	-4.9	-4.5	-6.5	-6.6	-5.8
ARIMA(p,d,q)-f.states	-11.3	-11.8	8.5	-9.5	22.2	-1.8	10.2	-1.9	-4.5	-7.0	-9.5	-12.5	-4.9	-4.5	-13.2	-6.6	-5.8
ARIMAX(2,d,2)	3.9	-2.7	12.3	-14.5	30.9	3.3	0.4	5.1	3.5	-6.4	-7.8	0.8	-6.3	-1.1	-12.8	-4.1	19.0
ARIMAX(p,d,q)-national	-8.4	-12.1	-4.2	-8.2	22.3	-2.6	-11.1	3.9	-4.4	-8.4	-1.0	3.6	-2.4	0.4	-6.5	-2.7	-7.5
ARIMAX(p,d,q)-f.states	2.3	-12.1	14.7	-8.2	25.6	-2.7	9.9	3.9	-4.4	-8.4	7.8	8.7	-2.4	0.4	-4.3	-2.7	-7.5
Exponential Smoothing	-7.2	-11.0	-1.8	-10.3	14.3	-3.3	-8.3	-2.4	-4.8	-5.2	-1.6	-3.1	-5.6	-4.9	-6.8	-6.9	-4.8
Exp. Smooth. 2nd Order	-7.8	-11.6	-6.3	-14.8	19.3	-7.2	-7.4	-9.5	-4.8	-11.7	-4.1	-7.1	-11.5	-12.3	-13.2	-12.9	3.3

Table 15 Percentage Errors of 1-Step Forecasts of New Passenger Car Registrations in 2018

Federal State	BW	BY	BE	BB	HB	HH	HE	MV	NI	NW	RP	SL	SN	ST	SH	TH	n.s.
Forecast Year	2018	2018	2018	2018	2018	2018	2018	2018	2018	2018	2018	2018	2018	2018	2018	2018	2018
Bass - exog. (A)	-16.4	-17.9	-11.0	-21.9	12.4	-15.4	-12.3	-19.4	-8.4	-16.9	-16.0	-22.4	-17.0	-16.0	-18.1	-17.3	16.2
Bass - exog. (C)	-9.1	-10.3	-4.0	-14.8	20.0	-7.6	-4.5	-12.6	0.0	-9.9	-8.8	-15.9	-9.7	-8.8	-11.0	-10.2	25.8
Bass - endog. (A)	-8.4	-9.5	NA	-14.5	21.0	-7.1	-3.5	-12.6	0.9	-9.2	-8.4	-16.1	-9.5	-8.7	-10.6	-10.0	29.1
Bass - endog. (C)	-8.4	-9.5	NA	-14.5	21.1	NA	-3.4	-12.6	0.9	-9.2	-8.4	-16.1	-9.5	-8.7	-10.6	-10.0	29.1
Gompertz - exog. (A)	-8.2	-9.3	-3.1	-14.0	21.2	-7.0	-3.4	-12.7	1.0	-8.9	-8.1	-16.1	-9.2	-8.7	-10.2	-9.8	26.2
Gompertz - exog. (C)	-8.2	-9.3	-3.1	-14.0	21.2	-7.0	-3.3	-12.7	1.0	-8.9	-8.1	-16.0	-9.2	-8.6	-10.2	-9.8	27.4
Gompertz - endog. (A)	-9.0	-12.2	-1.8	-10.6	21.1	-5.2	-3.4	-8.8	1.0	-7.5	-5.9	-15.5	-4.3	-2.8	-5.0	-5.2	28.7
Gompertz - endog. (C)	-9.0	-12.2	-1.8	-10.6	21.2	-5.2	-3.4	-8.7	1.0	-7.5	-5.9	-15.5	-4.3	-2.8	-5.0	-5.2	28.7
Logistic - exog. (A)	-1.5	-0.8	2.5	-1.1	12.1	0.1	2.4	-4.3	2.5	-0.4	-2.9	-8.6	0.9	2.4	-0.4	1.5	38.3
Logistic - exog. (C)	-1.5	-0.8	2.5	-1.1	12.1	0.1	2.4	-4.3	2.5	-0.4	-2.9	-8.6	0.9	2.4	-0.4	1.5	38.4
Logistic - endog. (A)	-1.5	-0.3	2.0	-4.5	13.6	-0.9	4.6	-12.6	2.9	-1.0	-4.1	-7.5	-3.8	-6.8	-2.5	-4.3	382.2
Logistic - endog. (C)	-1.5	-0.4	2.2	-3.5	13.2	-0.6	4.0	-8.8	2.8	-0.7	-3.7	-8.5	-2.3	-2.8	-2.1	-2.1	241.0
Exponential Growth (OLS)	-8.3	-9.6	-3.1	-13.6	20.6	-6.9	-3.6	-11.8	1.0	-8.8	-7.8	-15.8	-8.4	-7.6	-9.7	-9.1	17.8
Exponential Growth (NLS)	-8.2	-9.3	-3.2	-14.0	21.3	-7.0	-3.3	-12.5	1.1	-8.9	-8.1	-15.8	-9.2	-8.5	-10.2	-9.8	31.5
Deterministic Trend	-8.7	-11.9	10.4	-5.5	20.9	9.1	15.4	-13.2	-2.3	6.5	-1.7	-16.5	2.7	-8.9	-3.1	3.1	53.8
ARIMA(2,d,2)	-10.6	-4.9	12.3	-9.2	33.9	9.5	12.1	-3.4	-7.7	-0.7	-3.8	-7.4	-2.3	1.4	-3.5	-3.2	40.3
ARIMA(p,d,q)-national	-8.7	-11.9	0.6	-6.6	17.1	1.9	-3.0	-2.9	-2.3	-6.0	-1.7	-8.5	-0.6	2.0	-4.1	-1.0	26.7
ARIMA(p,d,q)-f.states	-8.7	2.2	13.9	-6.6	17.1	4.2	4.1	-2.9	-2.3	-6.0	-1.7	-17.7	-0.6	2.0	-4.1	-1.0	26.2
ARIMAX(2,d,2)	2.3	-1.1	9.8	-5.4	-0.1	4.2	19.0	15.9	7.8	-15.7	-3.8	-25.1	4.5	12.5	-17.0	5.0	45.6
ARIMAX(p,d,q)-national	-0.7	-6.3	2.5	-2.5	11.4	4.2	-2.4	7.8	-0.5	-0.2	0.7	2.4	5.4	11.5	-2.0	6.4	28.4
ARIMAX(p,d,q)-f.states	-0.7	1.1	14.3	-2.5	11.4	4.5	5.4	7.8	-0.5	-0.2	0.7	-18.3	5.4	11.5	-2.0	6.4	28.1
Exponential Smoothing	-7.4	-10.4	2.1	-6.9	10.2	0.9	-2.0	-3.2	-2.9	-2.2	-3.1	-8.3	-0.8	2.0	-3.0	-0.8	26.2
Exp. Smooth. 2nd Order	-7.7	-10.6	-2.4	-11.3	10.2	-4.2	-1.4	-10.3	-2.9	-9.0	-5.5	-12.2	-7.0	-5.9	-9.8	-7.1	45.2

Table 16 Percentage Errors of 1-Step Forecasts of New Passenger Car Registrations in 2019

Federal State	BW	BY	BE	BB	HB	HH	HE	MV	NI	NW	RP	SL	SN	ST	SH	TH	n.s.
Forecast Year	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019
Bass - exog. (A)	-22.8	-20.1	-18.6	-19.3	4.3	-16.6	-17.5	-20.6	-15.4	-22.4	-20.0	-27.7	-19.9	-19.1	-21.1	-20.2	-20.6
Bass - exog. (C)	-13.7	-10.2	-10.7	-9.1	11.5	-6.5	-8.1	-11.1	-5.7	-13.8	-10.7	-18.4	-10.6	-10.0	-12.0	-10.9	-14.3
Bass - endog. (A)	-12.8	-9.0	-10.0	-8.4	7.5	NA	-6.8	-11.0	-4.8	-12.9	-10.1	-18.1	-10.2	NA	NA	-10.6	-12.6
Bass - endog. (C)	-12.8	-9.0	-10.0	-8.4	7.5	-5.8	-6.8	NA	-4.8	-12.9	-10.1	-18.1	NA	NA	-11.3	NA	-12.5
Gompertz - exog. (A)	-12.6	-8.9	-9.8	-7.8	12.3	-5.7	-6.8	-10.9	-4.7	-12.6	-9.9	-18.0	-9.9	-9.7	-10.9	-10.4	-13.7
Gompertz - exog. (C)	-12.6	-8.9	-9.8	-7.8	12.3	-5.7	-6.7	-10.9	-4.7	-12.6	-9.9	-18.0	-9.9	-9.7	-10.9	-10.4	-13.2
Gompertz - endog. (A)	-15.1	-8.9	-8.8	-5.3	11.4	-4.4	-6.8	-5.9	-4.7	-12.9	-7.9	-15.7	-5.2	-3.7	-7.5	-5.7	-12.8
Gompertz - endog. (C)	-15.1	-8.9	-8.8	-5.3	11.4	-4.4	-6.8	-5.9	-4.7	-12.9	-7.9	-15.7	-5.2	-3.7	-7.5	-5.7	-12.8
Logistic - exog. (A)	-7.1	-2.4	-7.7	2.7	-2.5	-0.6	-4.5	-1.5	-5.4	-6.6	-4.2	-6.9	-3.3	-3.5	-3.8	-3.3	-25.3
Logistic - exog. (C)	-7.1	-2.4	-7.7	2.7	-2.5	-0.6	-4.5	-1.5	-5.4	-6.6	-4.2	-6.9	-3.3	-3.5	-3.8	-3.3	-25.3
Logistic - endog. (A)	-6.8	-1.1	-8.1	0.7	-2.8	-1.1	-1.9	-8.5	-5.2	-6.7	-5.0	-10.3	-7.1	-11.5	-5.0	-7.6	32.0
Logistic - endog. (C)	-6.9	-1.5	-8.0	1.3	-2.8	-0.9	-2.7	-5.6	-5.2	-6.6	-4.7	-9.6	-5.9	-7.9	-4.7	-6.3	5.4
Exponential Growth (OLS)	-12.8	-9.3	-9.7	-7.4	11.7	-5.6	-7.0	-9.8	-4.7	-12.6	-9.6	-17.7	-9.1	-8.6	-10.5	-9.6	-15.9
Exponential Growth (NLS)	-12.6	-8.8	-9.8	-7.8	12.3	-5.7	-6.6	-10.8	-4.7	-12.6	-9.9	-17.9	-9.9	-9.6	-11.0	-10.3	-11.5
Deterministic Trend	-14.9	1.8	1.0	-1.6	7.2	4.1	-7.1	-11.1	-7.8	1.6	-5.0	-6.9	0.7	-9.9	3.2	1.1	-27.4
ARIMA(2,d,2)	-16.5	0.2	-1.4	-6.0	18.0	1.8	-1.9	-0.5	-9.0	-5.7	-8.5	-10.9	-0.7	3.7	1.2	0.5	-24.3
ARIMA(p,d,q)-national	-14.9	-7.0	-7.2	-1.6	8.2	-0.6	-6.8	-1.2	-7.8	-11.6	-5.0	-10.5	-2.2	0.1	-6.1	-2.3	-47.0
ARIMA(p,d,q)-f.states	-14.9	3.7	-7.2	-1.6	-10.8	-0.1	-2.8	-1.2	-7.8	-11.6	-5.0	-3.1	-2.2	0.1	-3.9	-2.3	-30.9
ARIMAX(2,d,2)	-8.9	-4.1	-6.1	-2.0	19.2	-2.1	0.8	21.9	-10.2	-2.3	-6.2	-4.4	4.7	22.7	-2.8	7.8	-33.2
ARIMAX(p,d,q)-national	-8.7	-4.2	-6.9	0.0	8.5	-3.8	-10.9	6.1	-6.7	-7.3	-3.8	-4.7	1.7	7.2	-5.6	2.5	-39.5
ARIMAX(p,d,q)-f.states	-8.7	1.4	-6.9	0.0	-6.5	-2.5	-0.4	6.1	-6.7	-7.3	-3.8	15.1	1.7	7.2	-0.1	2.5	-39.4
Exponential Smoothing	-13.4	-7.5	-6.3	-1.3	6.8	0.0	-6.5	-1.2	-8.5	-7.4	-5.7	-10.5	-2.3	-0.1	-4.6	-2.1	-30.9
Exp. Smooth. 2nd Order	-13.5	-12.0	-9.5	-6.0	6.8	-3.3	-4.7	-8.4	-8.5	-11.6	-8.0	-14.2	-8.2	-7.6	-10.9	-8.1	-14.0

Appendix G: Percentage Errors in Forecasts of New Registration Figures of Battery-Electric Passenger Cars in the German Federal States

Table 17 Percentage Errors in 1-Step Forecasts of New Registrations of Battery-Electric Passenger Cars in 2017

Federal State	BW	BY	BE	BB	HB	HH	HE	MV	NI	NW	RP	SL	SN	ST	SH	TH	n.s.
Forecast Year	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017	2017
Bass - exog. (A)	-28.2	-24.8	-35.8	-50.1	-20.9	-16.4	-23.7	-38.7	-31.0	-31.9	-12.7	-55.9	-38.2	-40.6	-27.4	-41.5	-100.0
Bass - exog. (B)	-27.9	-24.5	-35.7	-49.9	-20.9	-16.3	-23.7	-38.7	-30.8	-31.7	-12.3	-55.9	-38.1	-40.6	-27.1	-41.2	-100.0
Bass - exog. (C)	-27.9	-24.5	-35.7	-49.9	-20.9	-16.3	-23.7	-38.7	-30.8	-31.7	-12.3	-55.9	-38.1	-40.6	-27.1	-41.2	-100.0
Bass - endog. (A)	-27.9	-24.5	-72.1	-49.9	-20.9	-16.3	-23.7	-38.7	-30.8	-31.7	-12.3	-64.7	-56.3	-40.6	-27.1	-41.2	-100.0
Bass - endog. (B)	-27.9	-24.5	-35.7	-49.9	-20.9	-16.3	-23.7	-38.7	-30.8	-31.7	-12.3	-55.9	-38.1	-40.6	-27.1	-41.2	-100.0
Bass - endog. (C)	-27.9	NA	-35.7	-49.9	-20.9	-16.3	-23.7	-38.7	-30.8	NA	-12.3	-55.9	-38.1	-40.6	-27.1	-41.2	-100.0
Gompertz - exog. (A)	-31.8	-30.8	-31.6	-52.0	9.3	-18.1	-1.4	-40.3	-24.2	-35.6	-20.2	-45.6	-38.1	-38.5	-31.5	-43.5	-84.0
Gompertz - exog. (B)	-30.9	-29.6	-31.0	-51.5	9.4	-17.3	-0.4	-39.7	-23.7	-34.9	-18.8	-45.3	-37.4	-37.9	-30.4	-42.7	-84.0
Gompertz - exog. (C)	-30.5	-29.1	-30.7	-51.3	9.5	-16.9	0.1	-39.4	-23.5	-34.5	-18.1	-45.2	-37.1	-37.7	-29.9	-42.4	-84.0
Gompertz - endog. (A)	-50.3	-46.2	-52.0	-65.8	-100.0	-41.9	-24.7	-57.9	-100.0	-53.2	-28.7	-63.4	-53.8	-56.0	-50.9	-53.3	-87.3
Gompertz - endog. (B)	-50.3	-46.2	-52.0	-65.8	-100.0	-41.9	-24.7	-57.9	-100.0	-53.2	-28.7	-63.4	-53.8	-56.0	-50.9	-53.3	-87.3
Gompertz - endog. (C)	-50.3	-46.2	-52.0	-65.8	-100.0	-41.9	-24.7	-57.9	-100.0	-53.2	-28.7	-63.4	-53.8	-56.0	-50.9	-53.3	-87.3
Exponential Growth (OLS)	214.6	180.6	44.2	-14.2	-6.9	128.0	91.1	-2.3	136.9	179.4	26.0	35.6	111.0	25.5	100.9	68.6	-96.6
Exponential Growth (NLS)	-28.2	-26.4	-33.4	-51.9	-10.7	-20.3	2.1	-44.7	-25.9	-33.2	-15.4	-50.8	-36.6	-38.6	-27.8	-41.4	-92.2
Deterministic Trend	-38.1	-40.3	-45.9	-56.7	19.7	-37.1	-56.6	-50.2	-30.4	-41.6	-31.2	-56.0	-54.7	-45.4	-41.1	-51.3	-95.3
ARIMA(2,d,2)	-35.5	-36.8	-69.6	-59.5	-118.0	-43.4	65.3	-47.3	-50.0	-52.4	-27.7	-31.3	-54.9	-62.3	-39.2	-48.5	-78.7
ARIMA(p,d,q)-national	-54.5	-47.8	-32.4	-65.5	-18.7	-26.9	-73.4	-50.6	-59.7	-52.5	-30.4	-42.9	-36.9	-96.1	-55.1	-52.7	-73.8
ARIMA(p,d,q)-f.states	-45.6	-43.1	-47.0	-63.5	-40.7	-46.6	36.5	-47.4	-55.2	-52.5	-31.0	-43.4	-55.9	-73.6	-48.4	-48.9	-79.0
ARIMAX(2,d,2)	-38.7	-43.7	-58.0	-60.4	-38.8	29.7	-120.4	-42.4	-68.0	-54.0	-29.0	-33.0	-48.1	-48.5	-58.4	-56.9	-93.5
ARIMAX(p,d,q)-national	-57.8	-43.3	-48.2	-59.1	-214.2	-47.5	-122.0	-56.7	-83.6	-53.9	-22.0	-23.1	-21.8	-56.1	-54.6	-49.3	-303.0
ARIMAX(p,d,q)-f.states	-43.2	-43.2	-38.9	-58.7	-20.4	31.0	-123.3	-39.7	-54.2	-53.9	-28.0	-33.6	-57.5	-52.4	-54.1	-50.8	-90.5
Exponential Smoothing	-51.6	-52.7	-52.8	-67.5	-35.3	-41.3	-51.5	-57.3	-54.7	-57.7	-44.6	-59.1	-56.4	-64.2	-55.2	-61.2	-92.9
Exp. Smooth. 2nd Order	-39.8	-36.1	-41.4	-57.2	-12.4	-27.7	-42.2	-47.9	-37.7	-42.8	-22.6	-55.0	-46.4	-48.5	-38.6	-48.2	-91.8

Table 18 Percentage Errors in 1-Step Forecasts of New Registrations of Battery-Electric Passenger Cars in 2018

Federal State Forecast Year	BW 2018	BY 2018	BE 2018	BB 2018	HB 2018	HH 2018	HE 2018	MV 2018	NI 2018	NW 2018	RP 2018	SL 2018	SN 2018	ST 2018	SH 2018	TH 2018	n.s. 2018
Bass - exog. (A)	1.0	-1.0	-35.8	-22.9	-52.0	-32.1	3.2	-18.0	-15.7	-3.6	-1.8	-34.6	-27.5	-19.9	-13.6	-12.5	255.6
Bass - exog. (B)	2.1	-0.1	-35.3	-22.5	-52.0	-31.7	4.2	-17.6	-15.2	-2.9	-1.1	-34.2	-27.0	-19.6	-12.7	-12.1	266.7
Bass - exog. (C)	2.2	0.0	-35.2	-22.3	-52.0	-31.7	4.3	-17.6	-15.1	-2.9	-1.1	-34.2	-27.0	-19.6	-12.6	-12.0	266.7
Bass - endog. (A)	2.2	0.0	-35.2	-22.3	-77.2	-33.0	4.3	-17.6	-15.1	-2.9	-1.1	-34.2	-27.0	-19.6	-12.6	-12.0	266.7
Bass - endog. (B)	2.2	0.0	-35.2	-22.3	-52.0	-33.0	4.3	-17.6	-15.1	-2.9	-1.1	-34.2	-27.0	-19.6	-12.6	-12.0	266.7
Bass - endog. (C)	2.2	NA	-35.2	-22.3	-52.0	-31.7	4.3	-17.6	-15.1	NA	-1.1	-34.2	-26.9	-19.6	-12.6	-12.0	266.7
Gompertz - exog. (A)	-5.8	-8.7	-36.1	-20.1	-38.2	-35.3	6.7	-20.3	-15.0	-9.7	-9.9	-28.2	-29.1	-22.4	-20.2	-13.6	1558.0
Gompertz - exog. (B)	-2.9	-5.8	-34.6	-16.9	-37.9	-34.1	9.0	-18.0	-13.4	-7.1	-7.5	-26.5	-27.1	-20.3	-17.5	-10.8	2252.7
Gompertz - exog. (C)	-1.6	-4.5	-33.9	-15.5	-37.8	-33.6	10.0	-17.0	-12.7	-5.9	-6.5	-25.7	-26.2	-19.3	-16.3	-9.5	2599.6
Gompertz - endog. (A)	-1.5	-4.1	-34.4	-14.0	-55.8	-38.1	-35.0	-16.6	-31.6	-5.7	-6.8	-25.8	-26.0	-19.3	-16.0	-8.5	2930.6
Gompertz - endog. (B)	-1.3	-3.9	-34.5	-14.0	-55.8	-38.1	-35.1	-16.4	-31.6	-5.4	-6.6	-25.6	-26.0	-19.2	-15.8	-8.4	3008.6
Gompertz - endog. (C)	-1.0	-3.8	-34.6	-13.9	-55.8	-38.1	-35.1	-16.2	-31.6	-5.3	-6.5	-25.6	-25.8	-19.1	-15.7	-8.2	3021.1
Exponential Growth (OLS)	260.7	198.0	11.3	-14.6	-44.5	58.2	148.3	-5.6	125.3	199.6	31.4	36.9	81.1	17.1	88.2	64.2	-13.3
Exponential Growth (NLS)	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Deterministic Trend	-25.2	-20.2	-49.2	-40.3	-49.8	-47.9	-29.7	-40.9	-31.0	-30.8	-20.4	-56.7	-44.7	-44.8	-30.6	-32.7	56.4
ARIMA(2,d,2)	-4.6	38.0	-33.6	24.7	-57.8	-29.9	-19.4	-10.3	-1.0	-8.1	-6.1	3.2	-19.8	-62.8	23.0	-9.8	144.0
ARIMA(p,d,q)-national	18.8	46.3	-33.4	24.9	-20.2	-38.4	-22.6	-3.9	25.0	-8.2	6.8	18.5	-18.8	-50.7	31.6	-10.4	302.3
ARIMA(p,d,q)-f.states	-4.6	24.2	-11.2	26.9	-49.7	-16.7	-22.6	2.8	54.3	11.1	15.6	14.8	-8.0	-42.2	-8.6	2.9	392.2
ARIMAX(2,d,2)	-78.5	-57.5	-94.2	-96.8	111.6	-88.2	132.5	42.9	-52.8	-79.0	-12.8	31.2	-71.4	-29.4	-73.8	-76.7	-477.2
ARIMAX(p,d,q)-national	73.1	-57.6	-95.1	-9.6	-201.6	-94.3	134.8	42.9	-29.3	2.4	-39.9	34.8	-71.1	-28.2	-72.2	-57.9	-352.7
ARIMAX(p,d,q)-f.states	15.9	-64.7	39.3	-9.4	15.4	-77.6	134.8	41.8	-25.3	-2.1	-36.2	37.4	-67.0	15.4	-78.9	-62.6	-460.2
Exponential Smoothing	-24.4	-31.9	-43.4	-45.1	-56.9	-46.0	-39.8	-37.2	-26.5	-28.6	-34.2	-29.2	-41.8	-47.0	-41.1	-40.2	31.6
Exp. Smooth. 2nd Order	-5.3	0.9	-41.3	-19.5	-48.8	-37.6	-24.2	-20.0	-26.3	-9.4	0.7	-40.3	-30.6	-31.2	-17.3	-1.9	75.7

Table 19 Percentage Errors in 1-Step Forecasts of New Registrations of Battery-Electric Passenger Cars in 2019

Federal State	BW	BY	BE	BB	HB	HH	HE	MV	NI	NW	RP	SL	SN	ST	SH	TH	n.s.
Forecast Year	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019
Bass - exog. (A)	-17.4	-11.5	-42.3	31.2	-60.8	3.7	37.7	-8.8	-39.7	-27.9	-28.4	-32.0	16.7	-7.3	1.3	-61.1	-57.1
Bass - exog. (B)	-16.1	-10.2	-41.3	32.8	-60.5	4.7	39.8	-8.0	-39.0	-27.1	-27.7	-31.3	18.0	-6.7	3.2	-60.7	-57.1
Bass - exog. (C)	-16.0	-10.1	-41.3	33.0	-60.5	4.9	40.0	-8.0	-39.0	-27.0	-27.6	-31.3	18.1	-6.7	3.3	-60.7	-57.1
Bass - endog. (A)	-16.0	-10.0	-41.2	33.0	-60.5	4.9	40.1	-8.0	-39.0	-27.0	-27.6	-31.3	NA	-6.7	3.4	-60.6	-92.9
Bass - endog. (B)	-15.9	-10.0	-41.2	33.0	-60.5	4.9	40.1	-8.0	-39.0	-27.0	-25.4	-31.3	NA	-6.7	3.4	-60.6	-57.1
Bass - endog. (C)	-14.8	NA	-41.2	33.0	-60.5	NA	40.1	-8.0	-38.9	NA	-27.6	-31.3	NA	-6.7	3.4	NA	-57.1
Gompertz - exog. (A)	-23.5	-18.7	-42.2	30.6	-55.9	1.0	32.7	-10.7	-41.5	-32.8	-34.3	-28.5	17.2	-11.4	-5.9	-62.9	-24.4
Gompertz - exog. (B)	-21.2	-16.1	-40.0	35.1	-55.0	4.2	36.0	-8.3	-40.0	-30.9	-32.4	-26.5	20.7	-8.8	-2.2	-61.7	-23.2
Gompertz - exog. (C)	-20.2	-15.0	-39.1	37.1	-54.7	5.6	37.4	-7.3	-39.3	-30.1	-31.6	-25.6	22.2	-7.6	-0.7	-61.2	-22.7
Gompertz - endog. (A)	-20.3	-15.0	-38.4	38.1	-55.3	6.4	4.8	-6.9	-39.8	-30.0	-31.8	-24.9	23.2	-7.2	0.2	-61.2	-35.1
Gompertz - endog. (B)	-20.1	-14.9	-38.2	38.2	-55.4	6.7	4.8	-6.6	-39.8	-29.8	-31.6	-24.9	23.3	-7.1	0.1	-61.1	-35.5
Gompertz - endog. (C)	-20.1	-14.7	-38.3	38.5	-55.3	6.8	4.8	-6.6	-39.9	-29.6	-31.6	-24.9	23.6	-6.8	0.3	-61.1	-35.5
Logistic - exog. (A)	-21.4	-16.8	-35.4	27.9	-45.5	13.3	31.4	-8.7	-37.3	-31.0	-32.8	-21.3	22.3	-10.0	-2.6	-63.1	-61.3
Logistic - endog. (A)	5.7	5.1	-24.9	30.9	-49.4	37.5	68.1	-2.8	-12.6	-8.9	-20.8	-16.0	41.8	-2.9	10.0	-60.4	-54.4
Exponential Growth (OLS)	193.7	158.4	-24.2	21.4	-62.7	83.7	267.9	-9.3	39.3	110.5	-4.5	12.4	128.4	13.0	94.2	-36.9	-65.8
Exponential Growth (NLS)	-15.5	-9.4	-34.7	47.7	-56.7	12.3	43.8	-1.9	-36.9	-25.9	-27.5	-21.5	30.6	-1.0	6.9	-58.5	-35.4
Deterministic Trend	-30.4	-25.6	-55.5	-0.5	-70.7	-20.0	10.7	-28.4	-50.1	-41.2	-39.8	-38.1	-7.3	-32.1	-18.2	-69.5	-65.3
ARIMA(2,d,2)	-30.5	-30.9	-29.9	14.6	-34.0	43.5	-11.8	-2.1	-53.0	-25.1	-32.6	-27.4	40.5	-24.4	-20.4	-62.5	10.8
ARIMA(p,d,q)-national	-28.1	-13.9	-25.1	33.0	-21.1	33.1	93.1	-3.0	-34.9	-19.5	-30.8	-19.4	30.9	1.2	1.6	-60.6	-21.4
ARIMA(p,d,q)-f.states	-40.8	-24.3	-32.7	20.8	-30.6	33.1	16.1	-13.4	-39.6	-19.5	-34.6	-23.2	20.3	-17.1	-9.5	-60.6	25.8
ARIMAX(2,d,2)	-38.0	-1.8	-35.8	37.1	-29.0	29.6	63.2	-11.6	-64.6	-28.1	-31.6	-28.0	30.3	-2.1	13.2	-60.7	-79.0
ARIMAX(p,d,q)-national	-17.8	-6.6	-28.0	32.5	-14.9	36.3	24.6	-6.9	-19.2	-29.5	-30.9	-31.3	40.0	1.6	4.1	-62.3	-49.5
ARIMAX(p,d,q)-f.states	-10.1	-22.6	-33.7	32.6	-31.5	36.3	48.4	-9.8	-37.5	-29.5	-31.5	-37.8	23.5	-14.6	-13.8	-62.3	-59.7
Exponential Smoothing	-43.2	-42.6	-54.6	-21.9	-55.0	-19.3	-15.4	-38.4	-52.2	-51.4	-53.3	-41.7	-18.0	-41.7	-35.8	-76.4	-64.6
Exp. Smooth. 2nd Order	-21.1	-12.1	-28.1	45.4	-62.7	35.7	6.4	-1.1	-44.1	-29.4	-27.5	-26.0	36.9	-4.6	8.5	-59.3	-57.6

Appendix H: Ranges of Percentage Errors from Predictions with the Different Models, Means and Standard Deviations of Percent Errors

Table 20 Margins of Error (in Percentage Points) for 1-Step Forecasts of New Passenger Car Registrations

	Direct National Forecasts				Pooled National Forecasts				MAPE Federal States' Forecast			
Forecast Year	2017	2018	2019	2020	2017	2018	2019	2020	2017	2018	2019	2020
Range (in Percentage Points)	12.9	19.9	18.6	30.6	27.7	17.0	16.8	27.3	10.5	13.4	15.0	13.6
Interquantile Range (90 %)	8.9	10.7	9.4	13.2	14.5	13.4	13.7	18.9	6.3	6.9	7.1	9.5
Interquantile Range (75 %)	8.3	7.4	6.1	12.7	8.0	8.8	7.1	11.7	4.9	5.2	5.2	7.1
Interquartile Range (50 %)	3.3	1.9	5.8	7.3	5.5	6.3	4.9	5.4	3.4	4.1	3.6	5.3
Standard Deviation	3.1	4.0	3.7	6.0	5.4	4.3	4.1	6.1	2.3	2.7	3.0	3.5
Arithmetic Mean	-8.6	-5.4	-8.4	17.3	-8.5	-4.9	-8.1	17.6	8.8	7.1	7.2	17.8
Median	-8.8	-6.8	-9.7	17.3	-8.3	-5.8	-7.7	18.7	8.4	7.2	5.8	19.2

Table 21 Margins of Error (in Percentage Points) for 1-Step Forecasts of New Registrations of Battery-Electric Passenger Cars

	Direct National Forecasts				Pooled National Forecasts				MAPE Federal States' Forecast			
Forecast Year	2017	2018	2019	2020	2017	2018	2019	2020	2017	2018	2019	2020
Range (in Percentage Points)	311.3	282.0	1359.0	467.8	210.2	205.7	534.1	937.1	66.8	69.3	56.6	623.1
Interquantile Range (90 %)	38.9	98.0	196.4	193.3	151.2	95.9	107.9	92.8	52.8	65.4	48.2	21.3
Interquantile Range (75 %)	33.3	60.3	23.2	19.8	32.6	60.5	24.6	28.5	28.2	54.3	29.6	13.7
Interquartile Range (50 %)	25.6	10.2	7.3	8.3	24.1	20.9	10.5	11.6	21.6	30.3	8.8	4.1
Standard Deviation	54.6	53.0	252.8	92.5	47.9	38.3	89.5	151.1	16.7	23.1	15.8	107.7
Arithmetic Mean	-29.2	1.3	42.6	-24.6	-23.9	3.4	3.5	-23.2	47.7	37.8	35.6	76.2
Median	-36.1	-8.8	-16.6	-52.2	-28.9	-5.8	-17.0	-50.0	47.3	22.9	28.1	57.6

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References

Al-Alawi, B.M. & Bradley, T.H. (2013) Review of hybrid, plug-in hybrid, and electric vehicle market modeling studies. *Renewable and Sustainable Energy Reviews*, 21, 190-203. https://doi.org/10.1016/j.rser.2012.12.048

Andersen, B. (1999) The hunt for S-shaped growth paths in technological innovation: a patent study. *Journal of Evolutionary Economics*, 9, 487-526. https://doi.org/10.1007/s001910050093

Bass, F.M. (1969) A New Product Growth for Model Consumer Durables. *Management Science*, 15 (5), 215-227. https://doi.org/10.1287/mnsc.15.5.215

Box, G.E.P. & Jenkins, G.M. (1970) *Time Series Analysis: Forecasting and Control*. Holden-Day, San Francisco.

Brown, R.G. (1956) *Exponential Smoothing for Predicting Demand*. Arthur D. Little Inc., Cambridge, Massachusetts. Last accessed 7 June 2021 https://www.industrydocuments.ucsf.edu/tobacco/docs/#id=jzlc0130

Brown, R.G. (1959) *Statistical Forecasting for Inventory Control*. McGraw-Hill, New York.

Cramer, J.S. (2004) The early origins of the logit model. *Studies in History and Philosophy of Science Part C: Studies in History and Philosophy of Biological and Biomedical Sciences*, 35 (4), 613–626. https://doi.org/10.1016/j.shpsc.2004.09.003

Dickey, D.A. & Fuller, W.A. (1979) Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *Journal of the American Statistical Association*, 74 (366), 427-431. https://doi.org/10.2307/2286348

Dimitropoulos, A., Rietveld, P. & van Ommeren, J.N. (2013) Consumer valuation of changes in driving range: A meta-analysis. *Transportation Research Part A: Policy and Practice*, 55, 27-45. https://doi.org/10.1016/j.tra.2013.08.001

eurostat (2020) *Statistical regions in the European Union and partner countries - NUTS and statistical regions 2021, 2020 edition*. Eurostat (European Commission), Luxembourg. https://doi.org/10.2785/850262

Gnann, T., Plötz, P., Funke, S. & Wietschel, M. (2015a) What is the market potential of plug-in electric vehicles as commercial passenger cars? A case study from Germany. *Transportation Research Part D: Transport and Environment*, 37, 171-187. https://doi.org/10.1016/j.trd.2015.04.015

Gnann, T., Plötz, P., Kühn, A. & Wietschel, M. (2015b) Modelling market diffusion of electric vehicles with real world driving data – German market and policy options. *Transportation Research Part A: Policy and Practice*, 77, 95-112. https://doi.org/10.1016/j.tra.2015.04.001

Gompertz, B. (1825) XXIV. On the nature of the function expressive of the law of human mortality, and on a new mode of determining the value of life contingencies. In a letter to Francis Baily, Esq. F.

R. S. &c. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, 115, 513-585. https://doi.org/10.1098/rstl.1825.0026

Gujarati, D. (2003) *Basic Econometrics*, 4th Ed., McGraw-Hill, New York.

de Haan, P., Mueller, M.G. & Scholz, R.W. (2009) How much do incentives affect car purchase? Agent-based microsimulation of consumer choice of new cars - Part II: Forecasting effects of feebates based on energy-efficiency. *Energy Policy*, 37 (3), 1083-1094. https://doi.org/10.1016/j.enpol.2008.11.003

Hackbarth, A. & Madlener, R. (2016) Willingness-to-pay for alternative fuel vehicle characteristics: A stated choice study for Germany. *Transportation Research Part A: Policy and Practice*, 85, 89-111. https://doi.org/10.1016/j.tra.2015.12.005

Hamilton (1994) *Time Series Analysis*, Princeton University Press, Princeton, New Jersey.

Holt, C.E. (1957) Forecasting seasonals and trends by exponentially weighted averages, *O.N.R. Memorandum*, 52. Carnegie Institute of Technology, Pittsburgh, USA. https://doi.org/10.1016/j.ijforecast.2003.09.015

Kim, S. & Kim, H. (2016) A new metric of absolute percentage error for intermittent demand forecasts. *International Journal of Forecasting*, 32 (3), 669-679. https://doi.org/10.1016/j.ijforecast.2015.12.003

Kourentzes, N., Barrow, D. & Petropoulos, F. (2019) Another look at forecast selection and combination: Evidence from forecast pooling. *International Journal of Production Economics*, 209, 226-235. https://doi.org/10.1016/j.ijpe.2018.05.019

Kraftfahrt-Bundesamt (2017) *Neuzulassungen von Personenkraftwagen im März 2017 nach Marken und Modellreihen*, Flensburg, Germany.

Lebeau, K., Van Mierlo, J., Lebeau, P., Mairesse, O. & Macharis, C. (2012) The market potential for plug-in hybrid and battery electric vehicles in Flanders: A choice-based conjoint analysis, *Transportation Research Part D: Transport and Environment*, 17 (8), 592-597. https://doi.org/10.1016/j.trd.2012.07.004

Letmathe, P. & Suares, M. (2017) A consumer-oriented total cost of ownership model for different vehicle types in Germany. *Transportation Research Part D: Transport and Environment*, 57, 314-335. https://doi.org/10.1016/j.trd.2017.09.007

Longford, N.T. (2021) Model uncertainty. In: *Statistics for Making Decisions.* Chapman & Hall, Oxon, 217-246. https://doi.org/10.1201/9780429324765-11

Mahajan, V., Muller, E. & Bass, F.M. (1990) New Product Diffusion Models in Marketing: A Review and Directions for Research. *Journal of Marketing*, 54 (1), 1-26. https://doi.org/10.2307/1252170

Mahajan, V., Muller, E. & Wind, Y. (2000) *New-Product Diffusion Models*. Kluwer Academy Publishers, Massachusetts.

Makridakis, S. (1993) Accuracy measures: theoretical and practical concerns. *International Journal of Forecasting*, 9 (4), 527-529. https://doi.org/10.1016/0169-2070(93)90079-3

Malthus (1798) *An Essay on the Principle of Population, as it Affects the Future Improvement of Society. With Remarks on the Speculations of Mr. Godwin, M. Condorcet, and Other Writers.* Printed for J. Johnson, in St. Paul's Church-Yard, London.

Massiani, J. & Gohs, A. (2015) The choice of Bass model coefficients to forecast diffusion for innovative products: An empirical investigation for new automotive technologies. *Research in Transportation Economics*, 50, 17-28. https://doi.org/10.1016/j.retrec.2015.06.003

Meade, N. & Islam, T. (2006) Modelling and forecasting the diffusion of innovation – A 25-year review. *International Journal of Forecasting*, 22 (3), 519–545. https://doi.org/10.1016/j.ijforecast.2006.01.005

Meyer, P.E. & Winebrake, J.J. (2009) Modeling technology diffusion of complementary goods: The case of hydrogen vehicles and refueling infrastructure. *Technovation*, 29 (2), 77-91. https://doi.org/10.1016/j.technovation.2008.05.004

Mueller, M.G. & de Haan, P. (2009) How much do incentives affect car purchase? Agent- based microsimulation of consumer choice of new cars - Part I: Model structure, simulation of bounded rationality, and model validation. *Energy Policy*, 37 (3), 1072-1082. https://doi.org/10.1016/j.enpol.2008.11.002

Neusser, K. (2015) *Time Series Analysis in Economics.* Last accessed 6 June 2021 http://neusser.ch/downloads/TimeSeriesBook.pdf

Ruth, K. (2008) Macroeconomic forecasting in the EMU: Does disaggregate modeling improve forecast accuracy? *Journal of Policy Modeling*, 30 (3), 417-429. https://doi.org/10.1016/j.jpolmod.2007.12.002

Schacht, R.M. (1980) Two Models of Population Growth. *American Anthropologist*, 82 (4), 782-798. https://doi.org/10.1525/aa.1980.82.4.02a00040

Steel, Mark F.J. (2020) Model Averaging and its Use in Economics. *Journal of Economic Literature*, 58 (3), 644-719. https://doi.org/10.1257/jel.20191385

Timmermann, A. (2006) Forecast Combinations. In: Elliott, G., Granger, C.W.J. & Timmermann, A. (eds) *Handbook of Economic Forecasting,* Volume 1. Elsevier, North-Holland, Amsterdam, 135–196. https://doi.org/10.1016/S1574-0706(05)01004-9

Tjørve, K.M.C. & Tjørve, E. (2017) The use of Gompertz models in growth analyses, and new Gompertz-model approach: An addition to the Unified-Richards family. *PLoS ONE*, 12 (6). https://doi.org/10.1371/journal.pone.0178691

Vieira, S. & Hoffmann, R. (1977) Comparison of the Logistic and the Gompertz Growth Functions Considering Additive and Multiplicative Error Terms. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 26 (2), 143-148. https://doi.org/10.2307/2347021

Wan, S.K. & Song, H. (2018) Forecasting turning points in tourism growth. *Annals of Tourism Research*, 72, 156-167. https://doi.org/10.1016/j.annals.2018.07.010